Categorically Right? How Firm-Level Distinctiveness Affects Performance Across Product Categories *

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Abstract

In their pursuit of "optimal distinctiveness," firms need to simultaneously adhere to norms and stand out from the competition. Using longitudinal data from Amazon Launchpad, an online B2C marketplace for entrepreneurial products, we offer a multi-level perspective on optimal distinctiveness from a consumer goods market in which firms are active across different and heterogeneous product categories. Arguing along categorization, organizational identity, and the fit with audiences' theory of value, we challenge the assumption that firm-level distinctiveness, i.e., the distinctiveness of a firm's organizational identity and category claims, delivers equal benefits to all products it offers and showcase the decisive role of product category context. In product categories that share less overlap with other categories and thus occupy a more distinct position in the classification system, products offered by firms with high firm-level distinctiveness benefit, whereas in product categories that share frequent relations to other categories and thus occupy a non-distinct position, products do not benefit at all. This offers researchers and managers alike a new and more nuanced perspective on firm-level distinctiveness: It is not invariably efficient in addressing audiences once the "optimal" level is found, but requires careful consideration of both the firm-level appeal and the product category in which a firm seeks to operate. Firm-level distinctiveness provides firms with the means to increase the differentiation of their own products, yet this effect is most meaningful in product categories with an increasingly distinct position.

Keywords: Optimal distinctiveness, categories, new ventures

JEL Codes: M13, L26, L22

Published version available at https://doi.org/10.1016/j.jbusvent.2022.106228

*The authors are very gratefull to Greg Fisher and three anonymous reviewers for outstanding guidance and support during the review process. The authors further thank Dimitri Graf, Christoph Ihl, Hannes Lampe, Daniel Lüdecke and Stephanie Weiss for their valuable feedback on this work.

1 Introduction

A core challenge that firms face is attaining optimal distinctiveness, i.e., becoming as differentiated as possible while still being perceived as legitimate (Deephouse, 1999). This optimal level of distinctiveness ensures that firms stand out and attract attention while simultaneously adhering to market norms that appeal to institutionalized audiences (Zuckerman, 1999). While such audiences' preferences may be heterogeneous (Kim and Jensen, 2014) or even detrimental (Pontikes, 2012), there is recent consensus that whether a single or multiple points of optimal distinctiveness will prevail depends on context (Haans, 2019).

The prominence of research on optimal distinctiveness gives rise to challenges as "studies employ different conceptual terms and operationalizations, creating ambiguities in the literature" (Zhao et al., 2017, p.94). One of these conceptual ambiguities is the observational level of distinctiveness, i.e., a focus on either a firm- or a product-level perspective of optimal distinctiveness. On the one hand, research that focuses on the firm level often overlooks possible differences in individual elements of a firm's offerings, assuming more or less implicitly that firm-level distinctiveness benefits all its products equally (Paolella and Durand, 2016). Analogously, research that focuses on distinctiveness on a product level (Barlow et al., 2019; Zhao et al., 2018) assumes that an optimally positioned individual product generalizes to the firm's success, neglecting the fact that audiences evaluate a firm "as the aggregate of the full array of its offerings" (Paolella and Durand, 2016, p.333) and that membership in a single, individual product category can significantly alter a firm's overall performance for the better or worse (Barlow et al., 2018; Gehman and Grimes, 2017). This is particularly relevant in consumer goods markets, where firms are active across multiple different product categories whose audiences have heterogeneous preferences (Kim and Jensen, 2011).

Following recent calls for a more nuanced perspective incorporating both observational levels (Paolella and Durand, 2016; Zhao et al., 2017), we provide insights from such a setting, where consumer audiences frequently include firm-level perceptions in their product evaluation (Brown and Dacin, 1997), allowing us to ascertain the extent to which firm-level distinctiveness delivers equal benefits to all products a firm offers. To do so, we perceive firm-level distinctiveness as the result of the distinctive inter-category position firms obtain from their market activities (Goldenstein et al., 2019), and thus as part of their organizational identity (Glynn and Navis, 2013; Smith, 2011; Whetten and Mackey, 2002). We argue that audiences use firm-level distinctiveness as a lens (Smith, 2011) to determine whether a specific product fits their theory of value (Lamont, 2012) and show that the extent to which audiences use this lens—and consequently the extent to which firm-level distinctiveness is able to improve product performance—varies across product categories. Distinguishing them based on their own position in the broader classification system, i.e., based on the overlap and relations they share with other product categories (Lo et al., 2020; Taeuscher et al., 2022), we highlight that firm-level distinctiveness is only meaningful in those product categories whose cultural code facilitates its evaluation (Vergne and Wry, 2014) and whose audiences value it (Paolella and Durand, 2016).

Audiences in product categories with a distinct position, i.e., those that expect novel and/or unconventional products (Taeuscher et al., 2021; Vossen and Ihl, 2020), value the more capable and specialized performance that high firm-level distinctiveness stands for (Paolella and Durand, 2016; Pontikes, 2012), which improves the performance of the respective product. In contrast, audiences in product categories with a non-distinct position, i.e., those that expect conventional products that are easy to evaluate (Smith, 2011; Paolella and Durand, 2016), ignore or reject firm-level distinctiveness, as using it as a lens complicates evaluation and contradicts their expectations of conformity, thus worsening the performance of the respective product.

Following a call for a longitudinal study on optimal distinctiveness (Haans, 2019), we use an unbalanced panel data set for our analysis that contains 335 new ventures selling 2,198 products over a time window of 169 weeks (from February 2015 to April 2018) on Amazon Launchpad. Launchpad is an Amazon initiative to foster inclusion of new ventures in its online marketplace and to provide them with an opportunity to present their products alongside other new ventures. In this consumer goods market setting, we find the average effect of firm-level distinctiveness on product performance to be U-shaped, as products offered by firms with either very high or very low firm-level distinctiveness perform best (Haans, 2019; Zhao et al., 2017). However, the presence and magnitude of this U-shaped effect on product performance differs across individual product categories. In product categories with a distinct position, the U-shaped effect steepens, accentuating the positive effects of both low and high firm-level distinctiveness, yet also the negative "stuck in the middle" problem (Cennamo and Santalo, 2013). The less distinct the position of product categories, the smaller the effect of firm-level distinctiveness on product performance.

Our work is a direct response to several calls for research (Haans, 2019; Paolella and Durand, 2016; Zhao et al., 2017) and in line with recent work that emphasizes the important role of categories (Cudennec and Durand, 2022; Durand and Haans, 2022; Taeuscher et al., 2022) and multiple observational levels (Bu et al., 2022; Zhao and Glynn, 2022) for the research on optimal distinctiveness. Our results indicate that, if an effect of firm-level distinctiveness on product performance is found, it is most likely not the result of universal acclaim in all product categories a firm is active in (Bowers, 2015). By using an adaptive and evolving longitudinal measure of optimal distinctiveness that entails both the firm and the product level, we show that firm-level distinctiveness can be used to differentiate individual products a firm offers. However, this effect is strongly contextualized by the distinctive position of the respective product category (Lo et al., 2020), as firm-level distinctiveness is only beneficial in the categories in which it is deemed to be in line with the category's cultural code (Vergne and Wry, 2014; Vossen and Ihl, 2020) and with audiences' theory of value (Durand and Paolella, 2013) and expectations (Smith, 2011). Our work also introduces the important notion that evaluations of firm-level distinctiveness differ not only across audiences, i.e., consumers versus venture capitalists (Pontikes, 2012), but also within consumer audiences across different product categories (Barlow et al., 2018; Kim and Jensen, 2011). Thus, the market context that shapes the effect of firm-level distinctiveness on performance is contingent not only on competing actors and their approach to firm-level distinctiveness (Haans, 2019), but also on the evaluative boundary conditions set out by the product categories themselves.

In determining how to strategize optimal distinctiveness on a firm level, managers need to be aware that this appeal may be different for individual products in their portfolio. Only by being "categorically right" and selecting the right product categories to operate in can they leverage their firm-level distinctiveness and reap the benefits to the fullest extent.

2 Theoretical background

2.1 Firm-level distinctiveness and product performance

Achieving an optimal level of distinctiveness, i.e., being as different as legitimately possible, is a core strategic issue for firms that significantly shapes how evaluating audiences perceive them (Deephouse, 1999; Durand and Haans, 2022; Zhao and Glynn, 2022). As the term "optimal" implies, there is a trade-off they need to consider between generating competitive advantage by being different from others and appearing legitimate by being similar (Navis and Glynn, 2011). Differences in audience evaluations have been put forward as a causal mechanism, resulting from, among others, heterogeneous audience preferences for conformity or differentiation (Pontikes, 2012; Paolella and Durand, 2016), as well as the competitive context (Durand and Haans, 2022; Haans, 2019).

