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What drives demand for content creator-generated product reviews, the product or the creator?

GÁBOR MURAI[1]

Product reviews produced by content creators are popular on social media and constitute an important source of brand information for consumers. Understanding the consumption of such content is, therefore, important for marketing scholars and practitioners interested in how consumers learn about brands.

This paper examines whether the demand for content creator-generated reviews is driven by the product reviewed, or by the content creator's personality. In order to study the underlying drivers behind the demand for reviews, hierarchical regressions were estimated using longitudinal data on video reviews of personal smart devices posted on YouTube. The results show that both the product and the content creator are significant drivers of demand. Up to now, the literature has not offered evidence supporting either of these approaches. We discuss the implications of this finding and draw conclusions for managers.

Keywords: product review, content creator, earned media, user-generated content, YouTube.

JEL codes: D83, M31.

Introduction

Consumers spend an increasing amount of time on social media, which makes it an ever more important source of product and brand information. Product-related content on social platforms can be classified as owned, paid and earned media, depending on whether the content is commissioned by or independent from the vendor of the product or brand featured in the content. In this paper, I focus on the latter group, the earned media.

A prominent stream of prior literature on earned media focused on user-generated reviews (UGR). Such content impacts sales (Chevalier–Mayzlin 2006; Babić Rosario et al. 2016; Moon–Kamakura 2017; Marchand et al. 2017), product evaluations (Langan et al. 2017), firm profit (Zhao et al. 2013; Wu et al. 2015), firm strategy (Chen–Xie 2005), firm value (Chen et al. 2012; Tellis–Johnson 2007), product choice (Kostyra et al. 2016) and can be used to extract information

[1] PhD candidate, University of Pécs, Faculty of Business and Economics, Department of Economics and Econometrics, e-mail: murai.gabor@ktk.pte.hu.

Publishers: Hungarian Economists' Society from Romania, Department of Economics and Business Administration in Hungarian Language at Babeş–Bolyai University, and the Partium Christian University
www.kozgazdaszforum.ro

about consumer preferences (Decker–Trusov 2010) and the brand's customer base (Moon–Kamakura 2017).

In recent years, another genre of earned media has been gaining in popularity among consumers, namely the reviews created by content creators. Content creators are commercial enterprises, usually individuals or small companies, producing product reviews which they publish on social media platforms. These product reviews are the topic of this study.

Thus, I define content creator-generated reviews (CCGR) as a genre of earned media characterised by the following features: the content of the CCGR is a review of a specific product, it is available to the public free of charge via an online social media platform and it is produced by a person or organisation producing multiple reviews. The creators of the reviews get financial incentives based on the size of the audience reading the review.

Despite the importance of understanding the CCGR for marketers, there is a gap in the literature examining the nature of this new phenomenon. The literature has not studied the demand for the CCGR. Therefore, in this paper, I study a fundamental aspect – the key drivers of demand for content creator-generated reviews: the product being reviewed and the content creator.

The paper is organised as follows: review of the literature on earned media and the possible drivers of demand for the CCGRs, model development, data, and results. It ends with the discussion of the results, their implications, the limitations of the study, and suggestions for future research.

Literature review

Content creator-generated reviews, on the one hand, can be considered earned media, as they are brand-focused content which is not generated by the brand vendor (Stephen–Galak 2012; Lovett–Staelin 2016; Colicev et al. 2018)[2]. This understanding of the phenomenon is in line with Huang et al.'s (2022) and Silaban et al.'s (2022) studies, showing that consumers' purchase intentions are impacted by the CCGRs on YouTube, which implies that there is a product information seeking motive behind the demand for reviews.

[2] A common argument regarding the independency of product reviews mentions that content creators often have sponsorship deals with brands. Given that, in these cases, product reviewers have to disclose that the content was sponsored, Pfeuffer et al. (2021) examined the effect of those disclosures and found that they did not have a significant impact on the attitudes towards the product, the brand, or the reviewer.

