Paying twice to have it your way? The backfiring effect of mass customization on a product’s resale value

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ABSTRACT

Across industries, mass customization has been hailed a winning strategy because customers are willing to pay substantially more for being able to purchase a unique product that is customized to their individual preferences. In this research, we highlight a so-far hidden downside of this strategy. Results based on a data set containing more than 500,000 cars offered on the second-hand car market suggest that customers pay a second time for customization: when selling their products. In particular, we find that the more unique a car’s color, the lower its resale value. A series of controlled follow-up experiments show that the effect is generalizable and causal. While consumer-designers are willing to pay more for more unique products, the opposite applies to customers on the second-hand market. Finally, we demonstrate that this loss can be minimized by making consumer-designers aware of the second-hand market at the time of self-customization. While consumer-designers’ willingness-to-pay for the resulting self-customized product does not change, they increase their products’ resale value by proactively considering the preferences of others in their self-customization.

Keywords: Mass Customization, Self-Customization, Self-Design, Resale, Second-hand Market
Customers are increasingly offered the possibility to self-customize products according to their unique preferences—ranging from cars to sneakers, from apparel to kitchens, from bikes to skis, and from backpacks to furniture (Dellaert and Stremersch 2005; Franke, Schreier, and Kaiser 2010; Moreau and Herd 2010). The underlying business concept, mass customization, has been considered “a strategic mechanism that is applicable to most businesses” (Salvador, de Holan, and Piller 2009, p. 71). While the cost of producing single unit quantities are constantly reduced due to advancements in production technologies, customers are willing to pay a substantial price premium for the resulting unique products that better fit and communicate their tastes, preferences, and identity (Franke and Piller 2004; Franke and Schreier 2008; Moreau et al. 2020; Townsend, Kaiser, and Schreier 2015). For this reason, mass customization is frequently considered the future of retailing (D’Angelo, Diehl, and Cavanaugh 2019; Halzack 2017) and Howe and Strauss (2007, p. 41) even predict that “older generations will look back wistfully to a time when products […] came in standard shapes and sizes.”

In this research, we point to a hidden and so-far neglected downside of mass customization: customers might be paying twice to have it their way; once when customizing the product and once again when selling it. Ironically, this effect may be fueled by marketers’ attempt to sell the idea of self-customization in the first place. For example, Nike markets its customized sneakers with the slogan “Nike by You,” inviting customers to “create something uniquely your own.”¹ Similarly, BMW advertises its cars as “being as unique as their drivers.”² When configuring a new car, for example, choosing a unique color may indeed help customers to

express their uniqueness (D’Angelo, Diehl, and Cavanaugh 2019; Franke and Schreier 2008; Kaiser, Schreier, and Janiszewski 2017). The likelihood that this unique color will be also appealing to other customers on the second-hand market (possibly several years later), however, is arguably much lower compared to a more mainstream color.

Although this second-hand market argument has not been raised so far, it seems an important one. Selling and buying products such as cars, apparel, and household goods on second-hand markets is becoming increasingly popular; in some cases, second-hand markets even exceed the markets for the respective new products in terms of size. For example, in 2019, the American second-hand car market was more than twice the size of the new car market: 40.8 million used cars were sold compared to 17 million new cars (Statista 2020). Moreover, while used car sales increased by +9.4% since 2015, new car sales decreased by -2.9%. Another example is StockX, a website reselling sneakers, which proclaims it generates sales worth more than $2 million every day.3 Finally, the global second-hand furniture market is forecast to grow to $16.6 billion in 2025, up 66% from $10 billion in 2017.4 Especially younger consumers are keen to buy second-hand products, with more than 40% of American consumers younger than 24 report having bought used apparel, footwear, or accessories in 2019.5

We report three studies that aim at testing this so-far neglected downside of mass customization and, taken together, offer a number of important contributions to the literature. First and foremost, we caution the interested reader about the so-far mostly positive picture

4 https://apnews.com/press-release/pr-businesswire/e3ba0790109844e8a89aa9668c51f3cf, Retrieved October 26th, 2020
5 https://www.thredup.com/resale/, Retrieved October 26th, 2020
drawn by the extant literature on mass customization. The “win-win” for customers and firms might not hold up against a more holistic product life cycle perspective. Indeed, results based on a large data set comprising more than 500,000 cars offered on the second-hand market show that the more unique a car’s color, the lower its asking price (Study 1). Interestingly, we find this effect to be particularly pronounced for professional sellers. For individual sellers, in contrast, the effect fully reverses and turns positive. Given that individual sellers are presumably also the ones who had originally self-customized their car, this latter finding mirrors previous findings reported in the mass customization literature (i.e., the more unique the self-customized product, the higher the product’s value to the consumer-designer; Franke and Schreier 2008). Critically, this finding further suggests that the focal effect is nontrivial such that individual customers, and later sellers, of self-customized products might not be aware of the detrimental effect of having the product their way.

A caveat of the field data reported in Study 1 is that the evidence is correlational and alternative interpretations are possible. To address causality, we conducted two controlled follow-up experiments, one in the context of sneakers (Study 2) and another one in the context of furniture (Study 3). The experimental work replicates and extends the findings from the field. While consumer-designers are willing to pay more for more unique products, the opposite indeed applies to customers on the second-hand market. Once again, we find that consumer-designers are unlikely to be aware of this effect given they were still demanding higher prices on the second-hand market in case their self-customized products were more versus less unique. Our second experiment builds on these findings and asks whether customers and firms can do anything about this dilemma. We show that the focal welfare loss can be substantially reduced by making the consumer-designer aware of the second-hand market at the time of self-
customization. While consumers are still able to design an appealing product for themselves, they increase their product’s resale value by proactively considering the preferences of others in their self-customization activities.

Finally, and more broadly, we contribute to the marketing literature by pointing to potentially consequential trade-offs between maximizing utility and creating value for brands and consumers at the point of first purchase versus optimizing long-term maintenance of value across the entire product life cycle (Cherrier, Türe, and Özçağlar-Toulouse 2018). The consideration of such trade-offs in consumers’ decision-making processes seem particularly relevant today due to omnipresent trends including the rise of the sharing economy (Bardhi and Eckhardt 2012; Belk 2007), the diffusion of online platforms selling second-hand products (PR Newswire 2020), and consumers’ increased quest for a more sustainable and responsible way of consumption (Gollnhofer, Weijo, and Schouten 2019; Guillard 2018; Schaefer and Crane 2005).

