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Does Stylistic Similarity to Popular Competitors affect Consumer Evaluations of Quality? Evidence from Online Movie Evaluations

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DOES STYLISTIC SIMILARITY TO POPULAR COMPETITORS AFFECT CONSUMER EVALUATIONS OF QUALITY? EVIDENCE FROM ONLINE MOVIE EVALUATIONS

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ABSTRACT

This work addresses how consumer perceptions of quality may be influenced by the composition of competition. I develop a theoretical framework that explains how consumer evaluations of quality can be negatively impacted by a product's stylistic similarity to popular competitors. These issues are examined empirically using more than 75,000 online consumer evaluations, from the evaluation aggregator Rotten Tomatoes, of 123 feature films released in the United States during 2007. Results suggest that during a movie's opening week, movies that are stylistically similar to the top-performing box office movie are evaluated less favorably. Additional analyses indicate that this negative effect may persist in later periods due to social conformity pressures, and that there is reduced demand for those movies that are stylistically similar to the top box office performer. This article contributes to the broader literature in strategic management by depicting how stylistic features of competitors can affect consumer behaviour and perceptions of quality in markets. This work also suggests managerial implications for entry-timing decisions and positioning choices.

Keywords: Evaluation; competition; style; third parties; categorization; online reviews; social construction; social attention; ratings and rankings; entry timing; positioning choices

INTRODUCTION

On 7 September 2007, the action/adventure movie *Shoot 'Em Up* was released into theatres and has since been evaluated by more than 300,000 *Rotten Tomatoes* users, earning an average rating of 3.4 out of 5 stars while having had 67% of professional critics offering positive reviews of the movie. In the same week, *3:10 to Yuma*, a stylistically similar action/adventure movie, was also released into theatres and attracted the largest share of that week's movie-going audience. How did the stylistic overlap with a movie receiving the most social attention during their opening week of release affect evaluations of quality for *Shoot 'Em Up*? Would evaluations of quality have been the same had *Shoot 'Em Up* entered the market just a week earlier when the stylistically dissimilar movie *Halloween*, a horror film, was the top-grossing box office movie?

This prior example highlights fundamental questions about how stylistic similarities and differences between competitors may shape perceptions and performance in markets. These issues have intensified with the rise of the Internet and e-commerce in the late twentieth and early twenty-first centuries, which has supported the dramatic increase and prevalence of consumer evaluations (Lamont, 2012). Indeed, recent scholarship has shown that consumer evaluations can impact firm performance (e.g. Cui, Lui, & Guo, 2012; Luca, 2016). Correspondingly, mangers are becoming increasingly aware of the strategic importance of third-party evaluations (Cattani, Sands, Porac, & Greenberg, 2018; Rindova, Martins, Srinivas, & Chandler, 2018). Despite digital evaluations being a still emerging topic, researchers from multiple disciplines have contributed to our understanding of evaluation in markets. Recent work has examined how different social forces affect evaluations, including research on category/genre-spanning (e.g. Hsu, 2006; Hsu, Hannan, & Koçak, 2009; Kovács & Hannan, 2015), (in) authenticity (e.g. Frake, 2017; bib_citation_to_be_resolvedKovács, Carroll, & Lehman, 2014) and status (e.g. Aadland, Cattani, & Ferriani, 2018; Kovács & Sharkey, 2014; Sgourev & Althuizen, 2017). Nonetheless, within strategic management, there has been limited research detailing how the composition of competition affects consumer evaluations of quality.

To the extent that firms have some say over the composition of their competitors – for example, through their entry-timing decisions or positioning choices (Adner, Csaszar, & Zemsky, 2014; Anthony, Nelson, & Tripsas, 2016; Bresnahan & Reiss, 1991; Fuentelsaz & Gomez, 2006; Greve, 2000; Porter, 1980) – then understanding the effects of competition on consumer evaluations of quality is both a theoretically rich and managerially relevant line of enquiry. Perceptions of quality are formed through implicit comparisons with other products in the market (Askin & Mauskapf, 2017; Becker, 1982; Festinger, 1954; Schwarz & Bless, 1992; Zuckerman, 1999). This suggests that some characteristics of competitor products may shape how consumers perceive and evaluate quality for other products (e.g. Oakley, Duhachek, Balachander, & Sriram, 2008). In this chapter, I examine two dimensions of competition that may be especially relevant in shaping consumer evaluations of quality: (1) style

PRE-PRINT OF:
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2020 Advances in Strategic Management Volume 42, 199–226

and (2) social attention. In bringing these dimensions together, I argue that products that are stylistically similar to a most popular competitor receive discounted evaluations. That is, these products are evaluated less favourably than they otherwise would have been as a consequence of the composition of competition.

I use the movie industry as a research setting in order to examine these issues empirically. Analyses of more than 75,000 consumer evaluations from *Rotten Tomatoes,* of 123 major motion pictures released in the United States during 2007, indicate that movies that are stylistically similar to the top box office performer receive less favourable consumer evaluations – with point estimates of the magnitude of this effect implying that consumer evaluations on *Rotten Tomatoes* are 5% less favourable when a movie is stylistically similar to the top box office performer in its opening week of release. Supplementary analyses also suggest that this evaluative discount may persist in later weeks due to social conformity pressures, though the magnitude of the effect may be diminished in later periods. Additionally, there is evidence to suggest that being stylistically similar to the top box office movie reduces demand for a movie, which may also affect the composition of consumers evaluating a given movie. The empirical analyses also imply some stylized facts about these consumer evaluations, including that early evaluations (those that were posted during a movie's opening week) may display bimodal properties and are, on average, more favourable than late evaluations, which are more normally distributed. This work ultimately shows that stylistic similarities and differences between competitors may matter a great deal for consumer evaluations. Thus, this work speaks to the broader literature in strategic management, organization theory and economic sociology by examining how perceptions of quality are affected by the composition of competition in markets.

EVALUATION IN MARKETS

Researchers in strategic management and related disciplines, such as marketing, information systems and economics, have recently begun to highlight the relationship between online consumer evaluations and firm/product performance (e.g. Cattani, 2018; Chevalier & Mayzlin, 2006; Cui et al., 2012; Luca, 2016). While these digital consumer evaluation platforms represent a new and important development, there also exists a stream of research on this topic that extends from a long tradition in economic sociology and organizational theory, going as far back as Simmel (2004) and Dewey (1939). Along with many other contributions, this large body of research highlights how evaluations and valuations are socially constructed (see Zuckerman, 2012). That is to say that quality measures, such as consumer evaluations, are not isolated projections of individual preference, but instead are formed through implicit and explicit social interactions. Indeed, research spanning multiple empirical contexts has focused on explaining how collective sentiments emerge and evolve – as well as their consequences (e.g. Antal,

PRE-PRINT OF:
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2020 Advances in Strategic Management Volume 42, 199–226

Hutter, & Stark, 2015; Caves, 2000; Durand, Rao, & Monin, 2003; Lieberson, 2000; Porac, Thomas, & Baden-Fuller, 1989; Rao, 1994).

For strategists, one pertinent insight from the literature on evaluation is that perceptions of quality are constructed through comparison of similar objects (e.g. Festinger, 1954; Lamont, 2012; Schwarz & Bless, 1992; Zuckerman, 1999). Building from Becker (1982), Askin and Mauskapf (2017, p. 911) help summarize this perspective:

> Rather than existing in a vacuum, cultural products are perceived in relation to one another in feature space, and these relationships shape how consumers organize and discern the art worlds around them.

This suggests consumer perceptions of quality for a focal product may be a function of implicit comparisons made with competitor products (e.g. Ashby, Walasek, & Glöckner, 2015; Dekker, 2016; Laroche, Teng, & Kalamas, 2001; Oakley et al., 2008). Since different consideration sets may yield different implicit comparisons, variance in the composition of competition may affect consumer perceptions of quality. As a consequence, strategic decisions such as market entry-timing may affect how consumers perceive product quality since it affects the composition of competition (e.g. bib_citation_to_be_resolvedEngelstätter & Ward, 2018; Fuentelsaz & Gomez, 2006; Greve, 2000).

Consumer Evaluations and Implicit Comparisons

Two dimensions that may provoke implicit comparisons with competitor products, and therefore influence consumer evaluations of quality, are (1) style and (2) social attention. I follow Godart's (2018a, p. 114) definition of style as a 'durable and recognizable pattern of aesthetic choices'.[1] Social attention refers to the general awareness and recognition that a product receives from audiences of potential and realized consumers. Popularity rankings (e.g. Salganik, Dodds, & Watts, 2006), for example, reflect stratifications in social attention. I expand on these in the following sub-subsections.

Style and Evaluation

Style has long been identified as a core component of quality judgements in markets (e.g. Caves, 2000; Hirsch, 1972). Much of the related literature on product styles and evaluation has largely examined product attributes in isolation (see Bloch, 1995; Maheswaran, Mackie, & Chaiken, 1992). That is, these works investigate the direct relationship between a stylistic attribute and consumer evaluations of quality. Since evaluations of product quality emerge from implicit comparisons made with other products (Schwarz & Bless, 1992), stylistic

[1]Note that Godart's (2018a) definition of style allows for overlap with other related constructs, such as categories/genres/status, but it is conceptually distinct. I come back to this point in greater detail in the 'Discussion and Conclusion' section.

relationships between products may also be relevant in shaping perceptions of quality (Godart, 2018b; Godart & White, 2010).