On the other hand, the fact that the review is devoted to a particular product does not imply that learning about the product is the sole reason behind the audience's interest in a given CCGR. It is possible that the demand for content creator-generated reviews is driven by other motivations. For instance, similarly to television, magazines or shows, the audience can look for entertainment (Haridakis–Hanson 2009; Khan 2017) or to connect with the content creator through parasocial interaction (McCracken 1989, Lee–Watkins 2016; Sokolova–Kefi 2020). While these studies do not focus on product reviews specifically, it is possible that these non-product related motivations are also what drives CCGR audiences. In conclusion, demand for the CCGR can be driven by product or/and non-product related motivations.

From the perspective of product information-related motives, content creator-generated reviews are similar to user-generated reviews such as those hosted by Amazon or Yelp examined by Chevalier–Mayzlin (2006), Babić Rosario et al. (2016), Zhao et al. (2013), Wu et al. (2015), Tirunillai–Tellis (2012) and Hu et al. (2012), or product reviews published by traditional media. These types of earned media can serve as a source of product information, highlighting the consumers' information-seeking motive to consume these media. More recently, Huang et al. (2022) and Silaban et al. (2022) also examined whether consumers' purchase intentions were affected by the CCGRs. They found a significant positive relationship, which further implicates that this motive could be present in the case of YouTube product reviews as well. The CCGRs are also related to news media as they provide news about the product in a fashion that resembles traditional news or magazine segments on a specific topic. The audience can have similar motivations to watch the news and the CCGR, stemming from their need to be informed (Lacy 1989) about a specific topic or to confirm their prior beliefs (Mullainathan–Shleifer 2005).

Individual reviews have been conceptualised as noisy product quality signals, and consumers have been shown to learn by attending to multiple such signals (Zhao et al. 2013; Wu et al. 2015). For example, in their study of book reviews, Zhao et al. (2013) show that consumers learn from the body of multiple UGRs more than from their direct product experiences, Wu et al. (2015) show that consumers learn from the UGRs about their restaurant preferences. In a similar vein, a collection of content creator-generated reviews can be conceptualised as a series of quality signals and can be expected to facilitate consumer learning.

Audience members seeking information about a specific product can select content, for example the CCGRs, based on such observable attributes as title or description.

Consumers' desire to learn about the product can drive the demand for content creator-generated reviews. However, the CCGRs are part of social media where consumers may want to read the content for other reasons than just learning about products. Indeed, Shao (2009) distinguishes between information, entertainment, and mood management needs among the consumers of social media content. He links these motivations with the features of social media environment such as interactivity, the creation of virtual communities, the ease of producing own content (e.g., comments) and sharing it, features which are absent from traditional media (Neuberger–Nuernbergk 2010) but are present in the case of the CCGR. Sokolova–Kefi (2020) observe that, on social media, the content is entertaining and that social attractiveness (including e.g., the entertainment value) is associated with parasocial interaction (i.e., fan-celebrity relationship). Examining consumers' purchase intentions and stickiness, Huang et al. (2022) and Silaban et al. (2022) show the presence of social and parasocial interactions between the audience and the content creator in the case of the CCGRs as well. This means that the previous findings on social motives could also apply to the CCGR domain.

Studies on the motivations of YouTube audiences found that, besides information seeking, video viewing is driven by the audience's need for entertainment (Haridakis–Hanson 2009; Khan 2017) and for social interaction (Haridakis–Hanson 2009). While these studies do not focus on product reviews specifically, it is possible that these non-product related motivations are also what drives CCGR audiences.

Over time, YouTube content creators have developed an idiosyncratic content style (Lee–Watkins 2016; Sokolova–Kefi 2020). Thus, the viewers are expected to choose the content based on the content creator's style to satisfy their non-product related needs, such as entertainment or social interaction.

In conclusion, the CCGR audience can have either one motivation or both types of motivations, interest in a product and/or non-product related motivations. The non-product related audience motivations are something that sets the CCGR apart from user-generated reviews. In the case of user-generated reviews, the audience has not been found to develop preferences for particular reviewers. For example, Banerjee et al. (2017) observed that the feature allowing the audience to follow Yelp reviewers is seldomly used.

