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The value of distinctiveness: Product uniqueness in crypto marketing ☆

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ABSTRACT

Marketers across industries appeal to consumers' need for uniqueness in their marketing and product strategies. While there is an understanding of the many benefits of such a strategy and its underlying mechanisms, the effects are often linked to product scarcity, leaving a product's distinctiveness compared to similar products unexplored. In this study, we examine the effect of product attribute distinctiveness using transaction data of a large non-fungible token (NFT) collection. Despite identical initial launch prices for all products in the collection, secondary sale prices vary substantially. Using a selection model, our results show that a unique product is less likely to be resold. We also find a positive relationship between attribute distinctiveness and transaction value. This indicates the importance of such product information to consumers. The implications of our empirical study add to the literature on uniqueness, NFTs, and crypto marketing.

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1. Introduction

Many product and marketing strategies go beyond satisfying functional needs and aim to enhance consumers' personal and social identities. Research recognizes consumption as a means of expressing or enhancing one's identity (Lynn & Harris, 1997b; Tian et al., 2001). A common example is clothing. In addition to functional benefits, clothing allows one to express one's personal style. Each clothing product has several attributes: its cut, material, color, and optional details, such as buttons, zippers, or embellishments. Based on these different attributes and compositions, there is a wide variety of clothing products ranging from highly distinctive to easily recognizable and widely popular pieces. This variety allows for differentiation in consumption and the possibility to signal conformity or disconformity to different types of social groups by the selection of a product. This is true for clothing and many other product categories, such as cars, accessories, electronics, and even food. But do consumers actively consider the distinctiveness of a product in their decision-making and does it influence how they value the product?

Despite the benefits of social conformity, the differentiation potential of products is relevant to consumption choices because people refrain from high levels of interpersonal similarity (Snyder & Fromkin, 1977). Instead, they seek positive distinctiveness from others. This pursuit is known as consumers' need for uniqueness (Cheema & Kaikati, 2010; de Bellis et al.,

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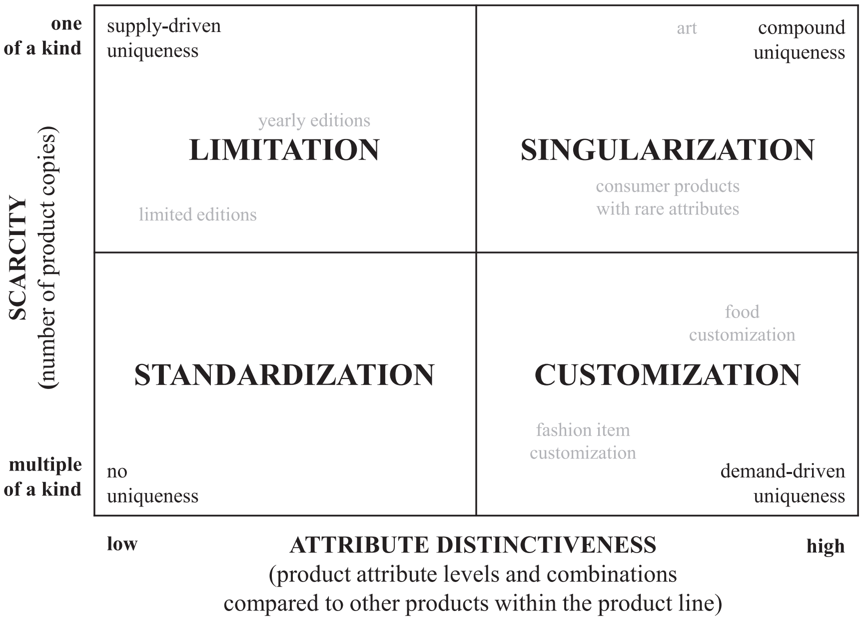


Fig. 1. Classification of Product Uniqueness.

2016; Irmak et al., 2010; Roy & Sharma, 2015; Tian et al., 2001). The motivation and extent to which consumers pursue this need can vary according to different situations or personal dispositions and can substantially affect consumer behavior. Existing research highlights the impact of uniqueness-seeking on consumer decision-making (Simonson & Nowlis, 2000), their willingness to pay (Franke et al., 2010), firm profits, and competitive positioning (Amaldoss & Jain, 2005). These findings suggest that consumers derive value from conditions that allow them to differentiate themselves from others.

The goal of this research is to investigate whether consumers value product uniqueness so that marketers can use uniqueness as a product attribute to differentiate prices. Product uniqueness results from variations in the composition of product attributes that can make a product more or less unique within a product line. Using real market data, we examine whether such variation affects consumers' product valuation and, thereby answer the following research question:

RQ: How do consumers value product attribute distinctiveness across a product line?

The definition of what constitutes a unique product varies substantially in the existing literature. Krause et al. (2023) define product uniqueness in the strict, literal sense of being "one of a kind". However, most previous research also includes "few of a kind" products in the definition of uniqueness as long as these products are somewhat limited in availability and thereby elicit a perception of uniqueness (Cheema & Kaikati, 2010; Franke & Schreier, 2008; Lynn & Harris, 1997a; Tian et al., 2001). This latter definition of uniqueness emphasizes the limitation of product copies, i.e., the scarcity of the product.

As Fuchs and Schreier (2023) point out, in addition to scarcity, it is also important to consider whether a product is perceived as different from similar products. Thus, attribute distinctiveness captures the extent to which a product differs from other products within the same product line based on its attribute levels and their combinations. In this sense, products with many attributes, attribute levels and combinations can achieve a higher degree of distinctiveness, regardless of their limitation in product copies. Examples include automobiles[1] or customized consumer products such as sneakers.[2] The degree of distinctiveness is thus the result of the number and frequency count of product attributes, levels and their combinations within the product line, as opposed to the mere scarcity of a product.

Therefore, we propose a classification of product uniqueness integrating the two dimensions of scarcity and attribute distinctiveness in Fig. 1. For illustrative purposes, we structure the different combinations of dimensions into three strategies: *Limitation* denotes uniqueness based on supply-driven scarcity with low attribute distinctiveness (e.g., limited editions). *Customization* denotes demand-driven uniqueness of multi-unit products with higher attribute distinctiveness, such as customization of fashion items. *Singularization* denotes few or one-of-a-kind products with high attribute distinctiveness, such as art. *Standardization* refers to the lack of product uniqueness.

In understanding why and to what extent uniqueness is important to consumers, previous research has devoted considerable effort to understanding and identifying the nature of individual differences in consumers' need for uniqueness and its effect on behavior (Irmak et al., 2010; Lynn & Harris, 1997b; Moldovan et al., 2015; Snyder & Fromkin, 1977; Tian et al., 2001;

[1] Caterham, a sports car manufacturer, offers a configuration tool that yields 58,338,005,483,520,000 permutations (Car Dealer Magazine, 2020).
[2] Bullfeet, a leather goods and footwear brand, promotes its customization tool by emphasizing the millions of possible combinations (Bullfeet, 2024).

Tian & McKenzie, 2001). Although such research efforts provide substantial evidence for the importance of addressing consumers' need for uniqueness and its variation across individuals, the findings are primarily applicable to general marketing and communication strategies (Lynn & Harris, 1997a; Snyder, 1992). However, uniqueness in the context of product classification and design has so far received little attention in previous research. One possible reason may be data limitations, such as the lack of public transparency on product lines and product attribute configurations. Now, the emergence of non-fungible tokens (NFTs) provides real-world cases where product uniqueness arises solely from attribute distinctiveness.

NFTs are cryptographic assets based on blockchain technology and represent unique identification codes linked to associated metadata. These identification codes make each NFT unique by definition. Since all products are one of a kind (i.e., unique), this setting provides a new opportunity to study different degrees of attribute distinctiveness and their relevance to product valuation. Despite significant volatility, the NFT market has developed beyond niche applications, with transactions exceeding $25 billion in 2021 (Howcroft, 2022) and applications continuing to expand (Kireyev & Evans, 2021), generating relevant data for scientific analysis.

In this paper, we study such a novel NFT dataset to shed light on the potential of using various degrees of attribute distinctiveness as one dimension of product uniqueness. In doing so, we also contribute to the understanding of how data specific to blockchain applications can help advance marketing knowledge (Peres et al., 2023). Specifically, we analyze the so-called "Bored Ape Yacht Club (BAYC)" NFT collection. This collection is a product line consisting of 10,000 products, where we observe all transactions over 14 months.

This NFT dataset has several characteristics that make it suitable to address our research question. First, each (NFT) product in this collection consists of different attributes that are publicly displayed (i.e., transparent) in the product profile. However, these product attributes are only revealed after the first sale. In addition, attributes occur more or less frequently across the product line, thus affecting the degree of product distinctiveness. Such product lines of NFTs are interesting to study because their attribute-based product composition has many similarities to a wide range of digital and physical products. Second, despite design variations, all (NFT) products in this product line have identical launch prices, which avoids a price-based signal of product uniqueness. Thanks to these identical launch prices, it is possible to study consumers' valuations of product distinctiveness by observing the prices paid in secondary market transactions. Third, the immutability of the product data makes it impossible to change, add, or remove a product from the product line once it has been launched. Using this immutable data allows us to understand whether these fixed differences in product design affect the prices in secondary market transactions. For each product, we analyze the first resale to study the unbiased consumer valuation of differences in product design. All available products initially sold at an identical launch price, but 13 % of all products were not resold on the secondary market during the observation period. We operationalize attribute distinctiveness as a rank score metric, but also test the robustness of our results to alternative measures.

