Why Tastes Lose Popularity and How to Prevent It

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Why Tastes Lose Popularity and How to Prevent It

Abstract:

Fashion brands and styles rise and fall in popularity. While marketing scholars have intensely studied adoption, there is little understanding of why such identity-relevant cultural tastes are abandoned. The authors generalize previous research in non-commercial domains to a marketing-relevant domain demonstrating that faster increases in popularity of apparel brands lead to faster abandonment. They develop a theoretical explanation for this phenomenon rooted in identity signaling theories and empirically analyze the role of potential moderators. They find that higher levels of conspicuousness (i.e., brand prominence) reinforce the negative relationship and that higher levels of popularity attenuate it. Brands at lower brand prominence levels can nullify the negative effect of growth rate on decline rate by lowering brand prominence before the peak, but brands at higher levels cannot. The authors discuss contributions to marketing theory and implications for managers and society.

Keywords: Brand prominence, conspicuous consumption, abandonment

Track: Product and Brand Management

1. Introduction

Why do cultural tastes lose popularity? Brands, styles, names, and phrases rise and fall in popularity. For marketing managers, answering this question is crucial because a brand's profitability is dramatically attenuated when consumers abandon[1] it. However, empirical research studying abandonment is sparse and those who consider abandonment focus more on the individual and less on the aggregate level (Lehmann & Parker, 2017).

Related research on non-commercial tastes finds that faster increases before popularity peaks accelerate the abandonment of dog breeds (Acerbi, Ghirlanda, & Enquist, 2012), infant names (Berger & Le Mens, 2009), and the use of individual words (Denrell & Kovács, 2015). A visual inspection of Google Trends data for three fashion apparel brands hints that growth rate and decline rate may be associated with each other (see Figure 1).

To date, it is unclear whether this phenomenon generalizes to brands, and knowledge about boundary conditions for it is non-existent. Are marketers at the mercy of these potential social dynamics or can they prevent abandonment? Since consumers' decision to adopt and avoid tastes is influenced by identity signaling concerns (Berger & Heath, 2007, 2008; Bourdieu, 1984), popularity dynamics of brands may depend on their level of conspicuousness (i.e., the extent to which a taste is recognizable by others). Brands can change their products' average level of brand prominence which describes the overall extent to which a brand displays the logo or identifying marks on its clothing (Han, Nunes, & Drèze, 2010). We find that even though apparel brands vary it over time, it is still unclear how such decisions influence brands' popularity dynamics. The relationship between growth and decline rate may depend on additional factors. Abandonment depends on a taste's popularity level (Berger & Le Mens, 2009). Popularity dynamics may also depend on the price level since higher prices promise exclusivity (Amaldoss and Jain 2005) which may lead to differing consumer responses.

We suggest that the faster the popularity of fashion brands increases the faster it declines. Furthermore, the goal of this paper is to investigate the role of three moderators of this potential relationship to understand why growth and decline rate around popularity peaks of tastes may be associated with each other. How may this relationship be moderated by (1) conspicuousness of taste (i.e., brand prominence), (2) level of popularity, and (3) price level?

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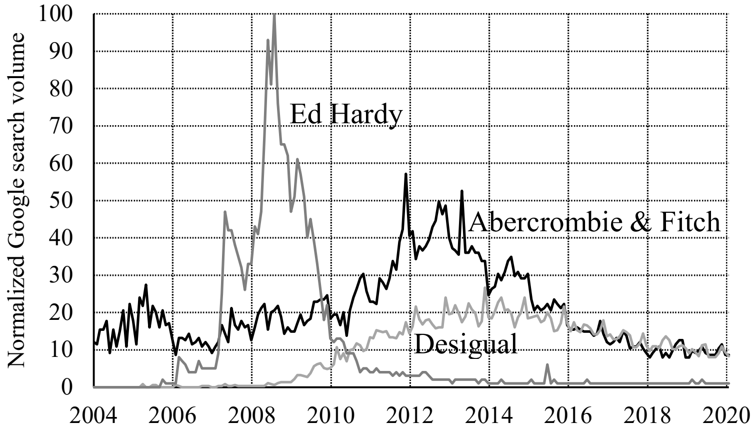
[1] Lehmann and Parker (2017) distinguish between the latent constructs discontinuance, suspension, and disadoption. Focusing on the aggregate level, we use the term abandonment following Berger and Le Mens (2009).