Within many product markets, especially for creative and cultural goods, there exists significant within-category diversity of stylistic attributes (Godart, 2018a; Jones, Lorenzen, & Sapsed, 2015). At a high level, style reflects recognizable constellations of product attributes. Stylistic similarity then is the recognition that two or more products share a sufficient subset of these attributes. Hence, if consumers believe there is stylistic similarity between two products, then they are more likely to make implicit comparisons between these products because they have a recognizable dimension of overlap. In turn, quality judgements are more likely to emerge from comparisons between stylistically similar products, as opposed to stylistically dissimilar products. That is not to suggest that implicit comparisons between dissimilar products do not occur – only that implicit comparisons between stylistically similar products are more likely because they are perceived as more informative and cognitively less difficult, *ceteris paribus* (see also Althuizen & Sgourev, 2014; Bettman, Luce, & Payne, 1998; Johnson, 1984).

Social Attention and Evaluation

Similar to the relationship between stylistic similarity and evaluation, heterogeneity in social attention may affect implicit comparisons between particular products. In the case of product markets, social attention may affect implicit comparisons to the extent that consumers pay attention to what they believe others are paying attention—which is often is the most popular products (Salganik, Dodds, & Watts, 2006).

Unlike styles, social attention inherently lends itself to being treated as a hierarchical dimension. Prior research has highlighted how popularity and status may positively affect perceptions of quality (e.g. Lynn, Simpson, Walker, & Peterson, 2016; Lynn, Podolny, & Tao, 2009; Rindova, Pollock, & Hayward, 2006; Sgourev & Althuizen, 2014). Thus, products that receive more social attention are in superior positions relative to those receiving less, while the product receiving the most social attention is in a dominant position within a market. Products that are in these top positions often benefit from additional positive externalities that may make them even more salient to consumers (Cabral & Natividad, 2016; Moretti, 2011). Hence, products that receive the most social attention in a given market are likely to be used as implicit comparisons.

Being Stylistically Similar to the Product Receiving the Most Social Attention

In the prior sections, I discussed the role of implicit product comparisons in facilitating consumer evaluations. Building upon that, I described how stylistic similarity and social attention help establish implicit comparisons with particular products. In this section, I hypothesize how the alignment of these two dimensions affects consumer evaluations.

While both stylistic similarity and social attention may serve to stratify a given product market, and thus facilitate implicit comparisons with some products and not others, these dimensions differ in a critical way. On one hand, the stylistic dimension elicits comparisons with similar products, thus without an inherent hierarchal ordering.[2] On the other hand, the social attention dimension evokes comparisons with potentially dissimilar others but with an inherent hierarchal ordering. If these two dimensions are aligned, however, the implicit comparison is with a similar product that is dominant in a hierarchal ordering – there exists a salient contrast to an otherwise similar exemplar (Bless & Schwarz, 2010). As a consequence, consumers may evaluate the inferior social-positioned product less favourably.

The broader literature on rankings in markets also helps to highlight why stylistic differences may or may not lead to evaluative discounts (see Esposito & Stark, 2019; Rindova et al., 2018). As Espeland and Stevens (1998, p. 315) note, the commensuration of social attention into rankings is a 'fundamental feature of social life' that shapes our interpretation of what is important. However, when comparisons are made between stylistically dissimilar products, quality judgements are likely to be rejected, and these stylistic differences serve as justifications (e.g. Elsbach & Kramer, 1996). Indeed, this suggests stylistic differences may discount the relevance of hierarchical orderings. Under conditions of stylistic similarity, however, hierarchical stratifications in social attention can shape perceptions of quality by making salient the superior social position of one product relative to another.

In summary, when a consumer evaluates a product, they make implicit comparisons to stylistically similar products and products that receive the most social attention. If the product that receives the most social attention is stylistically similar to the product being evaluated, then a consumer may evaluate it less favourably because the consumer recognizes the evaluated product's inferior social position. From this, I derive *H1*:

H1. Consumer evaluations are less favourable for products that are stylistically similar to the product receiving the most social attention.

EMPIRICAL SETTING, DATA AND METHOD

Research Setting

The major motion picture industry in the United States (i.e. Hollywood feature films) serves as the research setting for this chapter. In translating the dimensions from the prior section into the language of the empirical setting, stylistic dimensions of movies can be thought of as movie attribute classifications, and social attention corresponds to box office popularity. Hence two action/adventure movies are stylistically similar, while the top-grossing movie at the box office is the movie that is receiving the most social attention. Per Hypothesis 1, we should

[2]Note that in many settings, stylistic stratifications reflect hierarchical orderings, such as classification in art (see DiMaggio, 1987).

PRE-PRINT OF:
Does Stylistic Similarity to Popular Competitors affect Consumer Evaluations of Quality? Evidence from Online Movie Evaluations
2020 Advances in Strategic Management Volume 42, 199–226

expect less favourable consumer evaluations for movies that are stylistically similar to the top box office movie.

One advantage of the movie industry as the empirical setting for this chapter is that this industry is a well-studied domain. Thus, we are able to leverage diverse findings from various disciplines in order to better understand pertinent issues related to a relatively new phenomenon: digital consumer evaluations. Likewise, research on the movie industry has led to more generalizable insights, and some notable prior studies have explored key issues in strategic management and organizational theory, such as the following: how strategic naming of movies mitigates the illegitimacy discount by directing audience attention to known characteristics (Zhao, Ishihara, & Lounsbury, 2013); the role of network ties in generating creative performances (Cattani & Ferriani, 2008, 2013) and explaining entry/exit rates of producers (Cattani, Ferriani, Negro, & Perretti, 2008; Ferriani, Corrado, & Boschetti, 2005); the effects of genre spanning on critic and audience perceptions (Hsu, 2006); professional and personal career patterns (Jensen & Kim, 2015; Zuckerman, Kim, Ukanwa, & Von Rittmann, 2003); how the presence of a movie star in a given movie impacts long-term film revenues (Wallace, Seigerman, & Holbrook, 1993); the relationship between ratings of different critics (Boor, 1992; Olson & Waguespack, 2018).

Critically, the movie industry offers an ideal setting to study how the composition of competition affects evaluations. Since each week there are new movies released into theatres, isolating the effects of competition on evaluation is possible to the extent that each week can be treated as a distinct set of competitive relationships, with different sets of stylistically similar or dissimilar competitors. The movie industry is also well suited for isolating the effects of competition on consumer evaluations of quality because prices are largely held constant across different movies and locations. That is, movies that receive a great deal of social attention are generally not more expensive than others. Similarly, stylistic differences in movies do not affect the costs to consumers. Moreover, movies are watched by consumers in similar settings across geographic locations since theatres are relatively homogenous within the United States. The movie-going audience in the United States represents a broad set of consumers – more than 225 million individual people went to see at least one movie in theatres during 2013, with the average consumer viewing six different movies (MPAA, 2014).

Data

Data used in this study are based on the set of 123 different major motion pictures that were released into theatres during 2007. Only major box office releases are included because they were more widely available and intended to target general movie-going audiences. Movies with staggered releases, small independent films and foreign movies were not included because they were released to different audiences at different times, which would make it impossible to discern particular competitive relationships from aggregated data. I collected information about each of these movies from various sources, as well as the consumer evaluations that were posted on the third-party evaluation

PRE-PRINT OF:
Does Stylistic Similarity to Popular Competitors affect Consumer Evaluations of Quality? Evidence from Online Movie Evaluations
2020 Advances in Strategic Management Volume 42, 199–226

aggregator *Rotten Tomatoes*. Table 1 presents descriptive statistics and a correlation matrix for selected variables.

Model

The empirical goal is to estimate how consumers evaluate products that are stylistically similar to a top-performing competitor. The following model specification, where movie *j* is evaluated by individual *i*, serves as the starting point for subsequent analyses:

$$Y[\text{Evaluation}]_{ji} = \alpha + S_j + C_j + \psi_j + \gamma_j + \varepsilon_{ji}$$

This baseline model seeks to estimate how being stylistically similar to the top box office performer affects consumer evaluations. The independent variable of interest is designated by S_j, which is a binary variable that is equal to 1 if a movie is stylistically similar to the top box office performer. The empirical strategy is based on including the variable C_j, which is the professional critic score for movie *j*. Variables ψj and γ_j represent vectors of controls for a given movie *j* that are, respectively, composed of continuous variables and binary measures. These variables will be discussed in greater detail in the following sub-sections. ε_{ij} represents the error term.

In the subsequent analyses, I will use both OLS and ordinal logistic (hereafter, ordered logit) regression in order to leverage the strengths of each statistical specification, while taking into account the nature of the underlying data. In either case, I also use robust standard errors clustered at the movie level to account for potential serial correlation in evaluations. When using an OLS statistical model, the dependent variable is treated as a continuous variable. Though it may be more appropriate to think of evaluations as being non-continuous since they are selected from scaled options, researchers often consider ordinal variables to be continuous if the dependent variable has more than five ordinal outcomes (Menard, 2002), as is the case with recent evaluation research conducted by Kovács and Sharkey (2014) on awards and book evaluations. A conservative

Table 1. Movie Descriptive Statistics and Correlation Matrix for Selected Variables.