The findings are twofold. First, our results suggest a positive relationship between product uniqueness based on attribute distinctiveness and value. Products with higher levels of attribute distinctiveness are valued more than those with lower levels of attribute distinctiveness. This finding is robust across the 8,709 resold products during our observation period. Second, we are also interested in the 1,291 products that were not resold. In these cases, we find that among supply and demand indicators, the degree of product attribute distinctiveness to also play a role in predicting whether a product resells on the secondary market or not. The results suggest that the more distinct a product, the less likely it resells.

Our results contribute to two streams of literature. First, we add to the existing literature on product uniqueness. Ranking the products in a product line according to their attribute distinctiveness transparently reveals product differences independent of consumer tastes. This represents a novel operationalization of an empirical approach to product uniqueness by extending common measures of individual differences (Lynn & Harris, 1997b; Snyder & Fromkin, 1977; Tian et al., 2001) and perceptions (Franke & Schreier, 2008; Whitley et al., 2018). Also, it allows for a deeper understanding of the complex nature of product uniqueness. In an attempt to better understand the relevance of attribute distinctiveness in the definition of product uniqueness, we derive a classification (Fig. 1) that allows us to identify different forms of product uniqueness. In addition, the NFT dataset demonstrates how uniqueness can be translated into a specific product portfolio strategy and extends research beyond business-enhancing appeals in marketing messages (Lynn & Harris, 1997a; Snyder, 1992).

Second, this paper contributes to the emerging literature on marketing applications of blockchain technology and cryptomarketing. Peres et al. (2023) discuss the importance of understanding the implications of blockchain technology for marketing applications, highlighting relevant research avenues for marketing strategy, marketing mix elements, and the impact on intangible marketing assets. Some of the key benefits of advancing blockchain as a general-purpose technology include different forms of products, data structures, and the empowerment of peer-to-peer networks. Each of these aspects has the potential to disrupt current marketing practices. Hofstetter et al. (2022) also raise awareness that NFTs have the potential to challenge traditional marketing practices and call for more research in this regard. In this paper, we use NFT data and its market specifics, such as its highly differentiated product line and immutable transaction history, to uncover the benefits of using blockchain technology in marketing research. More specifically, our findings complement recent studies aimed at understanding the value drivers of NFTs (Colicev, 2023; Dowling, 2022; Nadini et al., 2021; Zhang, 2023) by examining the effects of attribute distinctiveness as a form of product uniqueness. Furthermore, our results have implications for NFT creators, NFT marketplace operators, and marketers who want to use NFTs as part of their product design and promotion strategy, including digital twins of physical products (Sundararajan, 2022).

The remainder of this paper is organized as follows: In Section 2, we discuss the theory and related literature on uniqueness-seeking behavior in marketing to understand the value of product uniqueness in marketing strategies. Section 3 describes our dataset and methodological approach. In Section 4, we present and discuss the results of our analyses, followed by implications for theory and practice, as well as limitations and opportunities for further research in Section 5. Section 6 concludes the paper.

2. Theory and related literature

2.1. Uniqueness-seeking in consumer products

People have a need to differentiate themselves from others in their social environment. Social science and marketing literature establish this thrive as peoples' need for uniqueness (Snyder & Fromkin, 1980; Tian et al., 2001). In these definitions, interpersonal deviance has a positive connotation with the pursuit of moderate distinctiveness to express one's individual nature (Snyder & Fromkin, 1977, 1980) within the bounds of social assimilation (Ruvio, 2008). Roy and Sharma (2015) define the need as a personal characteristic that allows one to establish, to some extent, a separate identity through self-differentiating behavior. If possessions are viewed as an extension of one's identity (Belk, 1988), products are essential to satisfy this need, which also explains the interest and involvement of marketers in the topic.

In consumption contexts, the uniqueness-seeking behavior is broader to extend the pursuit of differentiation by capturing the underlying motivations that manifest in consumption. These include personality traits such as status-seeking and materialism (Lynn & Harris, 1997a). Also, as a trait and state of mind, narcissism lets consumers pursue differentiation through consumption (de Bellis et al., 2016; Lee et al., 2013). Tian et al. (2001) extend the similarity avoidance motive to include creative and unpopular counter-conformity product choices. These also reflect individualization, linking uniqueness-seeking to product design and use. Irmak et al. (2010) recognize the acquisition, utilization, and disposal of certain types of products as expressions of uniqueness-seeking behavior, highlighting the need for products to respond to the underlying consumer motivations.

However, the expression of uniqueness-seeking behavior and its impact on consumption are subject to variance. In addition to dispositional differences among consumers (Snyder & Fromkin, 1977), the influence of external factors leads to a perceptual view of uniqueness that is highly dependent on social comparisons (Ames & Iyengar, 2005; Irmak et al., 2010). As such, the perception of moderate to high levels of similarity to others leads people to project their own evaluations onto others (Ames & Iyengar, 2005). This can ignite and cause variations in consumers' need for uniqueness (Snyder, 1992), make consumption decisions subject to social approval and (dis)conformity motives (Tian et al., 2001), and increase the complexity of product design requirements.

Research shows that products are particularly effective in signaling uniqueness to others when their access is restricted and consumers are aware of such conditions. By this, product visibility allows for recognition by others and thus manifests differentiation through symbolism in consumption (Belk et al., 1982; Richins, 1994). A lack of social comparison may not make it worthwhile for consumers to pursue such unique products (Barton et al., 2022). Gierl and Huettl (2010) support this argument by showing that product visibility moderates the effects of scarcity on conspicuous consumption. Nevertheless, consuming a unique product of low visibility may still enhance one's uniqueness but not reduce one's similarity to others in a setting of social comparison. In this line of thought, Song and Sela (2023) find that self-focused settings, such as smartphone shopping, also trigger the choice of more unique product options based on motivations different from those of social comparison.

Thus, situational and dispositional variation can implicitly affect the product choice and expectations about the product's potential to achieve a desired level of differentiation. Such variation also explains the natural tension between the need to differentiate from others and the need to assimilate with others. Chan et al. (2012) show that this tension adjusts product choices so that they are still within the social frame of reference. This variety of influencing factors highlights the multifaceted nature of uniqueness-seeking in consumption. Thus, successful appeals to uniqueness depend on the individual's need level, several external influencing factors, and the resulting perception of product uniqueness. This poses a challenge to marketers in making and evaluating strategic decisions in the communication and design of their products.

2.2. Impact of uniqueness-seeking on product choice and valuation

Consumers with a high need for uniqueness have been found to engage in more extensive search processes (Tian & McKenzie, 2001), tend to select unconventional reasons to motivate and make their product choices (Simonson & Nowlis, 2000), and consider more extensive assortments for their choices (Whitley et al., 2018). However, it is also the product choice itself that provides valuable insights into the importance of uniqueness-seeking in marketing and its relevance for product design. Examples include unusual, and prestige-priced products or limited editions (Lynn & Harris, 1997a), but can also be reflected in early product adoption, a preference for vintage goods, or conspicuous consumption (Ames & Iyengar, 2005; Hinz et al., 2015). All of these product types signal some form of limitation, reducing the likelihood that a large number of other consumers will purchase the same product and increasing the likelihood of differentiation. Consumers rely on these product types as cues to approximate the product's potential need satisfaction, which in turn affects product valuations, product use, and even word-of-mouth behavior (Cheema & Kaikati, 2010). Thus, acknowledging uniqueness in product design can create opportunities for differentiation, value creation, and new business models, such as customization (Franke & Schreier, 2008).

Research has attempted to directly manipulate product uniqueness in order to assess its effects on consumer behavior and perceptions. While Ames and Iyengar (2005) categorize objects into ordinary or unusual objects based on a pretest, Amaldoss and Jain (2005) initialize consumer uniqueness through utility-based modeling. Even when such settings allow for the representation of a spectrum of uniqueness levels, findings are dichotomous, and the link between product uniqueness and value is often built on the scarcity argument (Lynn, 1991, 1992) and the interaction between scarcity appeals and consumers' need for uniqueness (Lynn, 1991; Snyder, 1992).

The *meta*-analysis by Barton et al. (2022) categorizes scarcity appeal strategies and assigns them to product types. Based on this analysis, supply-based scarcity seems to have the largest effect on purchase intentions. Whether scarcity is due to quantity, price, time, or usage restrictions, fewer consumers have access to the same product, which in turn makes the product more desirable. Amaldoss and Jain (2005) show the effects of price restrictions. As prices rise, demand increases among consumers with a high need for uniqueness. Those who own the product can differentiate themselves from others, satisfy their need for uniqueness, and thus place a higher value on products that allow such differentiation. Consumers seeking uniqueness are thus expected to pay higher prices to achieve their desired level of differentiation.

An alternative strategic approach is to signal higher product quality through limitation, thereby increasing product valuation (Stock & Balachander, 2005). This notion is supported by Tian and McKenzie (2001), who find that consumers with a high need for uniqueness pay higher prices than consumers with a low need level in order to increase their confidence that they have purchased a truly unique product. Support for the relationship between perceived product uniqueness and a higher willingness to pay can also be found in studies of mass customization (Franke & Schreier, 2008; Franke et al., 2010; Hunt et al., 2013; Krause et al., 2023).