Figure 1. Google searches for three apparel brands in Germany



2. Related Literature

Empirical research studying abandonment of brands or products is sparse. Most previous studies focus only on the adoption diffusion process and disregard abandonment and they selectively study tastes that once attained a high level of popularity (for exceptions see Acerbi et al., 2012; Berger & Le Mens, 2009; Denrell & Kovács, 2015; Gureckis & Goldstone, 2009; Yoganarasimhan, 2017). Moreover, those who do consider abandonment are rarely published in marketing journals (for exceptions see Palacios Fenech & Longford, 2014; Yoganarasimhan, 2017) and focus more on the individual and less on the aggregate level as shown in a marketing literature review (Lehmann & Parker, 2017). Therefore, this study extends marketing literature on the abandonment of brands on the aggregate level.

Yet understanding the underlying dynamics beneath the development of popularity has a long tradition in various research disciplines (e.g., Bourdieu, 1984; Gureckis & Goldstone, 2009; Rogers, 1995; Veblen, 1899). Apart from the influence of external factors, popularity has its own dynamics as well (Bourdieu, 1984; Lieberson, 2000). Research on popularity dynamics of non-commercial tastes demonstrates that faster increases before peaks of popularity accelerate the abandonment of dog breeds (Acerbi et al., 2012), infant names (Berger & Le Mens, 2009), and the use of individual words (Denrell & Kovács, 2015). This study extends this research to the marketing-relevant domain of identity-relevant brands and additionally proposes and empirically investigates the role of three potential moderators.

3. Conceptual Framework

Despite the tendency to act conformably with others, individuals simultaneously have a need to distinguish themselves (e.g., Leibenstein, 1950; Snyder & Fromkin, 2012). They adopt tastes to signal desired identities to themselves and others and avoid tastes that communicate undesired ones (Berger & Heath, 2007, 2008; Bourdieu, 1984; Veblen, 1899). Innovators have a relatively high need for differentiation (Snyder & Fromkin, 2012) and a relatively high level of cultural capital (Rogers, 1995). Informational cascades begin when other individuals blindly follow the innovators' adoption decisions (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992). In domains that are symbolic of identity (e.g., names or fashion apparel), individuals abandon tastes once members of an out-group adopt the same taste to avoid signaling undesired identities (Berger & Heath, 2007, 2008). These out-group members are typically individuals with less cultural capital (Berger & Ward, 2010; Bourdieu, 1984; Yoganarasimhan, 2017). The taste's represented identity is increasingly diluted and the sense of belonging is progressively lost as first innovators and then fellow adopters increasingly abandon it, while out-group individuals increasingly adopt it. Once out-group individuals outnumber in-group ones, a downward spiral of popularity begins (Yoganarasimhan, 2017). The adoption diffusion process moves at a certain velocity and the pace at which a taste is abandoned depends on the pace at which out-group members adopt it.

H_1: Growth rate and decline rate around popularity peaks of tastes are negatively correlated.

A higher level of conspicuousness facilitates the observation of a taste's popularity development because it is more transparent who carries it. On the one hand, adopters of a taste can easily observe the adoption by out-group individuals when conspicuousness is high and, on the other hand, the risk of being associated with the out-group and therefore the risk of signaling undesired identities is high too.

H_2: The level of a taste's conspicuousness moderates the relationship between growth rate and decline rate around popularity peaks, so that the negative impact of growth rate on decline rate becomes stronger with increasing levels of conspicuousness.

The level of conspicuousness is adaptable. Reducing the level of conspicuousness before the peak impedes adopters to observe the adoption by out-group individuals. And the impediment is stronger the lower the level of the brand's conspicuousness generally is.

H_3: Change in conspicuousness before the peak moderates the moderating impact of the level of conspicuousness on the relationship between growth rate and decline rate around popularity peaks, so that a reduction in conspicuousness leads to a stronger attenuation of negative effect of growth rate on decline rate for tastes at lower levels of conspicuousness than for tastes at higher levels.

Popularity level is a taste's average popularity within a defined timeframe before the peak relative to a benchmark taste. When the level of a taste's popularity is low and innovators begin abandoning it, the sense of belonging is relatively low and the risk of being identified with the out-group is high as a relatively small number of adopters remains. In contrast, when the level of popularity is high and innovators begin abandoning the taste, the sense of belonging remains relatively high and the risk of being associated with the out-group is small.

H_4: The level of popularity moderates the relationship between growth rate and decline rate around popularity peaks, so that the negative impact of growth rate on decline rate becomes weaker with increasing level of popularity.

Higher prices usually promise exclusivity (Amaldoss & Jain, 2005). For individuals with an expensive taste, it is important to disassociate themselves from lower classes – the outgroup. They intend to signal status by purchasing pricier products (Han et al., 2010; Leibenstein, 1950; Veblen, 1899). Such individuals should abandon a taste quicker than less status-driven individuals in response to quicker adoptions by out-group individuals.