	Descriptive Statistics			Correlation Matrix					
	Observations	*Mean*	*SD*	*1.*	*2.*	*3.*	*4.*	*5.*	*6.*
Stylistic Similarity with Top Box Office Movie (1)	123	0.114	0.319	1					
Critic Score (2)	123	42.82	28.01	−0.109	1				
Top Box Office Movie (3)	123	0.244	0.431	−0.204	0.032	1			
Production Budget (4)	123	46.64	51.37	−0.07	0.183	0.468	1		
Opening Screens (5)	123	2,457.3	876.3	−0.04	0.044	0.543	0.669	1	
Runtime (6)	123	105.6	17.71	−0.116	0.382	0.168	0.326	0.119	1
Mean Consumer Evaluation (7)	123	57.86	14.69	−0.162	0.866	0.056	0.174	0.069	0.43

approach for addressing concerns about using OLS is to demonstrate that ordered logit and OLS produce similar results (see Williams, 2006; 2015). In this work, I adopt such an approach and present both model specifications for all subsequent analyses.

Empirical Strategy

A key empirical challenge associated with this work is the fact that movies that enter a market in the same week as a stylistically similar top box office performer may be of lower quality than other movies.[3] If this were to be the case, then estimating the effect of stylistic similarity to the top box office performer may also capture differences in underlying quality rather than just changes in consumer perceptions as stemming from the composition of competition. The empirical challenge could be overcome by incorporating an alternative underlying quality measure as a control, as long as this quality measure is derived from an audience that is not (at least in the same way) systematically affected by the composition of competition. Fortunately, in this setting, there exist quality measures from an alternative audience that meet these criteria: Professional movie critics.

Professional movie critics are experts at evaluating movies for quality. Though they may or may not have different preferences from laypeople audiences (Eliashberg & Shugan, 1997; Wallentin, 2016), professional critics are not affected by the composition of competition in the same way that lay consumers are affected. This is because professional critics often see movies before they are released to the general public. Since professional critic evaluations are designed to inform consumption decisions (Basuroy, Chatterjee, & Ravid, 2003), professional critics see and evaluate movies before their opening week of release, and many professional critics even see movies at different times from each other (Olson & Waguespack, 2018). Therefore, quality measures from professional critics can help overcome this empirical challenge. The *Rotten Tomatoes'* 'Tomatometer' rating is used as the professional critic quality rating. As *Rotten Tomatoes* states on their website,

> The Tomatometer rating – based on the published opinions of hundreds of film and television critics – is a trusted measurement of movie and TV programming quality for millions of moviegoers. It represents the percentage of professional critic reviews that are positive for a given film or television show. (Rotten Tomatoes, 2016)

By including the *Rotten Tomatoes'* Tomatometer rating for each movie, we can therefore control for underlying quality in order to better isolate how stylistic similarity and social attention interact to affect consumer evaluations.

Variables

Dependent Variable

The dependent variable for the primary analyses is the evaluation for movie *j* given by individual *i* on the evaluation aggregator website *Rotten Tomatoes*. On

[3] Movie release date strategies are addressed in more detail in the 'Discussion and Conclusion' section (see also Einav, 2007; 2010).

PRE-PRINT OF:
Does Stylistic Similarity to Popular Competitors affect Consumer Evaluations of Quality? Evidence from Online Movie Evaluations
2020 Advances in Strategic Management Volume 42, 199–226

their webpage for each movie, *Rotten Tomatoes* presents consumer evaluation scores as an aggregated percentage. These evaluations, however, are generated when individual users evaluate a movie by assigning a desired number of stars; more stars indicate higher quality evaluations. A *Rotten Tomatoes* user can assign between zero and five stars, in half-star increments, resulting in 11 possible scores. In these data, the mean star rating is 3.21 stars out of 5. In order to ease the interpretation in the OLS estimates (and in line with how *Rotten Tomatoes* presents these aggregated data), I transform this variable to a 100% evaluation such that the mean evaluation is 64.17% with a standard deviation of 27.67.

Independent Variable of Interest

Stylistic Similarity with Top Box Office Movie is the independent variable of interest. It is a binary variable that is equal to 1 if the movie being evaluated is stylistically similar to the top box office performer in the movie's opening week of release and is equal to 0 otherwise. As a binary measure, this variable is designed to capture whether or not a consumer evaluator implicitly classifies the movie they saw (and are evaluating) as being stylistically similar to the top box office movie, which they likely have not seen. Thus, a binary measure of core movie styles may offer clear inferences: a movie being evaluated by a consumer can only be assessed as stylistically similar ($S_j = 1$) or stylistically dissimilar ($S_j = 0$) to the top box office movie. I discuss these core styles in greater detail in subsequent sections. A statistically significant negative coefficient on this variable would be indicative of less favourable consumer evaluations of quality relative to movies that are not stylistically similar to the top box office movie, offering empirical support to *H1*.

Control Variables

Critic Score is a variable of *Rotten Tomatoes'* Tomatometer rating. It is the percentage of professional critics who gave a particular movie a favourable rating. As described in greater detail in the 'Empirical Strategy' section, this variable is important since professional critics are not systematically affected by the composition of competition in the same way as the layperson audience – professional critics generally evaluate movies prior to a movie's theatrical release in order to provide information to consumers (see also Basuroy et al., 2003; Eliashberg & Shugan, 1997; Olson & Waguespack, 2018; Wallentin, 2016). Therefore, by including this alternative assessment of quality, we can better isolate how the composition of competition affects consumer evaluations.[4]

[4] Note that I am using the term score as opposed to evaluation because this is an aggregation (by *Rotten Tomatoes*) of professional critic quality judgements. As such, I wish to distinguish it conceptually from the individual-level evaluations that are used as the dependent variable.

PRE-PRINT OF:
Does Stylistic Similarity to Popular Competitors affect Consumer Evaluations of Quality? Evidence from Online Movie Evaluations
2020 Advances in Strategic Management Volume 42, 199–226

Top Box Office Movie is a binary variable that is equal to 1 if the movie is the top box office movie by revenue for the movie's opening weekend and 0 otherwise. This variable serves as a measure of social attention. Being the most popular movie at the theatre may have an impact on the composition of its consumers, affect consumer perceptions of quality and may affect demand in the current or subsequent period (see Cabral & Natividad, 2016; Hellofs & Jacobson, 1999; Moretti, 2011).

Budget is a continuous variable of the movie's production budget in millions of dollars. A movie's budget serves as a proxy for access to resources because, *ceteris paribus*, a larger budget allows for access to production inputs: movies produced with large budgets can afford more (or more expensive) actresses and actors, directors, writers and other staff. Budget size may affect consumer demand or perceptions of quality. However, prior research has found no evidence that budget influences professional critic evaluations (e.g. Simonton, 2005).

Opening Screens is a continuous variable of the number of screens that a movie appeared on across the United States during the movie's opening weekend. It serves to control for how available the film was to potential consumers. Given that screen allocation is one of the critical decisions that studios need to make in order to capture box office dollars (see Ainslie, Drèze, & Zufryden, 2005; Swami, Eliashberg, & Weinberg, 1999), this variable also serves as a control for studio-anticipated quality and general popularity.

Runtime is a continuous variable of the length of the movie in minutes. It is possible that the length of a movie might offer a substantially different experience, and length may shape perceptions of quality. A movie with a long runtime may also appeal to a particular audience type, and thus indirectly affect evaluations through the composition of consumers.

Style Classification is the style of a given movie. Movies were classified by style: Action-Adventure, Comedy, Drama, Horror, Kids & Family or Musical. These are core classifications that reflect distinct patterns of aesthetic choices of a movie. This is a holistic classification that transcends storyline, content and cinematographic characteristics. Binary variables were created for each style classification of movie, and their inclusion in the model controls for differentiation in taste for a particular style of product and for the different audience types that select into seeing specific styles of movies.[5] As Godart (2018a) notes, styles may or may not overlap with genre classifications (see also Lena & Peterson, 2008) or category classifications (see also Kovács & Hannan, 2015), and these boundaries/overlaps may not be static (e.g. Lena & Peterson, 2011). Here I use binary measures of style in order to present an account of the core and defining aesthetic choices that define a movie in an effort to provide an unambiguous definition of stylistic similarity between two movies. Additional discussion on this broader issue is found in subsequent sections.

[5]A description of the methodology for constructing the style classifications appears in Appendix.

MPAA Rating is the *Motion Picture Association of America* (*MPAA*) ratings for each film. The movies were rated as G, PG, PG13 or R by the *MPAA*. These are binary variables that were created for each rating to control for preferences differentiated by a movie's content. This controls for the movie characteristics that may correlate with evaluations from different types of audiences. The incorporation of MPAA ratings is common practice for analyses of major motion pictures (e.g. Basuroy et al., 2003).

Opening Month is the month of release for a given movie. This variable is equal to 1 for the month that a movie was released and 0 otherwise. Since movies in certain months might be released to attract particular types of audiences, this controls for different audience preferences. Moreover, this controls for strategic choices based on seasonality made by film studios with respect to movie release dates (see Einav, 2007; 2010). This is described in greater detail in subsequent sections.

