More than words! How narrative anchoring and enrichment help to balance differentiation and conformity of entrepreneurial products*

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Abstract

Entrepreneurs face the challenge of having to conform to gain legitimacy, while at the same time differentiating themselves to gain competitive advantage. We show how entrepreneurs can craft an entrepreneurial narrative to succeed in this task among the user audiences empowered to evaluate their products. Building on theories of categorization, optimal distinctiveness, and cultural entrepreneurship, we propose that entrepreneurs should utilize the narrative's semantic relations with cultural meanings of established products and categories. We measure these semantic relations using machine learning methods for natural language, applied to data on 2,901 independent video game proposals compared to 11,651 established games. Our findings reveal that semantically anchoring a product's narrative in the cultural meaning of claimed categories can help to leverage the benefits of differentiation, especially when spanning multiple, atypical categories. When a product focuses on few categories, semantically enriching a narrative with unclaimed categories' cultural meaning makes them more favorable to additional, possibly fragmented audiences that would not have considered them otherwise. Our results point to a key theoretical role of cultural entrepreneurship in shaping audience evaluation of categorization and differentiation by entrepreneurial ventures. It provides guidelines for entrepreneurs for managing the trade-off between differentiation and adherence to established cultural norms.

Keywords: cultural entrepreneurship, distinctiveness, narrative, categories

JEL Codes: M13, L26, L22

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1 Introduction

A central question at the intersection of strategy and organizational literature is how firms should manage the competing pressures of the pull toward conformity through isomorphic pressure and the competitive push toward differentiation to attain competitive advantage (Deephouse, 1999; Fisher, 2020; Zhao et al., 2017; Zuckerman, 2016). Explanations for the existence and relative strength of the countervailing forces of differentiation and conformity are centered around heterogeneous preferences and perceptions of evaluating audiences (Deephouse, 1999; Zhao et al., 2017) or the composition of competitors (Haans, 2019). Most research in this area to date concludes with a "strategic balance perspective" on how organizations should manage the opposing pressure to attain optimal distinctiveness, recommending a degree of strategic differentiation that renders a firm "as different as legitimately possible" (Deephouse, 1999, p.147). The uncertainty about such an optimal degree of differentiation is particularly high for entrepreneurial ventures that seek to introduce novel products (Greve and Taylor, 2000; Ferriani et al., 2009) or operate in markets with fuzzy category boundaries and identities (Zhao et al., 2017; Navis and Glynn, 2010, 2011). This context translates into high uncertainty about whom to express differentiation and conformity to and how (Fisher et al., 2017; Glynn and Navis, 2013), as well as whom to address as a target audience and how (Fisher et al., 2016).

To contribute to this puzzle, we combine current perspectives on optimal distinctiveness theory (Deephouse, 1999; Zhao et al., 2017) with those on categorization (Barlow et al., 2019; Cattani et al., 2017; Vergne and Wry, 2014) and cultural entrepreneurship (Garud et al., 2014; Lounsbury and Glynn, 2001). We argue that audiences use established categories as a lens to determine the favorability of differentiation and conformity claims. Entrepreneurs can "focus" or "widen" this lens by leveraging the cultural meaning and codes of product categories (Vergne and Wry, 2014) in their entrepreneurial narrative, i.e., the textual description of the product. In this way, categories are not only competitive groups to differentiate from, but also reservoirs of cultural codes and meanings that entrepreneurs can use in the construction of their narratives (Navis and Glynn, 2011; Soublière, 2019).

By semantically *anchoring* the narrative in *claimed* categories' cultural code and meaning, they "focus" the audience's lens to appear as a more representative and legitimate member of this category. By semantically *enriching* the narrative with *unclaimed* categories' cultural code and meaning, they "widen" the audience's lens to enable their product to appear favorable to additional, possibly fragmented audiences that would not have considered them otherwise.

Analyzing data on 2,901 video game proposals by independent developers and 11,651 established games, using machine learning methods for natural language, we compare entrepreneurial with existing products in a novel and integrative way based on their categories and narratives. We find that audiences in the entrepreneurial video game market on average embrace high levels of strategic differentiation. We further find that products presented using a narrative that is firmly anchored in claimed categories' cultural code and meaning suffer less from a lack of legitimacy, and that this practice helps to convey necessary information users need to make educated choices (Vergne and Wry, 2014). Especially when products span uncommon and distant category combinations, narrative anchoring allows entrepreneurs to create a coherence among disparate product elements that audiences find favorable.

Having covered their base audience, entrepreneurs can further enrich their narratives to resonate with audiences of categories beyond their own (Giorgi, 2017). Particularly in cases where the product spans only few categories or even a single one, entrepreneurs can enrich their narratives with cultural code and meaning of unclaimed categories to raise awareness and gather additional support from multiple audiences to further improve their evaluation (Fisher et al., 2016).

Our findings provide new and detailed empirical evidence on how narratives contribute to a product's "legitimate distinctiveness" (Lounsbury and Glynn, 2001; Navis and Glynn, 2011; van Werven et al., 2015). Previous research emphasizes the role of narratives as "a mediator between sense making and plausibility judgments" (Navis and Glynn, 2011, p.489). We extend this role by showing two ways how narratives utilize categories' cultural code and meanings to steer audience evaluation: Through a narrative *anchoring* effect, narratives are suited to accentuate entrepreneurs' categorization efforts in case of category spanning, as well as their differentiation efforts in claimed product categories. Through a narrative *enrichment* effect, in turn, narratives help to reach out to audiences in unclaimed product categories and gain their support. While past research has theorized and measured differentiation and conformity based on exact matches of concrete features (Zhao et al., 2018) or frequent words (Barlow et al., 2019), we show that narratives and the *meanings* they entail have also an immediate impact on audience evaluation of entrepreneurial claims.

From a managerial perspective, the results provide evidence on how entrepreneurs can use an important cultural resource to position themselves in product categories. Entrepreneurs should carefully design their narratives to fit the product categories they want to span by addressing their specific cultural meaning. In addition, they should include cultural codes from other product categories to appeal to additional audiences. These insights are particularly valuable for new ventures that seek to empower their users to take a more active stake in corporate decision-making, to explore crowdfunding platforms as a means of financing (Parhankangas and Renko, 2017), and to introduce novel and innovative products that differ from incumbents (Greve and Taylor, 2000). Being able to attenuate the negative effects of differentiation offers entrepreneurs a much better chance of presenting their products for evaluation while benefiting from lower competition. Thus, narratives are "more than words," allowing entrepreneurial ventures to reap the benefits of strategic differentiation rather than to suffer from its drawbacks, and to draw attention to themselves.

2 Theoretical background

2.1 Audience evaluation of strategic differentiation through a category lens

A key element of audiences' evaluation of organizations and their products is how they compare to others (Deephouse, 1999; Zuckerman, 1999). Organizations have developed several ways of strategically striking the balance between appearing legitimate while still being able to differentiate themselves from competitors (Barlow et al., 2019). This includes strategic categorization (Cattani et al., 2017; Vergne and Wry, 2014), i.e., aligning or linking themselves to an existing categorical schema, as well as strategic differentiation, i.e., deciding how to express conformity and differentiation and to whom (Zhao et al., 2017). Strategic categorization allows organizations and their products to shape the narrative of their positioning by establishing the grounds of competition (Barlow et al., 2019; Cattani et al., 2017), and gives them the chance to influence category boundaries and trajectories (Khaire and Wadhwani, 2010). In selecting a category (combination), they set out the framework and create a "lens" through which audiences perceive and evaluate them and their products (Barlow et al., 2019; Vergne and Wry, 2014; Zhao et al., 2013).

Audience evaluation often relies on categories because they "coalesce around a set of sufficiently similar features involving technologies, cultural features, values, and potential uses" (Vergne and Wry, 2014, p.68) and are particularly receptive to sociocultural interpretations (Bowers, 2014). In terms of products, established and predefined categories act as guiding posts or even constraints that one needs to adhere to when trying to position one's own products (Wry and Lounsbury, 2013; Navis and Glynn, 2011). They are social classification systems that reflect expectations and preferences (Zuckerman, 1999) and represent a shared understanding of common features of products offered within the same category (Paolella and Durand, 2016). As a consequence, they embody the material and symbolic resources, practices and meanings in the form of a "cultural code" that conveys meaning used to assess whether and how well a product fits into a category (Vergne and Wry, 2014). We propose that categories' cultural code and meaning sets the boundaries in audience evaluation of an organization's or product's differentiation efforts, i.e., their attempts to achieve optimal distinctiveness within their claimed categories (Barlow et al., 2019).

According to the literature on optimal distinctiveness, the effect of strategic differentiation on audience evaluation and, subsequently, on performance derives from two opposing cost-benefit mechanisms. The benefit of differentiation is that it allows firms and products to avoid competition (Deephouse, 1999; Haans, 2019; Zhao et al., 2017; Zuckerman, 2016), but it also implies a cost of decreasing conformity, and thus legitimacy (Deephouse, 1999; Haans, 2019; Zuckerman, 2016). Notwithstanding the managerial relevance of this trade-off, it is hardly possible to conclude on how firms should position themselves along this continuum (Deephouse, 1999; Haans, 2019; Zhao et al., 2017). Arguments have been brought forward in favor of optimal intermediate differentiation levels that balance costs and benefits (Deephouse, 1999; Roberts and Amit, 2003), while others have argued in favor of either low or high distinctiveness levels to avoid a position of being "stuck in the middle" (Cennamo and Santalo, 2013; Haans, 2019). The relative strength of these countervailing forces depends on contextual factors that can ultimately give rise to positive or negative as well as U-shaped or inverted U-shaped effects of differentiation (Haans, 2019; McKnight and Zietsma, 2018).

