

## Measuring the Role of Uniqueness and Consistency to Develop Effective Advertising

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### ABSTRACT



Prior research on creativity and the effectiveness of executional factors in advertising has focused on the impact of uniqueness and consistency in comparison to prior and competitive advertising. Relatively little is known about the specific impact of these variables and their relationship to each other, and few existing measures of consistency and uniqueness extend beyond subjective rating scales. In this research, we develop new measures of advertising uniqueness and consistency. We use data from 10 years of Super Bowl advertisements along with panel data on word-of-mouth communication for the advertised brands (buzz) to demonstrate the validity of this methodology. Our findings suggest it is not the presence of any particular element but whether the element and what it is combined with are unique and consistent. Advertisements are likely to be more effective if they are unique from earlier ads for all brands but also consistent with ads for the same brand from prior periods.

Research on the measurement of creativity and its components is critical to understanding its impact on different outcomes of advertising (Sasser and Koslow 2008). Creative ads have numerous benefits, including increased recall (Ang, Lee, and Leong 2007), positive affect (Yang and Smith 2009), and sales performance (Becker, Wiegand, and Reinartz 2019). Most prior work on the measurement of creativity either has used scale-based ratings to capture different underlying dimensions (e.g., Sasser and Koslow 2008; Till and Baack 2005) or has focused on concrete content features in advertisements (Stewart and Koslow 1989). These efforts are directed to facilitate a better understanding of creativity's impact on advertising effectiveness.

The stream of work using rating scales rests on the assumption that creativity is a function of the holistic character of an ad, such as its originality or divergence (Smith, Chen, and Yang 2008). Common to

these approaches is the recognition that uniqueness is a central element of creative and effective ads (Smith and Yang 2004). A second holistic element is consistency, that is, the extent to which an ad uses similar positioning and other relevant elements over time (West, Kover, and Caruana 2008). An alternative stream of research has focused on the coding of executional variables of an ad. For example, Stewart and Furse (1986) and Stewart and Koslow (1989) analyzed a large number of executional variables and found that product/brand focus and the presence of a brand-differentiating message were the only factors consistently correlated with both recall and persuasiveness.

Despite being used frequently, both the scale-based approach and the coding approach have disadvantages. The scale-based approach relies on specific samples of subjects for whom the meaning and interpretation of the concept “creativity” may differ (e.g., advertising

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creatives vs. various consumer groups, different cultures; West, Kover, and Caruana 2008; Lu et al. 2019). Most scale-based ratings have also been administered in a laboratory setting, raising questions about external validity. The third limit to scale-based approaches is that the application of subjective rating scales to archival data is not reliable, as prior exposure to ads can confound respondents' evaluations of the ads (McQuarrie and Mick 2003). While the coding approach has higher external validity due to the number of advertisements and executional factors typically used in the analysis, it is limited because it ignores the influence of other ads and their execution.

Both of the above approaches have advanced the understanding of creativity as the "heart of advertising business" (West, Koslow, and Kilgour 2019: 102). Yet, they also have disadvantages because they fail to consider whether ads are unique and consistent *relative to other advertisements*. This paper introduces a method that overcomes this limitation and that may be applied where the comparison of stimuli over time is of interest.

A primary goal of advertising is persuasion, and it is important to consider this underlying goal when investigating advertising effectiveness (Till and Baack 2005). Among the oldest persuasion theories is the rhetoric (or rhetorical) theory, dating to the work of Aristotle (Aristotle, translated by Kennedy 1991; Tevi and Koslow 2018). Rhetorical theory identifies various dimensions, or canons, of persuasive communication: invention, arrangement, elocution, memory, and delivery (Pudewa 2016). While *invention*—the creation of the basic message—is an important first step in the creation of a persuasive message, *arrangement* and *elocution*, that is, the selection, arrangement, and *delivery* of an individual element of a message, are also critical. Advertisers are most likely to influence these aspects because the content of the message is a function of the characteristics or benefits of the advertised product or service. Thus, it is not surprising that a significant amount of research and theory in advertising has focused on the selection and arrangement of individual elements of advertisements. Rhetoric theory suggests that it is this gestalt of selection and arrangement of different elements that affect an ad's persuasiveness.

Consistent with the rhetoric theory, this research introduces new measures of uniqueness and consistency based on empirically derived indices of similarity and uniqueness that reflect the presence or absence of specific executional elements, both within advertisements for the same brand as well as in comparison to advertisements for other brands. We use a multi-method approach. We start with a comprehensive data

set of Super Bowl ads that were content-analyzed using categories developed by Stewart and Furse (1986), among others. These codes are used to compute composite measures of similarity. The similarity scores are then used to estimate the uniqueness of each ad relative to other ads and their consistency with ads for the same brand that have appeared in prior years.