MAIN ANALYSES

The main analyses seek to estimate the effect of a movie being stylistically similar to the top box office movie on consumer evaluations of quality. Since the composition of competition is measured during the opening week of release, these analyses will examine only evaluations that were placed during the first seven days that a movie appeared in theatres. For the 123 movies in the data, this corresponds to 9,038 individual consumer evaluations. The results of these analyses are presented in Table 2. Models 1 and 2 are OLS and Models 3 and 4 are ordered logit regressions.

The coefficients for the variable of interest, *Stylistic Similarity with Top Box Office Movie*, in Table 2 are all negative and statistically significant. Using the OLS regression results in Model 2 as an example, we can interpret the results to mean that being stylistically similar to the top box office performer is associated with a 6.8 percentage point reduction in consumer evaluation of quality ($\beta = -6.833$; $p > 0.016$; 95% CI: $[-12.36, -1.308]$). Interpreting the ordered logit regression results from Model 4 is not as straightforward as OLS, but they can be immediately assessed for coefficient directionality and statistical significance. Here, we can observe that the coefficient on *Stylistic Similarity with Top Box Office Movie* is negative and statistically significant at the 1% level ($\beta = -0.519$; $p > 0.009$; 95% CI: $[-0.911, -0.128]$), which corroborates the OLS results. Note again that ordered logit is a non-linear model that stipulates that the dependent variable consists of ordinal measures and that ordered logit output is only conceptually similar to OLS in the sense that directionality and statistical significance is interpretable.

We can, however, convert the ordered logit results into predicted probabilities at each ordinal level of the dependent variable. As the dependent variable is constructed of 11 different star ratings (0 through 5 stars at half-star intervals), we are able to obtain the predicted probabilities of a movie being given a specified evaluation while holding all other variables at their means. In essence, this varies

PRE-PRINT OF:
Does Stylistic Similarity to Popular Competitors affect Consumer Evaluations of Quality? Evidence from Online Movie Evaluations
2020 Advances in Strategic Management Volume 42, 199–226

Table 2. Consumer Evaluations for Movies During Opening Week of Release.

	1 *OLS* Consumer Evaluation	2 *OLS* Consumer Evaluation	3 *Ordered Logit* Consumer Evaluation	4 *Ordered Logit* Consumer Evaluation
Stylistic Similarity with Top Box Office Movie	−7.761 (3.857)**	−6.833 (2.791)**	−0.585 (0.221)***	−0.519 (0.200)***
Critic Score		0.336 (0.044)***		0.0202 (0.003)***
Top Box Office Movie		0.0113 (2.238)		0.039 (0.174)
Production Budget		−0.027 (0.028)		−0.002 (0.002)
Opening Screens		0.0004 (0.003)		−0.00004 (0.0003)
Runtime		0.059 (0.058)		0.007 (0.004)*
Constant	69.36 (1.656)***	41.43 (10.83)***		
Style Classification Controls	None	Included	None	Included
MPAA Rating Controls	None	Included	None	Included
Opening Month Controls	None	Included	None	Included
Observations	9,038	9,038	9,038	9,038
Group Clusters (Movies)	123	123	123	123
R-Squared	0.0032	0.1414		

Note: Results are coefficients from OLS and ordered logit regressions. Robust standard errors are clustered at group (movie) level and appear in parentheses below coefficients; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

PRE-PRINT OF:
Does Stylistic Similarity to Popular Competitors affect Consumer Evaluations of Quality? Evidence from Online Movie Evaluations
2020 Advances in Strategic Management Volume 42, 199–226

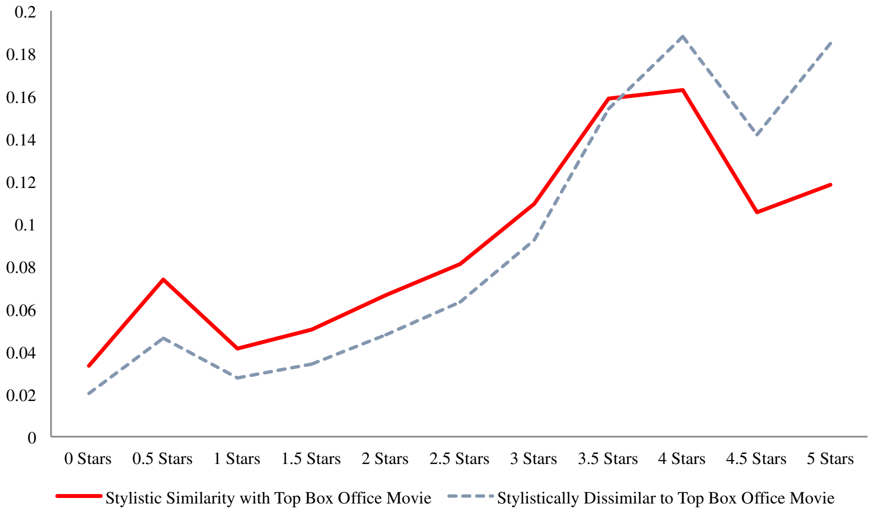

Fig. 1. Predicted Probabilities of Consumer Evaluations for Movies During Opening Week of Release.

the binary conditions for *Stylistic Similarity with Top Box Office Movie,* while holding everything else constant. Fig. 1 offers a graphical depiction of the distribution of predicted probabilities of *Rotten Tomatoes* user evaluations based on whether a movie is stylistically similar to the top box office movie in its opening week of release.

The distribution of predicted probabilities for each of the 11 possible star evaluations again suggests that lower evaluations (i.e. fewer stars) are more likely for movies that are released in a week when the top box office movie is stylistically similar to the movie being evaluated.

SUPPLEMENTARY ANALYSES AND ROBUSTNESS CHECKS

Temporary or Persistent Effects

Given the prior results, it is pertinent to consider whether or not the lower consumer evaluations, which are associated with a movie being stylistically similar to the top box office movie, are temporary or if they persist in later periods. Corresponding to the main analyses presented in Table 2, I again use both OLS and ordered logit regressions, but I now examine only user evaluations that were posted after a movie's first week of release. Here, we observe 66,095 consumer evaluations posted within 18 months after a movie's opening week for the set of 123 movies that were released into theatres in 2007 (Table 3).

Table 3. Consumer Evaluations for Movies During Opening Week of Release.

	1 *OLS* Consumer Evaluation	2 *OLS* Consumer Evaluation	3 *Ordered Logit* Consumer Evaluation	4 *Ordered Logit* Consumer Evaluation
Stylistic Similarity with Top Box Office Movie	−7.215** (3.445)	−4.067** (2.010)	−0.515** (0.201)	−0.351** (0.139)
Critic Score		0.389*** (0.022)		0.029*** (0.002)
Top Box Office Movie		−1.239 (1.407)		−0.079 (0.104)
Production Budget		−0.021 (0.018)		−0.002 (0.001)
Opening Screens		0.001 (0.002)		0.0001 (0.0001)
Runtime		0.079*** (0.029)		0.008*** (0.002)
Constant	64.42*** (1.686)	31.68*** (5.991)		
Style Classification Controls	None	Included	None	Included
MPAA Rating Controls	None	Included	None	Included
Opening Month Controls	None	Included	None	Included
Observations	66095	66095	66095	66095
Group Clusters (Movies)	123	123	123	123
R-Squared	0.0045	0.2259		

Note: Results are coefficients from OLS and ordered logit regressions. Robust standard errors are clustered at group (movie) level and appear in parentheses below coefficients; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The coefficients for *Stylistic Similarity with Top Box Office Movie* are all negative and statistically significant at the 5% level. We can interpret the coefficient from Model 2 to indicate that stylistic similarity with the top box office movie in the opening week of release is associated with −4.1% lower consumer evaluations in subsequent periods ($\beta = -4.067$; $p > 0.045$; 95% CI: [−8.045, −0.089]). The evidence, therefore, suggests that we see a persistent negative effect, and that the composition of competition upon market entry may have long-term consequences for consumer perceptions of quality. While the point estimates and the 95% confidence intervals suggest that this effect may reduce in magnitude after the first week, analyses do not indicate a statistical difference in these magnitudes (see Paternoster, Brame, Mazerolle, & Piquero, 1998). Consistent with the prior results, Fig. 2 depicts the distribution of predicted probabilities of *Rotten Tomatoes* user evaluations as a function of *Stylistic Similarity with Top Box Office Movie* for those consumer evaluations posted after a movie's opening week of release.