However, the existing literature also suggests that uniqueness appeals are much more complex than scarcity per se when investigating the effects of (intentional or unintentional) limited product availability, as in cases of innovative or outdated products (Lynn & Harris, 1997a). Therefore, we argue that the scarcity-building strategies in product design are incomplete in capturing a product's differentiation potential, pointing to the importance of attribute distinctiveness. Simply limiting the number of product copies may not be sufficient, especially when the products are highly similar in design. Following the logic of the product uniqueness classification (Fig. 1), such strategies achieve limitation but not singularization.

In Table 1, we provide an overview of the related literature and compare it to this paper. We list the different definitions of uniqueness in the field, classify its type according to Fig. 1, and provide an overview of its measurement, whether it is subjective or objective. We review uniqueness and its implications in marketing models, different research contexts, and methodological approaches and summarize the main contribution of each paper. While most of the literature considers product uniqueness in the form of customization or limitation based on a subjective assessment, our paper looks at singularization as a form of product uniqueness that combines scarcity and attribute distinctiveness, as well as an objective, continuous rather than dichotomous measurement based on observational data. In doing so, we highlight the precise use of product uniqueness and infer business-enhancing effects in a natural market setting.

3. Methodology

3.1. Data description

We use a large non-fungible token (NFT) collection dataset to study the effects of product uniqueness based on attribute distinctiveness across a product line on valuation. This type of data makes it possible to explore our specific research question because it provides immutable and transparent information on large-scale attribute variation that is difficult to find in traditional markets.

NFTs are cryptographic assets with unique identification codes and metadata that cannot be arbitrarily exchanged, unlike fungible tokens used in cryptocurrencies (Peres et al., 2023). NFTs are stored in the blockchain, a technology that records transaction data permanently and in chronological order through decentralized verification (Treiblmaier, 2018). NFTs aim to certify the true ownership of an electronic product and record its provenance, terms, and transaction history (Zhang, 2023). In this way, the blockchain, and thus the token data, is immutable. Although NFTs are often associated with virtual products (Sundararajan, 2022), their metadata can refer to any type of digital product, including images and music files, but also extend to physical products and even intangible brand assets (Colicev, 2023). Similar NFTs are often grouped into a collection, which we refer to as a product line.

For our study, we use data from a popular NFT collection in the digital collectibles category to ensure a clear operationalization of attribute distinctiveness and a sufficiently large number of transaction observations. Specifically, we obtain (by scraping) and analyze the publicly available transaction data from the Bored Ape Yacht Club (BAYC) NFT collection traded on OpenSea, one of the largest NFT marketplaces to date (Kireyev & Evans, 2021). Focusing on the BAYC, we study a verified, well-known, and frequently traded product line (Santillana Linares, 2023). Beyond the blockchain-specific nature of the data, two additional specifications make this dataset particularly well-suited for investigating how consumers value differences in attribute distinctiveness across a product line.

The first specification relates to the nature of the product design. A product consists of well-defined attributes in the form of image layers. Each attribute has numerous levels that occur more or less frequently across the product line. Programmatic image generation creates a random combination of attribute levels that compose the final image. Product attributes and

Table 1
Comparison of Studies on Uniqueness in Marketing.

STUDIES	DEFINITION OF UNIQUENESS	CLASSIFICATION			SCALE			ASSESSMENT		OUTCOME VARIABLE	CONTEXT	METHODOLOGY		MAIN CONTRIBUTION
		custom.	lim.	sing.	dich.	likert	cont.	subj.	obj.			exp.	obs. data	
Amaldoss & Jain (2005)	**Uniqueness seeking consumers:** Value a product less as the number of people who buy the product increases independently of income levels and social status.		x		x			x		indirect utility	hypothetical tourism market	x		Demand among consumers who desire uniqueness may increase as the product's price increases.
Ames & Iyengar (2005)	**Uniqueness motives:** A person's disposition to embrace new things, defy convention, and pursue rare and usual objects and experiences.	x			x			x		estimates of others' liking	consumer goods (e.g., clothing, shoes, accessories) & names	x		Individual differences in perceived similarity to a target group rather than uniqueness motives govern the projection of appraisals of unusual objects.
Cheema & Kaikati (2010)	**Need for uniqueness:** Individual-level trait with the consequence to desire the possession of unique products that allow for differentiation from other people.	x			x			x		willingness to generate WOM	physical products (privately vs. publicly consumed)	x		Consumers' need for uniqueness in interplay with whether a product is privately or publicly consumed influence the generation of WOM and whether such WOM is recommendation- or detail focused.
de Bellis et al. (2016)	**Need for uniqueness:** The desire to possess extraordinary characteristics.	x				x	x	x	x	product uniqueness	cars	x		Consumers with higher narcissism (both as a trait and as a state of mind) configure more unique products from mass customization systems.
Franke & Schreier (2008)	**Perceived uniqueness**: The extent to which the customer regards the product as different from other products in the same category.	x				x		x		consumers' WTP	mass customization	x		In addition to aesthetic and functional fit, perceived uniqueness independently contributes to the utility a customer experiences from a self-designed product.
Fuchs & Schreier (2023)	**Unique product**: A product that is perceived as different from other products in the same category.	x				x		x		asking prices & consumers' WTP	second-hand market	x	x	Product uniqueness negatively affects second-hand market consumers' WTP, as it is more challenging to meet their taste preferences.
Hunt, Radford & Evans (2013)	**Uniqueness:** The degree of difference between customized and other products in the same category.	x			x			x		perceived value of customized product	consumer products (e.g., alarm clocks & desk chairs)	x		Consumers' value for mass customized products differs according to individual differences in their need for uniqueness, need for optimization, and centrality of visual product aesthetics.
Irmak, Vallen, & Sen (2010)	**Consumers' need for uniqueness:** A trait of pursuing differentness relative to others through the acquisition, utilization, and disposition of consumer goods to enhance one's self- and social image.			x	x			x		product adoption	novel products (not specified)	x		Consumer with a high need for uniqueness are less likely than those with a low need for uniqueness to introject preferences for products.
Krause et al. (2023)	**Product uniqueness:** Products that are literally one of a kind.			x	x				x	conversion rate, amount ordered & consumers' WTP	mass customization	x		One-of-a-kind feedback can substantially increase consumers' product valuation, esp. in product domains where subjective taste matters.
Lee, Gregg, & Park (2013)	**Uniqueness:** The ultimate distinctiveness.		x		x			x		attitude, purchase intent & WTP	consumer goods (e.g., iPhone accessories, shirt & watches)	x		Narcissistic consumers show more interest in consumer products that enhance their positive distinctiveness.

Table 1 (*continued*)

STUDIES	DEFINITION OF UNIQUENESS	CLASSIFICATION			SCALE			ASSESSMENT		OUTCOME VARIABLE	CONTEXT	METHODOLOGY		MAIN CONTRIBUTION
		custom.	lim.	sing.	dich.	likert	cont.	subj.	obj.			exp.	obs. data	
Lynn (1991)	**Need for uniqueness:** Feelings of personal distinctiveness.		x		x			x		perceived value of customized product	meta-analysis mainly in the context of consumer goods	x		By the means of a meta-analysis, consumers' need for uniqueness is established as the driving mechanism for scarcity effects on product value.
Lynn & Harris (1997b)	**Uniqueness theory:** People dislike high levels of similarity and dissimilarity and therefore seek to be moderately distinct from others. The level of dislike can vary across individuals.		x			x		x		consumer dispositions (e.g., desire for scarce or innovative products)	not specified	x		Buying scarce, innovative, customized products reflects self-attributed uniqueness that is mediated by individual tendencies to pursue uniqueness through consumption.
Roy & Scharma (2015)	**Need for uniqueness:** Individual trait that represents the need to establish a separate identity by pursuing self-distinguishing behavior.		x		x			x		attitude & purchase intention	consumer goods (clothing & electronics)	x		Supply scarcity appeals show a greater impact on attitudes and purchase intentions of consumers with a higher need for uniqueness.
Simonson & Nowlis (2000)	**Need for uniqueness:** Buyers who are predisposed to express their uniqueness prefer reasons that are novel and make nonobvious, nonredundant points.	x			x			x		decision-making & reasoning	consumer goods (Television)	x		Buyers with a high need for uniqueness tend to select unconventional reasons when they explain their decisions and are more likely to make unconventional choices.
Song & Sela (2023)	**Uniqueness:** A result of private self-focus is attributing greater salience to one's private versus social identity to achieve distinctiveness at the expense of perceived similarity to others.		x		x			x		preference for uniqueness	consumer choice options (e.g., customized vs. popular)	x		Using a personal smartphone leads consumers to prefer more unique options.
Tian, Bearden & Hunter (2001)	**Consumers' need for uniqueness:** An individual's pursuit of differentness relative to others that is achieved through the acquisition, utilization, and disposition of consumer goods for the purpose of enhancing one's personal and social identity.		x			x		x		consumers' need for uniqueness	consumer groups with a tendency toward uniqueness (e.g., tattoo artists & art students)	x		Development and validation of a trait measure of consumers' need for uniqueness that is composed of creative and unpopular choice counterconformity and avoidance of similarity to account for individual differences.
Whitley, Trudel & Kurt (2018)	**Unique product preferences**: Consumers' perception of their inherently unique preferences as being distinct from their need for uniqueness.			x		x		x		assortment selection & choice task	media products (e.g., songs & documentaries)	x		When consumers with hedonic purchase motivations perceive their product preferences as highly unique, they experience greater difficulty in finding a preference-matching product, expanding the review of product alternatives.
Our Study	**Product uniqueness:** One-of-a-kind product; however, as part of a product line, this product can be more or less similar to other products of the same line.			x			x		x	product resale & valuation	digital goods		x	Objective assessment of uniqueness achieved through attribute distinctiveness.