While both audience preferences for conformity and differentiation, and categories' cultural codes are very well understood in mature market contexts, they can both be particularly hard to foresee in entrepreneurial markets (Cennamo and Santalo, 2013; Navis and Glynn, 2010, 2011; Zhao et al., 2017). These entrepreneurial markets can be conceptualized based on several criteria, often following the premise of innovative products as a central element (Greve and Taylor, 2000). Typical or dominant product designs have not yet emerged (Zhao et al., 2018) and new ventures exhibit fuzzy identities and heterogeneous market positions (Zhao et al., 2017; Navis and Glynn, 2010, 2011). This translates into high uncertainty about whom to express differentiation and conformity to and how (Fisher et al., 2017; Glynn and

Navis, 2013), as well as whom to address as a target audience and how (Fisher et al., 2016).

However, there is substantial reason to assume a strongly positive effect of strategic differentiation on audience evaluation (Taeuscher et al., 2020). Audiences such as customers or users are generally considered "market takers" (Pontikes, 2012), but have also been shown to exhibit a "taste for atypicality" (Goldberg et al., 2016a). They are often inclined to favor high levels of differentiation in entrepreneurial concepts, as uncertainty surrounding immediate commercial decisions and applications is not yet in the foreground (Fisher et al., 2016), and differentiation is strongly associated with novelty (Greve and Taylor, 2000). Especially when empowered as a target audience in entrepreneurial markets, as in crowdfunding settings, users may actually *expect* high levels of differentiation and novelty (Taeuscher et al., 2020). Differentiation may thus hold the dual benefit in entrepreneurial markets of not only deterring competitive pressure but also gaining normative (Suchman, 1995) or innovative legitimacy (de Clercq and Voronov, 2009).

Yet there is also reason to assume that differentiation can have a negative impact on audience evaluation in entrepreneurial markets. When everyone tries to be different, low levels of differentiation may fail to avoid competition, while at the same time inducing higher uncertainty and lower comprehensibility (Cennamo and Santalo, 2013; Haans, 2019; Zhao et al., 2018). In addition, high levels of differentiation may complicate audiences' evaluation, as they may lack the necessary cultural code for evaluation (Vergne and Wry, 2014). Condensing these arguments, we assume that this renders the positive effect of strategic differentiation more pronounced. Yet we also assume that a point of differentiation exists beyond which no further competitive pressure can be applied or normative legitimacy gained. At this point, only very limited benefits can be realized, and only by experiencing significant drawbacks, the positive effect of strategic differentiation diminishes and is eventually rendered negative (Deephouse, 1999). Thus, we hypothesize:

Hypothesis 1 *Strategic Differentiation has an inverted U-shaped relationship with Audience Evaluation.*

2.2 Adjusting audiences' category lens through entrepreneurial narratives

The preceding section put forward the argument that categories and their cultural codes serve as a lens that helps audiences to perceive, make sense of, and evaluate products and their differentiation efforts. In this section, we want to propose that this lens can be influenced by means of cultural entrepreneurship (Lounsbury and Glynn, 2001). "Cultural" in this context refers to a broader, interpretative framework that helps audiences with sense making and reflects their values and their social and cultural framework (Scott and Lane, 2000). At the core of the literature on cultural entrepreneurship lies the assumption that audiences are aided by cultural elements in determining the normative appropriateness of new ventures (Lounsbury and Glynn, 2001). The list of such cultural elements contains symbols, names, stories, and narratives (Lounsbury and Glynn, 2001; van Werven et al., 2015; Zhao et al., 2013) that all shape sense making and evaluation of entrepreneurial claims (Navis and Glynn, 2011). From the list of such elements, we propose entrepreneurial narratives as particularly suitable, as they are "the stories that are told about entrepreneurs and/or their firm" (Martens et al., 2007, p.1109). They help entrepreneurs to leverage resources (Martens et al., 2007), convey arguments to evaluators (van Werven et al., 2015), and contextualize innovation by way of relational, temporal, and performative efforts (Garud et al., 2014).

We propose that entrepreneurs can use narratives to adjust, expand, and reconnect categories' cultural code and meaning that audiences use when evaluating their product (Soublière, 2019). We argue that there are two ways that entrepreneurs can make use of this (Soublière, 2019): (1) By *anchoring the narrative* within the cultural code and meaning of claimed categories, entrepreneurs may try to appear more legitimate within claimed product categories (Navis and Glynn, 2011). (2) By *enriching the narrative*, entrepreneurs may try to include additional cultural code and meaning, such as those of unclaimed categories, and thus appeal to additional audiences by helping them relate to the product.

2.2.1 Narrative anchoring: Focusing the category lens

We argue that narratives can improve audience evaluation through *narrative anchoring*. Anchoring the narrative requires balancing familiarity and novelty, essentially "to leverage what is 'old and familiar' to make what is 'new and different' more palatable" and to "blend in prevalent cultural frameworks" (Soublière, 2019, p.121). Anchoring the narrative aligns the content and semantics with the cultural code of claimed product categories, thereby significantly facilitating audience evaluation (Zhao et al., 2013). This anchoring signals cultural alignment with an organizational field (Scott, 1995) as well as affiliation with one's peers (Srivastava et al., 2018; Goldberg et al., 2016b), which all positively contribute to evaluation (Dahl et al., 2015).

An anchored narrative signals adherence to established practices (Fisher et al., 2016, 2017) and allows entrepreneurs to "rely most heavily on symbolic affiliations and adherence to processes that are familiar and understandable" (Fisher et al., 2016, p.391). Narrative anchoring can also increase resonance by addressing the typical promotional, communicative, and symbolic cues that guide evaluators in their judgment of legitimacy (Lounsbury and Glynn, 2001; Navis and Glynn, 2011; Connelly et al., 2011). Anchoring the narrative facilitates the evaluation of products by conveying arguments in a familiar structure (van Werven et al., 2015), adding known reference points to aid audiences' sense making (Navis and Glynn, 2011; Wry et al., 2011). Consequently, we argue that narrative anchoring improves audience evaluation of the product it represents, as it makes it easier for audiences to interpret and access the cultural code needed for evaluation (Soublière, 2019).

Moreover, narrative anchoring is deemed useful in cases of multiple, possibly uncommon category combinations. To make sense of these combinations, audiences must not only have knowledge of the multiple cultural code and meaning of these categories, but also the ability combine them cognitively into a single evaluation standard. Narrative anchoring may overcome this issue by helping audiences to see more clearly how the product is related to claimed categories, emphasizing the cultural code and meaning that these categories entail

(Vergne and Wry, 2014). This aids audiences in reconnecting seemingly independent or unrelated categorical cultural codes (Soublière, 2019), helps them to relate to the product, and consequently improves their evaluation. Condensing these arguments, we hypothesize:

Hypothesis 2 *Narrative Anchoring has a positive relationship with Audience Evaluation that is strengthened by Category Spanning.*

Narrative anchoring can also extend the perceptual range of products that audiences still find acceptable or appropriate in spite of increasing strategic differentiation. It can achieve this by making products more relatable and easier to understand (Parhankangas and Renko, 2017) to help overcome the liability of differentiation (Zhao et al., 2018). Narrative anchoring can translate the idea of a product into a broader meaning by creating analogies and links to existing, typical product concepts (Navis and Glynn, 2011). This helps audiences to base their evaluation on a product's adherence to the norms, references, and legitimacy perceptions that prevail in a given context (Zuckerman, 2016).

For differentiated products, anchored narratives serve "as a metaphorical 'glue'—that weaves together disparate categories of new venture membership to lend coherence and resonance" (Glynn and Navis, 2013, p.1129) and leads to an improvement of audience evaluation. This positive effect should be particularly pronounced for products with low or intermediate levels of differentiation that are distinct enough to appear illegitimate, yet not distinct enough to generate competitive advantages (Cennamo and Santalo, 2013; Haans, 2019). Anchoring the narrative is particularly advisable for products with intermediate differentiation levels that exhibit a "stuck in the middle" problem (Cennamo and Santalo, 2013; Haans, 2019). Consequently, we argue that narrative anchoring can lower audiences' sensitivity to negative legitimacy effects of strategic differentiation, in particular for low to medium levels of differentiation.

However, we also argue that the positive effect will simultaneously be weakened, as it will be blurred and overridden by the anchored narrative that works against differentiation from competitors. When narrative anchoring is high, audiences exhibit a diminishing sensitivity toward incremental cues of differentiation (Nowlis and Simonson, 1996), and the overall potential to differentiate oneself from competitors is severely limited. Regardless of how well a product is designed to differ from existing ones, audiences will also directly factor the anchoring of concomitant narratives into their judgments. Anchored narratives could consequently cause products with higher differentiation to appear less unique and less able to stand out from their competitors. Moreover, by overly aligning the product with the legitimate and established categorical status quo, a highly anchored narrative could also reduce a product's novelty appeal (Taeuscher et al., 2020) and harm its innovative legitimacy (de Clercq and Voronov, 2009).