THE VALUE AND PRACTICE OF MASS CUSTOMIZATION

The core idea of mass customization is to serve every customer with a unique product at near mass-production efficiencies (Davis 1987; Piller and Stotko 2002; Pine 1993). The customer takes on the role of an active co-designer and is equipped by the firm with an easy-to-use online design interface or toolkit, which facilitates learning one’s preferences and translating them into a custom product design (Von Hippel and Katz 2002; Thomke and Von Hippel 2002). The resulting self-customized product is subsequently produced by the firm to order. Mass customization has been suggested to be particularly promising in domains where user preferences are heterogeneous or where standard, off-the-shelf products are unlikely to fully satisfy each customer in a given segment (Franke and Piller 2004). In the car industry, for
example, already 44% of new car buyers in Germany self-customize their car (DAT Group 2016). Although the US is lagging behind Europe in this regard, there has been an increase in made-to-order cars recently. For example, Tesla has collected nearly 300,000 deposits for a customized Model 3 in just 3 days\(^6\). Moreover, in 2018, 26% US consumers reported having already self-customized a product, up from 17% in 2015 (YouGov 2018). Most of them reported having self-customized footwear and apparel (29%, YouGov 2018). An example is Nike, which offers its customers the possibility to self-customize their own sneakers. Further, 22% reported having self-customized household goods. Correspondingly, brands like Crate & Barrel let customers self-customize all kinds of household appliances including furniture and couches.

A robust finding in the mass customization literature is that customers are willing to pay a substantial price premium for their self-customized products (Franke and Piller 2004; Franke, Schreier, and Kaiser 2010; Schreier 2006). This value increment has been attributed to several factors including a better preference fit and higher uniqueness perceptions of the self-customized product. As argued by Franke and Schreier (2008, p. 94), “the almost infinite variety of products offered by MC [mass customization] systems not only allows more effective adaptation to the customer’s aesthetic and functional preferences, but also facilitates enhanced differentiation from other customers and their belongings by means of a truly unique product.”

A unique product is one that is perceived to be different from other products in the same category (Tian, Bearden, and Hunter 2001). Unique products create intrinsic value by helping its owner to define oneself as distinct from others; put differently, unique products help to express one’s uniqueness, a need many consumers face (Fromkin and Snyder 1980; Lynn 1991; Tian,

Bearden, and Hunter 2001). Indeed, research has shown that customizing identity-related products is a way for consumers to express who they are (de Bellis et al. 2016; D’Angelo, Diehl, and Cavanaugh 2019; Kaiser, Schreier, and Janiszewski 2017; Klesse et al. 2019). D’Angelo et al. (2019, p. 762), for example, argue that “engaging in customization in and of itself may trigger motivations to express uniqueness” and they show that in order to make one’s product unique, customers are sometimes even willing to pay extra or sacrifice one’s truly preferred options.

Marketers are well aware of the importance of uniqueness to consumers and hence frequently advertise their products as rare, unique, special, and one-of-a-kind (Frank 1997; Lynn and Harris 1997; Snyder 1992; Thompson and Haytko 1997). In the context of mass customization, brands have also started to actively nudge their customers to express their uniqueness. As indicated in the introduction, Nike invites its customers to “create something uniquely your own” and BMW wants to sell cars that are as “unique as their drivers.” Similarly, Converse warms the idea of getting a unique pair of custom Chuck 70 by using slogans like “Every color tells a story. Find the ones that tell yours” or “Color shows more than your mood, it’s your signal. What do you stand for?”

One major reason why marketers would like customers to purchase more unique products is that “uncommon product options are likely more profitable than standard ones” (de Bellis 2016, p. 163). For example, while the colors black and white are included in the base price of a new BMW 1 series, more unique colors such as sunset orange (+682.36 EUR, ~ 800 USD) and storm bay metallic (+1,169.74 EUR, ~ 1,400 USD) cost significantly extra. Finally, Franke and Schreier (2008, p. 97) have shown that consumers’ incremental willingness to pay (WTP) for self-customized products is predicted by both the

extent to which consumer-designers perceive their designs to offer a high preference fit and the extent to which their designs are perceived as being “unique,” “one of a kind,” and “really special.”

In sum, the collective evidence suggests that mass customization systems in practice reinforce consumers’ quest for uniqueness and hence likely yield unique products, and that the more these products are perceived to be unique by the consumer-designer, ceteris paribus, the higher the respective WTP. But what happens when these products hit the second-hand market? We try to answer this question next.

**THE BACKFIRING EFFECT OF MASS CUSTOMIZATION**

The main proposition of this research is that there is a so-far neglected, hidden downside of mass customization. The aforementioned positive aspect of self-customized products might turn negative as soon as we switch perspective and consider likely reactions from second-hand market customers. For example, consider the study by Franke and Piller (2004) on wrist watches. Supporting the promise of mass customization, they find that if a manufacturer wanted to fully satisfy revealed preferences of 165 students, it would need to offer 159 different standard watches. While these watches might be highly unique and of “perfect fit” to the respective consumer-designer, it is unlikely that any given user-design will resonate similarly well with another customer. On the contrary, the more the consumer-designer accomplishes the goal of getting a truly unique product, the less favorable the consumer response on the second-hand market might become. For example, if a specific customer finds a sunset orange BMW 1 series to be both appealing (because he or she likes the color orange) and unique (because there are hardly any other sunset orange cars of that type), it is unlikely that a subsequent second-hand...
market customer may value the car to the same extent compared to a white BMW 1 series (a more common color). This is because a unique product is unlikely to hit the preferences of many other customers; if it did, it would most likely not be unique to begin with. If many customers would like the BMW 1 series to be orange, for example, BMW would follow suit and offer it. Perceived uniqueness, in turn, would diminish.

Second, a highly unique product might be recognized as such by the observing consumer, who might also correctly guess the consumer-designer’s underlying motive. Why else would someone buy a sunset orange BMW 1 series if not to express one’s uniqueness? This reasoning is consistent with what D’Angelo, Diehl, and Cavanaugh (2019) find in their studies. In particular, they show that unique user-designs are often attributed by other consumers to a uniqueness motive of their respective consumer-designers, which, in turn, ironically makes the observer want to distance oneself even further from that focal design. Put differently, if a consumer-designer purchased a BMW 1 series in sunset orange to express one’s uniqueness, another customer would hardly be able to express one’s own uniqueness by buying this consumer-designer’s car (on the contrary, that consumer would signal being similar to the focal consumer-designer).