Notes: custom: customization, lim: limitation, sing: singularization; dich: dichotomous, con: continuous; subj: subjective, obj: objective; exp: experiments, obs. data: observational data.

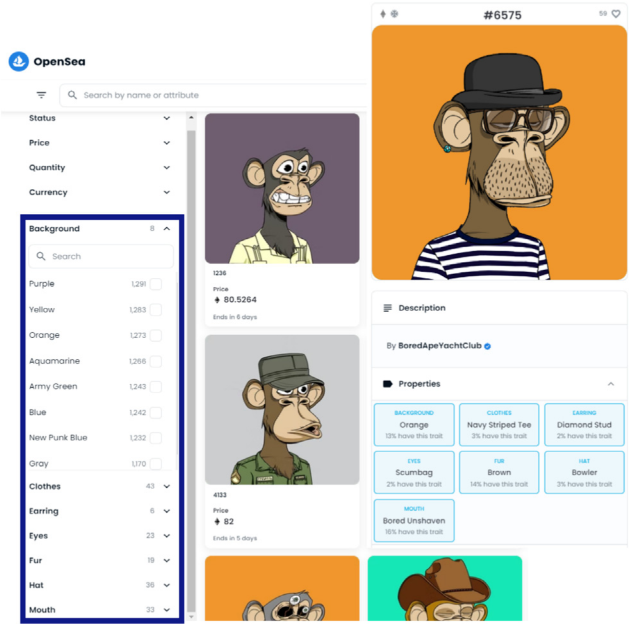


Fig. 2. BAYC Product Profile (OpenSea, 2022).

compositions are only visible after purchase and once the public image reveal date has passed. Accordingly, it is straightforward to operationalize attribute distinctiveness and, thus, the degree of uniqueness of each product within the product line. Each product consists of up to seven attributes (i.e., background, eyes, fur, mouth, earring, hat, and clothing), of which three (i.e., earring, hat, and clothing) are optional. Fig. 2 displays an overview of the different attributes and an example of a product profile that is part of the BAYC collection described above. Each attribute has multiple levels,[3] and in total, 171 different attribute levels exist. This number also includes the absence of optional attributes as a possible level. This definition of attribute levels results in 1,314,733,728 possible permutations.[4] But not all possible permutations exist. Instead, only 10,000 products compose the actual product line. As a result, some attribute levels occur more or less frequently, determining different degrees of distinctiveness across the product line. Importantly, by inspecting the public product profile, consumers can see how common the attributes of that particular product are across the entire product line. This publicly available information provides cues on how unique a product is within the product line. In Fig. 2, this information is included in the gray notes under the product attributes, where it says, for example, "13 % have this trait". This gives consumers a sense of the product's degree of distinctiveness, but only at the attribute level.

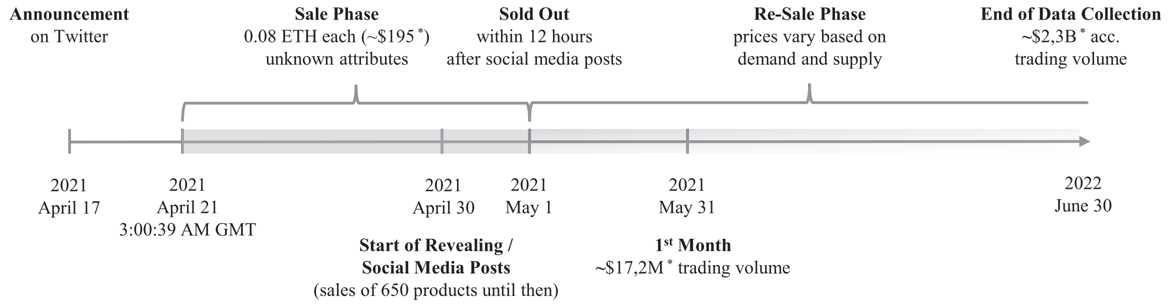
The second specification refers to a common pricing practice in NFT markets. When the collection is launched, the price of each product in the product line is identical. At this point, the consumer has no information about the design characteristics of the product, i.e., the levels and combination of the product attributes. These are only revealed after the *minting* of the product (i.e., the process of the initial token creation on the blockchain), which takes place after the reveal date (i.e., April 30, 2021) and after the initial sale is completed. When the product is revealed, all information about the product's metadata, i.e., the product's attribute levels, provenance, and transaction data, is publicly visible on the product profile page, and the NFT owner can decide to keep the product or sell it on the secondary market. Because of this market environment, the products we study initially all sold for the same price at the time of their launch despite design differences.[5] This is a major difference from most traditional markets, where distinct products usually have varying introductory prices. In this NFT setting, differences in product valuations are revealed only by secondary market trading. Transaction prices of secondary market sales indicate how consumers value product differences.

Fig. 3 illustrates the timeline of the data-generating process. On April 17, 2021 YugaLabs (2023) announced the sale start of the collection on social media. During the launch of NFT collections, it is common that the sale phase includes a predefined time period during which NFTs can be bought. However, it is not until the collection is sold out or a pre-specified

[3] For example, there are eight different background colors (i.e., purple, yellow, orange, aquamarine, army green, blue, new punk blue, and gray). The number of levels varies per attribute and can range from a minimum of 6 (in the case of the earring attribute) up to a maximum of 43 levels (in the case of the clothing attribute).

[4] Base combinations of four mandatory attributes: 8 levels of background * 23 levels of eyes * 19 levels of fur * 33 levels of mouth = 115,368; Products can have 4 to 7 attributes. Based on the three optional attributes (hat with 36 levels, earrings with 6 levels and clothes with 43 levels), $\binom{3}{1}+\binom{3}{2}+\binom{3}{3}=7$ additional attribute combinations exist. Example of the single additional attribute hat: 115,368 * 36 = 4,153,248. Example of two additional attributes, e.g., hat and earring: 115,368 * 36 * 6 = 24,919,488. Combinations when all 7 attributes are present = 115,368 * 36 * 6 * 43 = 1,071,537,984. The sum of all attribute level permutations across all 8 attribute combinations = 1,314,733,728.

[5] Each NFT as part of the BAYC collection initially sold for 0.08 ETH (YugaLabs, 2023).



Notes: The scale of the axis is not representative of actual time but serves the representative purpose of illustrating sequential events related to the BAYC announcement and sales. * The BAYC products are sold in Ether. The Dollar amounts can vary due to exchange rate fluctuations.

Fig. 3. Timeline of BAYC Collection Sales.

reveal date is reached that the NFT profile picture is revealed to its owner (YBM, 2022). In the case of the BAYC collection, only 650 out of 10,000 NFTs were sold until the reveal date. At this date, the 650 products were revealed, while the rest remained undisclosed until sold. However, the collection sold out within the next 12 hours due to social media posts on April 30, 2021 from well-known crypto traders (often referred to as "NFT whales") who purchased multiple products within the collection (Loh, 2022). As a result, all NFTs that are part of the BAYC collection were sold by May 1, 2021 and could only be purchased as secondary sales[6] on the OpenSea NFT marketplace. This is when our data collection starts. Our dataset consists of the 10,000 products that compose the BAYC collection, the attributes and levels of each product, and the transaction history of secondary sales over 14 months.[7] Secondary sales can be initiated by the product owner or by potential buyers. Owners have the ability to set an asking price for their product. Interested buyers, then, purchase the product outright at the set asking price or make a counteroffer, which the owner decides whether or not to accept. Offers can be submitted at any time, even if products do not have an asking price. They also do not have to match a set asking price or previous transaction prices. The asking and offer prices are publicly visible on the product profile page until a set expiration date. Sales of the BAYC picked up quickly, with a trading volume of secondary sales of around $17 million in the first month (Cryptoslam, 2023). The transaction data records all products' ownership and sale history between May 1, 2021, and June 30, 2022. We also recorded the number of favorite likes on the day of the data collection. We use the first resale after the initial sale to study how consumers value a given product. In total, we observe 8,709 first resale transactions on the secondary market. For 1,291 products, no resales were recorded after the initial sale during the observation period.

3.2. Operationalization of variables

First, we operationalize the main independent variable, *attribute distinctiveness*. The focal measure is a rank score based on the frequency count of the respective product attribute levels l_a. Within the stream of scarcity research, rank-based metrics have previously been used to capture differences in product availability and consumer preferences (Verhallen, 1982; Zhu & Ratner, 2015). In addition, the order resulting from a rank score allows for a clear comparison of all products within the product line. To capture product differences, we determine the frequency count $F_a(l)$ of all product attribute levels across the product line N.

$$N = \{P_0, \cdots, P_n\},\ \mathrm{l_{n,a}} \in \mathbb{N}_0; \Omega := \{(l_{0,1}, l_{0,2}, \cdots, l_{0,7}), \cdots, (l_{9999,1}, l_{9999,2}, \cdots, l_{9999,7})\} \tag{1}$$

$$F_a(l) = \sum\nolimits_{n=0}^{N} 1_{l_{n,a}=l} \tag{2}$$

In the next step, the frequency counts of all attribute levels composing a product P_n are summed up to produce an overall product score $S(P_n)$:

$$S(P_n) = \sum\nolimits_{a=1}^{7} ((F_1(l_{n,1})), \cdots, (F_7(l_{n,7}))) \tag{3}$$

Ranking the product scores $S(P_n) \in N$ of all products in the product line in descending order, where the lowest score (=lowest frequency of attribute level occurrence in the product line) indicates the highest level of attribute distinctiveness and equal scores are ranked equally, the result is a rank score per product that defines its level of distinctiveness within the product line:

$$R(P_n) = rank_{dsc}(S(P_n)) \tag{4}$$

To facilitate interpretation, we rescale the score according to equation (5), such that a *higher value* of R_s indicates a *higher level of distinctiveness* normalized to the target scale of $[s_{min} - s_{max}]$ = [1, 2].