A plausible mechanism explaining the persistence of this effect is social conformity in consumer evaluations of quality. That is to say, we continue to observe lower evaluations in later periods because late audiences have been exposed to

PRE-PRINT OF:
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2020 Advances in Strategic Management Volume 42, 199–226

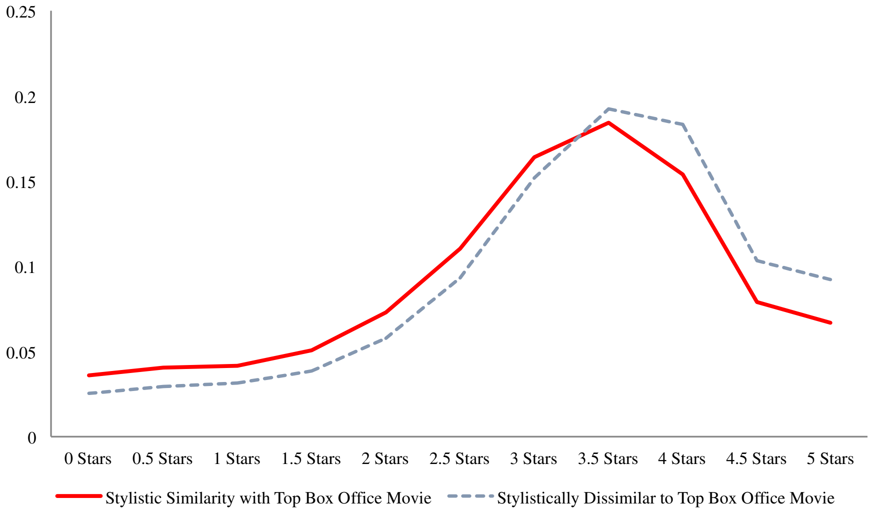

Fig. 2. Predicted Probabilities of Consumer Evaluations for Movies after Opening Week of Release.

early period consumer evaluations. Extending from the seminal Asch (1951) studies, this explanation also builds upon consistent findings across different empirical settings showing that late-period evaluators reconcile their judgements with those of early evaluators per social conformity pressures (e.g. Botelho, 2017; Cohen & Golden, 1972; Pincus & Waters, 1977). This result is pragmatically important for strategists as it demonstrates some possible long-term consequences extending from entry-timing decisions. Within the movie industry, these results suggest that the competitive space in which a film is introduced has long-term ramifications for both box office revenues (e.g. Cabral & Natividad, 2016) and for consumer perceptions of quality.

Changes in Demand and the Composition of Consumers

The preceding results suggest that consumer evaluations are lower for movies that are stylistically similar to the top box office performer, both in their week of release and then in subsequent periods. Aside from just changes in perceptions due to implicit comparisons with other movies, there is also the possibility that there is a reduced demand for movies that are stylistically similar to the top box office movie. This, too, may indirectly affect consumer evaluations if the reduction in demand also impacts the composition of the audience evaluating a given movie. Indeed, a growing body of research has highlighted that there may exist consequences for evaluations stemming from heterogeneity in audiences (e.g. Cattani, Ferriani, & Allison, 2014; Ertug, Yogev, Lee, & Hedström, 2016; Fini, Jourdan, & Perkmann, 2018; Kim & Jensen, 2014; Pontikes, 2012).

Table 4. Count of Consumer Evaluations for Movies.

	1 *Negative Binomial* Evaluation Count	2 *Negative Binomial* Evaluation Count
Stylistic Similarity with Top Box Office Movie	−1.018 (0.291)***	−0.406 (0.181)**
Critic Score		0.016 (0.002)***
Top Box Office Movie		0.415 (0.151)***
Production Budget		0.004 (0.002)**
Opening Screens		0.0004 (0.0001)***
Runtime		−0.002 (0.003)
Constant	3.221 (0.084)***	1.584 (0.300)***
Style Classification Controls	None	Included
MPAA Rating Controls	None	Included
Opening Month Controls	None	Included
Observations	123	123
Pseudo R-Squared	0.0071	0.2259

Results are coefficients from negative binomial regressions. Robust standard errors are clustered at group (movie) level and appear in parentheses below coefficients; $^{**}p < 0.05$, $^{***}p < 0.01$.

In order to help address this issue, I first examine whether being stylistically similar to the top box office movie affects demand. For the dependent variable, I use the number of *Rotten Tomatoes* user evaluations for each of the 123 movies in the dataset. The independent variables from the previous analyses are used to estimate the number of consumers that have evaluated each movie, which serves as our proxy for demand. As dependent variable is a count measure, I use a negative binomial regression model. These results appear in Table 4.

The results from Table 4 suggest a negative relationship between the count of consumer evaluations and stylistic similarity with the top box office movie. We can interpret the coefficient for *Stylistic Similarity with Top Box Office Movie* in Model 2 to indicate that we observe 33% fewer evaluations posted for movies that are stylistically similar to the top box office movie ($\beta = -0.406$; $p > 0.024$; 95% CI: [−0.76, −0.053]). This ultimately means that stylistic similarity with the top box office movie may result in lower consumer demand.

In order to examine if lower levels of consumer demand may be influencing the earlier estimates of consumer evaluations, I generate demand residuals (i.e. the actual demand minus the predicted demand) for each movie based on the results in Table 4 Model 2 while omitting *Stylistic Similarity with Top Box Office Movie.*[6] I separate these demand residuals into positive and (the

[6]As would be expected, the mean residual is negative in magnitude and statistically different than zero for movies that are stylistically similar to the top box office movie ($\mu = -10.65$; 95% CI: [−20.21, −1.083]) and insignificant otherwise.

absolute value of) negative demand residual variables and include them in the regression models estimating consumer evaluations. I label these variables *Negative Demand Residual* and *Positive Demand Residual*. Including these variables in the previous analyses does two things. Primarily, it holds constant discrepancies in estimations of consumer demand for each movie such that we may be able to more precisely estimate the effect of *Stylistic Similarity with Top Box Office Movie* on consumer evaluations. Second, it allows us to observe if differences between estimated demand and actual demand for each movie, either positive or negative, has a direct effect on the consumer evaluations that we observe. These analyses appear in Table 5 (evaluations posted during a movie's opening week) and Table 6 (evaluations posted after the opening week).

As with the previous analyses, we again find the coefficient associated with *Stylistic Similarity with Top Box Office Movie* is negative and statistically significant. However, the magnitude of the effect appears to be somewhat diminished, though we cannot determine that these magnitudes are statistically different from the previous analyses. Moreover, the demand residual variables do not offer a clear or consistent story beyond a possible positive association between the

Table 5. Consumer Evaluation for Movies During Opening Week of Release with Demand Residual.

	1 *OLS* Consumer Evaluation	2 *Ordered Logit* Consumer Evaluation
Stylistic Similarity with Top Box Office Movie	−5.047 (2.701)*	−0.354 (0.193)*
Negative Demand Residual	0.076 (0.061)	0.005 (0.004)
Positive Demand Residual	0.108 (0.047)**	0.009 (0.004)**
Critic Score	0.318 (0.046)***	0.019 (0.003)***
Top Box Office Movie	−1.216 (2.213)	−0.035 (0.157)
Production Budget	0.002 (0.031)	0.0001 (0.002)
Opening Screens	0.0002 (0.003)	−0.0001 (0.0002)
Runtime	−0.029 (0.059)	−0.0002 (0.004)
Constant	44.74 (10.17)***	
Style Classification Controls	Included	Included
MPAA Rating Controls	Included	Included
Opening Month Controls	Included	Included
Observations	9,038	9,038
Group Clusters (Movies)	123	123
R-Squared	0.1464	

Results are coefficients from OLS and ordered logit regressions. Robust standard errors are clustered at group (movie) level and appear in parentheses below coefficients; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

PRE-PRINT OF:
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Table 6. Consumer Evaluation for Movies after Opening Week of Release with Demand Residual.

	1 *OLS* Consumer Evaluation	2 *Ordered Logit* Consumer Evaluation
Stylistic Similarity with Top Box Office Movie	−3.799 (1.899)**	−0.309 (0.136)**
Negative Demand Residual	0.048 (0.027)*	0.003 (0.002)*
Positive Demand Residual	0.044 (0.037)	0.004 (0.003)
Critic Score	0.380 (0.024)***	0.028 (0.002)***
Top Box Office Movie	−1.928 (1.384)	−0.122 (0.104)
Production Budget	−0.011 (0.021)	−0.001 (0.002)
Opening Screens	0.001 (0.002)	0.0001 (0.0001)
Runtime	0.045 (0.039)	0.005 (0.003)*
Constant	34.13 (6.342)***	
Style Classification Controls	Included	Included
MPAA Rating Controls	Included	Included
Opening Month Controls	Included	Included
Observations	66,095	66,095
Group Clusters (Movies)	123	123
R-Squared	0.227	

Results are coefficients from OLS and ordered logit regressions. Robust standard errors are clustered at group (movie) level and appear in parentheses below coefficients; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

residual and consumer evaluations.[7] However, it may be preferable to use these more conservative results when making inferences. During a movie's opening week of release (see Table 5 Model 1), the effect of *Stylistic Similarity with Top Box Office Movie* can be interpreted as 5% less favourable consumer evaluations ($\beta = -5.047$; $p > 0.064$; 95% CI: [−10.39, 0.299]); for the periods after a movie's opening week of release (see Table 6 Model 1), the effect of *Stylistic Similarity with Top Box Office Movie* can be interpreted as 3.8% less favourable consumer evaluations ($\beta = -3.799$; $p > 0.048$; 95% CI: [−7.558, −0.040]).