Consequently, we expect narrative anchoring to moderate the relationship between strategic differentiation and audience evaluation. We further expect that this effect is more prominent and positive for low and intermediate levels of differentiation, while it is negative for high levels of strategic differentiation. We derive the following hypothesis:

Hypothesis 3 *The inverted U-shaped relationship between Strategic Differentiation and Audience Evaluation is moderated by Narrative Anchoring, such that it is accentuated when Narrative Anchoring is high and attenuated when Narrative Anchoring is low.*

2.2.2 Narrative enrichment: Widening the category lens

Narratives are able to resonate and carry meaning for a variety of audiences across product categories and cultural codes (Lounsbury and Glynn, 2001; Navis and Glynn, 2011). While anchoring uses the cultural codes of claimed categories to appeal to core audiences, it may not be able to easily increase awareness among additional, fragmented audiences, such as those of unclaimed product categories (Giorgi, 2017; Fisher et al., 2016). Those audiences are often skeptical, reluctant, and unfamiliar with the product in question, as they lack the cultural code needed to evaluate it (Soublière and Gehman, 2019; Pontikes, 2012). This gives rise to the need for a narrative that provides this code and shapes their attention and perception (Wry et al., 2011), facilitates a symbolic coupling with their values and expectations (Überbacher, 2014), and resonates with them on a cognitive level (Giorgi, 2017). In order for narratives to fulfill that role, we argue for their *enrichment* by adding cultural codes and meanings from unclaimed categories for audiences to use (Giorgi, 2017; Soublière, 2019).

Resonating with additional audiences constitutes a considerable task, and entrepreneurs need to enrich their narratives with additional culturally resonant meanings to do so (Soublière, 2019). When enriched with the cultural codes of other categories, the narrative increases familiarity and consequently provides meaning to additional audiences (Navis and Glynn, 2011), making it easier for them to relate to a product they lack experience or interest in (Giorgi, 2017). By corresponding to the cultural code available to these audiences, entrepreneurs build *cultural credibility* and provide those additional audiences with precisely the typical promotional, communicative, and symbolic cues they are familiar with (Giorgi, 2017). In this way, narratives can be appropriately "customized" to a target audience (Überbacher et al., 2015) and become a way of steering the evaluations of additional audiences towards a desirable outcome (Fisher et al., 2016). Enriching the narrative with the cultural codes of unclaimed categories allows additional audiences to evaluate a product based on better-known cultural elements that carry familiar meaning and resonance, which results in an easier and more favorable evaluation (Navis and Glynn, 2011). As a result, narrative enrichment draws the attention and support of additional audiences and provides them with references and logics known to them, resulting in a positive effect on evaluation.

However, we argue that such enrichment of the narrative is limited by the categories the product spans. If the product spans or "straddles" multiple categories, it becomes inherently harder for audiences to make sense of it (Bowers, 2014; Hsu et al., 2009; Negro et al., 2011). Having multiple categories to make sense of already, enriching the narrative may confuse audiences if an already complex narrative is further complicated with additional cultural codes of unclaimed categories (Durand and Paolella, 2013; Kennedy and Fiss, 2013). In such a case, enriching the narrative would actually worsen the audience evaluation. As a consequence, we hypothesize:

Hypothesis 4 *Narrative Enrichment has a positive relationship with Audience Evaluation that is attenuated by Category Spanning.*

3 Data and methods

3.1 Empirical setting

We place our study in the video game industry (Cennamo and Santalo, 2013; de Vaan et al., 2015; Zhao et al., 2018). To test our hypotheses, we use data from two different sources. The first data source is Steam, an online video game vendor with a large worldwide user community. In particular, we focus on Steam Greenlight, a community platform that the vendor introduced to efficiently handle requests from independent game developers to be included in the vendor's online store. Developers can present their game project to the user community, and if it gets enough positive user evaluations, it is included in the store, where the entire community can purchase it upon completion. From this public website, we collected information on all entrepreneurial game development projects that were available from the start of this community platform until the time of data collection, i.e., from August 2012 to June 2014.

The submission procedure for each video game proposal is standardized. Developers use a web interface to enter a textual description of their game project and of themselves. They can also upload images and videos for further illustration. Finally, they can assign predefined tags referring to available languages (English, Russian, etc.), compatible platforms (PC, Mac, etc.), player modalities (single-player, multiplayer, etc.) and—important for our research—15 different categories (shooter, adventure, etc.). For all products, we collected the textual descriptions and information on claimed categories and entrepreneurial teams, as well as user evaluations described next.

Once a game project is published on the platform, the time frame for it to receive votes is unlimited. Users can take two forms of action to express their evaluation of a game. First, they can vote to make a game project available in the store upon completion. The number of votes of this kind that a given game has received previously is not, however, visible to other users, so that observational learning cannot affect users' voting behavior during this early evaluation phase. Only once Steam perceives a game to have a sufficient number of positive votes does it turn on a "Greenlight" for this game that is visible to all users. These final decisions do not happen individually for each game but in irregular waves of multiple games. Second, users can add a game to their personal collection of favorite games. The number of times a given game has been added to users' personal collections is visible to others at all times.

The Steam Greenlight platform is one example of a crowd-based evaluation platform for entrepreneurial project proposals, which are also becoming increasingly popular in the form of crowdfunding (Parhankangas and Renko, 2017). As a consequence of this newly gained popularity, these platforms typically have a brief history and sometimes also a short lifespan. It follows that evaluating users will likely base their judgments of difference and similarity, which are important to our study, on knowledge and experience they have gained in markets for established products. To reliably base our measures on this assumption, we added a second data source on published games available in established markets. In particular, we collected data from MobyGames, a comprehensive public website that lists information on video game releases (de Vaan et al., 2015; Zhao et al., 2018). Following the approach of de Vaan et al. (2015), we focused on games published in the five years prior to our observation period for the Steam Greenlight games, i.e., from August 2007 to July 2012.

For the games on MobyGames, we collected information on the textual descriptions and claimed categories. We removed games that had textual descriptions of less than 20 tokens (after the cleaning steps described below) and those that claimed none of the 15 Steam categories. This yielded a final sample size of 2,901 games from Steam Greenlight and 11,651 games from MobyGames. This approach allows us to benchmark the newly proposed games against existing ones, in terms of both categories and narratives, to more reliably account for audience expectations in the evaluation of entrepreneurial products.

3.2 Measurements

3.2.1 Dependent variables

Our dependent variables are based on the two types of user behavior described above: (1) Users' votes to include a game in the Steam store and (2) users' additions of a game to their personal favorite lists. We assume both types of behavior to be reliable and correlated indicators of positive user evaluations. While the former is more closely related to users' actual economic impact, we only observe it as an aggregated binary indicator. Conversely, while the latter is not directly related to economic impact, it is a more nuanced indicator to quantify different levels of positive user evaluations. Therefore, our primary dependent variable *Number of Positive Audience Evaluations* is based on the number of times a given game was added to user collections of favorite games. This variable is a positive evaluation signal by users that should reflect their actual votes on the game with respect to the vendor. Given the count nature of this dependent variable and its overdispersion revealed in the analyses, we employ a negative binomial model in the regression analyses. In our robustness checks, we analyze the binary indicator *Overall Positive Audience Evaluation (Yes/No)* as a dependent variable in binary probit regressions.

3.2.2 Independent variables

Narrative-based measures are constructed with the textual descriptions of the entrepreneurial projects, which are also used in previous research (Allison et al., 2015; Manning and Bejarano, 2017). We assembled a corpus of textual descriptions of all 14,552 games from Steam and MobyGames. This corpus was thoroughly cleaned by means of tokenizing, lemmatizing, and part-of-speech tagging. This allowed us to focus the further analysis only on tokens that refer to English-language nouns, verbs, adjectives, and adverbs, and that occur at least twice in the entire corpus and thus hold the narratives' core meaning. The final corpus used in the further analysis includes a total of 1,574,627 tokens and 14,190 unique tokens across all 14,552 game descriptions.

In order to derive measures that can operationalize our theorizing around cultural entrepreneurship and narratives, it is important to construct a semantic space for the corpus, in which alignment (distance) between words implies similar (different) meanings. A suitable approach for this task, adopted from machine learning and natural language processing, is called *word embeddings*, which can be learned with the *word2vec* algorithm developed at Google (Mikolov et al., 2013). This algorithm follows the "distributional hypothesis" that the meaning of a word can be derived from the local context of words it appears together with. Accordingly, the algorithm predicts a focal word from its surrounding words (or vice versa) in a shallow (not deep) neural network structure to derive multidimensional vector representations of each word. These word embeddings have been shown to very effectively capture the semantic relationships between words in terms of synonyms and analogies. For example, a search for words similar to "beautiful" would yield "lovely" or "gorgeous," while a search for an analogy based on "man," "king," and "woman" would yield "queen."

Synonyms and analogies also play an important role in entrepreneurial narratives to create a broader understanding of a new product by defining it in terms of already familiar domains of meaning (Navis and Glynn, 2011). For example, in our context, what is generally a "gamer" in a video game could also be a "player" in a sports game, a "hero" in an adventure game, or a "student" in an education game; success in general means "to win a game" but could also be described in a game-specific way by "beating an opponent," "killing a dragon," "shooting an enemy," or "solving a puzzle."