We also demonstrate the validity of the measures by examining the relationships between the uniqueness and consistency scores and the buzz generated by the ads as assessed by a measure of buzz from market research firm YouGov (YouGov 2021). Buzz captures the extent to which consumers are exposed to positive or negative messages about brands through talking to other consumers and being in contact with media outlets (e.g., television, print, social media), both online and offline (Hewett et al. 2016).

This paper contributes to the literature on advertising by providing novel, objective, and concise measures of uniqueness and consistency. The method has three advantages: (1) scores are calculated in a straightforward manner, (2) the measures can be used to test relationships with a variety of dependent measures of ad effectiveness, and (3) the measures of uniqueness and consistency can be applied to archival data. The latter advantage makes it possible to measure the uniqueness or consistency of ads aired years ago, where subjective ratings may be biased by changes over time and context. Our approach also makes archival data accessible for analyses and provides a reliable and replicable instrument to compare characteristics of stimuli over time.

## Conceptual Background

Two factors linked to effective creative advertising programs are uniqueness and consistency. Uniqueness is the degree to which an ad's content deviates from that of other ads (Sasser and Koslow 2008). Consistency refers to the degree to which a brand's advertising reflects consumers' expectations based on prior experience with the brand (e.g., Aaker and Keller 1990; Keller 1993). Moreover, consistency describes the coherent integration of ideas within existing brand domains (Mumford et al. 1997).

### Advertising Uniqueness

Uniqueness is a principle long heralded as a factor in producing more effective ads (e.g., Ogilvy 1964; Stewart and Furse 1986). Unique content enhances recall and learning (Lee and Schumann 2004). Uniqueness refers to the degree to which an ad

contains elements that are novel, different from other ads, or unusual (Yang and Smith 2009). Research suggests that higher levels of uniqueness generate more attention (Pieters, Warlop, and Wedel 2002), partly because such ads trigger more elaborate cognitive processing and also because moderate levels of incongruity can produce stronger evaluative responses (Ang and Low 2000).

### **Advertising Consistency**

Brands advertise repeatedly and consumers build up associations with the brand over time. These associations, in turn, contribute to brand equity (Keller 2013). Consistency influences the relevance of an ad to consumers (Smith and Yang 2004). Constructing a coherent brand narrative ensures a strong and favorable image. The congruence of brand associations affects how easily these associations are recalled and how readily additional associations are linked to the brand (Keller 1993). Therefore, any new brand message that is consistent with existing beliefs about the brand should be assimilated more easily. Thus, ads that fit with the brand's existing strategy are more likely to result in advertising that resonates with consumers (Kilgour and Koslow 2009).

## **A New Measurement Approach for Advertising Uniqueness and Consistency**

### **The Context: Super Bowl Advertising**

The Super Bowl provides an appropriate context for measuring uniqueness and consistency because it is a discrete advertising event that provides a quasi-experimental setting, thereby enabling better identification of effects as compared to events in dynamic and heterogeneous environments (Raithel, Taylor, and Hock 2016). A substantial number of brands have advertised during the Super Bowl over time, which enables comparisons across brands and over time (Hartmann and Klapper 2018). Importantly, brands do not control the in-game ad format. For each event, the number, length, and timing of potential ads are exogenously determined. The number of events and their time-lag is fixed because the event takes place on the same date and time every year. In addition, creating word-of-mouth is a common objective of Super Bowl advertising. Both uniqueness and consistency impact word-of-mouth (Sasser and Koslow 2008), making it a particularly appropriate criterion for validation of the new measures.

### **Objective Measurement of Uniqueness and Consistency**

To derive the new measures, trained coders first independently watched and coded ads from an archival database using established coding schemes. The specific coding schemes used were chosen based on including those executional variables that are (1) included in prior large-scale studies of executional variables (e.g., Stewart and Furse 1986; Stewart and Koslow 1989) and (2) included in prior literature on variables commonly employed in Super Bowl advertising (e.g., Kim, Cheong, and Kim 2012; Li 2009; Nail 2007; Newell, Henderson, and Wu 2001; Siefert et al. 2009; Tomkovick, Yelkur and Christians 2001).

For the content analysis itself, general procedures described by Krippendorf (2012) and Kolbe and Burnett (1991) were followed, including creating a codebook and data coding instrument; using coders other than the researchers, independent coding of all ads, measuring reliability, and resolving disagreements in consultation with the researchers.

