On the determination of the own and competitive effects of different platforms and content on market shares

Annamaria Tuan
University of Bologna
Daniele Dalli
University of Pisa
Peter S.H. Leeflang
University of Groningen
Yuri Peers
Vrije Universiteit Amsterdam

Cite as:
Tuan Annamaria, Dalli Daniele, Leeflang Peter S.H., Peers Yuri (2022), On the determination of the own and competitive effects of different platforms and content on market shares. *Proceedings of the European Marketing Academy*, 51st, (106766)

Paper from the 51st Annual EMAC Conference, Budapest, May 24-27, 2022

On the determination of the own and competitive effects of different platforms and content on market shares

Abstract

Although the attention of academic literature about the relationship between social media and brand sales has grown, literature is still lacking analyses on competitive effects amongst brands. Additionally, effects of firm-generated content (FGC) is often generalized to the volume of posts, which combines the effects of different types of content and use of different platforms. We adopte a differential effects Market Share Attraction (MSA) model to capture different effects across brands allowing also for different effects across two social media platforms. We use a unique dataset covering 4 yoghurt brands in the Italian market spanning over 3 years, for which we focus on the social media posts of the brands (i.e., FGC) on both Twitter and Facebook, while controlling for the engagement (i.e., user-generated content derived from FGC) these posts create, as well as for traditional marketing-mix variables. We extend this analysis by looking at differences in effectiveness based on the type of content of the post (Informational, Emotional, and Activating), and consider whether effectiveness changed over time by employing a Dynamic Linear Model version of the MSA. Our preliminary findings indicate that different brands use different strategies over time and that the content of the message might influence the effectiveness in terms of market shares.

Keywords*: firm generated content, brand sales, brand competition*

Track*: Digital Marketing & Social Media*

1. Introduction

Social media are pervasive in the marketing communication realm. During the last years, the analysis on the impact of social media on firm performance and consumer behavior has received considerable attention by both academics and practitioners. In particular, previous studies have analyzed the impact of firm generated content (FGC) on consumer engagement metrics such as brand post popularity (e.g., De Vries et al., 2012; Dhaoui and Webster, 2021) and consumers' sentiment (Meire et al., 2019) as well as on performance outcome metrics such as brand sales (Cheng et al., 2021; Kumar et al., 2017) and real-time stock market (Lacka et al. 2021). Although the attention for the effects of social media on brand sales has grown (see Table 1), there are still some gaps that need to be addressed.

First, almost no prior research has considered the effects of competitive activities on social media and brand sales. A notable exception is by Sanchez et al. (2021) who analyze competitive spillover effects of eWOM on brand sales between two brands on Twitter.

Second, the impact of FGC on brand sales has been analyzed in the literature mainly from a volume perspective, i.e., frequency of brand posts, or valence perspective (e.g., Kumar et al., 2016; Unnava & Aravindakshan, 2021). The impact of the type of content of the social media posts on brand sales has been only recently analyzed. For instance, Kanuri et al. (2018) analyze the impact of high arousal emotional content versus cognitive processing content on gross advertising profits; Cheng et al. (2021) disentangle the effect of informative and emotional FGC posts on movie ticket sales. However, these studies focus on one brand or industry in general. Analyzing the content of FGC and the spillover effects across competitors is critical to effectively design content which can have a positive impact on own brand sales and which can also negatively affect competitors' brand sales (Berger et al., 2020; Chapman, 2019; Unnava and Aravindakshan, 2021).

Third, most of the studies have mainly focused on single platforms (e.g., Facebook or Twitter) with a notable and recent exception of Unnava & Aravindakshan (2021). These authors have analyzed the spillover effects across platforms finding that brand posts in one platform impact engagement not only within the same platform but also on other platforms in the firm's portfolio. This, however, does not show how different platforms could lead to different performance for a brand, and whether different platforms have different fit regarding posts' content.

By drawing on this background, our study aims to fill these gaps by analyzing a dataset covering 13 brands in 3 FMCG categories (yoghurt, milk, snacks) and a time span of three years. In particular, we model the effects of FGC on different platforms accounting for the kind of content that is communicated and determining the differential effects of different platforms on market shares of competitive brands. In so doing, we also account for the impact of consumer engagement as well as for dynamic effects on market share. In this abstract we will discuss the outcomes of one of the three categories ,viz. yoghurt.