Finally, time passes between self-customization and second-hand market offering. Therefore, underlying market trends evolve and what might be considered “chic and unique” today might be simply out of fashion tomorrow. Take the car color brown for example: In Germany, brown was considered a fashionable color for new cars in 2012 and 6.66% of all newly registered cars were brown. However, only 7 years later in 2019, brown was considered “out of fashion” (Focus Online 2019) and a mere 1.32% of all newly registered cars were brown – a decline of more than 80% (Kraftfahrt-Bundesamt 2020). Because loud signals are more
easily recognized by the market (Berger and Ward 2010; Han, Nunes, and Drèze 2010),
consumer-designers might pick such recognizable markers to establish positively-valenced
uniqueness. Once the fashion cycle has moved on, however, the respective markers might soon
turn negative (Pesendorfer 1995).

Taken together, we have reason to predict that while consumer-designers might be
willing to pay more for more unique products, the opposite shall apply to customers on the
second-hand market: the more unique the self-customized product to the respective consumer-designer, the lower its appeal to potential customers on the second-hand market. We provide an
initial test of this prediction in Study 1.

**STUDY 1: >500,000 CARS OFFERED ON THE SECOND-HAND MARKET**

In Study 1, we aim to provide an initial test of our primary hypothesis: the more unique
the self-customized product to the respective consumer-designer, the lower its appeal to potential
customers on the second-hand market. We do so by analyzing field data (n = 529,038) scraped
from one of the largest online platforms selling used cars in Germany. We focus on the car’s
color because its uniqueness can be reliably coded at scale. A car’s color is also a key feature
which customers typically customize. Having a uniquely colored car is highly self-expressive
and readily observable by other consumers.

The asking price in each car advertisement serves as dependent variable. It is important to
point out that the actual price realized (data not available) might slightly differ from the initial
asking price. Looking at the cars’ asking price, however, offers the advantage of being able to
study the seller’s perspective in detail. In particular, our data allows us to differentiate between
individual sellers (presumably the ones who have originally self-customized and purchased the
cars at hand) and professional sellers (middlemen between current car owners and prospective customers). As argued in the theory section, the individual consumer-designer is likely biased by one’s own perspective. This bias might stem from (1) the fact that a uniquely colored car did cost more at the time of self-customization and (2) the perception that one’s car is “unique,” “one of a kind,” and “really special” and hence valuable. Professional sellers, instead, should be better able to assess the car’s market value and the price it most likely can realize on the second-hand market.

Put differently, our predicted effect should be particularly visible when looking at the price asked for by professional sellers (the more unique the car’s color at the time of self-customization, the lower the car’s value to potential customers on the second-hand market). Due to their biased perspective, however, the effect shall be less pronounced and potentially even reversed for individual sellers (the more unique the car’s color, the higher the asking price).

Methods

Sample. We collected data of more than five hundred thousand advertisements for used cars (n = 529,038) posted on one of the leading German online car resale platforms between September and November 2019. Our data captured the 15 most sold brands in Germany (Statista 2019) and covered cars that were initially registered between 2005 and 2019, that is, during the past 15 years.

Procedure. We built a web scraper using the Python programming language to extract the values of interest from the website. A web scraper accesses a pre-defined or dynamically generated list of web addresses (URLs), retrieves the served website (HTML files) and extracts, cleans and organizes the data into a formal data set (cf. Boeing and Waddell 2017; Mitchell...
As a first step, our scraper requested the HTML data file for the specified URL. This file was then parsed by the Beautiful Soup package (Richardson 2018), to make individual pieces of the received HTML data file accessible to the scraper. Our scraper then extracted, cleaned, and organized the selected variables into a CSV file that was saved to the computer’s permanent storage. In order not to strain the webserver sending the HTML files, we built intentional pauses into the scraper, significantly slowing the process. The CSV file could then be analyzed using popular statistical software packages.  

Data preparation. We cleaned and filtered the data as follows. First, we removed duplicate entries. Duplicates might occur when sellers post the cars in ways that they appear under several different search queries or when the same search query was scraped twice by the scraper (which can happen when the scraper is paused and restarted). Second, we cleaned the data set, that is, we made sure that key variables were available for each entry. This included safeguarding that every car was a “used” car (as some dealers also posted “new” cars) and we filtered out dummy entries (several dealers had posted “test” versions). The cleaned data set contained n = 520,190 car advertisements. Descriptive statistics of the different versions of the data set (retrieved, unique, cleaned, and truncated) are summarized in the Web Appendix.

Dependent variable. The advertised asking price served as the dependent variable (asking price\(_{ij}\), where \(i\) is the car of model \(j\)). An initial analysis of the distribution of this measure indicated that there were extreme values. The measure showed a median of 17,850 EUR, a mean of 20,944 EUR, a standard deviation of 22,734 EUR, and a maximum value of 11,111,111 EUR. This implied that there was a long tail of extreme values above a value of around 65,505 EUR.

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9 Discussions of web scraping raise questions regarding its legality. However, we ensured that our process of data scraping was in adherence with German laws and jurisdiction (specifically Bundesgerichtshof 2014 and 2016).
Given the propensity of extreme values to bias statistical tests, the extreme values were truncated (McClelland 2000). We used the median absolute deviation (MAD) method to determine extreme values (Leys et al. 2013). The MAD method does not rely on the mean or standard deviation to identify outliers. Therefore, the criticism that the measures used to identify outliers are influenced by the outliers themselves, does not apply. Applying MAD, we determined the median of the price for each car model, calculated the absolute deviations from the median for each observation, calculated the median of these absolute deviations for each car model and finally, after adjusting for normality, determined a threshold deviation. Leys et al. (2013) recommend a threshold of 2.5 median deviations, which implies that a cutoff should capture 98.8% of the distribution. We applied the recommended 2.5 median deviations cutoff to our dataset; 13,515 observations (2.6%) featured a price above a MAD value of 2.5 and were therefore truncated to the maximum value for their respective car models.

**Independent variable.** The uniqueness of the advertised car’s color at the time of its configuration served as our independent variable. Practitioner literature pointed towards the idea that a car’s color is not unique per se but its uniqueness instead needs to be defined within the context of a given car model and vintage (WhatCar? 2019). We followed suit and calculated color uniqueness ($color_{uniqueness_{ij}}$) as the inverted proportion of the number of cars of a given model of the respective vintage that featured said color. For example, if there were 49 black and one red 2015 “BMW 116”, a black 2015 “BMW 116” would have a color uniqueness score of .02 (1 - [49 / 50]) and the red one would be assigned a score of .98 (1 - [1 / 50]). Consequently, the variable can take any value from zero to one with higher values indicating more uniqueness.