Paid graduate research assistants were employed as coders. The coders were trained extensively by the research team using 30 television ads that were not Super Bowl ads and at least three years old. Ads for the NFL were excluded as they are not paid for, as were movie ads because they generally feature a "movie trailer" format following a storyline rather than employing other ad appeals. For all coding dimensions, intercoder reliabilities were computed using Rust and Cooil's (1994) proportional reduction of loss (PRL) measure, where a PRL level of .70 and above is suggested as an acceptable threshold. Intercoder agreement rates range from 67% to 94%, and the corresponding PRL reliability levels range from .58 to .94 ( $M_{PRL} = .78$ ). Out of the 31 categories coded, 4 categories exhibit PRL levels below the .70 threshold. This is due to difficulties in coding the ethnicity of the principal characters (e.g., distinguishing between a South-East Asian and an Asian-American character). To improve the validity of the coding, disagreements were resolved through discussions with the researchers.

The coded elements were then used to compute a measure of similarity. A variety of measures for the determination and calculation of similarity exists. Among the 18 measures which we examined (see Web Appendix A), we selected the Jaccard (1901) metric. This metric is superior in our context because it defines similarity asymmetrically by including only the presence of features (positive matches) but ignoring the absence of features (negative matches) in two

ads. Hence, two ads get higher similarity only if, for example, humor is present in both, but not if humor is absent from both (as symmetric measures would do). This characteristic of the Jaccard metric is important because the number of 0's (absence of features) is much larger than the number of 1's (presence of features) for many of the coded elements in our data.

When calculating the similarity measures for advertising uniqueness and consistency, it is important to consider the temporal nature of the data. There are two dimensions of uniqueness: one that computes uniqueness relative to other ads in the current period and another that computes uniqueness compared to all previous ads in the data set. For within-year uniqueness, we calculated the average similarity score between a brand's ad(s) and all same-year ads for all other brands. For prior-year uniqueness, we calculated the average similarity of a brand's ad(s) with all other brands' prior-year ads.

### **Assessing Predictive Validity: The Impact of Uniqueness and Consistency on Brand Buzz**

#### **Data and Sample**

**Brand Buzz Data.** Data used to validate the measures were provided by marketing research firm YouGov. This data source is unique because it monitors consumer perceptions of more than 1,000 brands by surveying a representative sample of 5,000 people each day (from a panel of 1,500,000 U.S. consumers). The large panel size is advantageous because it is representative of the brand-user universe. Daily measurement is beneficial because it can pinpoint and reflect changes in brand-user perceptions. To ensure that responses are representative of the general U.S. population, YouGov weights respondents by age, race, gender, education, income, and region using U.S. census data.

This study used the YouGov indicator *Brand Buzz*. For a given industry sector, respondents select all brands for which they agree to the question, "Have you heard anything positive about the following brands?" Then, they select all brands for which they agree to the question, "Have you heard anything negative about the following brands?" Unrated brands are coded as neutral. Thus, for each brand, three responses are possible: positive, negative, and neutral. We calculate the *Brand Buzz* as a valence measure reflecting positive or negative information about the brand. The aggregated *Brand Buzz* score is calculated as the sum of positive votes minus the sum of negative votes divided by the sum of votes. The *Brand*

*Buzz* score, therefore, ranges between  $-1$  and  $1$ . Brand competition effects are also controlled for because respondents rate competing brands within one category simultaneously. YouGov selects the samples randomly from day to day. Thus, consumers rating brands before the Super Bowl and consumers rating brands after the Super Bowl are independent, which reduces measurement bias due to common method bias or interviewees' tendency to show consistent responses.

YouGov provided data for all available U.S. brands surveyed one week before and one week after the 10 Super Bowl events. To measure the impact of Super Bowl advertising on *Brand Buzz*, this study calculates  $\Delta$ *Brand Buzz* as the difference of the average five-day post-Super Bowl *Brand Buzz*( $t + 1$ ;  $t + 5$ ) and the average five-day pre-Super Bowl *Brand Buzz*( $t - 5$ ;  $t - 1$ ). For each brand in each year, the ratings represent on average 358 respondents pre-Super Bowl and 385 respondents post-Super Bowl.

**Advertisement Data.** To compile the advertising data, we built a comprehensive database of all Super Bowl advertisements from 2008 to 2017. The database included 566 national advertisements that took place during the regular in-game commercial breaks and the half-time show. Information on advertisements was gathered from *USA Today's Ad Meter*,<sup>1</sup> which provides video links to the ads.