Table 1: Overview of our study compared to related studies

Study	Market Competition	Multiple Social Media Platforms	Type of content	Impact on consumer engagement	Impact on Brand Sales
Cheng et al. (2021)			✓	✓	✓
Colicev et al. (2019)				✓	
Colicev et al. (2018)		✓		✓	
Dhauoi & Webster (2020)		✓		✓	
De Vries et al.(2012)		✓		✓	V
Kanuri et al. (2018)			✓	✓	
Kumar et al. (2016)				✓	
Kumar V. t al. (2016)				✓	✓
Lacka et al. (2021)			✓		
Meire et al. (2019)			✓	✓	
Sanchez et al. (2020)	✓		✓	✓	✓
Srinivasan et al. (2016)				✓	✓
Tellis et al. (2019)			✓	✓	
Unnava & Aravindakshan (2021)		✓		✓	✓
This study	✓	✓	✓	✓	✓

2. Data

In the yoghurt category we consider 4 brands where brand 1 is the leading brand and brands 2 and 3 are the followers having a smaller market share, brand 4 is an even smaller, but growing brand in the market. The weekly data, provided by Nielsen Italy, cover the weeks from January 2015 to September 2018. Table 2 gives an overview of the variables that are used in our study.

We use variables that measure FGC content through Facebook and Twitter posts. These are obtained by a manual content analysis technique where we follow the coding schemes which are used in FGC content analysis (e.g., De Vries et al. 2012; Taecharungroj, 2017). Three coders, instructed by the authors, have manually coded the content of tweets and posts and categorized them into three dummy variables: informative, emotional and activating. Cohen's kappa scores ranging from 0.90 to 0.95, indicate a high level of inter-coder reliability.

UGC is defined in the literature as brand-related content created by users (Tirunillai & Tellis, 2012) and it includes users' posts on the brand's wall; engagement with brand posts by liking, sharing and commenting; as well as user-created stories about the brand (Colicev et al., 2019). In this paper we consider UGC as only those activities which are induced by FGC and represent the number of likes, shares, and comments related to a post (i.e., consumer engagement). In section 3.1 we give some additional details on how we operationalize the different variables related to social media posts.

Table 2: Overview of Variables

Variable	Description
MS_{it}	Market share of brand i in week t
$StockFGC_{it}^{FB}$	Stock of firm generated posts on Facebook of brand i in week t
$StockFGC_{it}^{TW}$	Stock of firm generated posts on Twitter of brand i in week t
$StockUGC_{it}^{FB}$	Stock of consumer engagement to brand posts on Facebook of brand i in week t
$StockUGC_{it}^{TW}$	Stock of consumer engagement to brand posts on Twitter of brand i in week t
$Price_{it}$	The price of brand i in week t
$StockADV_{it}$	Stock of traditional advertising expenditures of brand i in week t
$Distr_{it}$	Number of distribution outlets carrying brand i
$FracInfo_{it}^{FB}$	Fraction of stock of posts on Facebook of brand i in week t that have informative content
$FracEmo_{it}^{FB}$	Fraction of stock of posts on Facebook of brand i in week t that have emotional content
$FracAct_{it}^{FB}$	Fraction of stock of posts on Facebook of brand i in week t that have activating content
$FracInfo_{it}^{TW}$	Fraction of stock of posts on Twitter of brand i in week t that have informative content
$FracEmo_{it}^{TW}$	Fraction of stock of posts on Twitter of brand i in week t that have emotional content
$FracAct_{it}^{TW}$	Fraction of stock of posts on Twitter of brand i in week t that have activating content
$TrendControl_{it}$	Trend controls, including a linear time trend and seasonal dummies

3. Model

We specify a Market Share Attraction (MSA) model to obtain results. In particular we use the base-level approach to estimate the MSA to account for the logical-consistency requirement of the market shares (Fok, Franses, and Paap 2002), meaning we have one equation less than the number of brands, and take one brand that is used as base level in each equation. Furthermore, we use the differential effects version of the MSA (e.g., Datta et al. 2017), which allows for brand specific elasticities, but puts restrictions on the variation of cross-elasticities. In a first analysis, we use a hierarchical structure on the individual brand parameters, which still allows for heterogeneity across brands, but shrinks the individual effects to a common hyper parameter. This hyper parameter can be seen as a balance between a pooled MSA model and the differential effects model.

