Brand competition on social media: investigating direct and indirect effects of FGC on sales

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Abstract

We empirically estimate the direct and indirect effects of firm-generated content (FGC) on sales accounting for the effects of user-generated content (UGC), marketing mix, competitor strategies, and situational variables. This is the first study that employs FGC and UGC from multiple social media platforms in a competitive marketplace. We calibrate a VAR model with exogenous variables (VARX). The full dynamic VARX model accounts for interrelations, feedback effects, direct and indirect effects between three sets of variables: (1) traditional marketing mix, (2) multiple dimensions of UGC and (3) brand sales. We use a unique dataset covering 13 brands in 3 FMCG categories in the Italian market spanning over 3 years.

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

Track: *Digital Marketing & Social Media*

1. Introduction

A plethora of studies capture the effects of social media on firm performance and consumer behavior (see Lamberton and Stephen, 2016). However, as reported by the 2018 CMO Nielsen Report “marketers are still struggling to generate and prove sales results in an increasingly omnichannel world”. By reviewing the literature about the relationship between social media and sales, we emphasize four main gaps (see Table 1). First, extant research analyzes the effects of FGC on UGC or the effects of FGC on brand sales (e.g. Colicev, Malshe, Pauwels, and O'Connor, 2018; Kumar, Bezawada, Rishika, Janakiraman, and Kannan, 2016; Kumar, Choi, and Greene, 2017; Srinivasan, Rutz, and Pauwels, 2016). Scant literature integrates the two dimensions of FGC and UGC within the same study (e.g. De Vries, Gensler and Leeflang 2017) and take UGC as a potential mediator of the effect of FGC on brand sales. Second, extant research investigates the drivers of online social-sharing by analyzing which brand posts features influence consumer behavior (e.g. Barcelos, Dantas, and Sénécal, 2018; De Vries, Gensler, and Leeflang, 2012; Taecharungroj, 2017), but not if and how the content is related to brand sales. Third, studies usually analyze only one social media platform within the same study, Facebook or Twitter (e.g. Kumar et al., 2017). Companies are actually using more than one platform to communicate their activities and therefore it becomes important, both from a theoretical and managerial perspective, to investigate the drivers of message rebroadcasting behaviors across platforms (Balducci and Marinova, 2018). Finally, it is worth noting that extant literature does not focus on competitors’ reactions on social media and how competitors may influence companies’ communication online.

Our study aims to fill these gaps by analyzing a big dataset covering 13 brands in 3 FMCG categories and a time span of three years to disentangle direct, indirect and feedbacks effects between company, consumer, and market variables.

Study	Market Competition	Multiple Social Media Platforms	FGC	UGC	ROI Measure (Sales)
Meire et al. (2019)	✗	✗	✓	✓	✗
Tellis et al. (2019)	✗	✗	✓	✗	✗
Colicev et al. (2019)	✗	✗	✓	✓	✗
Colicev et al. (2018)	✗	✓	✓	✓	✗
De Vries et al. (2017)	✗	✓	✓	✓	✗
Kumar et al. (2016)	✗	✗	✓	✓	✗
Kumar V. et al. (2016)	✗	✗	✗	✓	✓
Srinivasan et al. (2016)	✗	✗	✓	✓	✓
This study	✓	✓	✓	✓	✓

Table 1. Literature review of main studies

2. Conceptual Framework

In this section, we present our conceptual framework (see Figure 1) that helps explain the direct, indirect and feedback effects of FGC on market outcomes.