DISCUSSION AND CONCLUSION

This chapter theorizes as to, and then empirically examines, the effect of stylistic similarity and social attention on consumer evaluations of quality. The empirical results provide evidence in support of the hypothesis that consumer evaluations are less favourable for movies that are stylistically similar to a top box office

[7]In unreported analyses, available from the author upon request, variations of the demand residual variables led to similar results.

movie. Additional analyses suggest that this negative effect may persist in later periods and that it may be partially explained by differences in the composition of consumers due to reduced demand. Ultimately, this work highlights that consumer evaluations of quality may be significantly impacted by the composition of competition. These results offer pragmatic insights for strategists making entry-timing decision or positioning choices.

The empirical analyses also offer some interesting stylized facts about consumer evaluations of movies on *Rotten Tomatoes*. First, we observe different distributions of consumer evaluations of quality for early (opening week of release) and late consumers (post-opening week of release through 18 months). Early consumers, on average, posted more favourable evaluations than late consumers (diff = 5.1%; $p > 0.001$). Moreover, the distribution of early consumer evaluations may display some bimodal properties (see again Fig. 1), while late consumer evaluations appear more normally distributed (see again Fig. 2). Second, this work provides no evidence that box office performance affects consumer perceptions of quality, something for which prior research has found mixed-results (see Hellofs & Jacobson, 1999). Finally, this work offers no evidence that production budgets affect consumer evaluations, at least when holding constant critic scores (see also Simonton, 2005, for an examination of the relationship between budget and awards/professional critic quality judgements). Ultimately, future research will be needed in order to examine the stability and generalizability of these results.

This research also contains some limitations that are worth discussing here. For example, movie release and distribution strategies may limit our ability to make strong inferences from the preceding analyses to the extent that studios are able to manage movie distributions based on perfectly accurate forecasts of other studios and consumer responses. While movie studios are certainly attempting to be strategic in terms of their distributions, there is limited evidence to support the notion that studios can fully optimize their timing based on the release dates of potential competitors. Movie distributers are, in some sense, restricted from being overly strategic because movie release dates are usually scheduled far in advance due to the complicated coordination required to release a movie to an expansive audience across a range of different movie theatres (Fritz, 2011) – other creative industries are not necessarily as locked-in to a style so far in advance of a product's debut in the market (e.g. Godart & Mears, 2009). As any given Friday (the most common day of release) is necessarily composed of other opening releases, distributers are unable to fully anticipate or react to the actions of other movie placements. Moreover, a great deal of distribution strategy appears to focus on capturing revenues from seasonal effects – movies display stronger box office performance measures during specific times of the year – since this is relatively easier for distributers to manage (Eller & Friedman, 2008). Despite these efforts to ensure strategic placement has a positive impact on box office revenues, research by Einav (2007; 2010) provides evidence that movie seasonality effects are even often overstated, as seasonal effects are amplified by the biggest blockbusters being released when seasonal demand is highest, with release dates being clustered

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around holiday weekends as opposed to being optimally dispersed (see also Godart, 2018b, for an investigation of seasonality and stylistic clustering in the fashion industry). In addition to seasonality concerns, distribution appears to focus on strategic releases of movies based on the schedules of target audiences and award seasons because these, too, are relatively easy to manage (Meslow, 2012; Surowiecki, 2015). We can also observe this sort of strategic placement behaviour with respect to the Academy Award winners for Best Picture – only 13% of these winners were released in the first five months of the year, while 65% were released in the last three months of the year (Rodriguez, 2017).

The theory developed in this chapter takes into account the idea that styles are perceived relatively similarly across individuals such that there is a consensus as to the style of a particular product. While this work sought to be unambiguous in the sense that core styles were defined as a binary variable used for each movie, we are likely to gain additional insights by considering alternative measures of styles. Note that Hsu (2006) highlights there exists little consensus amongst film databases with respect to genres. Additionally, the differences between styles are treated as the same in this chapter. Kovács and Hannan's (2015) approach to measuring category contrast might be a useful application for refining stylistic similarities and differences. Eliashberg, Hui, and Zhang's (2014) use of natural language processing of movie scripts may provide another alternative measure of movie styles. Contrasting results from different conceptualizations of key variables may lead to insightful findings. Note also that this theory assumes that consumers are able to *ex ante* perceive social attention (i.e. which film will be the top box office performer on a given week), and the likelihood that an individual's perception is accurate is worth additional consideration. For instance, the difference between the number one and number two box office film in any given week could influence consumer perceptions.

In conclusion, this work helps us appreciate that competitive dimensions such as style and social attention are as relevant now as ever. Indeed, online activity just like in-person activity is inherently and inescapably embedded in social relations. This paper contributes to the emerging literature on aesthetics and style in strategy by depicting how stylistic elements of competition can affect perceptions of quality in markets. These findings offer managerial implications for firms making entry timing decisions or positioning choices in competitive markets.

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REFERENCES

Aadland, E., Cattani, G., & Ferriani, S. (2018). The social structure of consecration in cultural fields: The influence of status and social distance in audience–candidate evaluative processes. *Research in the Sociology of Organizations*, *55*, 129–157.

Adner, R., Csaszar, F. A., & Zemsky, P. B. (2014). Positioning on a multiattribute landscape. *Management Science*, *60*(11), 2794–2815.

Ainslie, A., Drèze, X., & Zufryden, F. (2005). Modeling movie life cycles and market share. *Marketing Science*, *24*(3), 508–517.

Althuizen, N., & Sgourev, S. V. (2014). Pièces de Résistance? Core and casual consumers' valuations of aesthetically incongruent artworks. *Psychology and Marketing*, *31*(8), 604–614.

Antal, A. B., Hutter, M., & Stark, D. (Eds.). (2015). *Moments of valuation: Exploring sites of dissonance*. Oxford: Oxford University Press.

Anthony, C., Nelson, A. J., & Tripsas, M. (2016). "Who are you?… I really wanna know": Product meaning and competitive positioning in the nascent synthesizer industry. *Strategy Science*, *1*(3), 163–183.

Asch, S. (1951). Effects of group pressure upon the modification and distortion of judgments. In H. Guetzkow (Ed.), *Groups, leadership, and men* (pp. 222–236). Pittsburgh: Carnegie Press.

Ashby, N. J., Walasek, L., & Glöckner, A. (2015). The effect of consumer ratings and attentional allocation on product valuations. *Judgment & Decision Making*, *10*(2), 172–184.

Askin, N., & Mauskapf, M. (2017). What makes popular culture popular? Product features and optimal differentiation in music. *American Sociological Review*, *82*(5), 910–944.

Basuroy, S., Chatterjee, S., & Ravid, S. A. (2003). How critical are critical reviews? The box office effects of film critics, star power, and budgets. *Journal of Marketing*, *67*(4), 103–117.

Becker, H. S. (1982). *Art worlds*. Berkeley, CA: University of California Press.

Bettman, J. R., Luce, M. F., & Payne, J. W. (1998). Constructive consumer choice processes. *Journal of Consumer Research*, *25*(3), 187–217.

Bless, H., & Schwarz, N. (2010). Mental construal and the emergence of assimilation and contrast effects: The inclusion/exclusion model. In M. P.Zanna (Ed.), *Advances in experimental social psychology* (Vol. 42, pp. 319–373). San Diego, CA and London: Academic Press.

Bloch, P. H. (1995). Seeking the ideal form: Product design and consumer response. *Journal of Marketing*, *59*(3), 16–29.

Boor, M. (1992). Relationships among ratings of motion pictures by viewers and six professional movie critics. *Psychological Reports*, *70*(3), 1011–1021.

Botelho, T. (2017). *From audience to evaluator: The effect of social influence, status, and expertise in evaluation processes*. Yale SOM Working Paper.

Bresnahan, T. F., & Reiss, P. C. (1991). Entry and competition in concentrated markets. *Journal of Political Economy*, *99*(5), 977–1009.

Cabral, L., & Natividad, G. (2016). Box-office demand: The importance of being# 1. *The Journal of Industrial Economics*, *64*(2), 277–294.

Cattani, G., & Ferriani, S. (2008). A core/periphery perspective on individual creative performance: Social networks and cinematic achievements in the Hollywood film industry. *Organization Science*, *19*(6), 824–844.

Cattani, G., & Ferriani, S. (2013). Networks and rewards among Hollywood artists: Evidence for a social structural ordering of creativity. In J. Kaufman & D. Simonton (Eds.), *The social science of cinema* (pp. 185–206). Oxford: Oxford University Press. ISBN 9780199797813.