We then extend these models in multiple ways. First, we remove the hierarchical structure, allowing for more heterogeneity across brands. Second, we include time-varying parameters by means of a DHLM approach (Gamerman and Migon 1993, Neelemaghan and Chintagunta 2004, Peers et al 2017). The latter allows us to find common time trend in the social media effectiveness per platform. An additional advantage of the DHLM approach is that it allows us to *later* add time-varying covariates in the second-stage equations (Peers et al. 2017).

3.1. Variable operationalization. Our dependent variable is the market share of a brand compared to that of the base brand, where we first take the logarithms of the market shares.

The key independent variables are firm generated content (FGC) of both Facebook and Twitter where we determine the values of these stock variables in the following manner:

$$StockFGC_{it}^{m} = FGC_{it}^{m} + \lambda \times StockFGC_{it-1}^{m}$$

With m, the platform that is used (Twitter or Facebook), and i the brand. For our first analysis we set the decay at 0.794, which has been found to have the most common half-life across categories (Fry et al. 1999).[1]

Our model also includes a variable for User Generated Content (UGC). In particular, we consider the engagement (i.e., likes, comments and shares) created by the FGC. Given the high collinearity between our FGC and UGC variable, we use the method by Batra et al. (2000), where we use an auxiliary regression of the log-transformed stock of UGC on the log-transformed stock of FGC, per brand and platform, and take the estimated residuals as variable for the additional effect of UGC "cleaned" for the activity in FGC.

Regarding the type of content, we consider the fraction of the stock in FGC that comes from each type of content. By considering the stock, rather than the actual posts, our share measures are more robust to weeks not having a certain content type.

For the variable *Traditional Advertising*, we create a stock variable to capture the dynamics of this variable. After creating the stock of *Traditional Advertising* we take the logarithm. Finally, we control for the *Price* (log-transformed) and *Distribution* of the brands.

3.2. Model specification.

The model starts with the Attraction:

$$(1) \qquad MS_{\mathrm{it}} = \frac{\mathrm{A_{it}}}{\sum_{\mathrm{i=1}}^{\mathrm{I}} \mathrm{A_{it}}}$$

where A_{it} is the attraction of brand *I* in week t:

$$(2) \qquad A_{it} = f(StockFGC_{it}^{FB}, StockFGC_{it}^{TW}, StockUGC_{it}^{FB}, StockUGC_{it}^{TW}, Price_{it}, StockADV_{it}, Distr_{it}, FracInfo_{it}^{FB}, FracEmo_{it}^{FB}, FracAct_{it}^{FB}, FracInfo_{it}^{TW}, FracEmo_{it}^{TW}, FracAct_{it}^{TW}, TrendControl_{it}, MS_{it-1})$$

As said, we use the differential effects MSA with base-platform approach to account for the logical-consistency requirement of the market shares (Fok, Franses, and Paap, 2002). This procedure allows us to estimate parameters for the focal brand (brand *i*) and base brand (brand *I*). This leads to the specification of Equation (3):

---

[1] In future analyses we are going to employ a grid search to find the optimal decay factor per variable.

(3) $\ln(MS_{it}) - \ln(MS_{It}) = \mu_i^* + \beta_{1it} \times StockFGC_{it}^{FB} - \beta_{1It} \times StockFGC_{It}^{FB} + \beta_{2it} \times StockFGC_{it}^{TW} - \beta_{2It} \times StockFGC_{It}^{TW} + \beta_{3it} \times StockUGC_{it}^{FB} - \beta_{3It} \times StockUGC_{It}^{FB} + \beta_{4it} \times StockUGC_{it}^{TW} - \beta_{4It} \times StockUGC_{It}^{TW} + \beta_{5i} \times \ln(Price_{it}) - \beta_{5I} \times \ln(Price_{It}) + \beta_{6i} \times StockAdv_{it} - \beta_{6I} \times StockAdv_{it} + \beta_{7i} \times \ln(Distr_{it}) - \beta_{7I} \times \ln(Distr_{It}) + \beta_{8i} \times FracInfo_{it}^{FB} - \beta_{8I} \times FracInfo_{It}^{FB} + \beta_{9i} \times FracEmo_{it}^{FB} - \beta_{9I} \times FracEmo_{It}^{FB} + \beta_{10i} \times FracAct_{it}^{FB} - \beta_{10I} \times FracAct_{It}^{FB} + \beta_{11i} \times FracInfo_{it}^{TW} - \beta_{11I} \times FracInfo_{It}^{TW} + \beta_{12i} \times FracEmo_{it}^{TW} - \beta_{12I} \times FracEmo_{It}^{TW} + \beta_{13i} \times FracAct_{it}^{TW} - \beta_{13I} \times FracAct_{It}^{TW} + \gamma_i \times \ln(MS_{it-1}) - \gamma_I \times \ln(MS_{It-1}) + \sum_{k=1}^{K} \alpha_{ki} \times TrendControls_{it} + \varepsilon_{it}^*$,