Yet, there is considerable variance in the literature on how optimal distinctiveness is conceptualized (Zhao, 2022), particularly in terms of the roles of categorization and differentiation (Cudennec and Durand, 2022; Goldenstein et al., 2019; Pontikes and Barnett, 2017), and thus whether distinctiveness refers to intra- or inter-category comparisons (Lo et al., 2020). The intra-category perspective often argues that category membership decisions precede differentiation, i.e., the decision on which category to enter is made before the decision to differentiate from other members of that category (Barlow et al., 2019). Most often, this includes first identifying a product category and then developing a strategy for how to position one's own product against categorical prototypes or exemplars (Zhao et al., 2018). Consequently, distinctiveness in this context often refers to the product level and a firm's own positioning within its chosen product categories, such as the extent to which a certain video game description differs from prototypical games of the same genre (Vossen and Ihl, 2020).

The inter-category perspective argues that market or product category membership itself provides firms with recognizable means of differentiation (Cudennec and Durand, 2022; Gehman and Grimes, 2017; Goldenstein et al., 2019; Kim and Jensen, 2011) and that this "composition of businesses bundled within the firm" (Litov et al., 2012, p.1799) is used by evaluating audiences to determine appropriateness (Pontikes, 2012). Consequently, distinctiveness in this context refers to the firm level and the overall positioning in the broader market context (Pontikes and Barnett, 2017), such as the extent to which a law firm's portfolio of legal counseling services differs from that of other law firms (Paolella and Durand, 2016).

These differences also extend to determining and measuring the effect of distinctiveness on audience evaluation and, subsequently, on product performance. In a more or less implicit yet common caveat, prior studies on both inter- and intra-category perspective often generalize from one observational level to another, as most evaluations happen "at the product level (e.g., movies, recipes, auctions, wines), and the results are aggregated at the organizational level" (Paolella and Durand, 2016, p.332). While this is less consequential in settings where firms are observed in just one clearly defined product category or industry (Haans, 2019), it is both conceptually and empirically relevant when firms "have heterogeneous audiences with different product preferences and therefore may be compelled to offer different products to different audiences" (Kim and Jensen, 2011, p.239-240), such as in highly crowded and competitive consumer goods markets (Cennamo and Santalo, 2013).

In such markets, firm- and product-level perceptions should be perceived jointly, as firm-level perceptions may influence audiences' perception of specific products and vice versa

(Brown and Dacin, 1997; Barlow et al., 2018). Besides it being an important gap in the literature on optimal distinctiveness (Zhao et al., 2017), conceptualizing and measuring this interplay is not a trivial task. On the one hand, simply averaging or aggregating individual product-level performance to measure audience evaluation of firm-level distinctiveness may be problematic, as it renders it impossible to distinguish between an overall lukewarm or a very polarized audience evaluation across product categories (Bowers, 2015). On the other hand, assuming that firm-level distinctiveness is equally favored by audiences in all kinds of product categories and market contexts seems ill-advised (Pontikes, 2012; Taeuscher et al., 2022).

We propose a way to reconcile both intra- and inter-category perspectives on firm-level distinctiveness and its effect on product performance: If firms need to appeal to multiple different product categories that consist of heterogeneous audiences (such as in consumer markets), their firm-level distinctiveness should be recognized as the sum of their market activities and the resulting distinctive inter-category positioning within the overall market (Smith, 2011). In the right categorical context, this positioning subsequently serves as a means for firms to differentiate their products on the intra-category level, as they may use it "to communicate information [to evaluating audiences] and to position themselves favorably with respect to competitors." (Pontikes and Barnett, 2017, p.73).

Our reasoning builds on three core assumptions: First, following the inter-category perspective, we perceive firm-level distinctiveness as part of the organizational identity, i.e., as who or what firms claim to be categorically (Glynn and Navis, 2013; Whetten and Mackey, 2002), which helps audiences to evaluate a firm's products by being a "filtering, screening, or sorting device," as well as "a lens through which various kinds of information pass and take on meaning" (Smith, 2011, p.62). Second, individual product categories are defined by individual audiences themselves (Vergne and Wry, 2014; Vossen and Ihl, 2020) whose evaluation of firm-level distinctiveness relies on their own theory of value (Lamont, 2012), i.e., on how they "identify issues and solutions, ascribe value, and rank solution providers" (Paolella and Durand, 2016, p.333). Third, in order to facilitate identification and ranking, product categories provide their audiences with "cultural codes that are associated with belonging to a particular category" (Vergne and Wry, 2014, p.63).

For both the intra- and the inter-category perspective, the effect of firm-level distinctiveness on audience evaluation and product performance is emphasized by the underlying cost-benefit relationship of non-conformance (Haans, 2019; Pontikes and Barnett, 2017). From the inter-category perspective, conformance resembles the strategic decision to conform to other market actors and their organizational identities, i.e., by seeking membership in similar product categories (Paolella and Durand, 2016). Audiences perceive firms with low firm-level distinctiveness and those whose organizational identity conforms to norms and expectations as more representative actors, which makes it easier to process information and evaluate them (Durand and Kremp, 2016). In its function as a filtering device and lens through which information is processed and takes on meaning, both these benefits enable a firm's conforming organizational identity to benefit and legitimize its products, which results in an increase in audience evaluation and performance (Smith, 2011). In spite of these legitimacy benefits, firms may also find that conformance renders their organizational identity interchangeable, and thus of little use in differentiating their own products and improving their performance. As a consequence, firms may want to make it more distinct; following the inter-category perspective, this can be facilitated by seeking membership in uncommon product categories (Kim and Jensen, 2011; Pontikes and Barnett, 2017).

The most common benefit of firm-level distinctiveness and a distinct organizational identity is mitigating competitive pressures. Evaluating audiences are commonly heterogeneous (Kim and Jensen, 2014), with some of them exhibiting favorable preferences for distinctiveness, as they often expect it (Taeuscher et al., 2021) and reward it excessively (Smith, 2011). This includes in particular consumer audiences that see firm-level distinctiveness as a favorable specialization (Pontikes, 2012), which renders it a highly salient part of the organizational identity and enables firms to stand out from their peers while still being evaluated as legitimate (Durand and Kremp, 2016; Kim and Jensen, 2011). As a lens through which information is processed and takes on meaning, the distinctive organizational identity thus helps the respective firms' products to stand out, catch audiences' attention, be seen as specialized, and thus be perceived favorably (Smith, 2011).

Besides the obvious advantages of standing out in the eyes of evaluating audiences, the extremely high cost of being distinct is losing legitimacy by not conforming (Zhao et al., 2013, 2017). If firm-level distinctiveness is rather uncommon in the overall market, it often results in sharp audience devaluation as firms become more difficult to interpret or may fail to catch the attention of evaluating audiences at all (Zuckerman, 1999). This may subsequently also affect their products, as audiences that use the distinct organizational identities to filter and process information about the product may find it both unappealing and of little use in their decision-making.

Based on this twofold perspective with costs and benefits for each, previous research has established a curvilinear effect of distinctiveness on audience evaluation and notes that the relative strength of the costs and the benefits determines its shape (Haans et al., 2016; Haans, 2019; Zhao et al., 2017) [1]. For our setting of a highly crowded and competitive consumer goods market, we expect the benefits of firm-level distinctiveness to outweigh its costs with growing levels of distinctiveness and thus expect a U-shaped relationship where either highly conform or highly distinct firms are evaluated best (Cennamo and Santalo, 2013). Although consumer audiences acknowledge the legitimizing effect of conformance, i.e., low levels of firm-level distinctiveness, and the fact that evaluating distinctive firms is cumbersome and complicated, they are also inclined to appreciate high levels of firm-level distinctiveness when they evaluate products, as they may perceive them as more specialized (Pontikes, 2012) or original (Kim and Jensen, 2011). Yet these benefits may only manifest above a certain level of

[1] While the inter-category perspective often assumes a linear relationship between distinctiveness and performance, the intra-category literature commonly advocates a curvilinear effect (Zhao et al., 2017). As we refer to the effect of firm-level distinctiveness on individual product performance, we therefore follow the intra-category literature and conceptualize a curvilinear effect to capture the cost-benefit relationship of firm-level distinctiveness and product performance.

distinctiveness. If firms exhibit only moderate firm-level distinctiveness, their products may experience a "stuck in the middle" problem (Cennamo and Santalo, 2013), as the benefits of differentiation from the distinct organizational identity may be minuscule, while respective products still bear the cost of a firm's non-conformance. We therefore believe firm-level distinctiveness has a U-shaped effect on product performance and hypothesize:

Hypothesis 1: *The effect of firm-level distinctiveness on product performance is U-shaped.*

2.2 The contextual role of product categories

In line with the three assumptions presented in the preceding section, we expect the effect of firm-level distinctiveness on product performance to vary across product categories. Due to the different cultural codes those product categories provide and the audiences they address (Vergne and Wry, 2014), firms may be more or less able to clearly convey their organizational identity (Glynn and Navis, 2013) and may elicit a different interpretation and reaction from audiences to otherwise similar information on a product when they evaluate it through the lens of dissimilar identities (Smith, 2011). Thus, product categories are not only important in determining firm-level distinctiveness as part of the organizational identity (Kim and Jensen, 2011; Whetten and Mackey, 2002), they also contextualize its effectiveness to differentiate their own products and improve their performance (Haans, 2019).