Cattani, G., Ferriani, S., & Allison, P. D. (2014). Insiders, outsiders, and the struggle for consecration in cultural fields: A core-periphery perspective. *American Sociological Review*, *79*(2), 258–281.
Cattani, G., Ferriani, S., Negro, G., & Perretti, F. (2008). The structure of consensus: Network ties, legitimation, and exit rates of US feature film producer organizations. *Administrative Science Quarterly*, *53*(1), 145–182.
Cattani, G., Sands, D., Porac, J., & Greenberg, J. (2018). Competitive sensemaking in value creation and capture. *Strategy Science*, *3*(4), 632–657.
Caves, R. E. (2000). *Creative industries: Contracts between art and commerce*. Cambridge, MA: Harvard University Press.
Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354.
Cohen, J. B., & Golden, E. (1972). Informational social influence and product evaluation. *Journal of Applied Psychology*, *56*(1), 54.
Cui, G., Lui, H. K., & Guo, X. (2012). The effect of online consumer reviews on new product sales. *International Journal of Electronic Commerce*, *17*(1), 39–58.
Dekker, E. (2016). Exemplary goods: Exemplars as judgment devices. *Valuation Studies*, *4*(2), 103–124.
Dewey, J. (1939). Theory of valuation. *International Encyclopedia of Unified Science*, *2*(4), 67.
DiMaggio, P. (1987). Classification in art. *American Sociological Review*, *52*, 440–455.
Einav, L. (2007). Seasonality in the US motion picture industry. *The RAND Journal of Economics*, *38*(1), 127–145.
Einav, L. (2010). Not all rivals look alike: Estimating an equilibrium model of the release date timing game. *Economic Inquiry*, *48*(2), 369–390.
Eliashberg, J., Hui, S. K., & Zhang, Z. J. (2014). Assessing box office performance using movie scripts: A kernel-based approach. *IEEE Transactions on Knowledge and Data Engineering*, *26*(11), 2639–2648.
Eliashberg, J., & Shugan, S. M. (1997). Film critics: Influencers or predictors? *Journal of Marketing*, *61*(2), 68–78.
Eller, C., & Friedman, J. (2008). Release date almost as important as good film. *SF Gate*, June 14. Retrieved from http://web.archive.org/web/20180121120228/http://www.sfgate.com/entertainment/article/Release-date-almost-as-important-as-good-film-3209001.php. Accessed on January 21, 2018.
Elsbach, K. D., & Kramer, R. M. (1996). Members' responses to organizational identity threats: Encountering and countering the Business Week rankings. *Administrative Science Quarterly*, *41*, 442–476.
Engelstätter, B., & Ward, M. R. (2018). Strategic timing of entry: Evidence from video games. *Journal of Cultural Economics*, *42*(1), 1–22.
Ertug, G., Yogev, T., Lee, Y. G., & Hedström, P. (2016). The art of representation: How audience-specific reputations affect success in the contemporary art field. *Academy of Management Journal*, *59*(1), 113–134.
Espeland, W. N., & Stevens, M. L. (1998). Commensuration as a social process. *Annual Review of Sociology*, *24*(1), 313–343.
Esposito, E., & Stark, D. (2019). What's observed in a rating? Rankings as orientation in the face of uncertainty. *Theory, Culture & Society*, *36*(4), 3–26.
Ferriani, S., Corrado, R., & Boschetti, C. (2005). Organizational learning under organizational impermanence: Collaborative ties in film project firms. *Journal of Management & Governance*, *9*(3–4), 257–285.
Festinger, L. (1954). A theory of social comparison processes. *Human Relations*, *7*(2), 117–140.
Fini, R., Jourdan, J., & Perkmann, M. (2018). Social valuation across multiple audiences: The interplay of ability and identity judgments. *Academy of Management Journal*, *61*(6), 2230–2264.
Frake, J. (2017). Selling out: The inauthenticity discount in the craft beer industry. *Management Science*, *63*(11), 3930–3943.
Fritz, B. (2011). Hollywood plays dating fame in scheduling movie sequels. *Los Angeles Times*, August 10. Retrieved from http://web.archive.org/web/20180402072617/http://articles.latimes.com/2011/aug/10/business/la-fi-ct-hunger-spider-20110810. Accessed on April 2, 2018.
Fuentelsaz, L., & Gómez, J. (2006). Multipoint competition, strategic similarity and entry into geographic markets. *Strategic Management Journal*, *27*(5), 477–499.

Godart, F. C. (2018a). Why is style not in fashion? Using the concept of "style" to understand the creative industries. *Research in the Sociology of Organizations*, *55*, 103–128.

Godart, F. C. (2018b). Culture, structure, and the market interface: Exploring the networks of stylistic elements and houses in fashion. *Poetics*, *68*, 72–88.

Godart, F. C., & Mears, A. (2009). How do cultural producers make creative decisions? Lessons from the catwalk. *Social Forces*, *88*(2), 671–692.

Godart, F. C., & White, H. C. (2010). Switchings under uncertainty: The coming and becoming of meanings. *Poetics*, *38*(6), 567–586.

Greve, H. R. (2000). Marketing niche entry decisions: Competition, learning, and strategy in Tokyo banking, 1894–1936. *Academy of Management Journal*, *43*(5), 816–836.

Hellofs, L. L., & Jacobson, R. (1999). Market share and customers' perceptions of quality: When can firms grow their way to higher versus lower quality? *Journal of Marketing*, *63*(1), 16–25.

Hirsch, P. M. (1972). Processing fads and fashions: An organization-set analysis of cultural industry systems. *American Journal of Sociology*, *77*(4), 639–659.

Hsu, G. (2006). Jacks of all trades and masters of none: Audiences' reactions to spanning genres in feature film production. *Administrative Science Quarterly*, *51*(3), 420–450.

Hsu, G., Hannan, M. T., & Koçak, Ö. (2009). Multiple category memberships in markets: An integrative theory and two empirical tests. *American Sociological Review*, *74*(1), 150–169.

Jensen, M., & Kim, H. (2015). The real Oscar curse: The negative consequences of positive status shifts. *Organization Science*, *26*(1), 1–21.

Johnson, M. D. (1984). Consumer choice strategies for comparing noncomparable alternatives. *Journal of Consumer Research*, *11*(3), 741–753.

Jones, C., Lorenzen, M., & Sapsed, J. (Eds.). (2015). *The Oxford handbook of creative industries*. Oxford: Oxford University Press.

Kim, H., & Jensen, M. (2014). Audience heterogeneity and the effectiveness of market signals: How to overcome liabilities of foreignness in film exports?. *Academy of Management Journal*, *57*(5), 1360–1384.

Kovács, B., Carroll, G. R., & Lehman, D. W. (2014). Authenticity and consumer value ratings: Empirical tests from the restaurant domain. *Organization Science*, *25*(2), 458–478.

Kovács, B., & Hannan, M. T. (2015). Conceptual spaces and the consequences of category spanning. *Sociological Science*, *2*, 252–286.

Kovács, B., & Sharkey, A. J. (2014). The paradox of publicity: How awards can negatively affect the evaluation of quality. *Administrative Science Quarterly*, *59*(1), 1–33.

Lamont, M. (2012). Toward a comparative sociology of valuation and evaluation. *Annual Review of Sociology*, *38*, 201–221.

Laroche, M., Teng, L., & Kalamas, M. (2001). Consumer evaluation of net utility: Effects of competition on consumer brand selection processes. *Japanese Psychological Research*, *43*(4), 168–182.

Lena, J. C., & Peterson, R. A. (2008). Classification as culture: Types and trajectories of music genres. *American Sociological Review*, *73*(5), 697–718.

Lena, J. C., & Peterson, R. A. (2011). Politically purposed music genres. *American Behavioral Scientist*, *55*(5), 574–588.

Lieberson, S. (2000). *A matter of taste: How names, fashions, and culture change*. New Haven, CT: Yale University Press.

Luca, M. (2016, March 15). *Reviews, reputation, and revenue: The case of Yelp.com*. NOM Unit Working Paper, (12-016). Harvard Business School, Boston, MA.

Lynn, F. B., Podolny, J. M., & Tao, L. (2009). A sociological (de)construction of the relationship between status and quality. *American Journal of Sociology*, *115*(3), 755–804.

Lynn, F. B., Simpson, B., Walker, M. H., & Peterson, C. (2016). Why is the Pack Persuasive? The Effect of Choice Status on Perceptions of Quality. *Sociological Science*, *3*, 239–263.

Maheswaran, D., Mackie, D. M., & Chaiken, S. (1992). Brand name as a heuristic cue: The effects of task importance and expectancy confirmation on consumer judgments. *Journal of Consumer Psychology*, *1*(4), 317–336.

Menard, S. (2002). *Applied logistic regression analysis* (Vol. 106). Thousand Oaks, CA: Sage.

Meslow, S. (2012). January: Dumping ground for terrible movies like 'Contraband'. *The Atlantic*, January 13, 2012. Retrieved from https://web.archive.org/web/20151012234912/http://www.theatlantic.com/entertainment/archive/2012/01/january-dumping-ground-for-terrible-movies-like-contraband/251326/. Accessed on October 12, 2015.

Moretti, E. (2011). Social learning and peer effects in consumption: Evidence from movie sales. *The Review of Economic Studies*, *78*(1), 356–393.

MPAA. (2014). U.S./Canada. Theatrical statistics summary. Retrieved from http://www.mpaa.org/wp-content/uploads/2015/03/MPAA-Theatrical-Market-Statistics-2014.pdf

Oakley, J. L., Duhachek, A., Balachander, S., & Sriram, S. (2008). Order of entry and the moderating role of comparison brands in brand extension evaluation. *Journal of Consumer Research*, *34*(5), 706–712.

Olson, D. M., & Waguespack, D. M. (2018). Competition and influence between critics. Working Paper. University of Washington, Washington, DC.

Paternoster, R., Brame, R., Mazerolle, P., & Piquero, A. (1998). Using the correct statistical test for the equality of regression coefficients. *Criminology*, *36*(4), 859–866.