**Measures of Uniqueness and Consistency.** We transformed the content data into 31 binary variables (e.g., humorous appeal, use of celebrity endorser, use of animals, gender of the principal actor) and calculated similarity scores for each ad (see Web Appendix A). **Table 1** displays the operationalization of the 31 binary ad content variables. For the two measures of uniqueness—one that computes uniqueness relative to other ads in the current year and the other that computes uniqueness compared to ads from all previous ads—we multiplied the similarity scores by  $-1$ , so that high values indicate low similarity (i.e., high uniqueness). To measure consistency, we calculated for each year, the (average) similarity score between a brand's ad(s) and all prior-year ad(s) of the same brand, given that the brand had an ad in the prior year.

**Control Variables.** We control for the content features' direct effects; gender of the principal actor; prominence of children, minorities, celebrities, or animals; as well as humorous appeal, sexual appeal, prominence of music, emotional message, brand-differentiating message, prominence of the product/service, and prominence of



**Table 1.** Variables used for Super Bowl advertising similarity measurement.

Dimension	Subdimension	#	Binary variable (1 = yes; 0 = no)
Principal actor characteristics in general	Gender of principal actor	01	Principal Actor Male
		02	Principal Actor Female
		03	Principal Actor Child
Minority actor appearance	Minority type of principal actor	04	Principal Actor African
		05	Principal Actor Asian
		06	Principal Actor Latino
		07	Principal Actor Middle East
		08	Principal Actor South Asian
		09	Principal Actor Mixed Minority Type
Celebrity actor appearance	Prominence of minority actor	10	Minority Actor Major Character
	Gender of celebrity as principal character	11	Principal Actor Male Celebrity
		12	Principal Actor Female Celebrity
	Type of celebrity as principal character	13	Principal Actor Athlete Celebrity
		14	Principal Actor Entertainer Celebrity
		15	Principal Actor Corporate Celebrity
Animal actor appearance	Minor prominence of celebrity	16	Celebrity Minor Character
	Type of animal as principal character	17	Principal Actor Dog
		18	Principal Actor Cat
		19	Principal Actor Other Animal
20		Animal Minor Character	
Appeal	Minor prominence of animal	21	Sexual Appeal
	Sexual	22	Humorous Appeal
	Humorous	23	Music Major Element
	Music	24	Music Minor Element
Brand message	Commercial approach	25	More Rational Message
		26	More Emotional Message
	Differentiation	27	Brand Differentiating Message
	Prominence of product/package	28	Major Prominence of Product
		29	Minor Prominence of Product
	Corporate social responsibility	30	CSR Appeal Major Element
		31	CSR Appeal Minor Element

corporate social responsibility (CSR) message. These control variables were used to avoid omitted variable bias because specific content features can affect both the similarity measures and the buzz metrics.<sup>2</sup> Then, we control for the awareness or “mere exposure effect” (e.g., Janiszewski 1993) by including the *number of ad stimuli* (number of ads of a brand in a year) and the number of viewers or “ad spread” (*TV rating*) in the model. We also include brand fixed effects to control for unobserved brand-level heterogeneity. We combined the 31 binary variables used for similarity calculation into a parsimonious set of 12 variables to reduce model complexity and degrees of freedom. We tested a variety of sets of control variables. Web Appendix C reports the models without any and with all of the control variables. Here we report the most parsimonious model specification which includes only relevant content variables.<sup>3</sup>

**Data Matching.** Each Super Bowl ad was matched with the *Brand Buzz* data. If a brand had multiple ads in a year, the averages of the uniqueness, consistency, and control variables were calculated first. Although 90 brands matched with the *Brand Buzz* data, only 36 brands had a Super Bowl ad in the prior year, which was required for the calculation of the consistency

measure. Because several brands have more than two Super Bowl appearances in a row, 111 observations remain for use in validation.

### Regression Model to Assess the Predictive Validity

We estimate the relationships using the following panel regression model:

$$\begin{aligned}
 \Delta \text{Brand Buzz}_{it} = & \beta_0 + \beta_{1a} \\
 & \cdot \text{Uniqueness (same year)}_{it} + \beta_{1b} \\
 & \cdot \text{Uniqueness (prior year)}_{it} + \beta_2 \\
 & \cdot \text{Consistency}_{it} + \beta_3 \\
 & \cdot \text{Uniqueness (same year)} \times \text{Consistency}_{it} \\
 & + \mathbf{Controls}_{it}^T \cdot \mu_i + \varepsilon_{it}
 \end{aligned} \tag{1}$$