While firms may have agency and strategic leeway in how they differentiate their products within specific product categories (Glynn and Navis, 2013), i.e., how they choose their intra-category differentiation for each product individually (Barlow et al., 2019), the differentiation appeal of firm-level distinctiveness as part of the organizational identity is largely the same across product categories. This does not, however, imply that this appeal is universally valued, as some product categories' audiences may recognize and richly reward firm-level distinctiveness in their evaluation of products, while others do not (Smith, 2011). Analogously, some product categories may provide audiences with a cultural code and logic to facilitate evaluation and test the extent to which the firm-level distinctiveness fits their own expectations and theory of value, while others do not (Glynn and Navis, 2013; Kim and Jensen, 2011; Vergne and Wry, 2014). Consequently, in certain product categories—those that provide the right cultural code and have an audience that recognizes and values it—the effect of firm-level distinctiveness on product performance should be stronger.

We propose that such product categories are those that share less overlap with other product categories in the broader classification system and thus occupy a distinct position (Lo et al., 2020). Products in such categories are often more complex for audiences to evaluate and thus require extensive information-seeking behavior (Paolella and Durand, 2016), which may be further complicated by the distinct position that, by definition, shares little to no relational overlap with other categories whose products may be helpful in terms of referencing or analogical thinking (Lo et al., 2020). This generates an evaluative complexity that requires audiences to educate themselves and enrich their sense- and decision-making with additional information from the firm's organizational identity (Brown and Dacin, 1997; Smith, 2011), which renders both the recognition of firm-level distinctiveness and the probability of audiences using it more likely.

In product categories with a distinct position, this increased recognition may accentuate both the benefits of conformance and high firm-level distinctiveness and therefore help audiences to determine which product may best fit their requirements and demands (Kim and Jensen, 2011; Paolella and Durand, 2016). On the one hand, audiences may be looking for cues of familiarity that they may find in the firm's overall positioning and thus more strongly reward firms that are familiar and conforming in their organizational identity. On the other hand, novelty-seeking parts of the consumer audiences (Taeuscher et al., 2022) may in particular appreciate the firm-level distinctiveness appeal that they associate with being more capable and able to deliver superior and more sophisticated products (Pontikes, 2012). As distinctiveness is part of the cultural code in such categories, higher firm-level distinctiveness is largely appreciated (Taeuscher et al., 2021; Vossen and Ihl, 2020) and may even be required under audiences' theory of value (Durand and Paolella, 2013; Pontikes, 2012; Taeuscher et al., 2022). However, this increasing recognition and appreciation of firm-level distinctiveness not only renders these audiences more receptive to the benefits of conformance and distinctiveness, it may also worsen the "stuck in the middle problem" experienced by products from moderately distinct firms (Cennamo and Santalo, 2013). Consequently, in product categories with a distinct position and less overlap with other product categories, where audiences are more likely to recognize, utilize, and appreciate firm-level distinctiveness in their product evaluation, the U-shaped effect steepens, as both advantages and drawbacks of conformity and firm-level distinctiveness on product performance are accentuated (Haans et al., 2016).

Product categories with a non-distinct position usually play a central and prominent role in the broader classification system and "are shaped by connections with other categories within a relational network" (Lo et al., 2020, p.91). Audiences may draw on these frequent connections and use referencing or analogical thinking to increase products' comparability for easier evaluation. Although these conditions would generally speak for the differentiation benefits that firm-level distinctiveness offers products, its appeal may be of little use in this categorical context. In such product categories, audiences' theory of value promotes a simple and effortless evaluation of products (Paolella and Durand, 2016) with little need for specialized requirements and demands. Such evaluations rarely require further information-seeking behavior, and a firm's organizational identity may not even catch audiences' attention. Even if it does, they would likely deem it too cumbersome to analyze and classify distinct firms (Bowers, 2015), as firm-level distinctiveness stands in stark contrast to the conforming cultural code of the category and audiences' expectation of conventional products. This renders it less likely that they will recognize firm-level distinctiveness and utilize it during product evaluation (Smith, 2011). However, this failure to recognize firm-level distinctiveness also makes these audiences less susceptible to its drawbacks, which in turn attenuates the "stuck in the middle" problem and flattens the U-shaped effect (Haans et al., 2016). As a consequence, the advantages and drawbacks of firm-level distinctiveness for product evaluation may be considerably lower in product categories with a non-distinct position, whose cultural code and evaluative conventions are shaped by both common and frequent relations to other categories, and by a strongly institutionalized focus on conformity (Vergne and Wry, 2014).

In summary, we propose that, particularly in consumer goods markets where firms are active across different and heterogeneous product categories, a product category's position in the broader classification system alters the effectiveness of firm-level distinctiveness to influence audiences in their evaluation of products. In product categories with a distinct position, the U-shaped effect of firm-level distinctiveness is accentuated. Parts of the audience may be actively looking for cues of familiarity in the firm's overall positioning and would thus more strongly reward firms that are familiar and conforming in their organizational identity, whereas for novelty-seeking parts of the audience higher firm-level distinctiveness is in line with both the category's cultural code and their theory of value. In both cases products offered by firms with high firm-level distinctiveness are evaluated more favorably and see their performance increase. In product categories with a non-distinct position, where firm-level distinctiveness is less likely to be recognized, familiarity is more common, and where higher firm-level distinctiveness is not part of the cultural code and does not match audiences' theory of value, products will benefit less. We therefore hypothesize:

Hypothesis 2: *The effect of firm-level distinctiveness on product performance will be accentuated (attenuated) in product categories that occupy a distinct (non-distinct) position in the broader classification system.*

3 Data and method

3.1 Data collection and sample

To test our hypothesis, we collected and compiled a unique secondary dataset from multiple online sources. Our starting point was Amazon Launchpad, a specific section of the Amazon webstore where new ventures can present themselves and their products to consumer audiences. Amazon Launchpad works with strategic partners, such as investors or crowdfunding platforms, to provide their invested new ventures with a well-established framework to present themselves and sell their new products. In addition to being integrated into the regular Amazon webstore, all products are added to a special Amazon Launchpad summary that allows consumers to specifically browse and search exclusively for products of new ventures. We used this special summary to identify the products and firms for our sample and collected information on all products available on the German version of Amazon Launchpad at the time of data collection, which was in the spring of 2018.

To ensure reliability, we assessed our data in multiple steps. We first checked every product available on the Amazon Launchpad web page to get its product information, such as the unique Amazon Standard Identification Number (ASIN) that we used for matching, and gathered all company-specific information, e.g., company name, tax number, or trade register number, to unambiguously identify each firm. In a second step, we double-checked each venture and cleaned the dataset of errors, false entries, pure resellers selling products they do not produce themselves, and firms that do not qualify as new ventures due to their size or age. To do so, we visited the websites obtained from the terms and conditions on all identified Amazon profiles and thoroughly double-checked the information provided there. We excluded any new ventures where the provided corporate tax and trade register number did not match the one stated on Launchpad, as well as any that listed a founding date before 2000 (such as, e.g., "Established 1995") or a statement of having been acquired by a multinational corporation. In total, this cleaning process resulted in about 30 new ventures being removed.

For all identified products, we used the commercial data analysis service Keepa.com to obtain time series data on price development and sales performance, as well as information on product categories. Keepa.com tracks hundreds of millions of products available on Amazon in many countries and offers subscribers the analytics via API. Consequently, we were able to identify 335 new ventures selling 2,198 products between February 2015 and May 2018 (169 weeks). By providing the unique Amazon ASIN, we were able to request a daily observation of price and sales rank changes. In the process, we discarded a few products for which this data was not available. To account for intraweek variability, we aggregated our data from a daily to a weekly basis (van Oest et al., 2010). As our 169-week time frame is quite large, we believe that a weekly analysis will provide sufficient detail over time. As products were added to and removed from the shop over the course of these 169 weeks, our panel is unbalanced.