As indicated, picking a unique color for one’s car is highly self-expressive, and the practitioner literature even suggests that “the color of a car can say a lot about a person and even
speak to the driver's purpose in life” (Joseph and Tate 2019, online). It is important at this stage to also repeat that picking a unique color typically involves incremental cost to the consumer-designer and buyer of the new car. While we were not able to capture whether, and if so, how much, the cars’ colors in our data set did cost extra at the time of configuration, it is important to recognize that this makes our empirical test more conservative. That is, any given car with a more unique color should be seen with a higher (and not lower) asking price on the second-hand market, ceteris paribus.

Fixed effects. We employed a series of control variables that are likely to predict a given car’s asking price (DAT Group 2016; WhatCar? 2019). In total we introduced three groups of variables into the model: Car specifications fixed effects, car sale circumstances fixed effects, and the median asking price of the model. First, car specifications fixed effects comprised variables that described the car in the advertisement and which are constant since the car’s production. The variables first included the car’s color. On the platform, sellers need to select one of 12 colors describing their car; we hence included 11 dummy variables (i.e., beige$_{ij}$ – yellow$_{ij}$, in alphabetical order) with the reference level (0) being black.$^{10}$ Moreover, we captured the car’s power in horse powers (power$_{ij}$), which the sellers enter as a numeric value. We summarized engine types entered by the sellers into the two dummy variables diesel$_{ij}$ and other fuel$_{ij}$ (e.g., hybrid or electric cars) with the reference level being gasoline. We then summarized transmission types entered by the sellers into the dummy variable manual$_{ij}$ with the reference level being automatic, which also included other variants of automatic transmission types like dual-clutch or continuously variable transmissions. In addition to the variables just discussed, robustness checks reported in the Web Appendix included further control variables including car...

$^{10}$ Our focal independent variable, color uniqueness$_{ij}$, was also included in this first group of fixed effects.
brand. As the car brand is implied by the car model random effect (e.g. “BMW 116”), we did not include car brand in the regressions in Table 1\textsuperscript{11}.

Second, car sale circumstances fixed effects comprised variables that described the moment of the second-hand market offering and included the seller type of the car as a dummy variable (where 0 = individual seller and 1 = professional seller \([\text{professional seller}_{ij}]\)), the mileage of the car in kilometers \((\text{mileage}_{ij})\), and the age of the car in days since the date of first registration \((\text{age}_{ij})\).

Last, we included the median asking price of the model \((\text{median asking price}_{j})\).

**Modeling approach.** The car advertisements are nested within car models. To determine whether a multilevel approach was warranted, we first conducted an ANOVA with car model as predictor and asking price as dependent variable. We found significant between-group variance \((F(414, 519,775) = 2,151, p < .001)\). Second, we tested a hypothetical null model with no fixed effects and car model as a random effect. The random effect of car model explained 97\% of the intercept’s variance \((\gamma_{00} = 34,992; \text{SE}_{\gamma_{00}} = 2,568)\). Both indicators suggest that a mixed-effects approach was warranted. Therefore, we specified the mixed-effect model in equation 1 with fixed effects for the car specifications, car sale circumstances, and car model and a random effect of the car model on the intercept as follows, where \(u_{0j}\) is the car model-specific error term and \(\varepsilon_{ij}\) is the car advertisement error term. We ran Model 1 in Table 1 ignoring the interaction term included in Equation 1 to perform a first basic hypotheses test.

\textsuperscript{11} Car models are exclusive to car brands. For example, one cannot buy a 116 from BMW or from Audi, as the model typology is unique to the respective brand.
(1) \[ \text{Asking Price}_{ij} = \gamma_{00} \]

\[ + \gamma_{10} \text{Color Uniqueness}_{ij} \]

\[ + \gamma_{20-110} \text{Car Color Dummies (Beige}_{ij} - \text{Yellow}_{ij}) \]

\[ + \gamma_{120} \text{Power}_{ij} \]

\[ + \gamma_{130-140} \text{Fuel Dummies (Diesel}_{ij}, \text{Other Fuel}_{ij}) \]

\[ + \gamma_{150} \text{Transmission Dummy (Manual}_{ij}) \]

\[ + \gamma_{160} \text{Seller Type Dummy (Professional Seller}_{ij}) \]

\[ + \gamma_{170} \text{Mileage}_{ij} \]

\[ + \gamma_{180} \text{Age in Days}_{ij} \]

\[ + \gamma_{01} \text{Median Asking Price}_{j} \]

\[ + \gamma_{200} \text{Professional Seller}_{ij} \times \text{Color Uniqueness}_{ij} \]

\[ + \mu_{0j} + \varepsilon_{ij} \]

Results

Direct effect of color uniqueness on asking price. We used the R package “lme4” (Bates et al. 2015) to estimate a mixed-effect model, which yielded the following results (see Model 1 in Table 1). First and most importantly, we found support for our primary hypothesis: the more unique a car’s color at the time of self-customization, the lower its asking price on the second-hand market (\(\gamma = -572.26, t = -6.59, p < .001\)). Furthermore, we found the following effects with regard to our control variables (most of which are as expected and consistent with the practitioner literature): First, a car’s horse power is positively related with its asking price (\(\gamma = 67.21, t = 222.27, p < .001\)); second, a diesel engine (\(\gamma = 738.90, t = 33.74, p < .001\)) or any other type of engine (\(\gamma = 3,421.62, t = 42.29, p < .001\)) is associated with a higher asking price.
compared to a car that runs on gasoline; third, a manual transmission is associated with a lower asking price compared to an automatic one ($\gamma = -2,077.61$, $t = -96.00$, $p < .001$); fourth, we find that professional sellers generally ask for a lower asking price ($\gamma = -157.39$, $t = -6.21$, $p < .001$) compared to individual sellers; fifth, mileage (in km) is negatively related with the car’s asking price ($\gamma = -.05$, $t = -226.45$, $p < .001$); sixth, the older the car, the lower its asking price ($\gamma = -3.52$, $t = -348.40$, $p < .001$); seventh, we find a significantly positive effect of the car model’s median price ($\gamma = .88$, $t = -93.38$, $p < .001$).

**Color uniqueness × professional seller interaction.** We next tested the predicted seller type interaction (i.e., while the negative effect of color uniqueness should be particularly visible when looking at the price asked for by professional sellers, it could potentially reverse for private sellers). We tested this prediction by running the full regression equation 1 including the respective interaction term (color uniqueness × professional seller, see Model 2 in Table 1). In support of our prediction, we found a significant interaction effect ($\gamma = 4,925.07$, $t = -30.26$, $p < .001$). When the car was sold by a professional seller, color uniqueness significantly and substantially reduced its asking price ($\gamma = -1,530.07$, $t = -16.6$, $p < .001$). However, when the car was sold by an individual seller (presumably the one who had originally self-customized the car), color uniqueness actually increased the asking price for the car ($\gamma = 3,395.01$, $t = 21.6$, $p < .001$). We visualize this interaction in Figure 1.
TABLE 1.  
STUDY 1: MIXED-EFFECTS MODEL PREDICTING THE ASKING PRICE OF USED CARS.