Prior marketing literature has not studied the demand for earned media and the CCGR. However, the reviewed literature suggests that the demand for the CCGR can be driven by both the product being reviewed and the creator of the review. Building on these studies, the following hypotheses were formulated:

H1: The reviewed product has a significant impact on the CCGR viewership.

H2: The content creators' characteristics have a significant impact on the CCGR viewership.

In the next sections, the data collection procedure and the data are described. Then, the random effects regression model of the CCGR views is specified and will be used to verify whether the reviewed product and the content creator contribute to CCGR views.

Data

The data about the CCGR comes from YouTube. This platform is an important source of product information for consumers and a popular outlet for CCGR publication.

The study is focused on a specific product category, namely personal computing devices, including smartphones and smartwatches. This is a relevant product category for studying the CCGRs due to high consumer demand and creator supply for product reviews.

The goal was to sample the CCGRs devoted to a product category of interest and posted by YouTube channels specialising in creating CCGRs for the selected product category. To generate the sample, YouTube's channel search feature was utilised to identify YouTube creators in the CCGR space, focusing on personal computing devices in the English language. Then, a list of search phrases was constructed, each phrase comprising one term from each of the following two sets. The first set included product category terms (Technology, Tech, Smartphone, Phone, Smartwatch, etc.). The second set included terms related to the CCGR genre (Product Review, Unboxing, Review). Using these terms, an initial set of creators was identified. Table 1 presents the number of subscribers observed for the creators in this initial set. For this sample, small creators with less than 10 000 subscribers were eliminated.

Table 1. Frequency of observed subscriber count per content creator

Subscriber count	Number of channels
0 – 999	985
1 000 – 9 999	334
10 000 – 99 999	189
100 000 – 999 999	101
1 000 000 –	33

Note: The table includes the initial set of creators before filtering out the creators with less than 10 000 subscribers, who were not publishing in English language and/or did not post at least one video on a new product from the new product list.

Source: Own editing

Next, a list of new personal computing devices launched between 1 January 2020 and 1 October 2020 was sourced from a leading consumer information website, www.gsmarena.com, and the creators who had not published any videos about any of the products on the list were eliminated. Finally, the content of the resulting set of creators was reviewed and those not publishing in English were removed. The resulting number of creators included in the sample is 68.

Next, the videos of the creators included in the sample were examined and the videos which did not feature a product from the new personal computing product list or the videos devoted to more than one product were filtered out. The resulting database includes 696 videos.

The data has a panel structure. The time dimension includes 106 days and covers the period between 16 June 2020 and 1 October 2020. The cross section refers to the individual CCGR videos. These videos were launched at different points in time during the data collection period, hence the panel is unbalanced. The sample includes daily data on videos and their creators, including video views, video title, description, date of posting and number of subscribers to the video creator's channel. In total, our data includes 44 015 observations for the 696 videos.

Table 2 presents key descriptive statistics for the data sample. TotalViews refers to the number of views for a given video generated up to a specific day. This data is strongly left skewed with the 75th percentile (94 704 views) being smaller than the mean (150 980 views). The maximum value for the variable, 7 768 909, represents the total views of the most popular video in the sample. The average total views of sample videos is 951 125.5. This value was calculated as the average of TotalViews in the last period, N=696. The table reports values for all periods and N=44 015.

DailyViews is the number of views a video generates in a single day. Again, the data is strongly left skewed with a mean of 1 484 views, being substantially larger than the 75th percentile (399 views).

CreatorSubscribersVolume refers to the number of viewers who have subscribed to creator channels on YouTube. The data is again left skewed with the mean and the 75th percentile having comparable values of 1 424 399 and 1 230 000, respectively.