[6] Due to the specifications in the smart contract of the BAYC collection, YugaLabs earns 2.5% royalty fees on every resale beyond the initial sale (YBM, 2022).
[7] Data and code are available at https://osf.io/b8px4/.

Attribute	Level	Frequency Count
Background	Orange	1273
Clothes	Navy Striped Tee	334
Eyes	Scumbag	233
Fur	Brown	1370
Mouth	Bored Unshaven	1551
Earring	Diamond Stud	222
Hat	Bowler	262
$S(P_{6575})$		5245
$R(P_{6575})$		8696
$R_S(P_{6575})$		1.87

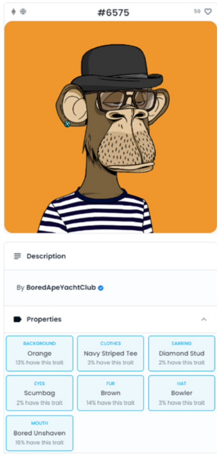


Fig. 4. Exemplary Rank Score Operationalization of Product #6575 (OpenSea, 2022).

$$R_s(P_n) = \left((R(P_n) - R(P_n)_{min})/(R(P_n)_{max} - R(P_n)_{min})\right) \times (s_{max} - s_{min}) + s_{min} \tag{5}$$

Fig. 4 shows an example of a rank score calculation for a product in the focal product line.

In addition, we analyze three alternative operationalization approaches of attribute distinctiveness to test the sensitivity of our results to changes in the measurement. In particular, we operationalize attribute distinctiveness by i) a *frequency score*, ii) a *likelihood score*, and iii) a *heuristic score*. The frequency occurrence of attribute levels forms the basis of distinctiveness. Therefore, we operationalize a basic frequency metric that continuously measures the product distinctiveness within the product line (represented by the frequency score). Second, given the complete set of attribute levels and combination rules, the likelihood score reflects the probability that a given combination of attribute levels occurs within a product. This way, the measure takes a more neutral perspective on the comparative nature of the rank score. In addition, we also include a heuristic score that reflects the actual scattered information available to consumers. For example, in Fig. 4, consumers see that only 3 % of the products in the product line feature a bowler hat, but 13 % have an orange background. In such an environment, consumers are likely to engage in heuristic decision-making, as forming an overall judgment requires additional information that is not immediately available and subject to an uncertain level of cognitive ability (Gigerenzer, 2008). Instead, the available scattered information may serve as decision cues to infer the best suitable option (Gigerenzer & Goldstein, 1999). Appendix A provides the detailed derivation of these three alternative operationalization approaches of product uniqueness and the corresponding correlation coefficients of all four measures.

In a setting where secondary market transactions form the basis for product valuation differences, we focus on two main outcome variables. The first is whether or not a product *resells* on the secondary market after the actual product attributes are revealed. This step is important because, otherwise, we cannot observe a transaction price that deviates from the initially uniform price. Once resold on the secondary market, the second and main outcome variable is the *value* assigned to a product reflected in the price paid in the transaction. To account for these two separate but related processes, we employ a Heckman (1979) selection model. We start by analyzing the resale-selection process to account for the endogenous nature of trading behavior before studying the effect of attribute distinctiveness on a product's valuation.

In the first stage, we consider *multiple ownership* during the sales phase as a factor influencing the supply of products on the secondary market. We observe that several first-hand buyers purchased more than one product during the sales phase when product details were still not revealed. Then, during the resale phase, many traded some or all of the products on the secondary market. It seems plausible that owners of multiple products assess and compare the products after their attributes are revealed for the first time, which affects their decision to resell and thus the supply on the secondary market. We operationalize multiple ownership by distinguishing product owners who purchased more than one product from those who purchased only a single product within the focal product line during the sales phase. Potential buyers also have the opportunity to identify multiple ownership. However, this information is not available in the product profile and is therefore unlikely to affect their purchase decision and the respective price.

Since secondary sales are determined not only by supply but also by demand variations, we also include the variable *favorite likes*. Typical of online environments is the ability to express interest in a product without purchasing it. In such environments, clicks and favorite likes are a form of behavioral response (van Doorn et al., 2010). To receive a like in an online environment, the product or content must be visible to a social group. A like is a behavioral response of approval of the product or content by participants who are part of the respective social group. The number of responses can thus signal social approval and a form of interest in the product or content that can be interpreted as product popularity and, therewith, a proxy for product demand. Instead of an immediate purchase, products can be placed on a kind of watch list. In our research setting, this feature is the heart button in the upper right corner of the product (see Fig. 2). Clicking the button links the product to the

Table 2
Summary Statistics of Variables.

Type[a)]	Variable	Description	Mean	SD	Min	Max
DV	Value	Price in Ether, paid in each transaction	7.26	23.45	0.04	420.69
DV (HSM)	Resale	Secondary product sales: yes or no	0.87	0.34	0.00	1.00
IV	Attribute distinctiveness	Normalized rank score based on attribute level frequency count across the product line	1.50	0.29	1.00	2.00
IV (HSM)	Multiple ownership	First product owner who holds or held more than one product within the product line	0.90	0.30	0.00	1.00
IV (HSM)	Favorite likes	Log-transformed number of favorite likes	3.44	0.93	1.10	9.99
CV	Price index	Assessment of market volatility in the form of a Paasche index based on two-month brackets	1.99	4.39	1.00	30.22

Notes: N = 10,000. [a)] DV: dependent variable, HSM: Heckman Selection Model, IV: independent variable, CV: control variable.
Due to high levels of skewness (49) and kurtosis (3,039), favorite likes are log-transformed.

Table 3
Correlation Coefficients of Variables.

	(1) Value		(2) Resale		(3) Attribute distinctiveness		(4) Multiple ownership		(5) Favorite likes	
(1) Value	1.00									
(2) Resale	– [a)]		1.00							
(3) Attribute distinctiveness	0.04	***	−0.04	**	1.00					
(4) Multiple ownership	−0.26	***	0.28	***	−0.01		1.00			
(5) Favorite likes	0.16	***	0.22	***	−0.03	**	−0.01		1.00	
(6) Price index	0.88	***	0.09	***	0.02	*	−0.19	***	0.13	***

Notes: N = 10,000. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
[a)] Since *value* (i.e., transaction price) is only observable in the case of a *resale*, no correlation exists between those two variables.

consumer's crypto wallet and saves it to the favorite section of the consumer's marketplace profile. In this way, the consumer can easily access the product page and follow the product's development before making a purchase. At the same time, anyone visiting the product profile can see all the wallet addresses of those interested in the product by clicking the heart button. It is also possible to remove the interest marker. This makes favorite likes a suitable proxy for product demand.

During the period of data collection, NFT and crypto markets have been highly volatile (Zhang, 2023). Starting in mid-2020, the NFT market grew by 150 percent in eight months (Nadini et al., 2021). Although these effects can be attributed to the interrelationship between the NFT and cryptocurrency markets, Dowling (2022) shows that despite the co-movement of these markets, volatility spillovers are limited. Thus, instead of cryptocurrency-related control variables, we compute a Paasche *price index* (Dodge, 2008) based on two-month time brackets (base period normed to 1) to account for the general market development at the time of the first resale (White et al., 2022) and control for this variable in our main outcome model. In the dataset, 93.3 % of all first resales occurred within the first two months after product launch and, therefore, fall within the base period.[8] Table 2 shows the summary statistics, and Table 3 the correlation coefficients of all variables that are part of our empirical model.

3.3. Model

We are primarily interested in products resold on the secondary market. However, our data also include cases where products are not resold and remain with the initial buyer. Such cases give reason to believe that whether a product resells is not random and that endogeneity should be considered. To address this concern, we employ a Heckman selection model. In the first stage, we estimate a binary probit selection model to predict whether a product resells on the secondary market using the latent function $Resale^* = \gamma' X + \mu$, where $Resale^* = 1$ if there are secondary sales of a product and $Resale^* = 0$ if the product remains with the original buyer. The selection model includes *attribute distinctiveness*, *multiple ownership* as a supply proxy, and *favorite likes* as a demand proxy to explain why some products resell, and others do not. Consequently, the selection model is as follows:

$$Resale_{P_n \in \ \Omega,t} = \gamma_0 + \gamma_1 multiple\ ownership_{t_n} + \gamma_2 favorite\ likes_{P_n} + \gamma_3 attribute\ distinctiveness_{P_n} + \varepsilon_{P_n,t} \quad (6)$$

Based on this model, we derive the inverse Mills ratio (IMR) as λ, where φ and Φ, respectively, indicate the probability and cumulative density functions.

$$\lambda = \varphi(\gamma X)\Phi(\gamma X) \quad (7)$$

[8] Around one year after the product launch, i.e., in period 6, the market reached its peak with an index of 30.22 compared to the base, decreasing again in the consecutive period.

Table 4
Main Results.