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Car Specifications</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Color Uniqueness (0-1 Scale)</td>
<td>-572.26***</td>
<td>3,395.01***</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car Color (0, 1)</td>
<td>See full table in Web Appendix.</td>
<td></td>
</tr>
<tr>
<td>Power (HP)</td>
<td>67.21***</td>
<td>67.16***</td>
</tr>
<tr>
<td>Diesel (0, 1)</td>
<td>738.90***</td>
<td>728.52***</td>
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<tr>
<td>Fuel Other (0, 1)</td>
<td>3,421.62***</td>
<td>3,421.38***</td>
</tr>
<tr>
<td>Manual Transmission (0, 1)</td>
<td>-2,077.61***</td>
<td>-2,076.31***</td>
</tr>
<tr>
<td><strong>Car Sale Circumstance</strong></td>
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<tr>
<td>Professional Seller (0, 1)</td>
<td>-157.39***</td>
<td>3,586.17***</td>
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<tr>
<td>Fixed Effects</td>
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<tr>
<td>Mileage (KM)</td>
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<td>-0.05***</td>
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<td>Age (Days)</td>
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<td>-3.53***</td>
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<td><strong>Car Model Fixed Effects</strong></td>
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</tr>
<tr>
<td>Median Price of Car Model (EUR)</td>
<td>0.88***</td>
<td>0.88***</td>
</tr>
<tr>
<td><strong>Interactions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Professional Seller × Color Uniqueness</td>
<td>-4,925.07***</td>
<td></td>
</tr>
<tr>
<td><strong>Intercept</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-</td>
<td>44.04</td>
<td>-2,973.30***</td>
</tr>
</tbody>
</table>

Observations: 520,190 520,190  
Log Likelihood: -5,238,151 -5,237,688  
Akaike Inf. Crit.: 10,476,353 10,475,427  
Bayesian Inf. Crit.: 10,476,632 10,475,718  

Note: * p < .05, ** p < .01, *** p < .001; Values are unstandardized coefficients, with standard errors in parentheses.


Discussion

Study 1 provides initial evidence in support of our primary hypothesis. In particular, we find that the more unique a car’s color at the time of self-customization, the lower its asking price once it is offered on the second-hand market. This effect unfolds even after having controlled for a host of significant predictors of a car’s resale value. Consistent with our theorizing, we further find that this effect depends on the type of seller. While the effect is particularly pronounced in case a given car is offered by a professional seller, the effect fully reverses and hence turns positive for private sellers, presumably the ones who have originally self-customized and paid for the car at hand. A limitation of Study 1 is that the evidence is
correlational and hence not causal. We hence proceed by presenting a controlled follow-up experiment aimed at establishing the effect’s causality.

**STUDY 2: ASSESSING CAUSALITY**

In Study 2, we aim to extend the findings obtained in Study 1 in several major ways. First, by devising a controlled experiment, we assess the causality of our primary prediction that the more unique the self-customized product to the respective consumer-designer, the lower its appeal to potential customers on the second-hand market. In terms of dependent variable, we ask the consumer-designer to either indicate one’s willingness to pay (WTP) or, alternatively, one’s willingness to accept (WTA) for one’s self-customized product. While the former measure captures the value the product delivers to the consumer-designer, the latter measure captures the asking price, or, the “minimum compensation demanded for the entitlement” (Knetsch, Thaler, and Kahneman 1990, p. 1326). Because we also measure the uniqueness of the self-customized product, as perceived by the respective consumer-designer, we can assess whether the uniqueness of a given self-customized product will be differently related to WTP versus WTA. Furthermore, we expose the products self-customized by the consumer-designers to a sample of other consumers. Their WTP provides the second-hand market valuation of the self-customized products. Importantly, we can thereby assess how the consumer-designers’ uniqueness perceptions are related to the second-hand market WTP. If our theorizing is correct, we should obtain a significantly negative relationship. Finally, we changed the context from cars to sneakers to test the robustness of the proposed effect.

**Methods**
Consumer-designers. For the first part of the experiment, we recruited 502 US consumers (M_{age} = 36 years, 59% female, Amazon Mechanical Turk) in exchange for a nominal payment. Participants were randomly assigned to either a WTP or WTA condition. Participants in both conditions were asked to self-customize a pair of sneakers for themselves. To do so, they could use a self-customization interface which was specifically created for this study. The interface made sure that we could automatically store participants’ creations in the survey flow; the interface was a simpler version of the Nike By You toolkit. The customizable sneakers were the “Nike Blazer Mid” (a unisex shoe) and participants could customize it by selecting one of 22 colors for each of five customizable features of the shoe (main color, swoosh color, backtab color, sole color, and lace color). The selected colors were instantly rendered graphically on the participants’ screen to facilitate effective self-design (von Hippel and Katz 2002; Thomke and von Hippel 2002).

Participants were then either requested to indicate their WTP (WTP condition) or WTA (WTA condition) for their self-customized sneakers. In the WTP condition, we asked participants “What's the maximum amount of money (in US $) you would be willing to pay for the pair of sneakers you designed? (The average retail price for a new pair of sneakers of this type is circa 100 US $.)”. They could select a value on a $0 to $151 scale in $1 increments (0 = “I'm not willing to pay anything.”, 151 = “More than 150 US $.”). We ensured to make this and all the following slider scales easy-to-use and intuitive, in spite of the large number of selectable values. The Web Appendix contains screenshots of the slider scales we used in Study 2.

In the WTA condition, we asked participants “Imagine you purchased the pair of sneakers you designed. After some time (i.e., after a few weeks), however, and without having
used the sneakers much, you decide to sell them on the second-hand market. What is the minimum amount of money (in US $) that you would be willing to accept in order to actually sell the sneakers? (Assume that the sneakers are in excellent conditions and appear to be almost new. The average retail price for a new pair of sneakers of this type is circa 100 US $.)”. They could select a value on a $0 to $151 scale in $1 increments (0 = “I'm willing to give them away for free.”, 151 = “I'm not willing to sell them for 150 US $ or less.”).