Table 2. Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
TotalViews	44 015	150 980	493 003	21	4 743	94 704	7 768 909
DailyViews	41 670	1 484	21 880	-10 112	10	399	2 641 000
Creator-Subscribers-Volume	8 320	1 424 399	2 816 021	16 300	184 000	1 230 000	17 200 000

Note: The minimum observed value for DailyViews is negative. This is most likely due to YouTube filtering out the views which they deem illegitimate (Google Help).

Source: Own editing

Model development

The main goal of the analysis is to examine whether the product and the creator are significant drivers of CCGR views. The random effects model of daily video views is described below and will be used to answer these questions.

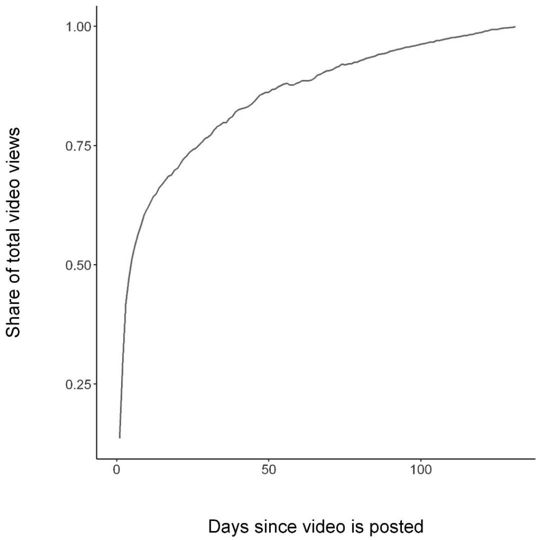
Control variables

Before the focal variables are discussed, several other variables are introduced to control for sources of time and cross-sectional variation in the video views data.

Video age

The literature on the evolution of online content popularity documents a 'burst' and 'slow' evolution path (Figueiredo et al. 2014; Li et al. 2016) whereby consumption of the content bursts right after publication, and then it slows down.

Indeed, in the collected data, the CCGRs accumulate views at a decreasing rate after posting, and the rate of decrease in views is dropping (Figure 1). On average, the first third of total views is accumulated in 3 days, the second third in 9 days, and 90% of them in 68 days.



Note: To produce the figure, the cumulative daily views for each video in our sample was calculated and divided by the total views of that video at the end of the sample period. Then, the resulting values were averaged across all sample videos.

Source: Own editing

Figure 1. Cumulative video views per day

To control for this dynamic, a parsimonious approach is taken, resulting in a continuous function. Two terms are introduced, $STVideoAge_{it}$ and $LTVideoAge_{it}$, representing the video age at short (ST) and long (LT) term for video *i* at time *t*, to capture the initial, fast, and subsequent, slow accumulation of views. Model fit comparison is used to select the day after the CCGR publication in which the switch between $STVideoAge_{it}$ and $LTVideoAge_{it}$ takes place.

$STVideoAge_{it}$ and $LTVideoAge_{it}$ are defined as follows:

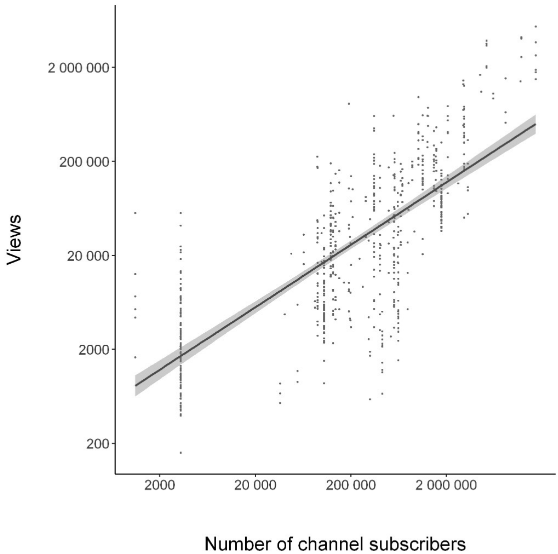
$$STVideoAge_{it} = \begin{cases} VideoAge_{it} & \text{if } VideoAge_{it} < \gamma \\ \gamma & \text{if } VideoAge_{it} \geq \gamma \end{cases}$$
$$LTVideoAge_{it} = \begin{cases} \gamma & \text{if } VideoAge_{it} < \gamma \\ VideoAge_{it} & \text{if } VideoAge_{it} \geq \gamma \end{cases} \qquad (1)$$

where γ is the number of days after video *i* is published.