Hence, precisely defining semantic relationships such as synonyms and analogies is an important advantage of word embeddings for our purposes over algorithms such as topic models that work under the "bag of words" assumption, which implies that the order of words in documents does not matter. Thus, topic models do not rely on local word contexts but use global co-occurrences of words within documents across the entire corpus. While relationships between words could be implied from the per-word topic distributions yielded by topic models, they are not suited to this task and do not perform as well. Word embeddings capture semantic relationships more precisely, even for words that have never actually appeared together in the same document, using the rich relations that these words share with other words in their local contexts throughout the corpus.

A special prerequisite for creating a measure of *narrative anchoring* is being able to locate a game's claimed categories in the same semantic space as the words in the narratives. To achieve this goal, we use an extension of the *word2vec* algorithm, i.e., *paragraph vector* (Le and Mikolov, 2014). This algorithm also allows for the creation of word embeddings for chunks or subsets of variable length in a corpus; for instance, a sentence, a paragraph, an entire document or, as in our case, all games claiming a certain category. The variant of the algorithm that we use, the distributed memory model, predicts a focal word based on its local context words *plus* an additional indicator for the respective subset of the corpus the focal words belong to. In the implementation of that algorithm we use, i.e., *doc2vec* in *Python's gensim* package, it is possible to add more than one indicator to the prediction that may also refer to several cross-level aggregations of the corpus. This is useful in our case, as a given game can claim several categories that are each shared with different other games. This procedure allows us to locate not only each word in a semantic space, but also the 15 categories based on the words that games within a certain category typically use in their narratives.

We train this model with 100 dimensions for the word embeddings and a local context window of 15 words. Some descriptive results that show how this algorithm performed in our setting are presented in Table 1. This table illustrates that for (almost) each category the name itself is a representative word, i.e., it is also used in the narrative to underline category membership. This makes sense and is also evidence that the algorithm works as intended. The other words are all inherently related to the respective categories as well.

Table 1: Representative words for each category

Category	Representative words
Action	action, drone, samurai, outrageous, crouch, kick, grab, hungry, man, pie
Adventure	adventure, click, hotspot, surreal, inventory, logical, dear, self, inquiry, bizarre
Arcade	arcade, endlessly, imp, luminosity, nonsense, decade, breakout, retro, invader, hamster
Education	educational, math, arithmetic, learning, sat, multiplication, reader, reading, tutor, vocabulary
Horror	horror, zombie, haunt, werewolf, nightmare, flashlight, ammunition, psychological, scare, vampire
Multiplayer	persistent, guild, server, roam, subscription, free, fan, siege, membership, beta
Music	song, music, conductor, hip, guitar, rhythm, musical, sing, dance, drum
Platformer	platform, jump, scroll, jumping, bit, temporary, level, double, squirrel, collect
Puzzle	puzzle, solve, puzzler, disappear, vanish, cryptogram, anagram, magnet, object, manipulation
Racing	racing, car, race, racer, track, drift, bike, driver, vehicle, steering
Role-Play	dungeon, quest, combat, fantasy, craft, loot, class, cleric, monster, party
Shooter	shooter, bullet, shoot, kill, cover, ship, weapon, intent, ion, third
Simulation	simulation, simulate, simulator, geopolitical, clinic, functional, economic, hypothetical, maintain, vet
Sports	football, soccer, dunk, stadium, pro, pitch, batting, coach, pitching, basketball
Strategy	strategy, unit, resource, tactic, tactical, logistic, turn, build, army, artillery

Our first key independent variable is *Strategic Differentiation*. While past research has based differentiation measures on exact matches of concrete features (Zhao et al., 2018) or frequent words (Barlow et al., 2019), our measure is supposed to capture differentiation in the cultural meaning space of the market domain. Thus, our measure of *Strategic Differentiation* is based on the distance between a new game's narrative and an incumbent game's narrative. The distance is measured as pairwise cosine distance, typically used for word embeddings, between the embedding vector of a focal Steam game i, $\boldsymbol{\vartheta}_i$, and the embedding vector of a game p_i, $\boldsymbol{\vartheta}_{p_i}$, that is prototypical for game i taking into account the incumbent games from the MobyGames sample in similar categories:

$$Strategic\_Differentiation_i = 1 - \left[\frac{\sum_{l=1}^{L} \vartheta_{li}\, \vartheta_{lp_i}}{\sqrt{(\sum_{l=1}^{L}\ \vartheta_{il}^2)} \cdot \sqrt{(\sum_{l=1}^{L}\ \vartheta_{lp_i}^2)}} \right] \quad (1)$$

where ϑ_{li} is the value of the embedding vector on the l-th out of L dimensions for game i, which is obtained by taking the average of the l-th embedding value of all words in game i's narrative, weighted by the respective word's *tf-idf* score[1]:

$$\vartheta_{li} = \sum_{t=1}^{T} \omega_{ti} * \vartheta_{lt} \tag{2}$$

where ϑ_{tl} is the value of the word embedding vector on the l-th dimension for the t-th out of T words in the corpus; ω_{it} is the tf-idf score for the t-th word of the corpus with respect to game i, which is zero if game i's narrative does not contain word t.

ϑ_{lp_i} is the value of the embedding vector on the l-th out of L dimensions for a game p_i that is prototypical for game i, taking into account the incumbent games from the MobyGames sample. In market domains where actors only claim membership in one single category, this value can be derived as the average of all incumbent games in that particular category. In our and many other settings, however, spanning multiple categories is the norm; the basis of comparison and competition therefore become fuzzy, especially when category combinations also vary in salience and popularity. We operationalize the category spanning context by measuring the category similarity between a focal game i and an incumbent game j, and use the category similarities with all incumbent games as weights to compute a weighted average embedding vector, $\boldsymbol{\vartheta}_{p_i}$, for a prototypical game p_i. The l-th element of this vector then becomes:

$$\vartheta_{lp_i} = \sum_{j=1}^{J} \eta_{ij} * \vartheta_{lj} \tag{3}$$

where J is the total number of incumbent games in the MobyGames sample and ϑ_{lj} is the value of the embedding vector on the l-th out of L dimensions for an incumbent game j, the same as defined in equation 2 for a new game i. The weight η_{ij} is derived from the category similarity between games i and j. The computation of η_{ij} is based on the Euclidean distance between the category assignment vectors of two games (Zhao et al., 2018). Zhao

[1] *Tf-idf* stands for term frequency–inverse document frequency and reflects how important a word is for a document. It is calculated by the number of times a term occurs in a document divided by the number of documents that contain that term throughout the corpus.

et al. (2018) proposes an adjustment of the category assignment vectors to account for the varying salience and popularity of category combinations. Combinations that have appeared more (less) often than random in the past may be perceived as less (more) distinct. To adjust for these variations in perceived distance, the games' raw assignment vectors are multiplied by a matrix of relative frequencies of category combinations before Euclidean distance is computed between them.[2]

Narrative anchoring of a game i is based on the cosine similarity between the embedding vector of game i, $\boldsymbol{\vartheta}_i$, and the embedding vector of a claimed category k, $\boldsymbol{\vartheta}_k$, averaged over all categories claimed by game i:

$$Narrative\_Anchoring_i = \sum_{k=1}^{K} \left[g_{ik} * \left(\frac{\sum_{l=1}^{L} \vartheta_{li}\, \vartheta_{lk}}{\sqrt{(\sum_{l=1}^{L} \vartheta_{li}^2)} \cdot \sqrt{(\sum_{l=1}^{L} \vartheta_{kl}^2)}} \right) \right] \Big/ g_i \tag{4}$$

where ϑ_{li} is defined as above, g_{ik} is a binary indicator of whether category k is claimed by game i, and g_i is the total number of categories claimed by game i. ϑ_{kl} is the value of the embedding vector on the l-th out of L dimensions for category k.

Narrative Enrichment captures the extent to which a narrative uses cultural codes from market categories outside those claimed by a product. It is therefore based on the average cosine similarity between its embedding vector and the embedding vectors of all categories that game i has *not* claimed. It is derived based on the same formula given in equation 4, but instead of g_{ik} and g_i, we use $1 - g_{ik}$ and $15 - g_i$ to account for unclaimed categories.

Category Spanning is based on the number of categories a product has claimed (Zhao et al., 2013). It measures the number of category affiliations each product entails by way of a function that calculates a vector for each product's so-called grade of membership i in each

[2]See Zhao et al. (2018) for an example of how to construct this matrix. To turn the distances into similarity-based weights, we reversed them by subtracting each from the maximum and scaled them to sum to one. Instead of computing a weighted-averaged, prototypical word embedding vector, these weights can also be applied to the pairwise cosine distances between a focal game i and all incumbent games to compute an average cosine distance. This procedure yields different ranges for *Strategic Differentiation*, but qualitatively the same downstream results. We prefer the procedure to construct an averaged embedding vector of a prototypical game, as this is common practice in the literature on optimal distinctiveness (e.g., Deephouse, 1999; Haans, 2019).

category k (Negro and Leung, 2013; Paolella and Durand, 2016). For instance, a product with the claimed categories *multiplayer* and *strategy*, out of the 15 possible categories in our sample, would have a grade-of-membership vector [0,0.5,0,0.5,0,0,0,0,0,0,0,0,0,0,0]. A product that has claimed the category *simulation* would have the vector [0,0.33,0,0.33,0,0.33,0,0,0,0,0,0,0,0,0]. *Category Spanning* is computed using Simpson's index of diversity (Simpson, 1949):

$$Category\_Spanning_i = 1 - \sum_{k=1}^{K_i} \mu_{ik}^2 \tag{5}$$

where μ_{ik} is the grade of membership, which equals $1/K_i$ if product i is affiliated with category k. K_i is the total number of categories product i has claimed.