DV:	Selection Model Resale coefficient	SE	z-value	(p)	Outcome Model Value coefficient	SE	t-value	(p)
Intercept	−1.21	0.13	−9.67	***	−3.83	0.64	−6.00	***
Multiple ownership	1.17	0.04	25.24	**				
Favorite likes	0.50	0.02	22.58	***				
Attribute distinctiveness	**−0.17**	**0.06**	**−2.89**	**	**1.50**	**0.42**	**3.59**	***
Price index					4.41	0.03	172.70	***
IMR					−2.89	0.76	−3.81	***
R^2							0.77	

Notes: N = 10,000. The outcome model deletes 1,291 observations due to missing price data for non-resold products. Unstandardized coefficients are reported. Value represents the price in Ether.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The outcome model is the second stage that depends on the selection equation. The main outcome model includes *value* as the dependent variable and *attribute distinctiveness* as the variable of interest, controlling for market volatility. By including the IMR λ in the model, we correct for possible endogeneity problems arising from a product being resold or not:

$$V_{P_n \in \Omega, t} = \beta_0 + \beta_1 attribute\ distinctiveness_{P_n} + \beta_2 price\ index_{t(2m)} + \lambda + \varepsilon_{P_n, t}\,; \quad \lambda = \varphi(\gamma X)\Phi(\gamma X) \tag{8}$$

4. Results

4.1. Effect of product uniqueness based on attribute distinctiveness on product valuation

Table 4 shows the results of the selection model (equation (6)) and the outcome model (equation (8)).[9] The significant IMR (λ = -2.89, p < 0.001) indicates that whether a product resells or not is not random. The overall model is significant (F (3, 8705) = 9,990.05, p < 0.001). In the selection model, a higher product attribute distinctiveness decreases the likelihood of a product to resell (γ_3 = -0.17, p < 0.01), controlling for other demand and supply mechanisms represented by favorite likes and multiple ownership, respectively. Both variables are significantly related to the likelihood of a product to resell on the secondary market.

Table 4 also displays the results of the outcome model. These indicate a positive association between attribute distinctiveness and product value (β_1 = 1.50, p < 0.001), controlling for market volatility with the composite price index. This result is consistent with existing literature in the field of scarcity research (Barton et al., 2022; Lynn, 1991). Knowing the attributes of different products, consumers deliberately pay more for those that are more distinct than others within the product line.

To show the robustness of our results in defining attribute distinctiveness, we replicate the selection model with the frequency, likelihood, and heuristic scores. As shown in Appendix B, the substantive results are consistent with our analysis in Table 4. We see a negative relationship between attribute distinctiveness and the likelihood of a product to resell on the secondary market. In the second stage, we find a positive relationship between attribute distinctiveness and product valuation, controlling for market volatility.

In order to not only test the robustness of the measurement but also of the model choice, we estimate a hurdle model. Such a model allows us to study the problem of zero observations, in our case, the products that are not resold on the secondary market, by exploring different approaches and variations in the model specifications. Carlevaro et al. (2012) outline three possible reasons for zero observations: a) the product selection process (Tobin, 1958), b) no consumption despite the selection of a product (Cragg, 1971), and c) missing observations due to infrequent consumption (Deaton & Irish, 1984). Thanks to the advantage of full trade transparency in our dataset, infrequent consumption as a reason can be rejected, leaving us to explore the selection and consumption process in the form of a two-step hurdle model. Unlike Heckman's (1979) selection model, this approach allows us to estimate an independent and a dependent model that can be compared in their model fit. We consider the models to be non-nested as the only difference relates to the assumption of error independence, which we integrate by correlation. The results are consistent with those of the Heckman selection in Table 4. In addition, we test the dependent versus the independent modeling approach using a Vuong test for non-nested models (Shi, 2015). A test statistic of 1.81 with a p-value of 0.07 indicates weak but significant evidence that a dependent model is better than an independent model. Therefore, we conclude that a two-stage approach is appropriate. Appendix C reports the hurdle models and the specifications.

4.2. Attribute importance

Our measures of product attribute distinctiveness – the focal rank score as well as the three alternative measures – are based on the frequency count of each attribute level within the product line, as specified in equation (2). Section 3.1 outlines

[9] We also run a regression model without the selection stage. This model replicates the effect of attribute distinctiveness on value (β_{AD} = 1.34, SD = 0.42, p < 0.01).

Table 5
Importance of Attributes to Product Value.

Attribute	BACKGROUND	EYES	MOUTH	FUR	CLOTHES	HAT	EARRING
Min value contribution	4.07	2.00	1.41	1.64	1.31	0.57	2.22
Max value contribution	5.73	24.84	33.63	24.82	17.88	10.24	9.26
Range	1.66	22.84	32.22	23.18	16.57	9.67	7.04
Importance weight	1 %	20 %	28 %	20 %	15 %	9 %	6 %
No. of attribute levels	8	23	33	19	44	37	7

Notes: N = 8,709. Intercept 3.43; Reference categories: Background = gray, Eyes = closed, Mouth = bored, Fur = brown, Clothes/Hat/Earring = none; Value represents the price in Ether.

in detail the nature of the attributes and their levels present within our dataset. Fig. 2 exemplifies how they can be combined to form a product. On this basis, we consider attributes not only in isolation but also relative to each other and in combination. This approach is applicable to a wide range of different products if they exhibit variance in the number of attributes and their occurrence.

To assess how consumers value certain attribute levels, we regress all attribute levels of a product on its value (based on the first resale), as depicted in the following model:

$$Price_{P_n} = \sum_{a \in A}^{7} \sum_{l_a \in L_a}^{L} \beta_{a,l} X_{a,l,P_n} + \varepsilon_{P_n}$$

$$\text{where} \quad X_{a,l,P_n} = \begin{cases} 1 \; if \; product \; P_n \; has \; attribute \; level \; l_a \\ 0 \; else \end{cases} \tag{9}$$

Results are displayed in Table 5. Lines two and three report the specific levels within an attribute that result in the lowest and highest value contributions.[10] The range indicates the spread of value contribution across all levels of an attribute. This metric is then used to determine the "importance weight" of the within-attribute variation. From the calculation of the importance weights, we can see that the background color is least associated with the value of a product. Specific to the dataset, there may be two reasons for this. First, the background only consists of a specific color and is thus not very distinct. Second, background color has only eight different levels and, therefore, the lowest variation of all attributes within the dataset. The three optional attributes, i.e., clothing, hat, and earring, exhibit the lowest importance weights following the background attribute. The attributes that form the central part of the image and are essential for it to represent the character of an ape are the most and almost equal in importance.

5. Discussion

Consumers' need for uniqueness is a social need that significantly influences product preferences but can vary in its magnitude depending on the characteristics of individual consumers and their social environment. This ambiguity makes it challenging for marketers to incorporate explicit need appeals into their product and marketing strategies. In product design, appeals to uniqueness are often linked to scarcity, either in the form of supply limitations, as in the case of limited editions, or from the demand side, as in mass customization. We argue that these scarcity-related approaches are incomplete in reflecting a product's distinctiveness when consumers seek uniqueness. Instead, we find that even when products are scare, they can have attributes that are highly similar to other products, thereby, impeding their overall potential for differentiation.

Therefore, we propose a classification that defines product uniqueness in terms of quantity limitations combined with attribute distinctiveness (see Fig. 1). This classification allows us to differentiate product uniqueness by limitation, customization, or singularization. While low attribute distinctiveness and few product copies define limitation, customization and singularization are based on high attribute distinctiveness and differ in the extent to which product copies are available in the market.

To shed more light on the dimension of attribute distinctiveness, we use novel data in the context of blockchain-enabled non-fungible tokens (NFTs). Thanks to the specifics of blockchain technology, the data provides complete portfolio and transaction transparency. Identical launch prices, despite differences in product attributes and composition, uncover the effect of uniqueness through attribute distinctiveness on consumer product valuations via secondary market transactions. The use of this data represents a first step toward an explicit assessment of product uniqueness. We operationalize attribute distinctiveness in terms of a rank score based on different product attribute levels and their combination relative to other products in the same product line. The focus on frequency occurrence makes the dataset informative about attribute distinctiveness across a product line in contexts beyond NFT collections.

[10] The value contribution reflects the level within a specific attribute (e.g., background) with the lowest and highest estimates if the attribute level is part of a product; otherwise, it is 0. The minimum and maximum scores result from adding the respective estimate to the intercept to ensure comparability across attributes. For example: Within the background attribute, if present, purple has the largest effect on value with an estimate of 2.30 and aquamarine has the smallest with 0.64. Combined with the intercept, the value contribution of purple is consequently 5.73 (= 3.43 + 2.30) and 4.07 (= 3.43 + 0.64) for aquamarine.

The results, based on transaction data from a large NFT collection, suggest significant benefits from an explicit employment of attribute distinctiveness and support our assumption that consumers value products with distinct attribute compositions differently. We also find that, within a product line, products that are more distinct are less likely to be sold on the secondary market and tend to remain for longer with their initial owner.

5.1. Theoretical implications

Our results provide several theoretical implications for research on product uniqueness in marketing. First, we extend the understanding of implicit appeals to consumers' need for uniqueness by objectively analyzing uniqueness in product design through attribute distinctiveness. The existing literature in this area mainly considers individual differences in consumers' need for uniqueness to explain deviations in consumer behavior (Irmak et al., 2010; Roy & Sharma, 2015; Simonson & Nowlis, 2000). However, this study investigates consumer responses to objective information on the occurrence of product attributes within a product line. With four types of operationalization for measuring attribute distinctiveness, we add to the methodological spectrum in uniqueness research. In addition to perceptual measures (Ames & Iyengar, 2005; Franke & Schreier, 2008), priming (Cheema & Kaikati, 2010), and utility-based modeling (Amaldoss & Jain, 2005), we propose an objective classification based on product design rather than consumers' individual tastes. We use available product-level and product-line-level information to estimate the attribute distinctiveness of a product within a given product line. This approach allows us to consider a continuous spectrum of distinctiveness within a market environment where each product is one-of-a-kind. Assuming product attribute and quantity information to be available to most marketers, we suggest an extension to traditional product descriptions in the form of uniqueness labels. When such product information is available, our findings suggest that consumers value this type of information and are willing to incorporate it into their decision-making. This is consistent with research on the scarcity-value nexus (Barton et al., 2022; Lynn, 1991).