To overcome the lack of lags for other variables, we do include lagged attraction in our model. This partial adjustment specification in the MSA is a parsimonious way to include general carry-over effects. Because we can't include the lagged attraction directly, we include the lagged market share as proxy (Fok et al. 2002). The error term of a MSA represents the difference between the error of the focal and base brand. We allow for a covariance structure between equations of the category. The brand-specific intercepts (μ_i^*) capture time-invariant unobserved effects on market shares and indicate that the relative baseline market share is the difference between the focal and base brand. In the first analysis we shrink the brand specific estimates to a common hyper parameters per variable. The general notation for the equation allowing for this hierarchical structure is:

(4) $\beta_i = \bar{\beta} + \nu_i$

We initially consider three versions of the model based on equations (3) and (4). First, the model with partial adjustment, but without content variables. Second, the same model but without partial adjustment. Finally, a model with partial adjustment and the content variables.

In the first extension of this model, we allow for heterogeneity between brands, and do not use the hierarchical structure. Second, we allow for time variation in the FGC estimates. Note, that in equation (3) we already added a subscript *t* to the FGC variables, which we ignore in the first analysis, so estimates are similar to the other variables only differing across brands. For this extension we however estimate the time-varying estimates using a DHLM structure. The DHLM structure is the same for each time-varying parameter.[2]

(5) $\beta_{mit}^{p} = \beta_{mt}^{p} + \nu_{mit}^{p}$ (6) $\beta_{mt}^{p} = \beta_{mt-1}^{p} + \omega_{mt}$

With p = {FB or TW} and m is FCG or UGC. So, in total there are four (2 x 2) time-varying parameters per brand, which we shrink to four common time-varying parameters in equation (6). Equation (5) is called a mapping function with transfer function.

[2] We now consider only a common pattern, but the DHLM allows us to later add time-varying covariates in equation 5 (Peers et al. 2017), such as the content type variables.

4. Preliminary Results

First, we present results of a model which are pooled over all brands of the category which allows for some heterogeneity across brands. All our models, in this and subsequent results are estimated with Bayesian estimation.

Table 3: Results of the MSA models with pooled estimates over brands

	Model 1	Model 2	Model 3
Price	-0.96 ***	-1.16 ***	-0.97 ***
Distribution	1.39 ***	1.74 **	1.28 **
Lag MS	0.33 ***		0.28 ***
Advertising	0.00	-0.01	0.00
FGC FB	0.06	0.09 *	0.06
FGC TW	-0.02	-0.02	0.00
UGC FB	0.00	0.00	-0.01
UGC TW	-0.02	-0.03	-0.02
Share Inf FB			-0.06
Share Emo FB			0.02
Share Act FB			-0.08
Share Inf TW			-0.21 *
Share Emo TW			-0.04
Share Act TW			-0.11

Results suggest that there is no effect of *Traditional Advertising* in all the three models. Given that we are investigating a mature market for Fast Moving Consumer Goods (FMGC) this might be a plausible explanation. We also find no effect of UGC or FGC on Twitter and a marginal significant effect of FGC on Facebook only in Model 2. In Model 3, by adding the content variables, results do not change substantially. It could be that the insignificant effects are a result of shrinking the individual brand effects (e.g., for one brand the FGC has positive and the other negative effects). In order to account for these brand differences we focus on the differential effects MSA model ; see where we do not pool the data over the four brands. Table 4. Model 1 is the basic model without content variables. Model 2 includes content variables.