We employ three alternative category-based measures in our robustness and post-hoc analyses. First, *Category Atypicality* is taken from Kovács and Hannan (2015) and Goldberg et al. (2016a), who study the atypicality of category combinations spanned by books, movies, and restaurants. It builds on category spanning but also takes into account the distance or similarity between categories spanned. In this measure, similarity between two categories a and b is captured based on their co-occurrences with Jaccard similarity:

$$j_{ab} = \frac{|a \cap b|}{|a \cup b|} \tag{6}$$

and based on Shepard's law Shepard (1986) translated into distance with a negative exponential relationship:

$$d_{ab} = -\frac{ln(j_{ab})}{\gamma} \tag{7}$$

This pairwise distance between categories is then aggregated across all categories a product i spans:

$$D_i = \sum_{a=1}^{K} \sum_{b=1}^{K} g_{ia} * g_{ib} * d_{ab} \tag{8}$$

where g_{ia} and g_{ib} is a binary indicator of whether categories a and b are claimed by product i. To let the final measure increase at a diminishing rate with the number of categories claimed and with the distances between them, the final measure of *Category Atypicality* becomes:

$$Category\_Atypicality_i = 1 - \left(\frac{1}{1 + \frac{D_i}{g_i - 1}} \right) \tag{9}$$

where g_i is the total number of categories claimed by product i. For $g_i = 1$, D_i is set to 0. To devise this measure in our setting, we calculate the distances between categories d_{ab} based on the N games in the MobyGames sample and use them to calculate *Category Atypicality* for each focal game i in the Steam sample. In our computations, we use $\gamma = 10$ to yield a smoothly shaped distribution of this measure.

Second, *Category Distance* is simply the average distance between the spanned categories of game i: $D_i/((g_i{*}(g_i{-}1))/2)$. Third, we measure the relative frequency with which a certain category combination of a game proposal on Steam has appeared before on MobyGames. To turn these highly skewed frequencies into a smoothly distributed measure of *Category Rareness*, we take the log and divide it by -10 to make its range comparable to the other measures. The lowest value of *Category Rareness* we obtain is $-0.1 * log(1,081/11,651) = 0.238$, while the highest value is $-0.1 * log(1/11,651) = 0.936$. Out of 455 realized category combinations in the Steam sample, 275 never appeared before in the MobyGames sample. For the 674 games in the Steam sample with one of these unique category combinations, we set the value of *Category Rareness* to one. [3]

3.2.3 Control variables

To increase the robustness of our analysis, we included several control variables. We control for narrative length using the count of total words to rule out effects of sheer narrative complexity. We included the age of a product proposal on the platform in days as a linear

[3] We thank an anonymous reviewer for the suggestion to look at these relative frequencies. There are 590 unique category combinations in the combined sample and 315 in the MobyGames sample. 2,227 games in the Steam sample have one of the 180 category combinations that also appeared in the MobyGames sample.

and squared term to account for possible non-linear effects (van Oest et al., 2010). Both of these variables were divided by 100 to enhance the interpretability of fairly small regression coefficients. We control for the number of supported operating platforms, such as PC, Mac, Linux, or consoles, as well as the number of player modes, such as single- or multi-player, local or cross-platform co-op, etc. These controls can be considered proxies for technology complexity. We also control for the number of languages a game supports, such as English, Chinese, or German. This measure serves as a proxy for market ambition, since each regionalized version of a game seeks to tap into an additional sales region but also requires localization efforts. Finally, we control for possible entrepreneurial team effects by measuring team size in terms of the number of people, and team experience in terms of prior product proposals submitted to the platform.

4 Results

4.1 Descriptive results

Table 2 and Table 3 show the descriptive statistics and correlations of all variables. Some initial observations can be made. Entrepreneurs are on average more likely to be anchored in their claimed categories than to adhere to unclaimed ones, but there is also higher variation in *Narrative Anchoring* as compared to *Narrative Enrichment*. Furthermore, the correlation between these two variables is only 0.03, making them empirically independent choices for entrepreneurs. However, the correlation with overall *Strategic Differentiation* is -0.27 and -0.45 for *Narrative Anchoring* and *Narrative Enrichment*, respectively. These negative correlations imply that entrepreneurs face some trade-offs and constraints in terms of *Strategic Differentiation* when narratives also need to be anchored in and enriched with existing cultural codes; but the medium effect sizes suggest that there is considerable freedom left.

Table 2: Descriptive statistics

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Number of Positive Evaluations	2,901	36.707	74.397	0	6	41	1,884
Final Valuation Positive (1 = yes)	2,901	0.426	0.495	0	0	1	1
Strategic Differentiation	2,901	0.636	0.098	0.322	0.568	0.700	0.953
Narrative Anchoring	2,901	0.217	0.091	−0.150	0.159	0.265	0.745
Narrative Enrichment	2,901	0.048	0.030	−0.053	0.029	0.069	0.148
Category Spanning	2,901	0.480	0.280	0.000	0.500	0.667	0.857
Category Atypicality	2,901	0.333	0.259	0.000	0.114	0.542	0.907
Category Distance	2,901	0.248	0.165	0.000	0.129	0.375	0.921
Category Rareness	2,901	0.633	0.280	0.238	0.336	0.936	1.000
Category Number	2,901	2.805	1.302	1	2	4	9
Word Count / 100	2,901	3.316	2.335	0.350	1.670	4.270	13.770
Number of Platforms	2,901	2.004	0.900	0	1	3	3
Number of Languages	2,901	2.408	3.377	0	1	2	25
Number of Player Modes	2,901	1.538	0.976	0	1	2	5
Number of Creators	2,901	1.726	1.587	1	1	2	29
No. of Creators' Prior Projects	2,901	0.352	1.210	0	0	0	14
Proposal Age [Days / 100]	2,901	3.341	2.319	0.090	1.170	5.750	6.760

Table 3: Pairwise correlations

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Number of Positive Evaluations	1																
2	Final Valuation Positive (1 = yes)	0.42	1															
3	Strategic Differentiation	0.06	0.08	1														
4	Narrative Anchoring	0.02	0.06	-0.27	1													
5	Narrative Enrichment	0.03	-0.02	-0.45	0.03	1												
6	Category Spanning	0.06	0.08	-0.05	-0.36	-0.14	1											
7	Category Atypicality	0.08	0.10	-0.03	-0.33	-0.14	0.89	1										
8	Category Distance	0.05	0.06	-0.02	-0.31	-0.07	0.81	0.79	1									
9	Category Rareness	0.05	0.07	-0.00	-0.30	-0.05	0.63	0.81	0.71	1								
10	Category Number	0.05	0.03	-0.03	-0.35	-0.13	0.80	0.89	0.63	0.66	1							
11	Word Count / 100	0.13	0.21	-0.25	0.13	0.18	0.11	0.10	0.08	0.06	0.07	1						
12	Number of Platforms	0.03	0.08	-0.01	0.00	0.01	0.11	0.10	0.09	0.09	0.08	0.04	1					
13	Number of Languages	0.06	0.07	0.02	0.03	-0.03	0.02	0.01	0.02	0.01	0.04	0.03	0.12	1				
14	Number of Player Modes	0.07	0.08	-0.20	0.09	0.19	0.13	0.15	0.13	0.11	0.15	0.15	0.15	0.10	1			
15	Number of Creators	0.30	0.20	-0.01	0.01	0.04	0.05	0.04	0.03	0.03	0.04	0.12	0.07	0.06	0.08	1		
16	No. of Creators' Prior Projects	-0.03	-0.02	0.13	-0.04	-0.13	-0.08	-0.08	-0.06	-0.07	-0.04	-0.05	-0.05	0.03	-0.03	0.03	1	
17	Proposal Age [Days / 100]	0.19	0.30	0.00	0.04	0.04	-0.06	-0.05	-0.02	-0.07	-0.05	0.11	-0.09	-0.03	0.01	-0.02	-0.11	1

n = 2,901. Correlations exceeding |.03| are significant at $p < 0.05$.

4.2 Regression results

All statistical analyses are conducted using the free statistics software *R*. We choose a negative binomial model for the regression analyses, as the test for overdispersion of the dependent count variable is highly significant ($p = 2.2e - 16$). [4]

Table 4 exhibits the main regression results with the dependent variable *Audience Evaluation* measured as the number of positive evaluations. Model 1 introduces the linear and squared terms of *Strategic Differentiation* to test Hypothesis 1. Both coefficients are significant with the expected signs, but, as Figure 1 reveals, the curvature is not strong enough to yield a significant inverted U shape. While we find significantly diminishing returns to *Strategic Differentiation*, we cannot (entirely) confirm Hypothesis 1.

By comparison, in Figure 2, we predict the direct effect of *Strategic Differentiation* based on Model 6, which controls for both *Narrative Anchoring* and *Narrative Enrichment*. As *Narrative Anchoring* and *Narrative Enrichment* mediate the diminishing effect of the squared *Strategic Differentiation* term and the effect becomes (almost) linear and strongly positive, this can be seen as evidence that the two constructs provide legitimacy by relating to existing category codes. Model 2 shows that the addition of *Narrative Anchoring* alone already mediates the negative squared term of *Strategic Differentiation*.