Second, our results have implications for research on the relationship between uniqueness and product resale. While there is evidence that consumers' need for uniqueness increases the intensity of their decision-making (Whitley et al., 2018), the data we use uncovers an effect of attribute distinctiveness beyond the initial purchase decision. We find that higher levels of attribute distinctiveness reduce the likelihood of a product to resell. This has implications for the literature examining whether consumers' need for uniqueness triggers an ongoing cycle of product evaluation (Snyder, 1992) and consumer strategies to maintain their uniqueness and avoid frequent product replacement cycles (Tian & McKenzie, 2001).

Finally, our results have implications for the uniqueness literature by introducing a conceptual classification that extends the definition of product uniqueness in marketing. So far, the existing literature has established the uniqueness-product link based on scarcity, where limitations of product copies drive product valuation (Barton et al., 2022; Lynn, 1991). We argue that not only quantitative limitation in the sense of one-of-a-kind products (Amaldoss & Jain, 2005; Krause et al., 2023) determines the potential to differentiate from others, but also the degree of attribute distinctiveness relative to other products. Product attribute specifications and combinations create variation in attribute distinctiveness. The scope of comparison, i.e., the definition of a product line, is context-dependent and has to be clearly defined by the marketer so that it is transparent and understandable to the relevant target consumer.

In addition, this research provides implications for the emerging stream of literature on NFTs as a blockchain-based application and their relevance to marketing research. First, the blockchain-based nature of the dataset allows for transparency that limits confounding effects. In uniqueness and scarcity research, this avoids potential misrepresentation of product-line information due to continuous expansion and modification of product lines. Blockchain data records and stores such data with precision and transparency. Second, the results of our study extend the understanding of how intangible assets, such as NFT profile pictures (PFPs), can create value for consumers through the transmission of uniqueness in the form of attribute distinctiveness. This suggests that NFT prices are not only speculative (White et al., 2022) but that product design matters in the NFT context. Third, we study effects based on secondary market sales that provide a better understanding of the effectiveness of C2C platforms with reduced intermediary power. Thanks to blockchain technology (e.g., smart contracts), platform members can trade directly and securely without the inference of intermediaries (Peres et al., 2023). Data from numerous C2C sales validates these mechanisms, even at high prices. Fourth, the blockchain-specific tokenization and storage of product information points to new ways to capture, display, and communicate product details compared to traditional product representations and descriptions.

5.2. Managerial implications

The results of our study are useful to marketing practitioners and various NFT stakeholders and provide them with actionable implications. The positive effect of product uniqueness through attribute distinctiveness on product valuation is of interest to several industries. The prerequisites are variation in product attributes and the product's potential to signal differentiation through consumption. This may even apply to perishable products, such as food and beverages, as long as they are to some extent consumed in public and thus visible to others (Gierl & Huettl, 2010). Given the role that consumers' need for uniqueness plays in conspicuous consumption (Amaldoss & Jain, 2005), marketers in the luxury and consumer goods industries, in particular, may benefit from an approach that identifies, uses, and communicates uniqueness as a product attribute. Explicit communication of product attribute distinctiveness allows for an even more nuanced segmentation and targeting of consumers. This enables companies to capture a greater share of consumers' willingness to pay and, as a result, increase company profits. Consumers of such products, in turn, benefit from complete transparency on product positioning within the product portfolio. This gives them a clearer picture of how well the chosen product conveys and could enhance their personal uniqueness. With this approach, the interpretation of scarcity cues and the need to re-evaluate choices (Snyder, 1992) becomes less relevant, facilitating consumer decision-making.

Especially in online environments, communicating the distinctiveness of product attributes can be valuable. Digital interfaces are efficient at communicating product details and using filters to direct consumers to the right product quickly. The current NFT market, for example, with profile pictures (PFPs) as a product, provides an interesting example of how uniqueness can be used in the same way as price, color, material, etc., in common e-commerce stores. As such, attribute distinctiveness can justify price differences for products currently priced the same.

The consideration of attribute distinctiveness also has long-term effects. Our results suggest that consumers care about product uniqueness and that those products are less likely to be resold. This is consistent with existing literature finding that consumers try to avoid reselling products that allow them to express their uniqueness (Tian & McKenzie, 2001). Even after a resale, information about product uniqueness can be valuable for secondary market transactions. Research shows that consumers with a high need for uniqueness turn to outdated products (Lynn & Harris, 1997a; Tian et al., 2001). Coupled with the fact that secondary exchanges are increasingly taking place online (Ertz et al., 2015) and the advantages that online environments offer for communicating product uniqueness, the use of such channels may validate and facilitate consumers' product choices and secondary market sales.

Analyzing a blockchain-based product dataset, we find interesting insights for different stakeholders of NFTs regarding reactions to their product design and description. First, we see that NFTs associated with intangible product forms, such as profile pictures (PFPs), increase consumer valuation through product design. This result informs NFT creators that variations in product design lead to different product valuations. At this point, it is important to note that we evaluated valuation differences across a product line. However, for these to occur, there must be variation in product design, including the presence of different product attributes. This provided, the inclusion and clear communication of different product attributes can be beneficial, especially in the form of a more general indication of attribute distinctiveness. Currently, in many cases, consumers only, if at all, receive cues at the attribute level. Based on our results, we believe that a combined score has the potential to be even more effective. This information is, therefore, also of interest to NFT marketplaces when designing user interfaces.

Second, NFT consumers gain insights into how to navigate marketplaces and make effective product choices. As they seek to enhance their uniqueness, paying attention to product attributes, composition, and favorite likes can facilitate the purchase decision and avoid re-evaluation. In the NFT space, consumers also often act as product sellers. For them, studying product attribute design and visibility can help to position and price their offering more effectively in the marketplace.

Third, brands that have already entered the NFT market or are considering doing so can benefit from this study. There are two ways to enter the NFT market. One way is to develop digital products that are unrelated or only vaguely related to the brand's core portfolio. The second way is to link NFTs to the brand's core products. To date, we see both approaches in the market (Guilbault, 2022). In both cases, designing products with specific attributes to attain variation within a product line and communicating the resulting distinctiveness of products benefits the product positioning. Thus, the use of blockchain technology to ensure transparency and traceability can be an interesting way to combine NFTs and physical products.

5.3. Limitations and opportunities for future research

We acknowledge several limitations of this work that may stimulate interest in further research on this topic. First and most important, although our analyses are based on 10,000 products and 8,709 resale transactions, the data is observational. Thus, the results are descriptive and relate to a single product line. Therefore, interesting extensions of this research would be cross-validating the results with other NFT product lines or – if possible – even in a physical setting or experimental studies. Experimental research could also investigate potential underlying mechanisms (e.g., the effect of consumers' need for uniqueness and resale motivations), thereby adding to the understanding of product uniqueness and its valuation. In addition, such research settings would allow distinguishing between horizontal and vertical attributes. This is important for understanding whether distinctiveness can be sufficiently modeled by frequency or whether it is necessary to incorporate metrics of attribute variation. If consumers disagree about attribute attractiveness, this could affect product valuations, both positively and negatively. Important conditions for such studies are clearly identifiable product attributes that vary and are available with full transparency across one product line.

Second, the focus of this analysis is on the first resale in the secondary market after the initial product sale. While some products are not sold on the secondary market, others are resold multiple times throughout the observation period. As the number of resales increases, the previous prices paid become reference cues that can further influence product valuation (Wolk & Spann, 2008). Therefore, it may be interesting to analyze the effects on product valuation over time once a product resells multiple times. Drawing on the notion that consumers constantly reevaluate their need satisfaction concerning uniqueness and consider the access of other consumers to this product (Snyder, 1992), multiple resales of the same product may also affect the valuation of attribute distinctiveness.

Third, we make use of a rank score as the focal measure of uniqueness. Ranks establish an order that allows for comparing products within a product line. However, the use of a rank distorts the absolute magnitude of the difference between rank positions. When using the results to derive nuanced pricing based on differences in product attribute distinctiveness, incorporating an additional measure that captures absolute product differences may be beneficial. The likelihood score, used for robustness checks of our analyses, provides a starting point. However, there is a need for future research on the derivation and especially the integration of such measures. Looking more specifically at the magnitude of the difference also raises the question of the optimal level of product uniqueness. Such information would be useful for firms in designing product lines.

Fourth, most firms do not offer a single product line, but several. Understanding such cross-category effects in portfolio strategies can be crucial for a more complete understanding of business implications and consumer choices under different market conditions (Gelper et al., 2016). Data from multiple product lines of a firm that are relevant to the same consumer could provide a good basis for studying such effects. Extending the focus to portfolio strategies also allows for a more precise positioning of product uniqueness in its proposed form within the literature on limited editions and scarcity strategies, as these strategies are more often observed across multiple rather than single product lines.