The dependent variable  $\Delta \text{Brand Buzz}_{it}$  measures the post- versus pre-Super Bowl change in *Brand Buzz* of brand  $i$  in year  $t$ . The focal variables,  $\text{Uniqueness (same year)}_{it}$ ,  $\text{Uniqueness (prior year)}_{it}$ ,  $\text{Consistency}_{it}$ , and  $\text{Uniqueness (same year)} \times \text{Consistency}_{it}$  are measures for brand  $i$  in year  $t$  for the

**Table 2.** Descriptive statistics and correlations of model variables.

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Change in Brand Buzz	1.000																		
2	Stimulus Uniqueness (vs. same year)	.111	1.000																	
3	Stimulus Uniqueness (vs. prior year)	.039	.863	1.000																
4	Stimulus Consistency	.203	.374	.285	1.000															
5	Prior Year Change in Brand Buzz	.179	.162	.165	.101	1.000														
6	C01_ProminencePrimeActorFemale	-.032	-.217	-.263	-.089	.003	1.000													
7	C02_ProminenceChild	.052	.137	.081	.469	-.014	-.013	1.000												
8	C03_ProminenceMinority	-.041	.316	.283	.092	.042	.000	-.005	1.000											
9	C04_ProminenceCelebrity	-.116	-.030	-.060	-.094	-.174	.338	-.188	.078	1.000										
10	C05_ProminenceAnimal	.072	.011	.040	-.055	.215	-.061	.016	.079	-.203	1.000									
11	C06_SexualAppeal	-.131	.352	-.107	.145	.041	.292	-.104	-.011	.339	-.199	1.000								
12	C07_HumorousAppeal	.013	.352	-.081	.237	.005	-.098	.142	-.136	.005	.177	-.127	1.000							
13	C08_ProminenceMusic	.013	-.218	-.081	-.122	.185	.050	-.119	.110	-.049	-.056	-.115	-.265	1.000						
14	C09_ProminenceEmotionalMessage	.214	.422	.483	.136	.254	.143	-.030	.097	.045	.120	.094	.074	.265	1.000					
15	C10_BrandDiffMessage	-.065	-.200	-.220	-.260	-.111	.058	.000	.075	-.073	-.116	.090	.017	.005	-.268	1.000				
16	C11_ProminenceProduct	-.110	.156	.248	-.192	-.148	-.009	-.103	.020	-.014	.001	-.277	-.009	.009	.047	-.026	1.000			
17	C12_ProminenceCSR	-.016	-.043	-.133	-.018	.082	.165	-.009	.012	-.096	.062	-.063	-.035	.138	.098	.142	-.045	1.000		
18	Number of Stimulus Exposures (# of ads)	.376	.027	.041	.023	.234	.046	-.030	-.074	-.079	.041	.123	-.071	.051	.124	-.004	-.030	-.101	1.000	
19	Stimulus Spread (TV Rating)	-.060	-.090	.017	-.124	-.166	.149	-.039	-.026	-.001	.070	-.003	.015	-.049	-.015	.160	.138	-.003	-.110	1.000
	Mean	.032	.000	.000	.000	.034	-.310	.182	.502	.311	.352	.045	.531	1.165	.746	.098	1.187	.105	.000	.000
	SD	.054	1.000	1.000	1.000	.064	.560	.349	.398	.447	.408	.197	.464	.481	.500	.263	.656	.384	.793	1.396
	Min	-.093	-.2.200	-.2.321	-.1.675	-.131	-.1.000	-.000	.000	.000	.000	.000	.000	.000	-.1.000	.000	.000	.000	-.577	-3.976
	Max	.187	1.967	2.286	2.604	.228	1.000	1.000	1.000	1.667	1.333	1.000	1.000	2.000	1.000	1.000	2.000	2.000	3.423	1.524

Note:  $p < .01$  if  $|r| > .230$ ;  $p < .05$  if  $|r| > .180$ ;  $p < .10$  if  $|r| > .150$ .