Model 3 adds the interaction effect of *Narrative Anchoring* with *Category Spanning*. The respective coefficient is strongly significant and positive. Therefore, we find strong support for Hypothesis 2. Model 4 investigates the moderation Hypothesis 3 between *Strategic Differentiation* and *Narrative Anchoring*. Both corresponding coefficients are significant and in line with a steepening of the inverted U-shaped relationship predicted in Hypothesis 3.

[4] We also tested for potential zero-inflation in two ways: First, for a baseline specification with all control variables, we estimated a negative binomial without zero-inflation and predicted the number of zeros. This exercise results in 156.2 predicted zeros, which aligns very well with the 155 observed zeros. Second, we conducted a Vuong test. In our case, the Vuong test statistic with the AIC correction is 1.77, which suggests a statistically significant advantage of the zero-inflated model ($p = 0.04$). The Vuong test statistic with the BIC correction is -2.80 and suggests a significant advantage of the standard negative binomial model ($p = 0.02$). Given our relatively large sample size, however, the BIC correction should be preferred. Hence, we stick to the more parsimonious negative binomial model.

Table 4: Negative binomial regression results

	DV: Number of Positive Evaluations					
	(1)	(2)	(3)	(4)	(5)	(6)
Strategic Differentiation	6.96***	5.15***	4.49**	−5.63	−5.70	−6.40
	(1.96)	(1.97)	(1.96)	(4.49)	(4.47)	(4.49)
Strategic Differentiation Squared	−3.70**	−2.06	−1.50	5.84*	6.48*	6.99**
	(1.52)	(1.53)	(1.53)	(3.35)	(3.34)	(3.36)
Narrative Anchoring		1.33***	0.54	−17.29***	−16.32**	−17.17***
		(0.25)	(0.33)	(6.60)	(6.57)	(6.59)
Narrative Anchoring × Category Spanning			2.68***	2.67***	2.79***	2.83***
			(0.77)	(0.77)	(0.77)	(0.77)
Strategic Differentiation × Narrative Anchoring				53.91***	52.15**	54.45***
				(20.59)	(20.51)	(20.55)
Strategic Differentiation Squared × Narrative Anchoring				−39.65**	−38.66**	−40.09**
				(15.88)	(15.81)	(15.83)
Narrative Enrichment					4.34***	6.18***
					(0.80)	(1.55)
Narrative Enrichment × Category Spanning						−3.45
						(2.51)
Category Spanning	−1.73***	−1.60**	−1.20*	2.18	1.67	1.80
	(0.64)	(0.63)	(0.64)	(1.48)	(1.48)	(1.48)
Word Count / 100	0.47***	0.61***	0.03	0.03	0.13	0.30
	(0.07)	(0.08)	(0.19)	(0.19)	(0.19)	(0.23)
Number of Platforms	0.10***	0.10***	0.09***	0.10***	0.09***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of Languages	0.05**	0.05**	0.05**	0.05**	0.05**	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Number of Player Modes	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of Creators	0.10***	0.10***	0.10***	0.09***	0.08***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No. of Creators' Prior Projects	0.17***	0.17***	0.17***	0.17***	0.17***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Proposal Age [Days / 100]	−0.05***	−0.04**	−0.05***	−0.05***	−0.04**	−0.04**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Proposal Age Squared	0.62***	0.62***	0.63***	0.62***	0.64***	0.64***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Constant	−0.06***	−0.06***	−0.06***	−0.06***	−0.06***	−0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2,901	2,901	2,901	2,901	2,901	2,901
Log Likelihood	−12,750.13	−12,737.43	−12,731.49	−12,726.55	−12,712.22	−12,711.30

Note: Standard errors reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

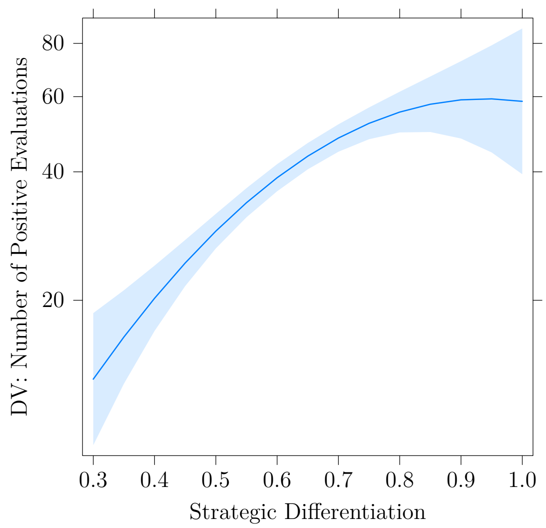

Figure 1: Effects of *Strategic Differentiation* predicted based on Model 1

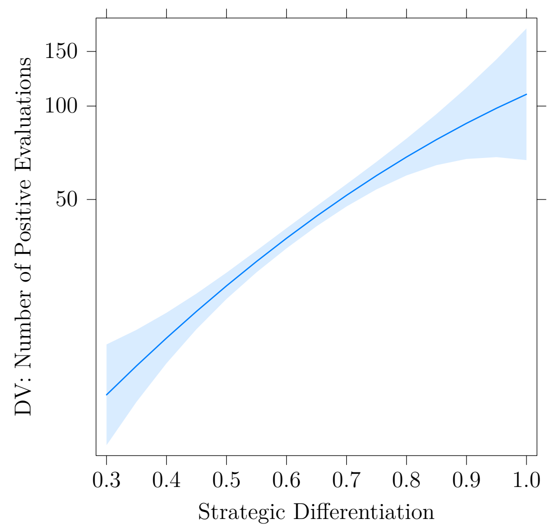

Figure 2: Effects of *Strategic Differentiation* predicted based on Model 6

Figure 3 further illustrates this moderation effect and confirms that the inverted U-shape effect of *Strategic Differentiation* is accentuated at high levels of *Narrative Anchoring*. Model 5 adds the direct effect of *Narrative Enrichment* and Model 6 its interaction effect with *Category Spanning*. However, we only find support for a strong direct effect of *Narrative Enrichment*, but no significant negative moderation as predicted in Hypothesis 4.

4.3 Robustness and post-hoc analysis

The objectives of the robustness and post-hoc analyses are threefold: First, we test whether our results are robust for the alternative binary dependent variable *Final Evaluation Positive* in probit regression analyses. Table 5 shows that we can replicate the basic pattern of results, although a few differences are worth noting. The inverted U-shaped effect of *Strategic Differentiation* seems to be more pronounced, as the squared term remains significant even after including *Narrative Anchoring* in Model 2.

The moderation of *Strategic Differentiation* by *Narrative Anchoring* is only marginally significant, as shown in Models 4 to 6. In non-linear models such as probit regression,

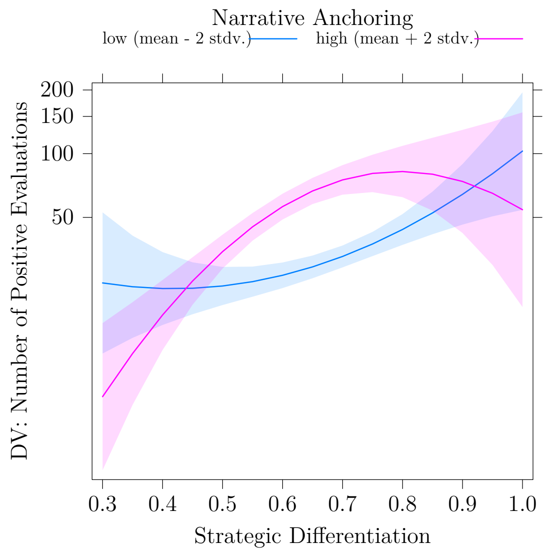

Figure 3: Effects of *Strategic Differentiation* moderated by *Narrative Anchoring* (Negbin Results: Model 4)

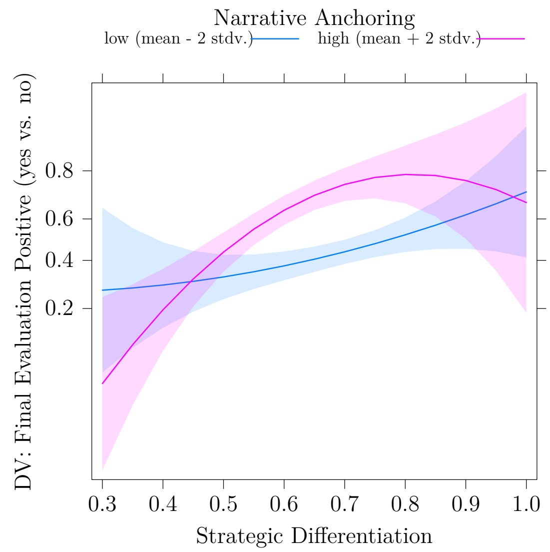

Figure 4: Effects of *Strategic Differentiation* moderated by *Narrative Anchoring* (Probit Results: Model 4)

however, a significant interaction effect is neither necessary nor sufficient for flattening or steepening, because these interaction effects are at least partly an artifact of the chosen regression model (Greene, 2010) and are more difficult to derive algebraically in such models (Hoetker, 2007). Therefore, we again plot this effect in Figure 4 and find a pattern that is consistent with Hypothesis 3.