H_5: The price level moderates the relationship between growth rate and decline rate around popularity peaks, so that the negative impact of growth rate on decline rate becomes stronger with increasing price level.

4. Data

We define fashion apparel brands sold in Germany in 2012 as our population. We use all 899 brands listed in the assortments of Germany's three leading online fashion retailers, namely Asos, Otto, and Zalando. Therefore, we consider a wide range of brands to rule out a potential selection bias (Denrell & Kovács, 2015). We use Google search data from January 2004 up to and including February 2020 for all brands on a monthly level in Germany. We defined the rule of including all brands with monthly search volumes greater than zero one year before and after the peak of transformed Google search data, because trajectories of brands with only a few number of searches contain insufficient data points to calculate growth and decline rates. Since we need at least one year to calculate growth rates and decline rates, we included all brands whose peak is at least one year away from the ends of the observation period. Furthermore, we included all brands that offered tops in 2012 to consistently assess brand prominence. As a result, our sample consists of n = 163 brands.

Apart from Google Trends data to measure growth and decline rates and level of popularity, we collected historical brand specific data per year on each brand's website accessed via the Wayback Machine. We transformed the downloaded Google data.[2] Variance inflation factors are less than 4. Thus, there is no indication of potential collinearity issues.

Growth rate is the rate of change within a defined timeframe (Berger & Le Mens, 2009). It is a continuous variable measured by the slope of the linear regression line within a timeframe of maximum two years up to and including the peak. The decline rate is calculated in an analogous manner beginning at the peak. Brand prominence (Han et al., 2010) is a latent construct variable running from "not present" (0) to "loud" (7). It was assessed for each brand by two independent coders in each year. We measured brand prominence change by calculating the difference in brand prominence between the peak month and the first month of the timeframe used to calculate the growth rate. Level of popularity is a continuous variable which represents the relative online interest for each brand in the same timeframe up to and including the peak (Stäbler & Fischer, 2020). We measured the average price level per brand per year using the price of the most basic T-shirt for women as an index as it is the item type all brands have in common. We collected two control variables from the brands' websites. Domestic brand is a dummy variable that is 1 for German brands. Number of categories is a continuous variable. All variables are mean-centered for analysis.

5. Estimation and Results

Following Berger & Le Mens (2009), we use regression analyses to test our predictions. According to Model 1 in Table 1, growth rate significantly negatively correlates with decline rate ($b = -.430$, $p < .01$), suggesting that the pace at which adopters abandon a fashion brand is determined by the pace at which others adopt it. Consistent with H_1 and across all five models, fashion brands that rise in popularity more quickly lose popularity more quickly.

In line with H_2, the main effect of growth rate on decline rate is significantly moderated by brand prominence ($b = -.090$, $p < .01$), referring to Model 2. This effect is robust across the other models. Since all variables are mean-centered, the main effects are to be interpreted as

[2] Trajectories of brands at low popularity levels are marked by relatively high volatility. To smoothen them, the 12-month moving average is taken, following Vosen and Schmidt (2011). To match the peak with the raw data, this curve is moved six months backwards. Since Google data is normalized, trajectories with high volatility lead to flatter growth rates when applying the moving average. Therefore, to make trajectories with different levels of volatility comparable, we normalized the shifted curve by dividing all values by the peak value multiplied by 100.

follows. While the conditional effect of growth rate at mean brand prominence level is significant (b = -.402, p < .01), the conditional effect of brand prominence at mean growth rate level is not significant (b = -.007, p > .30). Apparently, facilitation of observation of fashion brands' popularity development via higher levels of brand prominence intensifies the negative effect of growth rate on decline rate. We probe the interaction to test where in the distribution of brand prominence, growth rate significantly affects decline rate. Following standard probing procedures, we do this at one standard deviation below the mean, at the mean, and at one standard deviation above it (Aiken & West, 1991). Growth rate significantly decreases decline rate at all three tested levels of brand prominence and this effect intensifies with higher levels.