**Table 3.** Regression results for the parsimonious models.

Main Effects	$\Delta$ Brand Buzz (Valence)
a) Uniqueness (vs. same year)	-.022*** (.008)
b) Uniqueness (vs. prior year)	.028*** (.008)
Difference a) - b)	-.050***
Consistency (vs. prior year)	.020*** (.005)
<b>Moderation Effect</b>	
Consis.*Uniquen. (vs. same year)	.011** (.005)
<b>Control variables</b>	
Prior Year $\Delta$ Buzz (Valence)	-.130** (.049)
Sexual Appeal	-.117*** (.023)
Prominence Emotional Message	.023* (.013)
Number of Stimuli	.022*** (.008)
TV Rating	.005 (.003)
Intercept	.028*** (.010)
Brand fixed effects	YES
<b>Model fit</b>	
within- $R^2$	.352
adjusted within- $R^2$	.294
F test	16.224***
N	111

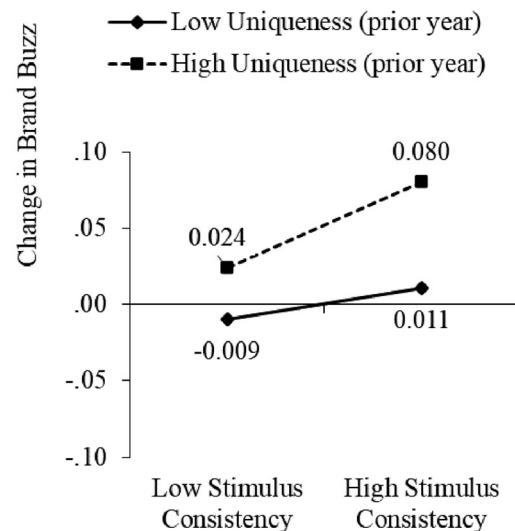
Note. \*\*\* $p < .01$ . \*\* $p < .05$ . \* $p < .10$  (cluster-robust standard errors in parenthesis).

average uniqueness, consistency, and interaction thereof, respectively, of ads aired during the Super Bowl.<sup>4</sup> The four regression coefficients,  $\beta_{1a}$ ,  $\beta_{1b}$ ,  $\beta_2$ , and  $\beta_3$  are expected to be positive. **Controls**<sub>*it*</sub> includes the control variables (see above), and the vector includes their regression coefficients. The parameter  $\mu_i$  represents the brand fixed effects, and  $\varepsilon_{it}$  is the error term. Standard errors are clustered by brands and adjust for heteroscedasticity and within brand serial correlation.

## Results

Table 2 shows the descriptive statistics and correlations for all model variables. On average, Super Bowl ads increase *Brand Buzz* ( $\beta = .032$ ,  $SE = .005$ ,  $t = 6.13$ ,  $p < .001$ ). Also, the heterogeneity is considerable: Changes in *Brand Buzz* range from  $-.093$  to  $.187$ . Can the uniqueness and consistency measures explain this heterogeneity?

Table 3 shows the model results.<sup>5</sup> We report the most parsimonious model including only those content control variables which add to the prediction of *Brand Buzz* (see Web Appendix C for results of models without any and with all control variables). *Sexual appeal* decreases *Brand Buzz* ( $\beta = -.117$ ,  $p < .01$ ). There is evidence that *prominence of emotional message* increases *Brand Buzz* ( $\beta = .023$ ,  $p < .10$ ). The fit of the model is moderate to good. About 35% of the brand within variation of *Brand Buzz* is explained by the model. Adding the three focal variables and the interaction improve prediction of *Brand Buzz* by



Note: Low = -1 SD of the variable High = +1 SD of the variable

**Figure 1.** Interaction plots for change in *Brand Buzz*.

about 16%. These findings demonstrate that consistency and uniqueness make a substantial contribution to the prediction of *Brand Buzz*.

**The Effect of Uniqueness on Brand Buzz.** The two *uniqueness* measures have different effects: the effect of *uniqueness (prior year)* on *Brand Buzz* ( $\beta = .028$ ,  $p < .01$ ) is positive. The effect of *uniqueness (same year)* on *Brand Buzz* is unexpected. It is significantly different from zero but negative ( $\beta = -.022$ ,  $p < .01$ ). These two effects are significantly different ( $\beta_{\Delta} = -.050$ ,  $p < .01$ ). These findings suggest that uniqueness versus prior year ads is beneficial, while uniqueness versus the same year ads is not beneficial for brands.<sup>6</sup> This phenomenon most likely results from the cognitive load on consumers in processing ads, reflecting an ability to process uniqueness relative to ads seen in the past, but not relative to those seen within a short period of time (e.g., three hours). Yet, the interpretation of these effects also depends on the effects of consistency, which we discuss next.

**The Effect of Consistency on Brand Buzz.** The results show that *Consistency* has a positive effect on *Brand Buzz* ( $\beta = .020$ ,  $p < .05$ ).

Finally, the interpretation of *Uniqueness's* and *Consistency's* main effects is conditional on the interaction of *Uniqueness*  $\times$  *Consistency*.