At this point, it is important to clarify that our sample consists only of new ventures and their products listed on Amazon Launchpad and does not include all hundreds of millions of Amazon products tracked by Keepa.com. Consequently, our measures focus on new ventures as the reference group. This setting gives us a unique perspective in examining new ventures that explicitly compete with each other in existing product categories for consumers that are particularly interested in entrepreneurial products. One could argue that consumer audiences that are trying to shop for a specific product are not concerned about other products that the firm sells on Amazon. However, existing research has highlighted that category membership affects organizational perceptions and subsequent performance in other categories (Barlow et al., 2018; Gehman and Grimes, 2017). Additional information such as “other offers from this seller” can be found easily, rendering it likely that—particularly in online market platforms with high uncertainty and low levels of trust—the seller of a product is evaluated before a purchase is made (Hong and Pavlou, 2014; Lanzolla and Frankort, 2016).

3.2 Measurements

3.2.1 Dependent variable

The dependent variable and a measure of product performance is the sales rank on Amazon, which indicates a product's sales performance (Chevalier and Mayzlin, 2006; Smith and Telang, 2009). This sales rank is product category–specific and does not represent sales performance in absolute terms; in our sample, it refers to the highest product category level (e.g., "Electronics"). A product in a smaller product category could reach a high ranking even with relatively low sales compared to a broader product category. To account for this, we use consumer review data as a sign of product category size and include a variable that cumulatively counts the total number of consumer reviews in our sample for each product category in each week. For example, if the specific product sales rank originates from a product in the product category "Electronics," we sum up all reviews that all products in "Electronics" in our sample received in that specific week and add that number as a control variable. To smooth out distribution, we log-transformed both the sales rank and the review count variable (Smith and Telang, 2009). Because a low sales rank denotes a better sales performance than a high sales rank (e.g., a craft beer with the sales rank 10 has lower sales than a craft beer with the sales rank 2), all negative coefficients on an explanatory variable would imply an increase in sales performance as the sales rank decreases. To correct for this circumstance, we multiplied the sales rank by negative one.

3.2.2 Independent variables

Our two key independent variables are firm-level distinctiveness and the product category position. We built our firm-level distinctiveness measure based on the product category information provided for each product of the firm. All products on Amazon Launchpad are assigned product category labels that we employ for our analysis (Cennamo and Santalo, 2013; de Vaan et al., 2015; Goldenstein et al., 2019). We summarized all product category labels a firm is affiliated with through its products in the given week; more specifically, we included the product category labels of all products that a firm offered in a specific week. This is based on the assumption that a firm can only compete in a product category that it also offers products in, and that the product category portfolio is the sum of its parts (Fernhaber and Patel, 2012). Due to the results of our testing and data exploration, we limited our product category labels to three, as any labels beyond that typically just included color and size variants of the focal product.

As an illustrative example, a smartwatch that can be connected to a smartphone would have the product category labels "Electronics," "Smartphones and Accessories," and "Smartwatches." If, for example, a firm offered only the smartwatch above, it would be associated with those three unique product category labels. If it additionally offered another product, such as a protective case for smartphones, it would be associated with a total of four unique product category labels, as the three product category labels of the protective case would be "Electronics" and "Smartphones and Accessories"—both already included as labels of the smartwatch product—and "Accessories," which would be added as a new product category label. If the same firm, for whatever reason, offered craft beer next to the smartwatch, it would have six unique product category labels, "Electronics," "Smartphones and Accessories," and "Smartwatches" for the smartwatch product, and "Food & Beverages," "Alcoholic Beverages," and "Beer" for the craft beer product. Although our product category data is nested, e.g., "Smartphones and Accessories" is a subordinate, lower-level element of the superordinate, higher-level element "Electronics," hierarchical categories have been used previously in similar settings (de Vaan et al., 2015; Gehman and Grimes, 2017).

Based on these product category labels, we applied an approach employed by prior research to compute our measure of firm-level distinctiveness and used the cosine similarity index, calculated for the focal portfolio of unique product category labels, against all portfolios of unique product category labels available in our sample at that point in time (de Vaan et al., 2015). By doing so, we computed a variable that dynamically measures the extent to which a firm's combination of product category labels differs from those of all other firms in the specific week. Thus, we computed the distance between the focal product category portfolio i and each other product category portfolio j as follows:

$$Product\ category\ portfolio\ distance_{ij} = 1 - \left[\frac{\sum_{k=1}^{K} f_{ik}\, f_{jk}}{\sqrt{(\sum_{k=1}^{K}\ f_{ik}^2)} \cdot \sqrt{(\sum_{k=1}^{K}\ f_{jk}^2)}} \right] \tag{1}$$

where f_{ik} equals $1/K$ if product category label k is present for product category portfolio i and K equals the total number of product category labels of a product category portfolio, and 0 otherwise. This results in a distance vector for all product category portfolios that summarizes distances between focal product category portfolio i and all other product category portfolios available at the focal point in time. Finally, we average the distances for each product category portfolio i and each week. Thus, we compose our measure of firm-level distinctiveness i in the focal week as:

$$Firm - level\ distinctiveness_i = \frac{\sum_{j=1, j \neq i}^{N} Product\ category\ portfolio\ distance_{ij}}{N} \tag{2}$$

where N stands for the total number of firms in the respective week.

To measure a product category's position, we employed an approach consistent with firm-level distinctiveness. We again used the products and their product category labels to determine the distinctive position, but limited them to the same "superordinate" product category (e.g., "Electronics") (Gehman and Grimes, 2017). As our category data is hierarchical, it is impossible for a product to share product category labels with others outside its superordinate product category (e.g., "Electronics"). Hence, we computed a variable that dynamically measures the extent to which a product's category labels differ from those of all other products in the same superordinate product category in a given week. The fewer products that share or have any overlapping category labels with any given product category, the more distinct its position in the broader classification system (Lo et al., 2020). Conversely, we refer to a product category's position as non-distinct if its labels are shared frequently by products within the same superordinate category (Brouthers et al., 2005; Tan et al., 2013). Picking up the example above, this would imply that the "Smartwatch" product category's position would become a bit less distinct with every "Electronics" product in the sample (with which it shares one product category label), somewhat less distinct with each "Smartphones and Accessories" product (with which it shares two labels), and much less distinct with every other "Smartwatch" product (with which it shares three labels).

In spite of Launchpad being a specific and somewhat shielded subsection of the Amazon webstore, one could argue that firms also stand in competition with established products from the general Amazon webstore in said product categories. The most important established competitors are the top-selling products in a given product category, which receive the most attention and serve as a point of reference for consumers searching for products. Amazon offers a specific web page that keeps track of the top 100 bestselling products in each superordinate product category ("Electronics," "Food," "Clothing," etc.). However, accessing that page only provides the bestsellers at the time it is accessed, not a chronological overview of how bestsellers have evolved over time. Especially in fast-moving entrepreneurial consumer goods markets, this could potentially bias our results, as the bestsellers in week 1 could easily be out of business in week 169.

To solve this dilemma, we collect that chronological information using Archive.org, the digital archive of the World Wide Web. For each of our superordinate product category labels ("Electronics," "Food," "Clothing," etc.), we collect all available instances of that bestseller list that match our time period (2015–2018). Unfortunately, Archive.org does not track all bestseller pages of all product categories on Amazon; it also saves the bestsellers at different time intervals. This could be problematic, as it is possible that a specific product was just added at the specific point in time that Archive.org saved the web page—a problem that becomes particularly relevant for products at the lower end of the list. To address this problem, we collected information on all bestselling products that appeared on these lists at least once and again accessed Keepa.com to check the sales rank of each of those products in every week of our sample. We then included the representative bestselling products and their product category labels that managed to stay in the top 100 the entire time in our calculation of the product category's distinctive position.