Participants were further asked to assess the uniqueness of their creations. We employed the following three-item scale: (1) “My sneakers’ design is unique,” (2) “My sneakers’ design is special,” and (3) “My sneakers’ design is one-of-a-kind” (where 1 = “Strongly Disagree” and 7 = “Strongly Agree”, α = .93; adapted from Franke and Schreier 2008). Lastly, participants indicated their gender and age.

Second-hand market customers. In order to assess the second-hand market appeal of the self-customized products, we recruited an independent sample of 1,230 US consumers (M<sub>age</sub> = 37 years, 46% female, Amazon Mechanical Turk) in exchange for a nominal payment. In particular, each respondent was asked to evaluate five self-customized pairs of sneakers which they learned were currently offered on the second-hand market. Participants first indicated their demographics (age, gender) and shoe size. We used their revealed gender to match it with the gender of the consumer-designers. We did so in order to avoid noise stemming from gender mismatches (although the shoe model used was unisex, design preferences likely differ between men and women). We then presented each participant with five pairs of customized sneakers “available in their size,” which were portrayed as currently being for sale on the second-hand market, and we asked them to indicate their WTP for each pair. To measure second-hand market customers’ WTP, we asked them “What's the maximum amount of money (in US $) you would
be willing to pay for these sneakers? (The average retail price for a new pair of sneakers of this type is circa 100 US $).” They could select a value on a $0 to $151 scale in $1 increments (0 = “I'm not willing to pay anything.,” 151 = “More than 150 US $.”).

The five presented designs were randomly drawn from the 298 (204) self-customized sneakers by the female (male) consumer-designers from the first part of the experiment. The five designs were presented randomly underneath one-another on the same page. In total, we had 1,230 participants indicating their WTP for five sneakers each, resulting in 6,150 total WTP data points. Put differently, we aimed at collecting at least ten data points for each self-customized pair of sneakers with an aim to get a valid second-hand market assessment of the various designs tested.

Results

We first regressed consumer-designers’ WTP on their uniqueness perceptions of their self-customized sneakers. Replicating prior research in this area (Franke and Schreier 2008), we found a significantly positive effect: the more unique one’s creation, the higher one’s WTP (b = 5.88, t(268) = 5.69, p < .001). Second, we also found a positive and significant relationship between a product’s uniqueness perceptions and consumer-designers’ WTA (b = 3.02, t(230) = 2.75, p < .01). As can be seen in Figure 2, however, the WTP-slope seems to be steeper than the WTA-slope, suggesting that consumer-designers realize, at least to some extent, that what they value for themselves might differ from what potential customers on the second-hand market might find appealing. To test this more formally, we tested whether the effect of uniqueness interacted with the type of dependent variable (i.e., consumer-designers’ WTP vs. WTA). We found a marginally significant interaction effect (b = 2.86, t(498) = 1.87, p = .06). Thus, findings suggest that the product’s uniqueness perceptions do seem to affect one’s WTP
more than one’s WTA. However, not sufficiently so to neutralize or invert the slope for WTA: the effect remains positive and significant.

In order to analyze the data with regard to second-hand market WTP, we estimated the linear mixed-effect model in Equation 2 with second-hand market WTP as dependent variable, product uniqueness (as perceived by the consumer-designer) and four dummy variables for the designs’ position in the survey (a given pair of sneakers could appear in five different positions in a given survey, with the reference being position 1) as fixed effects, and a design-identifier and a second-hand market participant-identifier as random effects on the intercept. The random effects were introduced as the sneaker designs were rated more than once and participants rated five configurations each. Thereby, some of the variance captured in the dependent measure could be ascribed to the specific design or participant using the random effects. The corresponding regression for the second-hand market WTP of participant $i$ for configuration $j$ is stipulated in Equation 2, where $u_{0j}$ is the design-specific error term and $r_{i0}$ is the participant-specific error term.

$$
\text{Second-hand Market WTP}_{ij} = \gamma_0 + \gamma_1 \text{Uniqueness}_j
+ \gamma_{02-05} \text{Configuration Position Fixed Effects}_j
+ u_{0j} + r_{i0} + \epsilon_{ij}
$$

As hypothesized, we found a significantly negative relationship between product uniqueness, as perceived by the consumer-designer, and second-hand market WTP ($\gamma = -.62$, $t = -3.87$, $p < .001$; Figure 2). Thus, the more unique the self-customized product, the lower its appeal to potential customers on the second-hand market.
Although it is implied by the aforementioned results, we formally tested whether the second-hand market WTP slope was significantly different from the other two slopes. To test this, we estimated a second mixed-effects model. This model featured the condition (i.e., consumer-designers’ WTP, WTA, and second-hand market WTP), the sneakers’ uniqueness perceptions, and the respective interaction (condition x perceived uniqueness) as fixed effects. However, we collapsed the three experimental conditions to two by grouping consumer-designer WTP and WTA into one “consumer-designer” category. Thereby, we created one dummy variable that could take the values “consumer-designer” or “second-hand market”. Lastly and like Equation 2, the model again featured a design identifier and a participant identifier as random effects on the intercept. Unlike the previous model, however, we were not able to feature
the survey position of the design as a covariate, as this information was not applicable to the two consumer-designer conditions.

Importantly, we find that the interaction between uniqueness and the collapsed conditions, that is, consumer-designers’ valuation (WTP and WTA) versus second-hand market WTP, is significant ($\gamma = -5.04$, $t = -5.04$, $p < .001$).

**Discussion**

Study 2 replicates and extends the findings obtained in Study 1 in a test setting that is characterized by high internal validity. In particular, we find that consumer-designers’ WTP for their self-customized sneakers is positively affected by the extent to which they perceive their products to be unique. A similar although less positive relationship is found for their WTA, suggesting that consumer-designers partially realize that what they value for themselves might differ from what potential customers on the second-hand market might find appealing. However, they fail to realize the extent to which these valuations differ. In stark contrast to consumer-designers, and in line with our Study 1 findings and theorizing, we find that second-hand market WTP is negatively affected by a product’s uniqueness. Thus, the more unique the self-customized product appears to the respective consumer-designer, the lower its appeal to potential customers on the second-hand market. Given these findings, we need to ask: Is there anything that can be done to mitigate this negative effect?