Given the assumed nonlinear nature of the variable, logarithmic transformations of the VideoAge variables are also taken while representing them in the regression.

Channel Subscribers Volume

Prior studies have shown that channel size is positively associated with viewership of the videos (Welbourne–Grant 2016; Hoiles et al. 2017). In the data, the CCGR views are positively correlated with the number of subscribers to the YouTube channel posting them (Figure 2).



Note: The line is fitted using OLS and the grey area indicates the standard error. The figure illustrates a positive correlation between channel subscribers and the number of views its videos attract (Correlation: 0.744).

Source: Own editing

Figure 2. Video views and the number of subscribers to the channel posting it

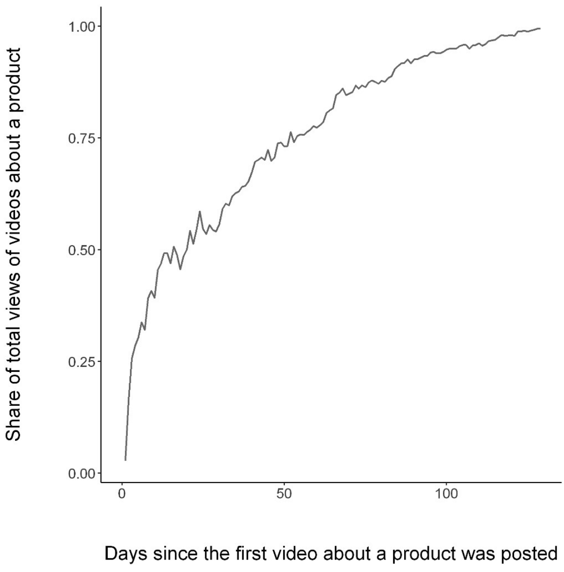
Thus, channels with more subscribers are expected to attain more views on average, and this relationship is expected to be nonlinear. This effect will be captured by the variable $ln\ Subscribers_{jt}$, denoting the natural logarithm of channel j's subscriber count at time t.

Weekend effect

The potential weekend effect is also controlled. However, there is not a clear expectation of which direction this effect will lean. Consumers may spend more time watching YouTube during weekends due to more leisure time available, however, they can also tend to spend weekends away from YouTube and/or the CCGRs. $Weekend_t$ variable is included to capture this effect.

Product Age

It has been observed that, on social media, the audience's attention to content can be short-lived (Zadeh–Sharda 2014). In the data, the views of the CCGRs about a given product display a similar pattern as the views of a single video over time, albeit the decrease in views per unit of time is smaller (Figure 3).



To generate the values represented in the figure, daily views for all videos about a given product are summed. Then, cumulative daily views are computed and divided by the cumulative daily views at the end of the sample period, i.e., total cumulative daily views. Finally, the resulting values were averaged across the sample products.

Source: Own editing

Figure 3. Views of reviews of a product per day

On average, the first third of total review views for a product is accumulated in 5 days, the second third in 34 days, and 90% of them in 84 days. Given its nonlinear nature, the variation in product interest over time is modelled with *ln* $ProductAge_{kt}$ variable, denoting the natural logarithm of product *k*'s age at time *t*.

Focal variables

The literature review discussed the possible motives why the audience watches the CCGRs and distinguished between product information and non-product related motivations.

Featured Product

To gauge the product interest-driven demand for the CCGRs, the Featured Product variable is introduced. This variable will capture the temporarily fixed demand for the CCGRs associated with each of the sample products. Thus, it will verify whether the products featured in the CCGRs are an important driver of viewership. Such evidence would be consistent with the notion that consumers watch the CCGRs to learn about products.