The direct effect of *Narrative Enrichment* is not significant in Model 5, but its interaction effect with *Category Spanning* in Model 6 is, so that we find (partial) support for Hypothesis 4. Figures Figure 5 and Figure 6 visualize the evidence in favor of Hypotheses 2 and 4. It becomes evident that *Narrative Anchoring* is even more beneficial for products with high *Category Spanning*, while *Narrative Enrichment* is beneficial only for products with low *Category Spanning* and may even be harmful for products with high *Category Spanning*.

Second, we tested the moderation effects of Hypotheses 2 and 4 with the alternative category-based measures described above. Without showing the regression table and plots, we summarize these results briefly as follows: The moderation Hypotheses 2 and 4 can both be replicated with all three alternative measures *Category Atypicality*, *Category Distance*, and

Table 5: Probit regression results

	DV: Final Evaluation Positive (yes vs. no)					
	(1)	(2)	(3)	(4)	(5)	(6)
Strategic Differentiation	8.92***	7.72***	7.59***	−2.26	−2.34	−3.99
	(2.52)	(2.54)	(2.54)	(5.81)	(5.81)	(5.88)
Strategic Differentiation Squared	−5.28***	−4.07**	−3.91**	2.95	3.09	4.27
	(1.94)	(1.97)	(1.97)	(4.31)	(4.32)	(4.37)
Narrative Anchoring		1.43***	0.88**	−14.74*	−14.69*	−16.73*
		(0.33)	(0.42)	(8.64)	(8.65)	(8.75)
Narrative Anchoring × Category Spanning			1.98**	1.76*	1.79*	1.83*
			(0.98)	(0.99)	(0.99)	(0.99)
Strategic Differentiation × Narrative Anchoring				45.40*	45.39*	50.85*
				(26.79)	(26.80)	(27.11)
Strategic Differentiation Squared × Narrative Anchoring				−31.86	−31.85	−35.13*
				(20.53)	(20.54)	(20.75)
Narrative Enrichment					0.76	5.27***
					(1.02)	(2.01)
Narrative Enrichment × Category Spanning						−8.40***
						(3.24)
Category Spanning	−6.01***	−6.10***	−5.94***	−2.54	−2.60	−2.30
	(0.83)	(0.83)	(0.83)	(1.93)	(1.93)	(1.94)
Word Count / 100	0.29***	0.48***	0.04	0.09	0.11	0.54*
	(0.09)	(0.10)	(0.24)	(0.24)	(0.24)	(0.30)
Number of Platforms	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of Languages	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Number of Player Modes	0.02***	0.02***	0.02**	0.02***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of Creators	0.06**	0.05*	0.05*	0.05*	0.05	0.05*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
No. of Creators' Prior Projects	0.20***	0.20***	0.20***	0.20***	0.20***	0.20***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Proposal Age [Days / 100]	0.01	0.01	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Proposal Age Squared	0.58***	0.58***	0.58***	0.58***	0.58***	0.58***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Constant	−0.05***	−0.05***	−0.05***	−0.05***	−0.05***	−0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2,901	2,901	2,901	2,901	2,901	2,901
Log Likelihood	−1,636.64	−1,626.89	−1,624.81	−1,622.61	−1,622.33	−1,618.97

Note: Standard errors reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

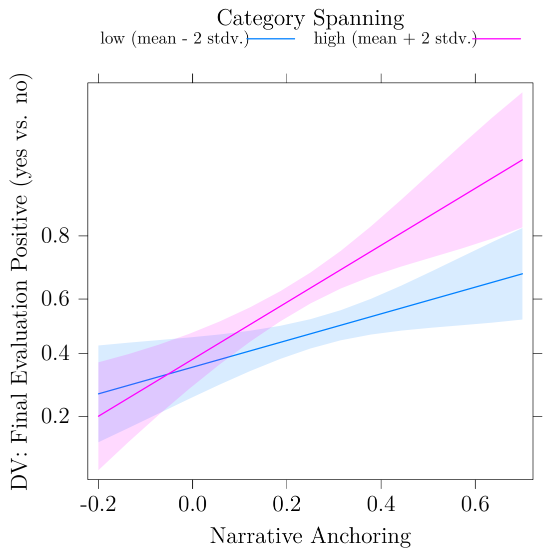

Figure 5: *Narrative Anchoring* moderated by *Category Spanning*

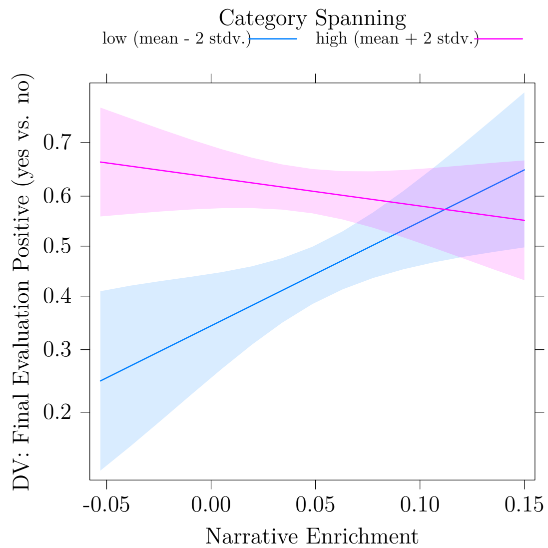

Figure 6: *Narrative Enrichment* moderated by *Category Spanning*

Category Rareness. Beyond the sheer number of spanned categories, these three measures all also capture the distance and rareness as an additional quality of spanned categories. In fact, the moderation effects are even more pronounced with these three measures in the following sense: There is no benefit to *Narrative Anchoring* if the spanned categories are not also atypical, distant, and rare, but at the same time *Narrative Enrichment* can be truly harmful under these conditions. It is thus not only the sheer number, but also the atypicality and distance between spanned categories as well as the rareness of spanned category combinations that drive the contingent benefits of either *Narrative Anchoring* or *Narrative Enrichment*.

Third, we explore the three-way interaction effect between *Strategic Differentiation*, *Narrative Anchoring*, and *Category Spanning* as a logical follow-up to the hypothesized two-way interactions. The left panel of Figure 7 shows that, for products with low *Category Spanning*, *Narrative Anchoring* only marginally leverages the benefits of *Strategic Differentiation*. The right panel for products with high levels of *Category Spanning* shows that *Narrative Anchoring* significantly leverages the benefits of *Strategic Differentiation* across a wide range of values. The inverted U-shaped relationship becomes very accentuated with increasing returns on *Strategic Differentiation* for values of up to 0.75. After that, the high values of *Narrative Anchoring* are still preferable to low values, but the gap closes from there. It becomes evident that the extent to which a new venture proposal can reap the benefits of *Strategic Differentiation* is constrained by *Narrative Anchoring* at high levels. We conclude that, for high levels of *Category Spanning*, *Narrative Anchoring* even more strongly accentuates the inverted U-shaped relationship of *Strategic Differentiation*, and the evidence in favor of 3 is stronger.

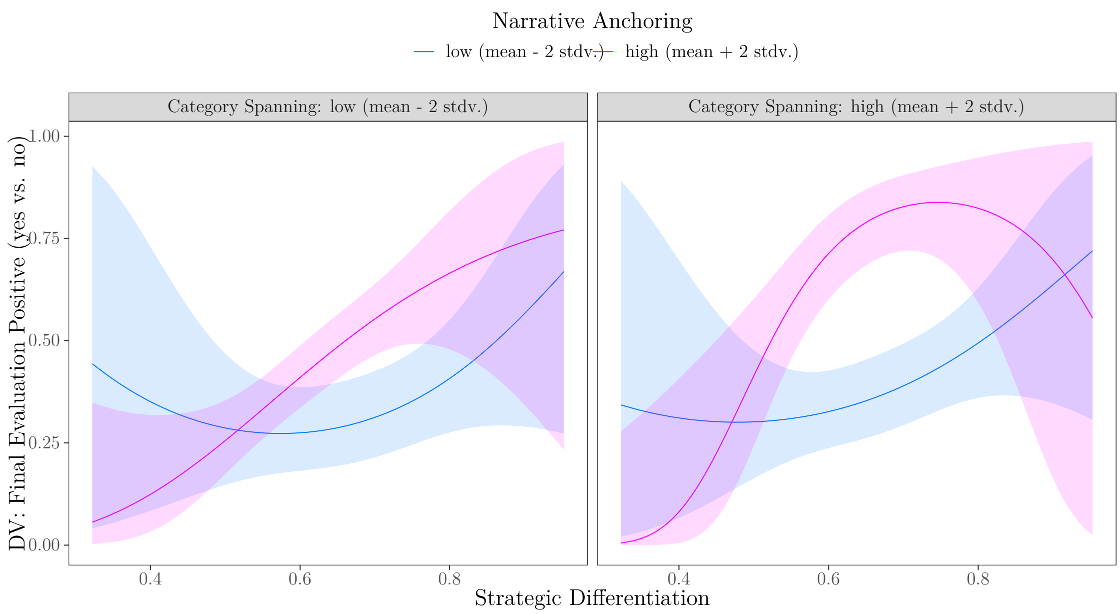

Figure 7: Three-way interaction effect between *Strategic Differentiation*, *Narrative Anchoring*, and *Category Spanning*

5 Discussion

We set out to ask how entrepreneurs can use narratives to shape the way audiences evaluate their products. Our results show that narratives are a crucial factor in determining how audiences perceive entrepreneurial products (Allison et al., 2015; Navis and Glynn, 2011; Manning and Bejarano, 2017) and that they play a key role in the interplay of entrepreneurs' differentiation and categorization efforts (Barlow et al., 2019). By expressing familiar meaning in narratives, entrepreneurs can enhance the relatability, understandability, and cohesiveness of the information provided both to core evaluating audiences and to additional ones that entrepreneurs may want to reach out to (Martens et al., 2007; Navis and Glynn, 2011; Parhankangas and Renko, 2017).