It is interesting to observe that *Traditional advertising* does not add, and in some cases even hurts the brand in gaining market share. A smaller brand such as Brand 4 has more direct benefit of building Adstock, whereas for the brand leader (Brand 1) it is possible that the category effect of its advertising is larger than its individual gain. So given that other brands might gain more of the increased attention for the category as a whole, the advertising effectiveness of the leaders can be negative. Given this result, it is interesting to see how the social media affect the brands' market shares. We observe that especially the brand followers (i.e., Brand 2 and Brand 3) gain from the FGC on Facebook. Twitter on the other hand is less effective, reporting also negative signs. Interestingly, the effect of engagement (i.e., UGC controlled for amount of FGC posts) is mixed across brands suggesting a positive or negative effect for the different brands for both platforms.

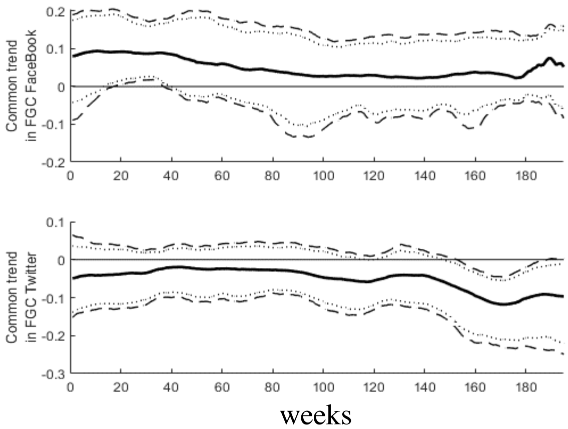
Table 4: Results Differential Effects MSA without pooling equations

		Model 1	Model 2			Model 1	Model 2
Price	Brand 1	-1.17***	-1.18***	**SHARE INF FB**	Brand 1		0.00
	Brand 2	-0.98***	-1.08***		Brand 2		-0.06
	Brand 3	-0.73***	-0.85***		Brand 3		0.12
	Brand 4	-1.09***	-1.30***		Brand 4		-0.50***
Distribution	Brand 1	1.71***	1.68***	**SHARE EMO FB**	Brand 1		-0.01
	Brand 2	0.00	0.32		Brand 2		-0.13
	Brand 3	1.49***	1.32***		Brand 3		0.46***
	Brand 4	1.60***	2.24***		Brand 4		-0.14
Lag MS	Brand 1	0.31***	0.23***	**SHARE ACT FB**	Brand 1		0.01
	Brand 2	0.23*	0.08		Brand 2		-0.09
	Brand 3	0.52***	0.29***		Brand 3		-0.06
	Brand 4	0.19***	0.08		Brand 4		-0.40**
Advertising	Brand 1	-0.02***	-0.02***	**SHARE INFO TW**	Brand 1		0.04
	Brand 2	-0.01	-0.01		Brand 2		-0.13
	Brand 3	-0.01	0.01		Brand 3		-0.46***
	Brand 4	0.02***	0.02***		Brand 4		0.04
FGC FB	Brand 1	0.04***	0.02*	**SHARE EMO TW**	Brand 1		-0.03
	Brand 2	0.11***	0.19***		Brand 2		0.01
	Brand 3	0.11***	0.07**		Brand 3		-0.36***
	Brand 4	0.01	0.00		Brand 4		0.41**
FGC TW	Brand 1	0.00	0.00	**SHARE ACT TW**	Brand 1		-0.01
	Brand 2	-0.04***	-0.04***		Brand 2		-0.23*
	Brand 3	0.00	0.00		Brand 3		-0.25***
	Brand 4	-0.01	-0.01		Brand 4		0.36
UGC FB	Brand 1	-0.03***	-0.04***				
	Brand 2	-0.02**	-0.03***				
	Brand 3	0.02*	-0.01				
	Brand 4	0.03***	0.04***				
UGC TW	Brand 1	-0.02*	0.00				
	Brand 2	-0.07***	-0.06***				
	Brand 3	-0.01	-0.02				
	Brand 4	0.02***	0.02**				

Considering the type of content, Model 2 suggests that on Facebook, the *Emotional* content works well, especially for Brand3, whereas the *Activating* and *Informative* contents seem to have a detrimental effect for Brand4. On Twitter, Brand4 will benefit from using an *Emotional* or *Activating* content to enhance the market potential of the brand, suggesting that content needs to be tailored among different platforms even for the same brand. We also calculated Model3 (not mentioned in Table 4) which includes the type of content variables and the interaction of FGC and UGC with these type of content variables. However, the highly collinear set of variables in this model makes it less stable. In next stages of the project, we will use more advanced pooling methods to reduce these effects.