In the next step, we coded each product as a binary vector of every possible product category label combination in the respective superordinate product category and compared it with the vectors of all other products in that superordinate product category available in the market at that point in time (including bestselling products). Thus, we computed the distance between the focal product i and each other product j in the same superordinate product category as follows:

$$Product\ distance_{ij} = 1 - \left[\frac{\sum_{k=1}^{K} f_{ik}\, f_{jk}}{\sqrt{(\sum_{k=1}^{K}\ f_{ik}^2)} \cdot \sqrt{(\sum_{k=1}^{K}\ f_{jk}^2)}} \right] \tag{3}$$

where f_{ik} equals $1/K$ if product category label k is present for product i and 0 otherwise. K equals the total number of labels in each product category. As we limited our product category labels to three, K is always three. This results in a distance vector for all products that summarizes distances between focal product i and all other products in the superordinate category available at the focal point in time. Finally, we averaged the distances and compose our measure of a product category's distinctive position i in the focal week as:

$$Product\ category\ position_i = \frac{\sum_{j=1,j\neq i}^{N} Product\ distance_{ij}}{N} \tag{4}$$

where N stands for the total number of products in the respective week and superordinate product category. As the measures of both firm-level distinctiveness and product category position are empirically closely related, multicollinearity issues may arise. We checked the correlation between the two variables and found it to be low, at 0.07; additionally, the variance inflation factor (VIF) for a main-effects-only model is unproblematic for both firm-level distinctiveness (1.28) and product category position (1.27) (McClelland et al., 2017).

To further clarify, we provide some illustrative examples to give an intuition of what new ventures look like that have high values of firm-level distinctiveness and a more (less) distinct product category position. It should be kept in mind that the measures of firm-level distinctiveness and product category position evolve due to the unbalanced panel structure of our sample and may therefore constantly vary from week to week. Based on our measurement, high values of firm-level distinctiveness can originate from affiliation with uncommon product category labels or alternatively from an uncommon combination of more common product category labels. As an example, a firm with high firm-level distinctiveness selling products in product categories with a distinct position offers an air-quality sensor for babies (labels "Baby," "Security," and "Baby Monitors") and an indoor security camera (labels "Home Improvement," "Security Technology," and "Surveillance Technology"). In this case, the labels of the two product categories are not shared by many others in the respective week and their combination (on a firm level) is rather unique. A new venture with high firm-level distinctiveness that sells products in categories with a non-distinct position sells a weight scale (labels "Sports & Leisure," "Fitness," and "Strength Training") and a smartphone case (labels "Electronics," "Smartphones and Accessories," and "Accessories"). In this case, the labels of the two product categories are shared by many in the respective week, but their combination (on a firm level) is rather unique. Following our hypothesis H2, we expect that the products of the former firm will benefit from firm-level distinctiveness and those of the latter will not.

3.2.3 Control variables

We used several control variables to increase the robustness of our results. First, we controlled for the product category size and built a variable that cumulatively counts the total number of consumer reviews in our sample for each product category per week. We log-transformed this variable due to skewness. We controlled for the product category portfolio size and built a variable that counts the number of unique product categories (lowest level) each firm offered for each of the 169 weeks. Our sample includes 24 product category labels on the highest level, 137 labels on the intermediate level, and 328 labels on the lowest level. Moreover, we controlled for a firm's overall product portfolio size and built a variable that counts the number of products of each firm in each of the 169 weeks.

Then, we controlled for the average price of the focal product (in euro cents) to account for price-related inferences on the sales rank. Further, we controlled for the number of recent price changes, computing a count variable that combined price in- and decreases for the last week. This variable captures the influence of a recent price increase or decrease as well as short-term price changes due to special offers such as "deal of the day." All price-related control variables were log-transformed. Additionally, we controlled for competition and built count variables that count the number of competing new ventures and the number of competing products in a specific product category for each of the 169 weeks. To do so, we chose to measure competition based on the superordinate product category label. Returning to the aforementioned example, the number of competitors for the smartwatch would be calculated based on other products with the product category label "Electronics."

To control for learning effects (Cohen and Levinthal, 1990), we built a variable that cumulatively counts the number of weeks a product is offered. We log-transformed it due to skewness. To account for audience evaluation, we included the customer reviews a product received that week, cumulatively counting the total number of reviews a product has each week, and log-transformed it due to skewness. Additionally, we included a product's average rating each week, ranging from one to five stars. Moreover, we controlled for the dispersion of consumer reviews by calculating the standard deviation between all of a product's ratings per week.

Unfortunately, we lack review data for 415 out of the 2,198 products that never received a consumer review. Moreover, not all products have reviews right from the first week of their appearance in the sample. To avoid dropping a significant number of observations from our sample, which could introduce a bias, we follow Taeuscher (2019) and use the sample mean in the respective week for review variables if a product had no review. This builds on the assumption of consumer reviews as a signal of organizational reputation (Rindova et al., 2005) and that if "an organization's reputation is unknown, the organization will most likely be treated as reputation neutral, since neither positive nor negative predictions about its future behavior normally can be made when there is a lack of information" (Bitektine, 2011, p.165).

Finally, we control for a product category's distinctiveness heterogeneity, i.e., the average firm-level distinctiveness of actors in a product category, to control for the fact that firm-level distinctiveness may be more common in certain product categories than in others (Haans, 2019). Distinctiveness heterogeneity of the product category k in the focal week is measured as:

$$Distinctiveness\ heterogeneity_k = \sum_{P=1}^{n} \sqrt{\frac{\sum_{i=1}^{N} \left(\Theta_{Pi} - \bar{\Theta}_{P,k}\right)^2}{N-1}} \tag{5}$$

where N is the number of firms with a product in that product category k in the focal week. $\Theta_{P,i}$ indicates a firm i 's firm-level distinctiveness value P, and $\bar{\Theta}_{P,k}$ indicates the focal product category *k's* average firm-level distinctiveness value P. Hence, distinctiveness heterogeneity is the standard deviation of values of firm-level distinctiveness in the focal product category (Haans, 2019). We calculated distinctiveness heterogeneity by using the superordinate product category label in our sample (e.g., "Electronics") and n refers to the total number of product category labels. To turn these highly skewed frequencies into a smoothly distributed measure, we take the log and scale it by -100. Examples of heterogeneous product categories are "Games" and "Baby," while examples of homogeneous product categories are "Industrial" and "Luggage." Table 1 summarizes all variables and their measurement used in our models [2].

[2] We thank all three anonymous reviewers for several important suggestions made for our empirical approach. This includes the illustrative examples, testing for multicollinearity, recoding the sales rank, including the bestselling products from the top 100 list, and selecting the superordinate product category

Variable	Variable description
Amazon sales rank	Average sales rank of product i in week t. Log-transformed and multiplied by -1.
Product category size	Cumulative count of reviews per product category (highest level) per week t. Log-transformed.
Product category portfolio size	Count variable of all product categories (lowest level) i a firm j has membership in in week t.
Product portfolio size	Count variable of all products i offered by new venture j in week t.
Product price	Average price in euro cents of product i in week t. Log-transformed.
Price changes prior week	Count of price increases and decreases of product i in week *t-1*. Log-transformed.
Product competition	Count of competing products i in the product category (highest level) in week t.
Firm competition	Count of competing firms j in the product category (highest level) in week t.
Product age	Cumulative count of weeks product i is in the sample. Log-transformed.
Consumer review volume	Cumulative count of consumer reviews of product i per week t. Log-transformed.
Consumer review rating	Average consumer review rating of product i per week t.
Consumer review dispersion	Standard deviation of consumer reviews of product i per week t.
Distinctiveness heterogeneity	Standard deviation between values of firm-level distinctiveness in the focal product category. Log-transformed and multiplied by -100.
Firm-level distinctiveness	1 - cosine similarity based on all product category labels k affiliated with each firm j in week t. Averaged.
Product category position	1 - cosine similarity based on all product category labels k affiliated with each product i in week t within its own superordinate product category. Averaged.

Table 1: Summary of variables used in analysis

3.3 Estimation approach

Due to the nature of our data, we used a panel model to estimate the effect of all independent and control variables on product performance. We deem random effects to be suited to our specific data set, as we selected a subsample of firms with uneven sampling. Our panel structure is nested, as the specific product is a lower-level factor that appears only within the upper-level factor of the firm. A firm can be affiliated with multiple products, but a product can only be affiliated with exactly one firm. Consequently, we estimated nested ("firm") random effects models with a nested individual ("product") effect. We used the free statistical software *R* and the package *plm* (Croissant and Millo, 2008) to estimate the panel models. As a robustness check, we also ran all models as fixed effects models with a fixed individual ("product") effect. The results are comparable and can be found in Table 4 as Models 3 and 4. Panel models are prone to biased standard errors (Arellano, 1987). To

level to determine the product category position. This also includes accounting for the product category size by the product reviews, the consumer review volume, rating and dispersion, as well as the suggestions to control for learning effects and distinctiveness heterogeneity. Our measurement of the latter differs slightly from Haans (2019) due to the nested structure of our product category labels.

account for group and time effects, we follow the procedure put forward by Petersen (2009) and use double clustered standard errors that are both clustered by product to capture unspecified correlation between observations of the same product in different weeks, and clustered by week to capture the unspecified correlation between observations on different products in the same week. We used the *vcovDC()* command provided by the package *plm* for the computation (Millo, 2017).