**STUDY 3: HOW TO MITIGATE THE LOSS OF VALUE**

In Study 3 we aim to assess whether customers are able to optimize their self-customized products in a way that also the second-hand market values their efforts. In particular, we ask
whether making the consumer-designer aware of the second-hand market at the time of self-customization will attenuate the negative effect identified. The idea is that while customers might still be able to find an appealing product for themselves, they might increase their products’ resale value by proactively considering the preferences of others in their self-customization activities. We experimentally contrast the common business practice of inviting consumer-designers to “express their uniqueness” to a condition, in which customers are invited to consider “optimizing the resale value” of their to-be-self-customized product. We change the product category to couches to further add generalizability. Other than that, we employ the same paradigm as utilized in Study 2. While a group of consumer-designers is invited to self-customize a product for themselves, an independent sample of consumers is subsequently asked to evaluate the respective self-customized products. Our primary prediction in Study 3 is that self-customized products generated in the “optimize resale value” condition yields more favorable second-hand market valuations compared to those generated in the baseline condition (“express your uniqueness”).

Methods

Consumer-designers. For the first part of the experiment, we recruited 202 US consumers (\(M_{\text{age}} = 38\) years, 40% female, Amazon Mechanical Turk) in exchange for a nominal payment. Participants were randomly assigned to either the “express uniqueness” or “optimize resale value” condition. Participants in both conditions were asked to self-customize a couch for themselves. To do so, they could use a self-customization interface, which was specifically created for this study and which would store participants’ creations in the survey flow. Participants in the “express uniqueness” condition were invited to self-customize the couch to
their own preferences and also to make it highly unique (e.g., “the couch design should express your uniqueness”). Participants in the “optimize resale value” condition, instead, were invited to self-customize the couch to their own preferences and also to keep the resale value high (e.g., “the couch design should be also appealing to other customers”). The customizable couch was the “Lune” couch by “Fritz Hansen,” a Danish furniture design brand (fritzhansen.com). Participants could customize it by selecting one of 22 colors for each of seven customizable features of the couch (arms and upper frame color, lower frame color, upper left cushion color, upper right cushion color, lower left cushion color, upper right cushion color, and legs color). The selected colors were instantly rendered graphically on the participants’ screen to facilitate effective self-customization (Von Hippel and Katz 2002; Thomke and Von Hippel 2002).

Participants were then asked to indicate the WTP for their self-customized couch: “What’s the maximum amount of money (in US $) you would be willing to pay for the couch you designed? (The average retail price for a new couch of this type is circa 1,000 US $.)”. They could select a value on a $0 to $1,501 scale in $1 increments (0 = “I'm not willing to pay anything.”, 1,501 = “More than 1,500 US $.”). As in Study 2, we ensured to make this and all the following slider scales easy-to-use and intuitive, in spite of the large number of selectable values. The Web Appendix contains screenshots of the slider scales we used in Study 3.

Participants were further asked to assess the uniqueness of their creations in a way similar to Study 2. We employed the following three-item scale: (1) “My couch’s design is unique,” (2) “My couch’s design is special,” and (3) “My couch’s design is one-of-a-kind” (where 1 = “Strongly Disagree” and 7 = “Strongly Agree”, $\alpha = .91$; adapted from Franke and Schreier 2008).

Second-hand market customers. In order to assess the second-hand market appeal of the self-customized products, we recruited an independent sample of 405 US consumers.
(M_{age} = 42 years, 49% female, Amazon Mechanical Turk) in exchange for a nominal payment. Specifically, each respondent was asked to evaluate five self-customized couches which they learned were currently offered on the second-hand market. Participants were presented with five customized couches, which were portrayed as currently being for sale on the second-hand market, and we asked them to indicate their WTP for each couch: “What's the maximum amount of money (in US $) you would be willing to pay for this couch? (The average retail price for a new couch of this type is circa 1,000 US $.)”. Respondents could select a value on a $0 to $1,501 scale in $1 increments (0 = “I'm not willing to pay anything.”, 1,501 = “More than 1,500 US $.”).

The five presented designs were randomly drawn from the 202 self-customized couches created in the first part of the experiment by the consumer-designers from both experimental conditions (i.e., “express uniqueness” and “optimize resale value”). The five designs were presented in random order underneath one-another on the same page. In total, we had 405 participants indicate their WTP for five couches each, resulting in a total of 2,025 second-hand market WTP data points. Put differently and parallel to Study 2, we aimed at collecting at least ten data points for each self-customized couch with an aim to get a valid second-hand market assessment of the various designs tested.

Results

We first conducted an ANOVA on consumer-designers’ uniqueness perceptions of their self-customized couches. Consistent with our manipulations, we found higher uniqueness scores in the “express uniqueness” condition (M = 5.17, SD = 1.42) compared to the “optimize resale value” condition (M = 4.31, SD = 1.75, F(1, 200) = 14.56, p < .001). In line with the prior
studies, we also found that these uniqueness perceptions were positively related with one’s WTP ($b = 50.47, t(200) = 3.90, p < .001$). Interestingly, however, this pattern of effects did not translate into a main effect of the treatment on the dependent variable. That is, our manipulations were not significantly related with the consumer-designers’ WTP for their self-customized couches ($M_{\text{uniqueness}} = 690.96, SD = 329.47, M_{\text{resale}} = 677.87, SD = 300.13, F(1, 200) = .09, p = .77$). It seems that participants in the “optimize resale value” condition were getting some value from their self-customized products that participants in the “express uniqueness” condition did not, hence compensating for the loss of perceived uniqueness.

In order to analyze the data with regard to second-hand market WTP, we estimated a linear mixed-effect model similar to the one used in Study 2 (see Equation 2); in particular, the model included second-hand market WTP as dependent variable, one dummy variable indicating the treatment condition (0 for “optimize resale value” and 1 for “express uniqueness”), four dummy variables for the configuration’s position as fixed effects, as well as a design-identifier and a second-hand market participant-identifier as random effects on the intercept. As predicted, the second-hand market WTP was significantly higher for designs created by consumer-designers in the “optimize resale value” condition ($\bar{M} = 440.09, SE = 16.57$) compared to those created by consumer-designers in the “express uniqueness” condition ($\bar{M} = 406.18, SE = 16.78, \gamma = -33.91, t = -2.55, p = .01$). Thus, inviting consumer-designers to keep second-hand market preferences in mind while self-customizing significantly increased second-hand market WTP for their creations by 8.4% or $33.91 (see Figure 3).
FIGURE 3.
STUDY 3: ESTIMATED CONSUMER-DESIGNERS’ AND SECOND-HAND MARKET WTP AS A FUNCTION OF UNIQUENESS VERSUS RESALE FOCUS AMONG CONSUMER-DESIGNERS.

Note: Error bars signify the 95% confidence interval of the estimated mean.