**The Interaction Effect of Uniqueness (same year)  $\times$  Consistency on Brand Buzz.** This interaction effect is significantly positive ( $\beta = .011$ ,  $p < .05$ ). While the

signs of the main effects of *Uniqueness (prior year)* and *Uniqueness (same year)* on *Brand Buzz* are different, the signs of their interactions with *Consistency* is the same (cf. also Web Appendix B). The relation between *Consistency* and *Brand Buzz* is generally more positive if *Uniqueness* of ads is high. Figure 1 illustrates this interaction effect of *Uniqueness (same year)*  $\times$  *Consistency*.

Generally, the best-performing ads in terms of *Brand Buzz* show high *Uniqueness* versus prior-year ads, low *Uniqueness* versus same-year ads, and high *Consistency* scores. However, the interaction plot provides a more nuanced insight. For *Uniqueness (same year)*  $\times$  *Consistency*, the strong positive effect of *Consistency* (dashed line) is mitigated if the same-year *Uniqueness* is low (solid line). While the combination of high *Uniqueness (same year)* and low *Consistency* is a less effective combination, brands can still increase *Brand Buzz* although *Consistency* is low when the ad's *Uniqueness (same year)* is also low.<sup>7</sup>

**Robustness Analyses.** In order to rule out that our findings are driven by variations in the model specifications, we tested a variety of alternative models.

First, we tested whether the effects heavily depend on the set of control variables. Web Appendix C reports the findings for the full set of control variables. The results remain stable.

Second, we report in Web Appendix D the results for the different similarity scores. In addition to the regression coefficients and their 95% confidence intervals, we also report the robustness coefficient (Neumayer and Plümper 2017), which is a measure of the overlap between the confidence intervals of the baseline model using the Jaccard metric and the confidence intervals of each of the alternative similarity measures. Web Appendix D explains technical details: Figure D1 shows how the robustness coefficient is defined, and Figure D2 visualizes the results of the robustness analysis. The average robustness coefficients are above .8. The robustness of findings therefore finds support.

Third, we test two alternative outcome measures (see Web Appendix E). The aggregated *Brand Buzz (Volume)* score is calculated as the sum of positive votes and the sum of negative votes divided by the sum of positive, negative, and neutral votes. Then, we combined the *Buzz (Valence)* and *Buzz (Volume)* into a single variable *Buzz (Valence\*Volume)* which measures whether valence changes coincide with high or low volume changes in buzz.<sup>8</sup> For *Buzz (Volume)*, the results are partially similar to the *Buzz (Valence)*

model (Table E1 in Web Appendix E); as for *Uniqueness (vs. prior year)* and *Consistency* the effect replicates, but for *Uniqueness (vs. same year)* and the interaction effects the effects do not replicate. However, for *Buzz (Valence\*Volume)*, the results are very similar to the *Buzz (Valence)* model, and all reported effects replicate (Table E2 in Web Appendix E).

## Discussion

Despite its importance in marketing, understanding and measuring advertising creativity remains challenging. Recent reports highlight that marketers are increasingly growing skeptical of advertising creativity (Parsons 2019). One of the factors that may be responsible for this skepticism is disagreement over how creativity should be measured (Smith, Chen, and Yang 2008). In addition, research assessing the impact of creativity on brand outcomes is limited (Rosengren et al. 2020). The present paper contributes to the literature by devising a method to objectively measure and estimate the separate and interactive effects of two central components of creativity, uniqueness and consistency, on *Brand Buzz*.

By documenting these effects using a large sample of advertisements, our findings provide evidence of the value of this method. In particular, we offer an explanation for why some advertisements create buzz while others do not. This method can be applied to other areas of research involving uniqueness and consistency (e.g., music or other cultural items) and extended to include even more nuanced advertising execution variables (e.g., different types of humor, visual language).

Our results confirm that uniqueness and consistency are important aspects of creativity that lead to buzz, but they also suggest that creating advertisements that lead to buzz is more complex than simply balancing the tradeoff of running ads that are high in uniqueness relative to other ads, yet consistent from year to year. We find that the uniqueness of an ad is positively associated with buzz but that this only applies to uniqueness in comparison to ads from past years. We also find that uniqueness relative to same-year ads hurts *Brand Buzz*. While this effect seems surprising at first, we believe that there is an explanation. Consistent with prior research, this effect arises because consumers need time to process new information on uniqueness and are more likely to evaluate uniqueness relative to the collective of ads they have seen in the past, as opposed to a small set of ads to



which they have just been exposed. For consistency, our results are more intuitive. Within-brand consistency enhances buzz, although not to the same extent as uniqueness. A consistent message eases processing relative to an existing brand schema and leads to more buzz. Our measurement approach also showed that the *Uniqueness*  $\times$  *Consistency* interaction has an especially strong relationship with *Brand Buzz*.