Pincus, S., & Waters, L. K. (1977). Informational social influence and product quality judgments. *Journal of Applied Psychology*, *62*(5), 615.

Pontikes, E. G. (2012). Two sides of the same coin: How ambiguous classification affects multiple audiences' evaluations. *Administrative Science Quarterly*, *57*(1), 81–118.

Porac, J. F., Thomas, H., & Baden-Fuller, C. (1989). Competitive groups as cognitive communities: The case of Scottish knitwear manufacturers. *Journal of Management Studies*, *26*(4), 397–416.

Porter, M. E. (1980). *Competitive strategy: Techniques for analyzing industries and competitors*. New York, NY: Free Press.

Rao, H. (1994). The social construction of reputation: Certification contests, legitimation, and the survival of organizations in the American automobile industry: 1895–1912. *Strategic Management Journal*, *15*(S1), 29–44.

Rao, H., Monin, P., & Durand, R. (2003). Institutional change in Toque Ville: Nouvelle cuisine as an identity movement in French gastronomy. *American Journal of Sociology*, *108*(4), 795–843.

Rindova, V. P., Martins, L. L., Srinivas, S. B., & Chandler, D. (2018). The good, the bad, and the ugly of organizational rankings: A multidisciplinary review of the literature and directions for future research. *Journal of Management*, *44*(6), 2175–2208.

Rindova, V. P., Pollock, T. G., & Hayward, M. L. (2006). Celebrity firms: The social construction of market popularity. *Academy of Management Review*, *31*(1), 50–71.

Rodriguez, A. (2017). The Oscar goes to… If a movie is released before June, it's probably not going to win Best Picture at the Oscars. *Quartz*, June 1, 2007. Retrieved from http://web.archive.org/web/20170601175216/https://qz.com/994733/except-for-classics-like-casablanca-to-the-godfather-movies-released-before-june-almost-never-win-the-oscar-for-best-picture/

Rotten Tomatoes. (2016). About: Rotten Tomatoes. Retrieved from http://web.archive.org/web/20160709200802/https://www.rottentomatoes.com/about/. Accessed on July 9, 2016.

Salganik, M. J., Dodds, P. S., & Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, *311*(5762), 854–856.

Schwarz, N., & Bless, H. (1992). Constructing reality and its alternatives: An inclusion/exclusion model of assimilation and contrast effects in social judgment. In L. Martin & A. Tesser (Eds.), *The construction of social judgments*. Hillsdale, NJ: Lawrence Erlbaum Assoc.

Sgourev, S. V., & Althuizen, N. (2014). "Notable" or "Not Able" when are acts of inconsistency rewarded?. *American Sociological Review*, *79*(2), 282–302.

Sgourev, S. V., & Althuizen, N. (2017). Is it a masterpiece? Social construction and objective constraint in the evaluation of excellence. *Social Psychology Quarterly*, *80*(4), 289–309.

Simmel, G. (2004). *The philosophy of money*, T. Bottomore & D. Frisby (Trans.). London: Routledge.

Simonton, D. K. (2005). Cinematic creativity and production budgets: Does money make the movie?. *Journal of Creative Behavior*, *39*(1), 1–15.

Surowiecki, J. (2015). Rethinking the seasonal strategy. *The New Yorker*, February 23, 2015. Retrieved from http://web.archive.org/web/20160622164728/http://www.newyorker.com/magazine/2015/02/23/rethinking-seasonal-strategy. Accessed on June 22, 2016.

Swami, S., Eliashberg, J., & Weinberg, C. B. (1999). SilverScreener: A modeling approach to movie screens management. *Marketing Science*, *18*(3), 352–372.

Wallace, W. T., Seigerman, A., & Holbrook, M. B. (1993). The role of actors and actresses in the success of films: How much is a movie star worth? *Journal of Cultural Economics*, 1–27.
Wallentin, E. (2016). Demand for cinema and diverging tastes of critics and audiences. *Journal of Retailing and Consumer Services*, *33*, 72–81.
Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *STATA Journal*, *6*(1), 58–82.
Williams, R. (2015, February 21). Ordered logit models – Overview. University of Notre Dame. Retrieved from https://www3.nd.edu/~rwilliam/stats3/L11.pdf. Accessed on May 19, 2017.
Zhao, E. Y., Ishihara, M., & Lounsbury, M. (2013). Overcoming the illegitimacy discount: Cultural entrepreneurship in the US feature film industry. *Organization Studies*, *34*(12), 1747–1776.
Zuckerman, E. W. (1999). The categorical imperative: Securities analysts and the illegitimacy discount. *American Journal of Sociology*, *104*(5), 1398–1438.
Zuckerman, E. W. (2012). Construction, concentration, and (dis) continuities in social valuations. *Annual Review of Sociology*, *38*, 223–245.
Zuckerman, E. W., Kim, T. Y., Ukanwa, K., & Von Rittmann, J. (2003). Robust identities or non-entities? Typecasting in the feature-film labor market. *American Journal of Sociology*, *108*(5), 1018–1074.

APPENDIX: CONSTRUCTING CORE STYLE CLASSIFICATIONS FROM ROTTEN TOMATOES TOP 100 MOVIES LISTS

This chapter uses a set of core style classifications in order to establish stylistic similarity between movies in competitive space. The theoretical conceptualization used in this work stipulates that consumers compare the product they are evaluating with other products available in the market. In the case of movies, they implicitly compare the movie they watched to other movies that they did not see when producing a quality judgement. In order to determine similarity and differences between products this chapter uses core movie styles. The core styles used in this chapter were derived from the larger *Rotten Tomatoes* style classification system. *Rotten Tomatoes* uses a classification schema that allows for a movie to be assigned to more than one classification, which may be indicative of the fact that product styles span multiple genres/categories, and multiple styles may exist within a genre/category. As is often the case, style/genre/category may be empirically intertwined – see Godart (2018a) for guidance on definitional clarity and for a detailed look at these conceptual issues within creative and cultural industries.

The following represents the stylistic that *Rotten Tomatoes* has constructed for their 'Top 100 Movies' lists: Overall, Action & Adventure, Animation, Art House & International, Classics, Comedy, Documentary, Drama, Horror, Kids & Family, Musical & Performing Arts, Mystery and Suspense, Romance, Science Fiction & Fantasy, Special Interests, Sports & Fitness, Television, and Western. Of these, Overall, Sports & Fitness, Television, and Western did not even have 100 movies assigned to their Top 100 classification. Hence I did not consider them for inclusion as a core style. Of the remaining 15 possible core styles, there existed 781 individual movies within the 1,500 possible positions. As such, we see considerable overlap in classification assignment by *Rotten Tomatoes*. Due to the empirical considerations outlined in this chapter, Art House & International, Classics, Documentary, and Special Interests were omitted as options for core styles. The following correlation matrix depicts the overlap between the remaining 10 styles:

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Does Stylistic Similarity to Popular Competitors affect Consumer Evaluations of Quality? Evidence from Online Movie Evaluations
2020 Advances in Strategic Management Volume 42, 199–226

	SciFi	Action & Adventure	Drama	Animation	Kids & Family	Mystery & Suspense	Romance	Comedy	Horror	Musical
SciFi	1									
Action & Adventure	0.2176	1								
Drama	−0.0907	0.0279	1							
Animation	0.0634	−0.067	−0.1618	1						
Kids & Family	0.1464	−0.0314	−0.15	0.4902	1					
Mystery & Suspense	−0.0059	0.137	0.1132	−0.1606	−0.1368	1				
Romance	−0.0907	−0.1381	−0.0907	−0.15	−0.1263	−0.1011	1			
Comedy	0.0279	−0.0314	−0.0314	0.0279	0.0753	−0.1487	0.0871	1		
Horror	−0.067	−0.15	−0.1381	−0.1737	−0.1855	−0.0059	−0.15	−0.1855	1	
Musical	−0.1144	−0.1618	−0.1737	−0.0907	−0.0314	−0.1844	−0.0788	−0.067	−0.1737	1

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2020 Advances in Strategic Management Volume 42, 199–226

The correlation matrix indicates that Musical & Performing Arts and Horror are negatively correlated to all other styles. Romance is correlated to one other style classification, Drama and Mystery are positively correlated to two, while Action & Adventure, Animation, and Kids & Family are positively correlated to three other style classifications. Comedy and Science Fiction & Fantasy are positively correlated to four. The style classifications of Kids & Family and Animation show the strongest correlation, at 0.49, and as such, these styles are merged into a core style that I label Kids & Family. Science Fiction & Fantasy shows a 0.21 correlation with Action & Adventure, and Mystery & Suspense also shows a high correlation, of 0.13, with Action & Adventure and Drama, of 0.11, which results in removing both Science Fiction & Fantasy and Mystery & Suspense from the set of core style classifications. Romance is similarly positively correlated to Drama, at 0.08, and thus is omitted as a core style classification.

Collapsing these supplemental styles results in following the six core style classifications that are used in this chapter: Action & Adventure, Drama, Kids & Family, Comedy, Horror, and Musical & Performing Arts. For the purposes of the empirical analyses, all the movies were assigned to one of these six core styles.

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2020 Advances in Strategic Management Volume 42, 199–226