Finally, NFTs are still a novel phenomenon in marketing and consumer research. As a result, research on their value to brands and consumers has only just begun (Colicev, 2023; Zhang, 2023). By including social need satisfaction in the discussion, we hope to shed more light on the factors that influence the value of NFTs. However, we also want to acknowledge research that considers other drivers of NFT value, such as the reference prices of similar NFTs within a collection (Nadini et al., 2021) or non-product-related factors, such as investment intentions (White et al., 2022). Different influencing factors may allow for potential interactions and cross effects that could provide a deeper understanding of NFT valuation and the resulting potential for marketing and brands.

6. Conclusion

Uniqueness-seeking behavior significantly influences purchase behavior and product choices and is, therefore, relevant to marketers in various industries (Tian et al., 2001). NFT data, which incorporates the benefits of blockchain technology, such as transparency and immutability, and the new markets that emerge from it, motivate a novel perspective on product design and the employment of uniqueness as a product attribute. Specifically, this research classifies different forms of product uniqueness and examines whether varying degrees of attribute distinctiveness lead to different consumer valuations. Our results suggest that consumers' product valuations increase with higher product distinctiveness regardless of the supplied quantity of a product. We also find that attribute distinctiveness is negatively associated with product resale. Marketers may explicitly use and communicate such product attribute distinctiveness in addition to limitations in quantity to benefit from an even more nuanced market segmentation. Using attribute distinctiveness as a product design factor extends current uniqueness research. In addition, the use of NFT data sheds light on the valuation of such tokens and their use in marketing. As such, this research aims to encourage further research on specific applications of uniqueness within product portfolios, as well as more detailed investigations into the role of blockchain-based applications in generating data or market settings that advance the knowledge of product design and valuation.

CRediT authorship contribution statement

Sophie M. Berghueser: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Martin Spann:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Data availability

Data and code are available on OSF (https://osf.io/b8px4/).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Alternative operationalization of product uniqueness

Similar to the first steps of the focal rank score, the *frequency score* is based on the frequency occurrence of attribute levels across the product line. L is a level of a given attribute $a \in \{1, \cdots, 7\}$. To capture product differences, we determine the frequency count $F_a(l)$ of all product attribute levels across the product line N and sum up the scores of each $F_a(l)$ composing product P_n. We then divide one by this sum so that the smallest frequency count indicates the most unique product to derive the frequency score $F(P_n)$:

$$N = \{P_0, \cdots, P_n\},\ l_{\mathrm{n,a}} \in \mathbb{N}_0; \Omega \equiv \left\{(l_{0,1}, l_{0,2}, \cdots, l_{0,7}), \cdots, (l_{9999,1}, l_{9999,2}, \cdots, l_{9999,7})\right\} \tag{A.1}$$

$$F_a(l) = \sum_{n=0}^{N} 1_{l_{n,a}=l} \tag{A.2}$$

$$F(P_n) = 1/\sum_{a=1}^{7}((F_1(l_{n,1})), \cdots, (F_7(l_{n,7}))) \quad (A.3)$$

To align all uniqueness measures, we adjust the scale to [1, 2] according to equation (5).

The *likelihood score* is also based on the frequency occurrence of attribute levels as a metric of probability occurrence in product line N.

$$c_a(L = l) = F_a(l)/N \quad (A.4)$$

$P_n = (l_{n,1}, \cdots, l_{n,7}) \in \Omega$ represents the seven attributes levels of a product $P_n \in \Omega$ under the assumption of independence between the attributes:

$$c(P_n) \equiv \prod_{a=1}^{7} C_a(L = l_{n,a}) = \prod_{a=1}^{7} (F_a(l_{n,a})/N) \quad (A.5)$$

Taken together, a logarithmic, inverse normalization of $c(P_n)$ forms the likelihood score of a product P_n:

$$C(P_n) = log\left(\sum c_{P_n}/c_{P_n}\right) \quad (A.6)$$

To ease subsequent analysis and align all uniqueness measures, the likelihood score is also scaled by applying equation (5) to [1, 2].

The basis for the *heuristic score* is the respective frequency occurrence c_a of all attributes forming a product P_n, as derived in A.4. The heuristic approach selects the attribute with the lowest frequency occurrence. It subtracts it from 1 so that a value closer to 1 corresponds to higher levels of uniqueness:

$$H(P_n) \equiv 1 - \left(\min_{a=1,\cdots,7}(c_a(l_{n,a}))\right) \quad (A.7)$$

Finally, we adjust the scale to [1, 2] according to equation (5).

Table A1

Correlation Coefficients of the Product Uniqueness Measures.

	(1) Rank score	(2) Frequency score	(3) Likelihood score
(1) Rank score	1.00		
(2) Frequency score	0.84***	1.00	
(3) Likelihood score	0.86***	0.74***	1.00
(4) Heuristic score	0.24***	0.16***	0.54***

Note: N = 10,000. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix B. Robustness checks of main results

Table B1

Replication of Main Results with the Frequency Score Measuring Product Uniqueness.

	Selection Model				**Outcome Model**			
DV:	Resale				Value			
	coefficient	SE	z-value	(p)	coefficient	SE	t-value	(p)
Intercept	−0.98	0.16	−6.28	***	−4.61	0.94	−4.83	***
Multiple ownership	1.17	0.05	25.27	***				
Favorite likes	0.50	0.02	22.60	***				
Attribute distinctiveness	**−0.44**	**0.11**	**−3.89**	***	**2.61**	**0.83**	**3.15**	***
Price index					4.41	0.03	172.66	***
IMR					−2.84	0.76	−3.74	***
R^2							0.77	

Notes: N = 10,000. The outcome model deletes 1,291 observations due to missing price data for non-resold products. Unstandardized coefficients are reported. Value represents the price in Ether. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B2

Replication of Main Results with the Likelihood Score Measuring Product Uniqueness.

	Selection Model				Outcome Model			
DV:	Resale				Value			
	coefficient	SE	z-value	(p)	coefficient	SE	t-value	(p)
Intercept	−0.15	0.20	−0.75		−14.44	1.25	−11.51	***
Multiple ownership	1.17	0.05	25.27	***				
Favorite likes	0.51	0.02	22.67	***				
Attribute distinctiveness	**−0.93**	**0.13**	**−7.36**	***	**8.96**	**0.88**	**10.16**	***
Price index					4.40	0.03	173.35	***
IMR					−3.19	0.75	−4.24	***
R^2							0.78	

Notes: N = 10,000. The outcome model deletes 1,291 observations due to missing price data for non-resold products. Unstandardized coefficients are reported. Value represents the price in Ether. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B3

Replication of Main Results with the Heuristic Score Measuring Product Uniqueness.

	Selection Model				Outcome Model			
DV:	Resale				Value			
	coefficient	SE	z-value	(p)	coefficient	SE	t-value	(p)
Intercept	2.34	0.52	4.49	***	−38.50	3.14	−12.28	***
Multiple ownership	1.18	0.05	25.45	***				
Favorite likes	0.52	0.02	22.96	***				
Attribute distinctiveness	**−2.07**	**0.28**	**−7.44**	***	**19.69**	**1.69**	**11.68**	***
Price index					4.40	0.03	173.81	***
IMR					−2.79	0.74	−3.74	***
R^2							0.78	

Notes: N = 10,000. The outcome model deletes 1,291 observations due to missing price data for non-resold products. Unstandardized coefficients are reported. Value represents the price in Ether. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix C. Robustness check of the modeling approach

Model specification

With a significant portion of zeros in the sample, the distribution is skewed. Therefore, the distribution is log-normal transformed. As an optimization method, we use the conjugate gradient method (Fletcher & Reeves, 1964). It is a deterministic, gradient-based optimization method designed for more complex functions and large optimization problems because it does not compute a Hessian matrix (Henningsen & Toomet, 2011). A robust transformation ensures that all parameters lie within the required range (i.e., positive values for the standard deviation and for the position parameter, and −1 to + 1 for the coefficients of correlation). It provides resistance to outliers and is less affected by misspecification of the error distribution or heteroscedasticity.

Table C1

Replication of Main Results Using a Hurdle Method Estimation.

	Dependent Model				Independent Model			
	coefficient	SE	t-value	(p)	coefficient	SE	t-value	(p)
Hurdle 1 – DV: Resale								
Intercept	−1.26	0.12	−10.12	***	−1.21	0.12	−9.71	***
Multiple ownership	1.09	0.05	22.16	***	1.17	0.05	25.20	***
Favorite likes	0.54	0.02	23.58	***	0.50	0.02	22.83	***
Attribute distinctiveness	**−0.17**	**0.06**	**−2.92**	**	**−0.17**	**0.06**	**−2.86**	**
Hurdle 2 – DV: Value								
Intercept	−1.03	0.07	−14.34	***	−1.08	0.07	−15.10	***
Attribute distinctiveness	**0.42**	**0.05**	**9.00**	***	**0.41**	**0.05**	**8.68**	***
Price index	0.22	0.00	76.96	***	0.22	0.00	76.72	***
σ	1.26	0.01	150.02	***	1.25	0.01	164.91	***
ρ	−0.27	0.09	−2.96	**				
α	0.00	0.43	0.00		0.00	0.50	0.00	
Log likelihood (df)	−17,573 (10)				−17,582 (9)			

Notes: N = 10,000. Model estimation with mhurdle package in R (Carlevaro et al., 2012). Log-normal distribution. Conjugate gradient optimization method (Fletcher & Reeves, 1964; Henningsen & Toomet, 2011). Robust estimation method. Value represents the price in Ether. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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