Table 1. OLS regression estimation results for decline rate

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Growth rate	-.430***	-.402***	-.412***	-.385***	-.366***
	(.055)	(.054)	(.054)	(.054)	(.054)
Brand prom.		-.007	-.005	-.008	-.008
		(.007)	(.007)	(.007)	(.007)
Growth rate x Brand prom.		-.090***	-.076***	-.080***	-.077***
		(.025)	(.026)	(.026)	(.026)
Brand prom. change			-.088**	-.089**	-.163***
			(.044)	(.043)	(.055)
Growth rate x Brand prom.			-.250*	-.249*	-.492***
change			(.131)	(.129)	(.173)
Brand prom. x Brand prom.			.022	.030	.068**
change			(.025)	(.025)	(.031)
Growth rate x Brand prom. x			.172**	.200***	.311***
Brand prom. change			(.074)	(.073)	(.090)
Level of popularity				.005**	.006**
				(.002)	(.002)
Growth rate x Level of				.018**	.019**
popularity				(.008)	(.008)
Price level					-.000
					(.000)
Growth rate x Price level					-.001
					(.001)
Constant	.000	.007	.008	.012	.014
	(.015)	(.014)	(.014)	(.014)	(.014)
# of observations	163	163	163	163	163
R^2	.273	.332	.362	.391	.408
Adjusted R^2	.269	.319	.334	.355	.365

Notes: All variables are mean-centered. Standard errors are reported in parentheses. *p < .10; **p < .05; ***p < .01.

Model 3 reveals a significant three-way interaction between growth rate, brand prominence, and brand prominence change (b = .172, p < .05). The conditional effect of brand prominence change at mean growth rate level and mean brand prominence level is significant (b = -.088, p < .05) and robust. Further facilitating the observability of popularity development before the peak, accelerates decline. Probing the interaction reveals that decreasing brand prominence before the peak more strongly attenuates the negative effect of growth rate for fashion brands at a low brand prominence level than for brands at higher levels, consistent with H_3. The effect of growth rate even becomes insignificant at the low brand prominence level ($b = .026$, $p > .80$). Given a high brand prominence, changing it before the peak, hardly affects the relationship between growth rate and decline rate.

Estimation results of Model 4 and Model 5 support H_4. The main effect of growth rate on decline rate is significantly moderated by level of popularity ($b = .018$, $p < .05$), suggesting that the more popular a brand is overall, the less decline rate depends on growth rate.

According to Model 5 and in rejection of H_5, the interaction between growth rate and price level is not significant ($b = -.001$, $p > .10$). We test potential effects of covariates, but none of these are significant. We perform several robustness checks including additional models where we left out or added potentially relevant variables, substituted variables, and extended timeframes to operationalize variables. Overall, results do not change substantially.

6. Discussion and Conclusions

This article makes important theoretical contributions to research on the abandonment of cultural tastes. While there is some literature analyzing this phenomenon on the individual decision level (e.g., Berger & Heath, 2007, 2008), we hardly know anything about it on the aggregate level (Lehmann & Parker, 2017). This study generalizes previous research yielding that decline rate of popularity of tastes is driven by growth rate (Acerbi et al., 2012; Berger & Le Mens, 2009; Denrell & Kovács, 2015) to the fashion apparel domain. We extend the literature by suggesting a theoretical explanation for this phenomenon.

Our findings are crucial for a broad range of brands in identity-relevant domains. If brands reach a high popularity level quickly, it is difficult to sustain that level since the pace of abandonment is driven by the pace of out-group adoptions. While our Google search data does not allow to assess overall success, Berger and Le Mens (2009) find that quickly rising infant names are chosen less in total. Thus, an overly aggressive growth strategy is likely to backfire later on – especially when the level of popularity is relatively low as we demonstrate.

Our findings suggest that brands with a low level of brand prominence can nullify the relationship between growth rate and decline rate if they lower it before the peak when out-group members begin adopting the brand leading to a dilution of the brand's identity. Therefore, firms should identify out-group segments and track their adoptions. Offline, this can be done by asking for the zip code at the checkout since cultural capital is related to geographic region (Yoganarasimhan, 2017). Online, this can be done by analyzing various user metrics.

However, if the brand prominence level is too high, brands lose the possibility to control their popularity development by lowering it. Therefore, brands should aim to prevent out-group members from adopting their brand in the first place. They have to clearly position which distinct social identity they represent and seed among influential consumers who match the identity. Online, advertising should target distinct social groups only and offline, brands should not be available in geographic areas associated with out-groups. Luxury brands should legally protect fashion designs against piracy to prevent them from being affordable for out-groups. Brands can also use subtle brand cues or change collection specific cues so that out-group individuals are less likely to recognize the brand. An alternative strategy to create differentiation may be the positioning of various lines targeted at distinct groups (e.g., rarely changing classic lines, lines that adapt to trending styles, and exclusive more expensive lines).

From a society perspective our research is important because the chase between social groups shapes society. Our findings are likely to be generalizable to other identity-relevant domains. Tastes that rise at a higher pace decline more quickly. And this process is further enhanced the smaller the group and the better the popularity development is perceivable.

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