Dynamic Effects of Ad Content on Ad Liking:
A Novel Study of 100 Ad Creatives

By

Edlira Shehu*
Associate Professor of Marketing
Department of Marketing
Copenhagen Business School
Solbjerg Plads 3
2000 Frederiksberg, Denmark
Email: es.marktg@cbs.dk

Daniel Zantedeschi
Assistant Professor of Marketing
Fisher College of Business and Translational Data Analytics
The Ohio State University
536 Fisher Hall, 2100 Neil Ave
Columbus, OH 43210
Email: zantedeschi.1@osu.edu

Prasad A. Naik
Professor of Marketing
Graduate School of Management
University of California Davis
One Shields Avenue
3314 Gallagher Hall
Davis, CA 95616
Email: panaik@ucdavis.edu

*Corresponding author

To understand how video ad content drives likeability, some market research companies collect moment-to-moment reactions of consumers towards ads. Previous studies investigated the effects of an ad's creative elements using moment-to-moment data but ignored analyzing it at the scene-by-scene level. Such analyses proceeded in two steps: in the first step, a few salient features from moment-to-moment liking (e.g., start, end, peak, trough, trend, duration) are selected and, in the second step, a cross-sectional regression model estimated their effects on outcomes such as overall liking (Baumgartner, Sujan and Padgett 1997) or purchase intent (Teixeira, Picard, and Kaliouby, 2014). The two steps can also be combined, e.g., via functional data analysis (Hui, Meyvis, and Assael, 2014). Yet, these analyses remain inherently *cross-sectional*, relying on the variation across multiple ads to estimate the effects.

Consequently, copywriters do not get diagnostic information to edit the specific scenes of *a single video ad*. In other words, because previous studies analyze a sample of multiple ads to estimate ad content effects, they cannot recommend diagnostics to edit the focal video ad. Furthermore, a specific scene may be disliked due to multiple characteristics of the scene itself, and so copywriters need to know what it is about that scene that they need to edit. Thus, the extant approaches do not offer diagnostic information on specific scenes of a single video ad or which of the ad's characteristics are associated with the low liking.

Extant approaches cannot yield such diagnostic information because scenes and liking evolve at unequal frequencies. The standard time series analysis requires observations to arrive at the same frequency. In contrast, to conduct a scene-by-scene analysis requires an approach that tackles *asynchronous* time series. Ghysels, Sinko and Valkanov (2007) proposed the mixed data sampling approach to analyzing the impact of fast-moving x-variables (e.g., weekly inflation) on slow-moving y-variables (e.g., quarterly gross domestic product). However, our empirical situation is reverse: regressors (scenes) evolve slower than the outcome (liking). The absence of a method to analyze such time series has impeded the progress in estimating asynchronous scene effects on ad liking.

In this research, we develop a general method to analyze multiple asynchronous time series, which accommodates multiple dependent variables and multiple regressors with either same or unequal frequencies. We apply the proposed method to 100 video ads and conduct a meta-analysis to discover findings that generalize across five different industry sectors.

The empirical results show that the dramatic impact of 60-second ads dwells in the persistence of the flow of liking. Furthermore, the heterogeneity in content effects relates to the narrative elements of plot structures. Indeed, the commonly used plot structure "stick-to-one theme" is not the only way to build and carryover liking for ads. Regarding content dimensions, the impact of entertainment, relevance, or warmth on liking can be either positive or negative for a given creative. In fact, the results suggest that warm, stimulating or familiar ads can be *hazardous* in building liking. Marketing managers can use the proposed method to estimate ad specific magnitude, direction, and significance of the content effects without being contaminated, as in the extant approaches, by the presence of other ads in the estimation sample.

References

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