In addition, combining the Featured Product with the Product Age described above, the topic popularity over time is modelled, showing the level of popularity for a given product and the speed at which this level decreases over time.

CCGR creator

To model the non-product related demand for the CCGRs, the CCGR Creator variable is introduced. It captures the time-invariant demand for the CCGRs made by a specific creator. The variable will provide evidence of creators' idiosyncratic characteristics drawing audiences to their content. This finding would set the CCGRs apart from user-generated reviews.

Using the control and focal variables listed above, the following regression model is specified:

$$\begin{gathered} ln\ DailyViews_{it} = \beta_{0jk} + \beta_1\ ln\ STVideoAge_{it} + \beta_2\ ln\ LTVideoAge_{it} + \\ + \beta_3\ ln\ CreatorSubscribersVolume_{jt} + \beta_4\ Weekend_t + \beta_5\ ln\ ProductAge_{kt} + \varepsilon_{it} \end{gathered} \tag{2}$$

where $ln\ DailyViews_{it}$ is the dependent variable denoting the natural logarithm of the number of views of the CCGR *i* at time *t* and $\beta_{0jk} = (\beta_{00} + \beta_{0j} + \beta_{0k})$.

$\beta_{00}, \beta_{0j}, \beta_{0k}, \beta_x$ *where* $x = \overline{1, 7}$, γ are parameters. Parameters *where* $x = \overline{1, 7}$, *and* γ are estimated. Parameters β_{0j}, β_{0k} are assumed to be normally distributed across *K* sample products and *J* sample creators respectively, having a zero mean and σ_{0j}, σ_{0k} variance.

$$\beta_{0j} \sim N(0, \sigma_{0j}^2)\ ;\ \beta_{ok} \sim N(0, \sigma_{0k}^2)$$

where σ_{0j}^2 and σ_{0k}^2 are estimated parameters.

The parameters of control variables include $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$. The parameters which are focal to our study include $\beta_{0j}, \beta_{ok}, \gamma, \sigma^2_{0j}$ and σ^2_{0k}.

β_{ok} shows the distribution of the featured products' effect on the daily views of the videos. Parameter σ^2_{0k} shows the variance of this effect. An estimate of this coefficient that is greater than zero would imply that the products featured in the CCGRs are an important driver of viewership and will be consistent with the notion that consumers watch the CCGRs to learn about products.

β_{oj} shows the distribution of the creators' effect on the daily views of the videos. Parameter σ^2_{0j} shows the variance of this effect. An estimate greater than zero would imply that the creators of the CCGRs are a significant driver of demand for the CCGRs. This would be consistent with the notion that the CCGR demand is driven not only by the audience's product interest but also by other more entertainment-related motivations.

Results

Table 3 presents the results from the dynamic, random effects regression model presented in Eq. 2. Since most of the variables have log-log specifications in the model, these parameters can be interpreted as elasticities.

Model fit

The proposed model as well as several other setups are estimated for model selection and robustness checks. First, to test the random effect model selection, a Hausman test was conducted against the fixed effects model. Given the p-value of 0.08444, the test shows that the random effects model should be preferred.

Then, several models are estimated for robustness checks. The robustness check models progressively exclude variables. Robustness check 1 excludes product heterogeneity, robustness check 2 removes channel heterogeneity and finally, robustness check 3 includes one slope coefficient (instead of two) accounting for video age.

As evidenced by the Log-likelihood, AIC and BIC, the proposed model fits the data significantly better than the robustness check models, even when accounting for the larger number of parameters it includes.

Results for control variables

Video age

The video age is expected to be negatively associated with daily views. Based on prior literature (Figueiredo et al. 2014; Li et al. 2016), the slope of the video age effect is also expected to be different in the short term and the long term.

Therefore, the video age variable is split into two variables: *ln* $STVideoAge_{kt}$ and *ln* $LTVideoAge_{kt}$. In order to determine the value for the split parameter between long term and short term, the model fit along various γ values is examined. The best fit can be found with splitting the video age at 8 days after posting.