Our method provides important insights for decision-makers. A key finding is that uniqueness and consistency are more highly correlated with buzz than any of the individual advertising content variables. Thus, our findings suggest that managers are well advised to employ Super Bowl ads that are unique from general patterns of execution used by advertisers in past years yet consistent with past ads for the brand. More broadly, these findings suggest that ads in all contexts are likely to be more effective if they are unique from earlier ads for all brands but also consistent with ads for the same brand from prior periods. A final managerial implication of this research concerns situations in which managers have to reposition a brand, potentially forcing lower consistency of the brand message from one year to the next. In such situations, managers should exercise caution and avoid creating ads that are also unique. One reason is that high inconsistency and high uniqueness exposes consumers to new cues, creating confusion and reducing their ability to decode the advertising message.

Consistent with rhetorical theory, our results clarify that the selection, arrangement, and delivery of the individual elements of persuasive communication need to be considered holistically. While the individual elements may be important in their own right, it is the gestalt that serves to make advertising consistent and unique. In other words, it is not the presence of any particular element but whether the element and what it is combined with are unique and consistent. For example, using a cat is not the critical executional decision; it is whether and in what way the cat is used that makes an ad unique and/or consistent. Moreover, even if the use of a cat leads to a unique combination of executional elements, it is also important to consider whether the use of this element is consistent with the brand's past advertising. Thus, being creative but consistent with the brand's heritage is well advised.

An especially useful contribution of the method developed in this paper is that it provides a means for measuring the relative uniqueness and consistency of alternative advertising executions. Such a measure

could provide creatives with a way to gauge degrees of uniqueness and consistency and relate such differences to the relative effectiveness of alternative advertising executions.

Most importantly, our findings have methodological implications for future research in advertising and beyond. Our approach provides researchers (and advertisers) with objective and concise measures that (1) can be easily applied to calculate uniqueness and consistency scores, (2) are related to ad effectiveness, and (3) are independent of the effects of any specific content features (e.g., humor, type of spokesperson). More generally, the approach provides a method for identifying and examining the arrangement and delivery of the individual elements of an advertisement that are associated with persuasion. Advertisers still need to be vigilant about the selection of specific advertising elements and trust their creative instincts. Our method provides a support tool to base these decisions to some extent on more generalizable, data-driven insight.

This approach is useful in measuring the uniqueness and consistency of archival data. Survey instruments to measure the uniqueness or consistency of ads that have been aired years ago cannot work due to confounds caused by temporal effects. Our content-coding approach makes archival data accessible for analyses and provides a reliable and replicable instrument to compare characteristics of stimuli over time. Given the availability of large online workforces that can code content at comparatively little cost (Kuhn and Maleki 2017), this approach has large potential for further applications.

## Notes

1. <http://admeter.usatoday.com/>
2. An advertiser often selects a content feature, such as humor, not to specifically increase/decrease uniqueness but because this feature may have favorable direct effects on the buzz metrics. Accordingly, the model would provide biased estimates for the focal regression coefficients if the content variables were not accounted for. However, we also report the results for the models without any control variables (we thank an anonymous reviewer for this suggestion).
3. We thank an anonymous reviewer for this suggestion.
4. We also estimated a model with the interaction *Uniqueness (prior year)*  $\times$  *Consistency*. However, we cannot include both interaction terms into the same model simultaneously due to multicollinearity. The correlation of the regression coefficients of the interaction effects is above .8 and would therefore not allow for separate interpretation of the interaction effects. We therefore focus the interaction effect *Uniqueness (same year)*  $\times$  *Consistency* which produces a better model fit in terms of higher  $R^2$ . Beyond the interaction effect *Uniqueness (same year)*  $\times$  *Consistency*,

Web Appendices B to E report also the detailed results and robustness checks for the interaction effect. Findings are largely consistent.

5. Web Appendix B reports the results for interaction *Uniqueness (prior year) × Consistency*
6. We also tested for nonlinearity of effects but did not find robust evidence of u-shaped or curvilinear effects.
7. Web Appendix B shows the findings for the interaction *Uniqueness (prior year) × Consistency*. Although the interaction effect is also positive, its interpretation is slightly different because of the reversed main effect of *Uniqueness (prior year)*.
8. We thank an anonymous reviewer for this suggestion.

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