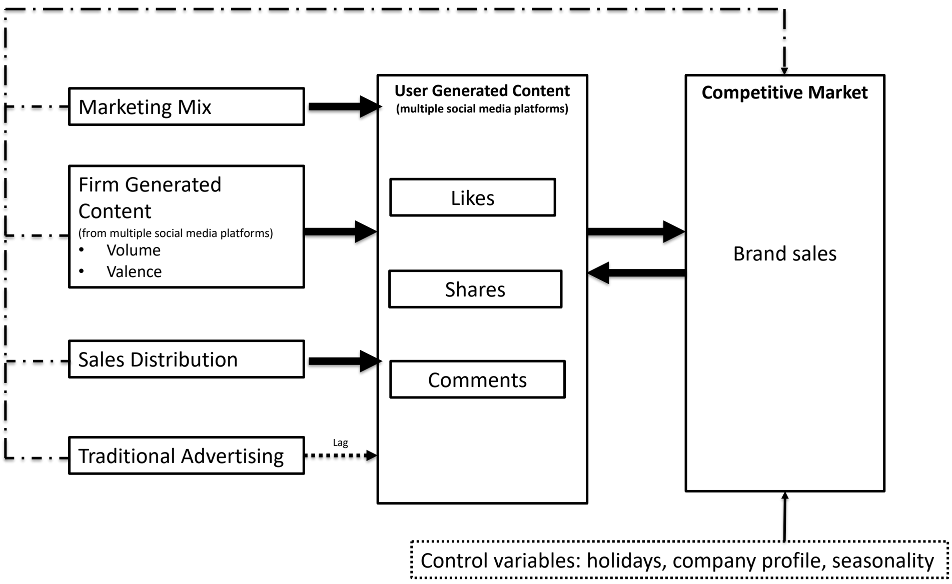

Figure 1. Conceptual framework

We focus on two platforms, namely Facebook and Twitter. Facebook and Twitter are intertwined with different types of content: *Firm Generated Content* (FGC), that is brand's communication created and shared through company online profiles, and *User Generated Content* (UGC), brand related content created and disseminated online by consumers (Colicev et al., 2018; Meire, Hewett, Ballings and Kumar, 2019; Srinivasan et al., 2016). FGC has been analyzed in the literature mainly from a volume perspective, i.e. frequency of brand posts (e.g. Kumar et al., 2016). Nevertheless, it is worth noting that the *type* of content (i.e. informative, emotional or persuasive) may influence consumers' reactions (Akpinar and Berger, 2017; Aleti, Pallant, Tuan and van Laer, 2019; De Vries et al., 2012) and purchase intentions (Barcelos et al., 2018; Meire et al., 2019). In addition, the richness of a brand post's formal features in terms of images and videos included in the post may influence the way consumers react to it (e.g. de Vries et al., 2012). Differently from extant literature that focuses on volume or valence (positive and negative sentiment), we also account for the actual content features of FGC. Analyzing the content of FGC helps to disentangle company's communication strategy and analyze which are more effective in terms of consumers' reaction both online (e.g. sharing) and offline (e.g. sales).

It is worth noting that on each social media platform, companies face competitors' communication and they have to react to them trying to gain attention from consumers, creating an "*online competitive arena*". Competitive reactions have been usually analyzed in the context of traditional marketing strategies (e.g. Horváth, Leeflang, Wieringa and Wittink 2005; Leeflang and Wittink, 2001; Steenkamp, Hijs, Hanssens, and Dekimpe, 2005). Yet no research has considered the effect of competitors' social media marketing strategies on market outcomes, as we illustrate in Table 1. In our conceptual framework we assume that all the relationships among variables are affected also by competitors' marketing strategies (both traditional and online) and consumers reactions which may affect focal company brand sales and competitors' brand sales.

By analyzing the interrelationships among variables, we advance various type of effects of FGC on market outcomes. Following recent studies, we argue that FGC will have a *direct* effect on brand sales (e.g. Kumar et al., 2016; Kumar et al., 2017; Srinivasan et al., 2016). However, differently from extant literature, we advance that FGC will also have an *indirect* effect on brand sales through UGC. The rationale behind this assumption is that the more consumers react and respond to FGC in terms of like, share and comments, the more consumer engagement is created which can ultimately affect brand evaluations (e.g. Chang and Li, 2019; Kumar et al., 2016) and impact actual consumer purchase behavior (Srinivasan, Vanhuele and Pauwels, 2010). Given that brand sales may have an effect on the consumer mind-set (Srinivasan et al., 2010, 2016), we also argue that it may translate in a positive feedback effect on UGC. Extant research emphasizes that consumers will spread word of mouth to communicate their experiences with their friends/relatives after purchasing the product which in turn stimulate consumer purchase and the retransmission of WOM (e.g. Baker, Donthu, & Kumar, 2016). Therefore, we assume that brand sales could also influence an increase in the number of consumers' likes, comments, shares on brand posts.

Although our primary focus in on the effect of FGC on the bottom line, we also supplement our framework by examining the role of traditional marketing mix strategies. Previous research has emphasized how distribution, price and promotion influence brand sales (Ataman, van Heerde and Mela, 2010; van Heerde, Leeflang and Wittink, 2004; Srinivasan et al., 2010). More recently, literature has started investigating how online media interact with traditional marketing mix strategies such as price, advertising and distribution and the impact on sales and consumer engagement (e.g. Srinivasan et al., 2016; Kumar et al. 2016; Kumar et al. 2017). Following these studies, in our framework, apart from the direct effects of traditional marketing strategies on brand sales, we examine the potential effects of promotional prices and distribution on UGC.