Finally, in order to check Time-Variation in FGC Dynamics we adopt the Dynamic Hierarchical Linear Model. Table 5 shows the development of the FGCs over time and the parameter estimates of this model. We find that in most weeks there is no significant effect of FGC. However, considering the pattern and the few weeks that have a significant effect, we can argue that in more recent years Twitter has moved from an ineffective to a potentially detrimental platform for brands. On the other hand Facebook started out significantly positive. In recent years, there seems to be a rise in effectiveness again.

Table 5: Results Dynamic Hierarchical Linear Model



	DHLM
Price	-1.34 ***
Distribution	1.70 ***
Lag MS	-0.01
Advertising	0.00
FGC FB	See figure
FGC TW	See figure
UGC FB	0.02
UGC TW	-0.07

5. Discussion and conclusion

In this study we analyze corporate communication strategies on different platforms finding that different brands use different strategies over time. We find that the content of the message might influence effectiveness, i.e. the degree to which weekly sales vary due to communication efforts. Preliminary results suggest that there is not a "way-to-go" strategy for brands on social media platforms. Twitter has no effect, and when looking over time might even move to a more detrimental effect. On the other hand, Facebook seems to have some effects for certain (types of) brands, and additionally after an initial positive effect seems to be increasing in effectiveness again, showing a potential learning effect of the media type.

In next stages of the study we are going to dive deeper into this time variation of the effectiveness. Additionally, we provide a closer look to content types, especially whether there are common patterns we can find across competing brands. Rather than the share itself, it could be that content type creates more or less engagement, and this engagement in turn can lead to a better performance. The latter, would require a more advanced operationalization of both content and engagement variables, one fruitful avenue for this operationalization is to consider the digital capabilities of brands in this process (e.g., Mu and Zhang 2021). Further, we will investigate the potential heterogeneity in cross-elasticities ,estimating a Fully Extended MSA model. Given the high collinearity of the independent variables in such a model, and the assumption that many (cross-)elasticities are insignificant, we employ advanced variable selection techniques to discover significant cross effects between platforms/brand combinations. Finally, we will also analyze the data of the other two categories (milk and snacks). Additional results and conclusions will be presented during the EMAC conference.

Selected References

Colicev, A., Kumar, A., & O'Connor, P. (2019). Modeling the relationship between firm and user generated content and the stages of the marketing funnel. *International Journal of Research in Marketing*, 36(1), 100–116.

De Vries, L., Gensler, S., & Leeflang, P. S. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing*, 26(2), 83-91.

Fok, D., Franses, P. H., & Paap, R. (2002). Econometric analysis of the market share attraction model. Emerald Group Publishing Limited.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R. & Kannan, P.K. (2016). From Social to Sale: The Effects of Firm-Generated Content in Social Media on Customer Behavior, *Journal of Marketing*, 80(1), 7–25.

Kumar, V., Choi, J.W.B. & Greene, M. (2017). Synergistic effects of social media and traditional marketing on brand sales: capturing the time-varying effects, *Journal of the Academy of Marketing Science*, 45(2), 268–288.

Lacka, E., Boyd, D. E., Ibikunle, G., & Kannan, P. K. (2021). Measuring the Real-Time Stock Market Impact of Firm-Generated Content. *Journal of Marketing*.

Leeflang, P.S.H., Wieringa, J.E., Bijmolt, T.H.A. & Pauwels, K.H. (2015), *Modeling Markets*, Springer Netherlands.

Meire, M., Hewett, K., Ballings, M. & Kumar, V. (2019), The Role of Marketer-Generated Content in Customer Engagement Marketing, J*ournal of Marketing,* 83(6), 21-42.

Mu, J., & Zhang, J. Z. (2021). Seller marketing capability, brand reputation, and consumer journeys on e-commerce platforms. *Journal of the Academy of Marketing Science,* 1-27.

Peers, Y., Van Heerde, H. J., & Dekimpe, M. G. (2017). Marketing budget allocation across countries: the role of international business cycles. *Marketing Science*, 36(5), 792-809.

Sanchez, J., Carmen A., & Haenlein M (2020). Competitive spillover elasticities of electronic word of mouth: an application to the soft drink industry. *Journal of the Academy of Marketing Science*. 48(2): 270-287.

Unnava, V., & Aravindakshan, A. (2020). How does consumer engagement evolve when brands post across multiple social media? *Journal of the Academy of Marketing Science,* 49.