The regression results are modified to incorporate double clustered standard errors, and the significance of coefficients was tested with the adjusted variance-covariance matrix. To more thoroughly test the commonly assumed curvilinear interaction term of firm-level distinctiveness, we followed the procedure presented by Haans et al. (2016) and Lind and Mehlum (2010). Hence, we visualized the magnitude of the interaction, calculated a turning point for the curvilinear relationship, and tested the sign and significance of the slope at both low and high values.

4 Results

Table 2 and Table 3 provide an overview of the descriptive statistics and correlations of our variables. As can be seen, most of our variables show only low correlation, with some exceptions that show medium correlation. Table 4 provides the output of our regression analysis. Before testing the proposed moderation effect of product category position, we followed the common procedure and first tested whether there is a curvilinear relationship between firm-level distinctiveness and product performance (Haans, 2019; Zhao et al., 2017). Thus, Model 1 in Table 4 introduces the linear and squared terms of firm-level distinctiveness. It shows that the main effect of firm-level distinctiveness is negative and significant, while the squared term is positive and significant, which means that there is a U-shaped relationship (Figure 1) (Haans et al., 2016). As the upward slope signifies better sales performance, it seems that audiences excessively reward firm-level distinctiveness (Smith, 2011). Conducting

Statistic	N	Mean	Median	St. Dev.	Min	Max
Sales rank	118,334	−8.647	−8.233	2.245	−15.590	0.000
Product category size	118,334	6.548	7.077	1.675	0.000	9.175
Product category portfolio size	118,334	4.074	3	3.487	1	15
Product portfolio size	118,334	58.611	13	96.534	1	361
Product price	118,334	7.776	7.596	1.058	4.595	13.570
Price changes prior week	118,334	0.208	0	0.508	0	3
Product competition	118,334	182.322	116	188.804	1	658
New venture competition	118,334	26.919	21	18.836	1	68
Product age	118,334	3.326	3.5	1.106	0	5
Consumer review volume	118,334	1.170	0.7	1.462	0	7
Consumer review rating	118,334	4.225	4.277	0.672	1.000	5.000
Consumer review dispersion	118,334	0.754	0.776	0.533	0.000	2.828
Distinctiveness heterogeneity	118,334	1.845	1.939	0.675	0.000	4.712
Firm-level distinctiveness	118,334	0.950	0.950	0.023	0.877	0.997
Firm-level distinctiveness sqrd.	118,334	0.904	0.903	0.044	0.769	0.994
Product category position	118,334	0.464	0.502	0.151	0.000	1.000

Table 2: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Sales rank	1															
(2) Product category size	0.264	1														
(3) Product category portfolio size	-0.027	0.217	1													
(4) Product portfolio size	-0.009	0.188	0.669	1												
(5) Product price	0	-0.028	-0.224	-0.287	1											
(6) Price changes prior week	0.018	-0.076	-0.062	-0.098	0.151	1										
(7) Product competition	0.156	0.504	0.366	0.605	-0.276	-0.157	1									
(8) New venture competition	0.221	0.74	0.16	0.284	-0.039	-0.101	0.719	1								
(9) Product age	0.157	0.128	0.08	0.024	0.037	0.108	0.069	0.078	1							
(10) Consumer review volume	0.408	0.16	-0.189	-0.278	0.177	0.101	-0.154	-0.02	0.268	1						
(11) Consumer review rating	-0.004	-0.007	0.015	-0.005	-0.06	-0.06	0.069	0.009	-0.074	0.02	1					
(12) Consumer review dispersion	0.151	0.069	-0.042	-0.041	0.126	0.087	-0.06	0.01	0.104	0.266	-0.396	1				
(13) Distinctiveness heterogeneity	0.087	0.235	0.267	0.29	-0.192	-0.06	0.395	0.31	0.006	-0.126	-0.013	-0.007	1			
(14) Firm-level distinctiveness	-0.021	-0.307	-0.066	-0.15	0.105	0.051	-0.299	-0.428	0.129	-0.045	-0.064	0.027	-0.371	1		
(15) Firm-level distinctiveness sqrd.	-0.018	-0.31	-0.071	-0.154	0.105	0.05	-0.302	-0.43	0.128	-0.044	-0.064	0.027	-0.371	1	1	
(16) Product category position	0.116	0.426	0.022	-0.048	0.1	-0.024	0.204	0.389	0.007	0.072	-0.01	0.053	0.06	0.073	0.07	1

Table 3: Correlations

the additional statistical testing proposed by Haans et al. (2016) and Lind and Mehlum (2010) shows that the slope is sufficiently steep at both ends, as the lower bound of the curve, at 0.877, is negative and significant (-20.886, p = 0.042) and the upper bound of the curve, at 0.997, is positive and significant (28.055, p = 0.003). The turning point located at 0.928 (95% Fieller's confidence interval: [0.884; 0.941]) is well within the data [min = 0.877; max = 0.997]. As another robustness check, we followed Qian et al. (2010) and built two sub-samples with firm-level distinctiveness values below and above the turning point to test whether two linear regressions would yield slopes that are consistent with the predicted shape of the curve (Haans et al., 2016). Both slopes of the two sub-samples show consistency.

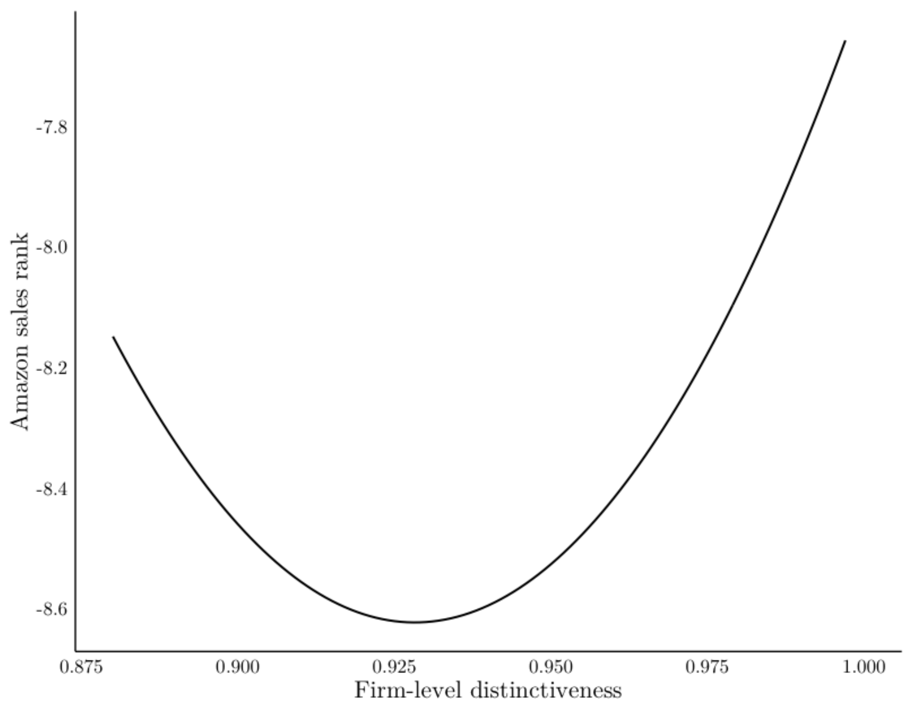

Figure 1: Effect of firm-level distinctiveness on product performance. Based on Model 1 in Table 4.