Finally, we also assume that traditional advertising will also affect UGC with a lagged effect. The link between traditional media and online WOM has received little coverage in the literature (Berger and Milkman, 2012; Hewett, Rand, Rust and van Heerde, 2016). As pointed out by Kumar et al. (2016) and is empirically confirmed by De Vries et al. (2017), traditional advertising and social media marketing serve as communication stimuli and create positive synergistic effects on consumers spending. In our conceptual framework we advance that traditional advertising may influence UGC not immediately after the exposure but after a short time period creating a recall effect on social media.

3. Data

The data cover relevant variables of 13 major national and international brands in 3 FMCG categories (yoghurt, milk, snacks) on the Italian market. The dataset spans for 196 weeks from January 2015 to September 2018, and are provided by Nielsen Italy. We have information on marketing mix, firm generated contents, and situational context. In detail, for each of these brands we have: Sales data operationalized as euro sales volume (i.e., €/week/brand); Brand's social media activities on Facebook and Twitter: post texts and the number of posts, shares, likes, and comments from the Facebook page, and the tweet texts and the number of tweets, retweets, and likes from the Twitter account (daily level); Traditional advertising expenditures (weekly level); Prices (weekly level); Weighted distribution, in-store communication (weekly level); situational context (holidays and seasons).

We have analyzed the content of FB and Twitter posts by using a manual content analysis technique following the coding scheme developed by reviewing the literature about FGC content analysis (e.g. De Vries et al. 2012; De Vries et al., 2017; Taecharungroj, 2017).

Content type	**Description**	**Measure**	**Label in the model**
Information-sharing content	Posts containing information about products/stores/campaign/brands	Dummy variable 0/1	InfoFBPost
Emotion-evoking content	Posts evoking positive emotions in followers, such as happiness, excitement, awe, serenity, peacefulness,	Dummy variable 0/1	EmoFBPost
Action-inducing content	Posts persuading followers to take a desired action, such as purchasing, participating, or registering.	Dummy variable 0/1	IntFBPost
Vividness	It reflects the richness of a brand post's formal features	Categorical variable (0=only text,1=images,2=videos)	VividFBPost

Table 2. Coding scheme

Three coders, instructed by the authors, have manually coded the content of tweets and posts. Cohen's kappa scores ranging from 0.90 to 0.95, indicating a high level of inter-coder reliability. We created two different price variables: price with support, $Price_{jt}^{S}$, and price without support, $Price_{jt}^{\bar{S}}$, for brand j at time t following Leeflang et al. (2015, p. 185). To this end we define a $PriceRatio_{jt}$, for brand j at time t as:

$$PriceRatio_{jt} = \frac{RegularPrice_{jt}}{MedianPrice_{jT}}, \tag{1}$$

where $MedianPrice_{jT}$ is the median price of brand j in quarter T. Subsequently, we operationalize price with and without support as:

$$\ln(PriceRatio_{jt}) = \begin{cases} Price_{jt}^{S} & \text{if } PriceRatio_{jt} \leq Price_{threshold} \\ Price_{jt}^{\bar{S}} & \text{if } PriceRatio_{jt} > Price_{threshold} \end{cases}. \tag{2}$$

$Price_{threshold}$ is an arbitrary number between 0 and 1. Based on historical patterns in many empirical studies of FMCG's, Leeflang, Wieringa, Bijmolt and Pauwels (2015) suggest this value to be greater than 0.8. We use grid search to arrive at the optimal value for this threshold.

Variable	Mean	SD	Variable	Mean	SD
Brand sales (million €/week)	1.02	1.01	Sales distribution (stores/week)	60.13	27.97
Facebook likes (#/week)	3116.89	4636.49	Informative Facebook post (#/week)	2.47	2.05
Facebook shares (#/week)	332.79	814.44	Emotional Facebook post (#/week)	1.03	1.18
Facebook comments (#/week)	46.54	68.32	Vivid Facebook post (#/week)	3.75	2.68
Twitter likes (#/week)	10.26	57.39	Interactive Facebook post (#/week)	1.11	1.42
Twitter shares (#/week)	9.44	66.83	Informative Twitter post (#/week)	0.78	2.27
Traditional advertising (1000€/week)	91.54	167.45	Emotional Twitter post (#/week)	2.82	9.09
Price (€/unit)	4.25	0.60	Vivid Twitter post (#/week)	2.03	5.69
Facebook posts (posts/week)	4.04	2.43	Interactive Twitter post (#/week)	0.69	1.98
Twitter posts (tweets/week)	4.01	10.66			