Mediation analyses. Lastly, we ran a mediation analysis to formally test for the indirect effect of the treatment on second-hand market WTP via consumer-designers’ uniqueness perceptions of their creations. However, as one cannot combine an OLS and a mixed-effect model into one mediation analysis, we first averaged all second-hand market WTP measurements for each of the 202 designs and ran all models involved as OLS regressions. The effect of the treatment on second-hand market WTP was fully mediated via consumer-designers’ uniqueness perceptions of their design, as depicted in Figure 4. The indirect effect was significant at (.86)*(-24.1) = -20.71 (95% CI = (-36.89, -8.32), p < .001) and fully mediated the effect of the treatments onto the second-hand market WTP.
Discussion

Study 3 asked whether customers are able to optimize their self-customized products in a way that also the second-hand market values their efforts. In particular, we show that making the consumer-designer aware of the second-hand market at the time of self-customization attenuates the negative effect identified in Studies 1 and 2. Interestingly, customers in the “optimize resale value” condition were able to find a similarly appealing product for themselves compared to benchmark participants in the “express uniqueness” condition (their WTP did not differ significantly). Second and critically, we find that second-hand market WTP was significantly higher for designs coming from the “optimize resale value” versus the “express uniqueness” condition. Third, this effect is shown to be mediated by consumer-designers’ uniqueness perceptions. That is, what consumer-designers perceive to be unique, special, and one-of-a-kind is detrimental to the second-hand market and thinking about second-hand market customers at the time of self-customization is an effective way to overcome the focal uniqueness dilemma.
GENERAL DISCUSSION

Mass customization is considered a winning strategy across industries because customers are willing to pay substantially more for being able to purchase a unique product that is customized to their individual preferences. In this research, we point to a hidden and so-far neglected downside of mass customization: customers might be paying twice for their efforts—first, when buying their self-customized product and second, when selling it on the second-hand market. Three studies reported in this manuscript provide support for this idea and, taken together, offer a number of important contributions to the literature and practice of mass customization.

First and foremost, we caution the interested reader about the so-far mostly positive picture drawn by the extant literature on mass customization. The “win-win” for customers and firms might not hold up against a more holistic product life cycle perspective. In particular, the canonical uniqueness hypothesis (the more unique the self-customized product, the higher its value to the customer) might fully reverse if the focal subject is not the consumer-designer but instead a second-hand market customer. Based on a data set comprising more than 500,000 cars offered on the second-hand market, Study 1 indeed shows that the more unique a car’s color, the lower its asking price. The correlational field evidence is backed by two controlled experiments conducted in the context of sneakers (Study 2) and furniture (Study 3). Demonstrating causality, the experimental work highlights that while consumer-designers are willing to pay more for more unique products, the opposite applies to customers on the second-hand market: the more unique the self-customized product to the respective consumer-designer, the lower the second-hand market WTP.
The evidence further suggests that the focal effects are nontrivial such that individual customers, and later sellers, of self-customized products are not aware of the detrimental effect of mass customization. First, Study 1 shows that in stark contrast to professional sellers, individual sellers (presumably the ones who have self-customized and purchased the underlying product in the first place) ask for higher prices for their cars in case they have a more unique color. Second, Study 2 demonstrates that consumer-designers are not only willing to pay more to acquire more unique sneakers, they also ask for higher prices in case they are asked to sell them. While the positive relationship between perceived uniqueness and WTA was slightly less pronounced compared to the focal relationship with WTP, it was still significantly positive. This implies that consumer-designers only partially acknowledge that what they value for themselves might differ from what potential customers on the second-hand market find appealing. In particular, they fail to realize the extent to which these valuations differ. As indicated, the same study shows that second-hand market WTP is negatively affected by a product’s uniqueness. Thus, the more unique the self-customized product, the higher its value to the respective consumer-designer but the lower its appeal to potential customers on the second-hand market.

These findings seem particularly relevant from a substantive perspective because marketers are frequently observed to reinforce consumers’ quest for uniqueness. Because consumer-designers are willing to pay more for more unique products, brands like BMW nudge consumers to self-customize cars that are as “unique as their drivers.” Initial research indeed shows that these firm efforts might pay off. De Bellis et al. (2016), for example, show experimentally (see their Study 2b) that framing a given car advertisement differently (e.g., using the slogan “You impress” vs. “You belong”) changes consumers’ subsequent self-customization decisions (i.e., the “You impress” advertisement made participants self-customize a more unique
Our research provides a strong warning signal for such practices. At first sight the related advice (think twice before going for a highly unique product) is beneficiary only to the customer and not to the firm because the firm might lose the incremental revenues related with more uniqueness. At a second glance, however, also firms might be interested in keeping customers happy in the long run. If customers realize at a later point that they might have taken a wrong decision, implicating negative economic consequences for themselves, brand loyalty and repurchase behavior with the underlying firm might be curbed (Morgan and Hunt 1994; Palmatier, Dant, and Grewal 2007).

Furthermore, we asked in Study 3 whether customers and firms can do anything about the focal uniqueness dilemma. In particular, we find that consumer-designers – in a condition in which they were asked to consider optimizing the resale value of their self-customized product – were able to create a similarly appealing product for themselves compared to benchmark participants in a condition, in which they were merely asked to express their uniqueness (their WTP did not differ significantly). More importantly, we also find that customers from the second-hand market are willing to pay significantly more for designs coming from the “optimize resale value” versus the “express uniqueness” condition. That is, thinking about second-hand market customers at the time of self-customization is an effective way to overcome the backfiring effects of mass customization reported in this research. These findings bear actionable implications for both consumers and firms. Consumers might be better off in the long run by considering the preferences of others in their self-customization activities and firms might consider nudging their customers proactively in this direction (e.g., by guiding the consumer-designer in their mass customization systems accordingly).
Finally, we contribute to and hope to stimulate further research in domains beyond mass customization. Most often marketing researchers have been looking at maximizing utility and value creation for brands and consumers at the point of first purchase, instead of trying to optimize long-term maintenance of value across the entire product life cycle (Cherrier, Türe, and Özçağlar-Toulouse 2018). Recent trends including the rise of the sharing economy (Bardhi and Eckhardt 2012; Belk 2007), the diffusion of online peer-to-peer platforms selling second-hand products (PR Newswire 2020), and consumers’ increased sustainability sensitivity (Gollnhofer, Weijo, and Schouten 2019; Guillard 2018; Schaefer and Crane 2005) have all contributed in fueling the quest for more holistic research in that space. Our work shows that applying a different perspective and timeframe to a given topic can yield fundamentally different conclusions and recommendations: that is, pushing consumer-designers to self-customize highly unique products may backfire in the long run.
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