Interacting both the firm-level distinctiveness linear and multiplicative term (Model 2 in Table 4) shows that firm-level distinctiveness is moderated by the product category position, as suggested by our hypothesis H2. To visualize the moderation (see Figure 2), we set

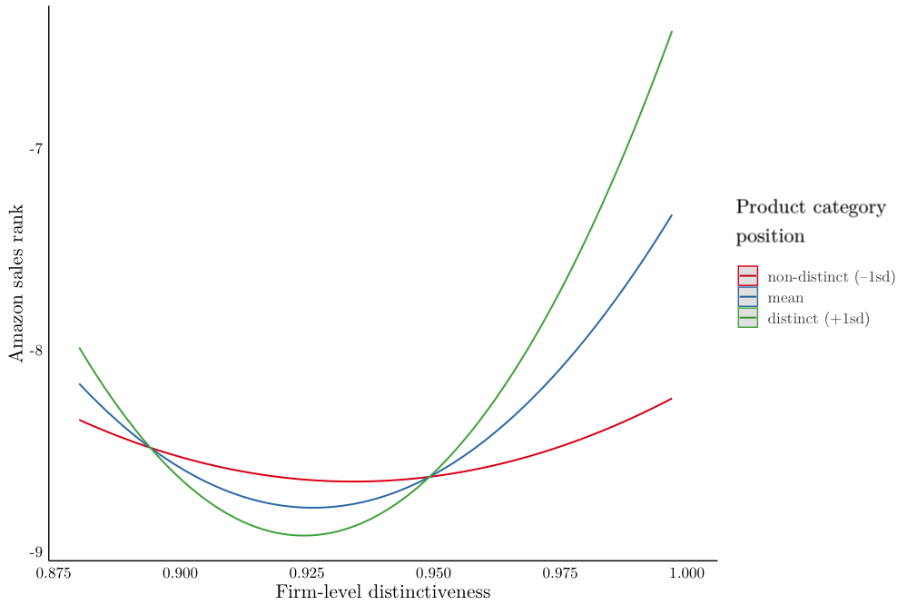

Figure 2: Effect of firm-level distinctiveness on product performance by product category position. Based on Model 2 in Table 4.

the values of the moderator product category position at mean (0.46) minus one standard deviation (non-distinct position) and mean plus one standard deviation (distinct position). As compared to its shape in Figure 1, analyzing the graphics shows that the interaction of the U-shaped effect of firm-level distinctiveness with the product category position steepens (flattens) the curve (Haans et al., 2016).

In absolute terms, a product offered by a firm with very high firm-level distinctiveness would have a sales rank of approximately 6.7 (log reconverted: 812) in a product category with a distinct position, compared to a sales rank of 7.5 (log reconverted: 1,808) in a product category with a moderately distinct position, and 8.2 (log reconverted: 3,641) in a non-distinct one. The effect of the product category position on product performance is significantly smaller for low firm-level distinctiveness, i.e., 8.0 for a product category with a distinct position (log reconverted: 2,981), 8.15 (log reconverted: 3,463) for a product category with a moderately distinct position, and 8.3 for a product category with a non-distinct position (log reconverted: 4,024) [3]. Models 3 and 4 in Table 4 show the regression results of the fixed effects model. As can be seen, the results are comparable.

5 Discussion and implications

The overarching goal of this paper is to determine the effectiveness of firm-level distinctiveness across different product categories in which a firm seeks to operate. While this question may not be of the utmost importance for firms that center around a single product or service, it is relevant for those with a portfolio of products or services and for those that aspire to grow and face the challenge of exploring additional markets and revenue streams (Bu et al., 2022; Kim and Jensen, 2011; Fernhaber and Patel, 2012). Instead of conceptualizing the effect of optimal distinctiveness on performance strictly from a firm or a product level, our work follows recent calls for a multi-level perspective (Zhao et al., 2017; Zhao and Glynn, 2022) that is highly dynamic and observed over time. Our results show that firm-level distinctiveness is actually capable of significantly boosting product performance only in product categories with a distinct position, i.e., those that share little or no overlap with others in the classification system (Lo et al., 2020). The less distinct a product category's position, the less effective firm-level distinctiveness is in improving product performance.

We explain this difference with the cultural code the categories provide for evaluation (Vergne and Wry, 2014) and the respective audiences they consist of (Vossen and Ihl, 2020). These audiences look for more sophisticated and elaborate solutions and are consequently willing to invest additional effort in evaluating their product options (Paolella and Durand, 2016). However, the categories' distinct position also requires additional information cues that help evaluating products, which audiences find in a firm's organizational identity (Smith, 2011). While evaluating such organizational identities, audiences may recognize familiarity more likely, which renders them more receptive to the benefits of conformity in case firm-level distinctiveness is low. However, the effect is more pronounced for high levels of firm-level

[3] We thank an anonymous reviewer for the suggestion to include this illustration.

	Dependent variable:			
	Amazon sales rank			
	(1)	(2)	(3)	(4)
Product category size	0.236***	0.225***	0.243***	0.233***
	(0.050)	(0.051)	(0.052)	(0.052)
Product category portfolio size	0.058*	0.056*	0.048	0.046
	(0.033)	(0.033)	(0.033)	(0.033)
Product portfolio size	0.003***	0.003***	0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Product price	−0.102	−0.102	−0.141	−0.150
	(0.075)	(0.074)	(0.112)	(0.112)
Price changes prior week	0.035	0.034	0.033	0.032
	(0.025)	(0.025)	(0.025)	(0.025)
Product competition	0.001***	0.001***	0.001**	0.001**
	(0.0005)	(0.0005)	(0.001)	(0.001)
New venture competition	0.029***	0.032***	0.032***	0.035***
	(0.005)	(0.005)	(0.006)	(0.006)
Product age	0.164***	0.159***	0.166***	0.161***
	(0.030)	(0.030)	(0.037)	(0.036)
Consumer review volume	0.410***	0.400***	0.393***	0.379***
	(0.047)	(0.047)	(0.055)	(0.055)
Consumer review rating	0.077	0.087	0.080	0.091
	(0.054)	(0.055)	(0.058)	(0.059)
Consumer review dispersion	0.074	0.070	0.074	0.070
	(0.066)	(0.065)	(0.069)	(0.068)
Distinctiveness heterogeneity	0.026	−0.017	−0.0002	−0.040
	(0.064)	(0.065)	(0.067)	(0.067)
Firm-level distinctiveness	−378.562**	510.012	−328.750**	585.239
	(147.298)	(347.878)	(154.046)	(371.069)
Product category position	0.924**	1,047.405***	1.301**	1,090.574***
	(0.438)	(370.430)	(0.537)	(398.385)
Firm-level distinctiveness sqrd.	203.920***	−278.127	176.776**	−319.076
	(78.334)	(184.231)	(81.914)	(196.428)
Firm-level distinctiveness x product category position		−2,275.077***		−2,368.526***
		(785.295)		(844.293)
Firm-level distinctiveness sqrd. x product category position		1,234.324***		1,285.080***
		(416.066)		(447.208)
Constant	163.453**	−245.246		
	(69.350)	(164.204)		
Nested individual effect (product)	Yes	Yes	No	No
Group effect (firm)	Yes	Yes	No	No
Fixed effect (product)	No	No	Yes	Yes
Observations	118,334	118,334	118,334	118,334
R^2	0.338	0.343	0.318	0.323
Adjusted R^2	0.338	0.342	0.305	0.310
Note: Double clustered standard errors (product and week) in parentheses				*p<0.1; **p<0.05; ***p<0.01

Table 4: Results of nested (firm) random (Model 1, 2) and fixed (Model 3, 4) effects regressions.

distinctiveness, as product categories with a distinct position provide a suited cultural code that allows audiences to evaluate and assess whether a firm is in line with their theory of value (Durand and Paolella, 2013) and include this information in their evaluation of the respective product (Vossen and Ihl, 2020).

Yet this additional information can result not only in benefits but also harm, as these audiences also recognize undesirable moderate levels of firm-level distinctiveness, which leads to a steeper devaluation as compared to product categories with a non-distinct position, thereby amplifying the "stuck in the middle" problem (Cennamo and Santalo, 2013). If used to compete in a product category that provides the suited cultural code to evaluate it and to address audiences that value more sophisticated solutions provided by seemingly more capable firms (Kim and Jensen, 2011; Pontikes, 2012), high levels of firm-level distinctiveness are rewarded excessively and have a strong impact on product performance (Smith, 2011). Thus, the market context that shapes the effect of firm-level distinctiveness on performance is contingent not only on competing actors and their firm-level distinctiveness approach (Haans, 2019), but also on the evaluative boundary conditions set out by the product categories themselves. This is our core contribution.

Our second contribution relates to the literature on categorization, particularly in contributing to the reconciliation of the intra- and inter-category streams of the literature on optimal distinctiveness (Bu et al., 2022; Lo et al., 2020). We showcase how firms can leverage their inter-category, i.e., firm-level distinctiveness appeal, to achieve intra-category differentiation, i.e., increase performance on the product level, as products offered by firms with high firm-level distinctiveness outperform those offered by firms with low or moderate firm-level distinctiveness. We also provide important boundary conditions by showcasing that this effect is only meaningful with audiences that value distinctiveness and know how to evaluate it (Paolella and Durand, 2016; Vergne and Wry, 2014), as firm-level distinctiveness has only very limited differentiation potential in product categories with a non-distinct position. In such categories, it may still be advisable for firms to rely on more product-centered means of differentiation, such as narratives or other forms of cultural elements (Taeuscher et al., 2022; Vossen and Ihl, 2020). We also highlight that the approach commonly applied in past research, in which the performance of distinctiveness is measured on the product level and averaged to draw inferences on the firm level, needs careful conceptual consideration (Paolella and Durand, 2016). It may very well be the case that the effect on a firm level is the result not of a consistent boost in performance across all product categories, but of strong performance in some and almost no performance in other categories (Bowers, 2015).