Table 3. Descriptive statistics

4. Model

Our modeling approach consists of two stages. In the first stage, we specify the dynamic relationship among the key variables pertaining to the firm, customer, and market responses. We account for the direct effect of FGC through a VARX Model:

$$
\begin{bmatrix} BrandSales_{jt} \\ FBLikes_{jt} \\ FBShares_{jt} \\ FBComments_{jt} \\ TWLikes_{jt} \\ TWShares_{jt} \\ TradAdv_{jt} \end{bmatrix} = \begin{bmatrix} \alpha_{BrandSales} \\ \alpha_{FBLikes} \\ \alpha_{FBShares} \\ \alpha_{FBComments} \\ \alpha_{TWLikes} \\ \alpha_{TWShares} \\ \alpha_{TradAdv} \end{bmatrix} + \begin{bmatrix} \beta_{1jj} & \beta_{2jj} & \beta_{1jc} & \beta_{2jc} \\ 0 & \beta_{3jj} & 0 & \beta_{3jc} \\ 0 & \beta_{4jj} & 0 & \beta_{4jc} \\ 0 & \beta_{5jj} & 0 & \beta_{5jc} \\ 0 & \beta_{6jj} & 0 & \beta_{6jc} \\ 0 & \beta_{7jj} & 0 & \beta_{7jc} \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Price^{S}_{jt} \\ Price^{\bar{S}}_{jt} \\ Price^{S}_{ct} \\ Price^{\bar{S}}_{ct} \end{bmatrix} + \begin{bmatrix} \phi_{1jj} & \phi_{1jc} & \varphi_{1jj} & \varphi_{1jc} \\ \phi_{2jj} & \phi_{2jc} & \varphi_{2jj} & \varphi_{2jc} \\ \phi_{3jj} & \phi_{3jc} & \varphi_{3jj} & \varphi_{3jc} \\ \phi_{4jj} & \phi_{4jc} & \varphi_{5jj} & \varphi_{4jc} \\ \phi_{5jj} & \phi_{5jc} & \varphi_{5jj} & \varphi_{5jc} \\ \phi_{6jj} & \phi_{6jc} & \varphi_{6jj} & \varphi_{6jc} \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} FBPost_{jt} \\ FBPost_{ct} \\ TWPost_{jt} \\ TWPost_{jc} \end{bmatrix} +
$$

$$
\begin{bmatrix} \lambda_{1jj} & \lambda_{1jc} \\ \lambda_{2jj} & \lambda_{2jc} \\ \lambda_{3jj} & \lambda_{3jc} \\ \lambda_{4jj} & \lambda_{4jc} \\ \lambda_{5jj} & \lambda_{5jc} \\ \lambda_{6jj} & \lambda_{6jc} \\ \lambda_{7jj} & \lambda_{7jc} \end{bmatrix} \begin{bmatrix} SalesDist_{jt} \\ SalesDist_{ct} \end{bmatrix} + \begin{bmatrix} \delta_{1jj} & \lambda_{1jc} \\ \delta_{2jj} & \delta_{2jc} \\ \delta_{3jj} & \delta_{3jc} \\ \delta_{4jj} & \delta_{4jc} \\ \delta_{5jj} & \delta_{5jc} \\ \delta_{6jj} & \delta_{6jc} \\ \delta_{7jj} & \delta_{7jc} \end{bmatrix} \begin{bmatrix} Holiday_{t} \\ Season_{t} \end{bmatrix} + \qquad (3)
$$

$$
\sum_{k=1}^{K} \left(\begin{bmatrix} \omega^{k}_{1,1} & \cdots & \omega^{k}_{1,7} \\ \omega^{k}_{2,1} & \cdots & \omega^{k}_{2,7} \\ \omega^{k}_{3,1} & \cdots & \omega^{k}_{3,7} \\ \omega^{k}_{4,1} & \cdots & \omega^{k}_{4,7} \\ \omega^{k}_{5,1} & \cdots & \omega^{k}_{5,7} \\ \omega^{k}_{6,1} & \cdots & \omega^{k}_{6,7} \\ \omega^{k}_{7,1} & \cdots & \omega^{k}_{7,7} \end{bmatrix} \begin{bmatrix} BrandSales_{jt-k} \\ FBLikes_{jt-k} \\ FBShares_{jt-k} \\ FBComments_{jt-k} \\ TWLikes_{jt-k} \\ TWShares_{jt-k} \\ TradAdv_{jt-k} \end{bmatrix} \right) + \begin{bmatrix} \epsilon_{BrandSales} \\ \epsilon_{FBLikes} \\ \epsilon_{FBShares} \\ \epsilon_{FBComments} \\ \epsilon_{TWLikes} \\ \epsilon_{TWShares} \\ \epsilon_{TradAdv} \end{bmatrix}
$$