By introducing algorithms from machine learning for natural language, we provide entrepreneurs and researchers alike with an effective analytical tool to analyze, design and implement their narrative to succeed in this task. In this point, our method goes beyond commonly applied ways of analyzing narrative similarity based on *similar words* or *similar topics* (Barlow et al., 2019; Haans, 2019) by introducing a way to analyze narratives based on *similar meanings*—an important distinction given that "narrating meaning" is a key narrative mechanism (Navis and Glynn, 2011). We extend recent studies on the interplay between categorization and differentiation by incorporating category spanning and category atypicality rather than single category membership (Barlow et al., 2019).

Our work highlights a key theoretical role of cultural entrepreneurship in activating the cultural code and meaning of an existing category schema to facilitate audience evaluation of entrepreneurs' categorization and differentiation efforts. We show that categories are not only competitive groups to differentiate from, but also reservoirs of cultural codes and meanings that entrepreneurs can use in the construction of their narratives (Navis and Glynn, 2011; Soublière, 2019). Anchoring the narrative in these cultural codes and meanings of claimed categories allows entrepreneurs to improve audience evaluation of products that span multiple categories or are distinct within their claimed categories. In addition, enriching the narrative with these cultural codes and meanings of unclaimed categories allows entrepreneurs to improve audience evaluation of products that focus narrowly on few or single categories. This is our core contribution.

Our second contribution relates to how cultural entrepreneurship influences evaluating audiences. We extend prior work on the mechanism of cultural entrepreneurship that finds particularistic reputations to be most relevant, i.e., cultural elements that tap into specific reputations, such as the name of a successful movie series (Zhao et al., 2013). We show that, in absence of such particularistic reputations, as is often the case for entrepreneurs, cultural entrepreneurship can also work through familiarity by using category-specific meanings and logics (Zhao et al., 2013). In addition, we show that this familiarity mechanism is able to cross category boundaries. When narratives are enriched to resonate with additional audiences and evoke familiarity by addressing cultural codes of unclaimed categories, audiences can be expanded, their support harnessed, and the overall evaluation improved. In this way, narrative enrichment can be used to face challenges from institutional pluralism (Fisher et al., 2016) or heterogeneous audiences (Kim and Jensen, 2014; Fisher et al., 2017).

Our third contribution relates to research on how audiences evaluate optimal distinctiveness. We introduce category-specific cultural codes as an influential context factor that shapes the effect of distinctiveness on performance (Haans, 2019; Zhao et al., 2017). We show that the curvilinear effect of strategic differentiation on audience evaluation flips when accounting for how it is presented by way of cultural elements. If strategic differentiation is presented with little to no familiarity-based cultural elements that address category-specific cultural codes, its effect on the evaluation follows a U-shaped form, speaking against a single optimal level of distinctiveness (Zhao et al., 2017) and suggesting a negative effect of intermediary distinctiveness due to a loss in legitimacy (Cennamo and Santalo, 2013; Haans, 2019). That loss is attenuated only when distinctive products are presented through anchored narratives that emphasize the cultural codes of claimed product categories (Vergne and Wry, 2014), particularly for low and intermediary levels.

In addition, little attention has been paid to the mitigation of an illegitimacy discount in strategic differentiation (Zhao et al., 2013). Our work adds to this by not only providing another cultural element in the entrepreneurial narrative that helps to overcome illegitimacy discounts but also showing how to overcome those arising from differentiation and atypicality and not mere category spanning or multi-category membership (Zhao et al., 2013). Our results further highlight that narrative anchoring can disentangle the typically inseparable effects of distinctiveness on audience evaluation (Haans, 2019), as narrative anchoring clearly only affects legitimacy perceptions and does not offer a means to stand out and reduce competitive pressure.

Our fourth contribution relates to the specifics of optimal distinctiveness in entrepreneurial markets. Haans (2019) recently showed that the market environment and individual organizational positioning determines whether the two opposing effects of distinctiveness form a U-shaped or an inverted U-shaped relationship. We show that such a positioning entails not only the categories claimed by the product but also how cultural elements are used to emphasize alignment with these categories. While early-stage product proposals in entrepreneurial markets must stand out in order to gain the attention of audiences with a certain appetite for novelty (Cennamo and Santalo, 2013; Navis and Glynn, 2011; Zhao et al., 2017), they nevertheless need to be anchored to cultural codes of claimed categories to unfold their full potential.

Our fifth contribution relates to the specifics of users as an evaluating audience. Our work serves as an example of audience evaluation from a user perspective; critical, for example, in exploring crowdfunding possibilities (Fisher et al., 2017). We provide an empirical test of how differentiation shapes the evaluation of audiences that follow a community logic (Fisher et al., 2017). Prior research has characterized users primarily as *market takers* (Pontikes, 2012), who tend not to value differentiation and prefer to buy conventional products they are used to. However, there is a growing number of new roles that users are granted by firms and sometimes even claim unsolicited and without approval. For instance, users provide online reviews and word-of-mouth marketing (Dellarocas, 2006) or become crowdfunders of new ventures (Parhankangas and Renko, 2017), but they also engage in illegal product modifications (Autio et al., 2013) or file-sharing (Liebowitz, 2008). These user behavior types can be conceived as social evaluation types since they (are meant to) produce signals for other market participants. In our context, users are empowered by the hosting firm to function as gatekeepers for new products (Ferguson and Carnabuci, 2017). In this role, they become *valuation entrepreneurs* (Zuckerman, 2012) who need to convince other peer users and the hosting firm with their evaluations of new products. We find evidence that users in this role can also become *market makers* (Pontikes, 2012) who embrace differentiation to a certain degree.

As with most empirical work, this study is not free of limitations and leaves a number of questions unanswered. One limitation is certainly that selection effects may exist, i.e., only a certain type of venture selects itself on the platform in the first place. Future research is needed that uses an empirical approach capable of accounting for and disentangling such an effect. Moreover, possible influences of the developer team and serial entrepreneurship are another interesting research venue. Only a very small fraction of our sample has proposed multiple products to the user audience, rendering it statistically impossible to identify meaningful serial entrepreneurship effects. Future research may benefit from such a setting in order to analyze how and under which conditions serial entrepreneurs change their narratives or categorization/differentiation approaches.

Future research could also examine further cultural elements; for example, the complimentary role of visual cues such as game play previews in their role as prototypes or imagery. It could be interesting to examine whether visual depiction could potentially add to the legitimacy of distinct games in a similar manner. Upcoming studies could rely on different measures of strategic differentiation, such as for example different reference levels.

More research is also needed on on the boundaries of narrative enrichment, such as possible negative effects of on core audiences. Another limitation arises from the fact that we only observed aggregated user evaluations, not individual behaviors. Future research could study how audience members select themselves into the evaluation of certain products. Finally, this study was situated in the gaming industry and user evaluations. Thus, our findings may not generalize precisely to other product domains and audiences. Future research should investigate entrepreneurial narratives' roles in the context of other technology products and different audiences such as venture capitalists.

6 Conclusion

We propose that entrepreneurial narratives are a key cultural element that can be used to signal alignment and coherence with a category that entrepreneurs seek membership in and as a means of getting noticed by the audiences they want to reach out to. Thus, we contribute to the emerging research stream on cultural entrepreneurship (Lounsbury and Glynn, 2001; Soublière and Gehman, 2019) and seek to inspire future research on entrepreneurial narratives in terms of narrative anchoring, enrichment, and beyond. On the other hand, we encourage further research on users as evaluators, who go from passive consumers to *valuation entrepreneurs* (Zuckerman, 2012), seeking to convince peers and other audiences to change their valuations.

From a managerial perspective, our insights are valuable particularly but not exclusively for entrepreneurial ventures in crowdfunding settings that address users as evaluators (Parhankangas and Renko, 2017). We show that entrepreneurs should focus strongly on the design process of a suitable narrative that entails researching the target market in which the venture is thought to compete and possible other markets with interesting audiences to tap into. By addressing the right meanings, entrepreneurs can ease evaluation and sense making (Navis and Glynn, 2011), particularly if their venture aims to develop distinct products. Moreover, by "borrowing" from cultural codes of unclaimed categories, entrepreneurs can reach out to additional audiences, raise awareness, and improve evaluations. Since users' evaluations also differ from those of other evaluators, it seems reasonable for entrepreneurial ventures that also want to exploit more traditional endorsements to position themselves differently towards those target audiences.

We trust that our work provides a good starting point for researchers and practitioners and that it will help to establish the notion that, particularly for distinct products, entrepreneurial narratives are clearly more than words!

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