In this regard, our work also provides further insight on how individual category affiliations interact with the overall organizational perception (Barlow et al., 2018; Cudennec and Durand, 2022; Gehman and Grimes, 2017). One explanation for the strong performance of firm-level distinctiveness in product categories with a distinct position could be that audiences perceive it as category promotion, i.e., an effort "to champion the labels or cultural artifacts signifying the category" (Gehman and Grimes, 2017, p.2294). Our results could be interpreted as category promotion on a more abstract level, as it does not require specific superior or subordinate product category membership, but only membership in a category that fits the organizational identity. However, if a highly distinct firm seeks category membership in product categories with a non-distinct position, firm-level distinctiveness can be perceived almost as a stigma and product performance decreases (Barlow et al., 2018).

Our third contribution relates to audience evaluation of organizational identities and introduces the important notion that evaluations of firm-level distinctiveness differ not only across types of audiences, i.e., consumers versus venture capitalists (Pontikes, 2012), but also within audiences (Kim and Jensen, 2011). Past research shows that consumer audiences express preferences for organizations with a distinct strategy (Pontikes, 2012). We find that this is not necessarily true for firms that compete in product categories with a non-distinct position, as consumers' preference only manifests for firms competing in product categories with a distinct position. This does not generally contradict the finding that, on average, consumers dislike ambiguity in firms (Pontikes, 2012)—as expressed by the good product performance of firms with high firm-level distinctiveness—but only adds to the importance of accounting for the product category context in which firm-level distinctiveness takes place: When firms offer more than one core service or product or a diverse product portfolio tailored to assumed heterogeneous consumer audiences, it may not be sufficient to rely on the general firm-level distinctiveness alone (Kim and Jensen, 2011; Zhao et al., 2017).

Our fourth contribution relates to firm strategies that intend to orchestrate firm-level distinctiveness, i.e., that want to make high firm-level distinctiveness more legitimate or low firm-level distinctiveness more differentiated by adding respective product categories (Pontikes and Barnett, 2017; Zhao et al., 2017). Although our results and prior research both highlight that category membership affects the organizational identity (Barlow et al., 2018; Gehman and Grimes, 2017), we do not find that seeking membership in specific product categories is able to orchestrate a firm-level distinctiveness appeal in a meaningful way. Due to the pronounced U-shaped effect, not much can be quickly achieved by differentiating low firm-level distinctiveness by adding product categories with a distinct position or legitimizing high firm-level distinctiveness by adding those with a non-distinct position. As such, our results suggest that product category membership decisions are only able to change the firm-level distinctiveness appeal and not to orchestrate it. If firms want to engage in orchestration, we suggest that they pursue additional intra-category efforts (Lo et al., 2020) and use additional cultural elements, such as accompanying narratives, that help in sense- and decision-making in case of "conflicting" distinctiveness of the firm and the product category (Navis and Glynn, 2011). As of now, we would advise firms that rely on high firm-level distinctiveness to expand to product categories with a distinct position in order to improve or retain their high firm-level distinctiveness, rather than to add ones with non-distinct positions to increase their conformity appeal.

From a managerial point of view, our results have some clear-cut implications for management practice. While a well-tailored and distinct bundle of business activities provides firms with many competitive advantages (Fernhaber and Patel, 2012), managers need to be aware that its effectiveness in altering audience evaluation may be severely limited in a certain product category context. Therefore, it is of the utmost importance that they consider their own firm-level distinctiveness appeal in deciding which product categories to enter. This makes our results highly valuable in particular for firms that seek to grow into additional product categories (Fisher et al., 2016). While it may be tempting to move from a distinct product category into a more mainstream one, our results suggest that this strategy is not necessarily advisable for firms in online consumer goods markets. In the short run, firms that intend to sustain their distinctiveness appeal during the growth stage are well advised to grow into product categories with a distinct position and sharpen their profile rather than try to enter mainstream product categories. Managers of new or younger firms also need to consider that their strategy of attaining optimal distinctiveness, developed to acquire funding or to launch their first product, may need significant adjustment should the firm begin to grow into additional product categories. In order to succeed in this task, managers should have a clear impression of whether audiences of those targeted product categories have both a preference and the right set of tools to evaluate their firm-level distinctiveness. If both conditions are satisfied, firms are likely to benefit.

6 Limitations, future research, and conclusion

Our study is not without limitations, several of which arise from the selection of our variables and our empirical setting. A product's sales rank as a dependent variable may facilitate the comparison of sales performance across very heterogeneous product categories, yet it still remains a well-established but also rather peculiar measurement (Chevalier and Mayzlin, 2006; Smith and Telang, 2009). In spite of "rank" variables being quite common (Barlow et al., 2019; Pontikes, 2012) and the longitudinal character of our study, they bear the limitation that they may also be partially driven by market dynamics, as a product's own rank can improve as a result of a decrease in the performance of competitors.

Our measure of firm-level distinctiveness follows our conceptual approach that perceives it as part of the organizational identity and thus focuses on the product category labels as the "raw material" to build it (Glynn and Navis, 2013). It will prove valuable to examine alternate operationalizations of firm-level distinctiveness in order to add to the robustness of our findings or introduce further meaningful boundary conditions to them (Zhao and Glynn, 2022). Our firm-level distinctiveness measure also focuses on product category breadth rather than depth (Fernhaber and Patel, 2012). While we control for depth by means of the number of products offered, our current approach does not allow us to draw any conclusions on the intra-category effect of firm-level distinctiveness within the same product category. This is again a consequence of our sample and our product category labels, which treat multiple products from the same product category as equally distinct. Future research could build on this issue and provide means to examine intra-category dynamics and the effect of product category depth on the effectiveness of firm-level distinctiveness in appealing to audiences across different product categories. This could, for example, entail analyzing firms' additional efforts to differentiate or conform, such as product narratives or other promotional activities (Zhao et al., 2017).

To outline differences in the reception of firm-level distinctiveness across product categories, we focus on the distinct position it occupies in the broader classification system and the respective differences in cultural code and audiences. This is, however, only one exemplary and inconclusive conceptual choice, as other categorical traits or concepts could provide useful insights that may be worth pursuing in future research (see, e.g., Vergne and Wry (2014) for an overview). Our approach of measuring the product category position was motivated by the notion of a distinct position being a consequence of a lack of overlap with other product categories. While category overlap is easy to conceptualize, its empirical measurement is inherently limited by the data and the empirical setting, such as in our case the hierarchical category labels and the consumer goods market. Both are likely influential (Cudennec and Durand, 2022; Durand and Haans, 2022) and testing a setting that differs in both may provide an interesting avenue for future research. One possibility for future research could therefore be using an empirical setting that allows to identify the (non)distinct position of product categories based on attributes that allow comparison even beyond the category tree.

Although the online consumer goods market setting offers obvious advantages in answering our research questions, it also holds additional limitations. Using data from Amazon Launchpad may imply a sample selection bias, as only new ventures that fulfill Amazon's requirements are included and Amazon could be inclined to only allow new ventures that they assume will be at least potentially successful. As we do not know the respective selection criteria, our approach renders us unable to account for them and we must leave that to future studies whose empirical context is capable of controlling for such effects. It also seems reasonable to assume that some of our results are partially driven by our focus on new ventures and their appeal to consumer audiences, who may have different expectations or preferences as compared to, for example, investor audiences (Fisher et al., 2017). Further research is needed to verify whether our results also hold true in a business-to-business setting, and to test whether differences exist between ordinary and business customers in the way they perceive firm-level distinctiveness in certain product categories. Arriving in the mainstream is particularly central and important for new ventures, and more research is needed that determines how new ventures can use firm-level distinctiveness to effectively compete in mainstream markets. Contrary to our expectations, firm-level distinctiveness seems not to be the answer to this, as it does not allow firms to differentiate their products in mainstream product categories, and more research is needed that identifies how new ventures can leverage their firm-level distinctiveness while continuously growing into those categories.

We set out to find out how firms can make the most of their firm-level distinctiveness. After discussing both our findings and their limitations, we can conclude that, although firm-level distinctiveness has the potential to dramatically shape product performance, it does not have a universally positive appeal. Referring to the title of this work, we hope that these insights help firms realize that, in order to succeed, they need to pair firm-level distinctiveness with membership in product categories with a distinct position. Only in this way can they become “categorically right” and enable their products to fully benefit from their firm-level distinctiveness appeal.

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