In (3) t refers to time (in weeks), j is the focal brand, c is an index that represents all other competitor brands, K represents lag length. We use Akaike information criterion (AIC) to determine the optimal lag length, K. The 5×5 ω matrix represents the lagged k autoregressive and endogenous cross-variable lagged parameters. Contemporaneous effects are captured in the variance-covariance matrix of residuals, Σ. Tests for both endogeneity and stationarity allow us to specify a vector autoregressive model (VAR) with exogeneous variables (X).

In the second stage, we capture the moderating role of the content characteristics (informative, emotional, action inducing content, and vividness) on the responses to FGC. Thus, the estimated customer response parameters from the first stage modeling, are specified as a function of content characteristics of FGC. For example, the response parameters of focal firm's Facebook post on Facebook likes, ϕ_{2jl}, where $l = \begin{cases} j, \ own\ brand\ effect \\ c, \ cross\ brand\ effect \end{cases}$ is modeled as:

$$
\phi_{2jl} = \alpha_r + \eta_1 InfoFBPost + \eta_2 EmoFBPost + \eta_3 VividFBPost + \eta_4 IntFBPost + \xi_{jl} \qquad (4)
$$

where the right –hand variables are defined in Table 2. The error term is assumed to be normally-distributed $\xi_{jl} = N(0, \sigma^2)$. We follow Lewis and Linzer (2003) for estimating Equation(3), and account for the underlying uncertainty of the estimated coefficients by employing the weighted EGLS estimates.

5. Preliminary Results

Here we present preliminary results from one category and from one platform, i.e. Facebook, to illustrate the model we developed.

Results of the first stage analysis indicate that FGC has a direct effect on brand sales as well as on UGC (Likes, Shares and Comments). Interestingly, Competitors' FGC have a negative and significant effect on brand sales and UGC of the focal brand, suggesting that the more the competitor provides content on its social media platforms, the more it has a negative effect on the focal brand sales and consumers reactions online.

	Sales	Likes	Shares	Comments
Own FGC	0.0043*	0.2427***	0.1690**	0.1666*
Competitor FGC	-0.0016*	-0.1203*	-0.0440**	-0.0584***

***$p \leqslant 0.01$, **$p \leqslant 0.05$, *$p \leqslant 0.10$

Table 4. Direct effects of FGC on Sales and UGC

The second stage analysis allows us to focus the attention on the content, as shown in Table 5. Results suggest that action-inducing content negatively affect Likes, Shares and Comments, whereas information and emotional content have a positive impact on UGC. This result supports that a more emotional content is more effective in terms of consumer engagement, in line with previous research (e.g. Akpinar and Berger, 2017; Chang et al. 2019).

	Likes			Shares			Comments		
	Estimate	Std.error	t-value	Estimate	Std.error	t-value	Estimate	Std.error	t-value
(Intercept)	24.586	13.775	1.785	21.038	7.952	2.645	15.816	7.186	2.201
Posts	0.347	0.177	1.963	0.209	0.115	1.826	0.258	0.098	2.636
Vividness	-0.018	0.010	-1.752	-0.016	0.006	-2.623	-0.012	0.005	-2.260
Information	0.006	0.004	1.523	0.006	0.002	2.743	0.005	0.002	2.853
Emotion	0.061	0.034	1.779	0.054	0.020	2.728	0.041	0.017	2.333
Action	-0.184	0.102	-1.810	-0.159	0.058	-2.732	-0.120	0.052	-2.312

Table 5. Direct effect of FGC type of content on UGC

Finally, we found significant indirect effects of UGC on sales, with FGC as the main predictor ($p(z=0.0154)=0.01$).

Results for the full model with other brands and some generalizations and conclusions will be presented during the EMAC conference. We also will report feedback effects, the effects of traditional marketing variables, direct and indirect effects of FGC for multiple brands.

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