β_1, the coefficient for the short-term effect, is -0.528 (p-value < .01), while β_2, the coefficient for the long-term effect, is -0.022 (p-value < .01). As expected, both coefficients are significantly negative.

This finding means that the daily video views of the CCGRs reach the highest level right after video publication and fall sharply up to day 8. After day 8, the daily views still decrease but at a rate which is an order of magnitude slower than before day 8.

Our estimates imply that, on average, CCGR views drop on the first day and on the seventh day since publication by 30% and 8%, respectively. In the second week since publication, the drops in daily views decrease between 2.5% and 1.4% each day.

To test if two separate coefficients are needed for video age, fit of robustness check model 4 (RCM4) and robustness check model 3 (RCM3) are compared. Both models are the same, except RCM3 includes two Video Age variables and it estimates a separate slope coefficient for each of them. The fit of RCM4 is much worse than the fit of RCM 3 validating our approach to modelling video age.

Subscription volume

The number of viewers subscribed to the creator channel was expected to be positively associated with CCGR views. Indeed, the estimate of β_3 is 0.031 (p-value < .01). This coefficient value implies that, on average, a 1% increase in subscribed audience is associated with 0.031% more views for each of the channel's CCGRs every day.

Weekend

The difference in CCGR view numbers between weekends and weekdays are found to be not significant. As a robustness check, a model with day dummies instead of a weekend dummy was tested, but the differences between weekdays were also insignificant.

Product Age

Product Age refers to the time since the posting of the first CCGR about a particular product. β_5, coefficient of $ProductAge_{it}$ is not significantly different from zero. Apparently $ProductAge_{it}$ has no effect on CCGR views once other variables are accounted for.

Table 3. Regression results

	Dependent variable			
	ln DailyViews			
		Robustness checks		
	Main model	(1)	(2)	(3)
Constant	10.193***	10.206***	10.246***	9.333***
	(0.040)	(0.034)	(0.019)	(0.011)
ln ST VideoAge	-0.531***	-0.541***	-0.530***	
	(0.007)	(0.007)	(0.008)	
ln LT VideoAge	-0.021***	-0.023***	-0.030***	
	(0.001)	(0.001)	(0.001)	
ln VideoAge *(Unsplit)*				-0.093***
				(0.001)
Weekend	0.001	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
ln CreatorSubscribersVolume	0.031***	0.036***	0.023***	0.024***
	(0.002)	(0.002)	(0.0004)	(0.0004)
ln ProductAge	-0.014***	-0.031***	-0.010***	0.004
	(0.002)	(0.002)	(0.002)	(0.002)
SD Across Channels	0.1503 ***	0.1485 ***		
SD Across Products	0.1456 ***			
Log Likelihood	14 676.66	13 695.84	8 346.51	6 386.32
Akaike Inf. Crit.	-29 335.33	-27 375.69	-16 679.02	-12 760.63
Bayesian Inf. Crit.	-29 257.59	-27 306.00	-16 618.56	-12 708.81

Note: *p<0.1; **p<0.05; ***p<0.01

Source: Own editing

Results for focal variables

Product intercept

Product intercepts as random coefficients β_{0k} were specified and their variance σ^2_{0k} was estimated. The estimate of $\sigma^2_{0k} = 0.1456$ (p-value < .01), supporting the notion that the product featured in a CCGR is a significant determinant of CCGR views.

The coefficient value indicates that, ceteris paribus, the standard deviation of daily CCGR views across products is about 14.56%. To illustrate the effect size of σ^2_{0k}, the cumulative views per video are computed in the first two weeks since posting for the 25th and the 75th percentiles of the distribution of β_{0k}. The reviews of products in the 25th percentile of β_{0k}, gather, on average, 56 589 views in two weeks, while the reviews of products in the fourth quantile gather, on average, 2 217 863 views in two weeks, which is a very sizable difference. Given the significance of the product intercept, I accept Hypothesis 1. The product reviewed in the video has a significant impact on the viewership of the videos.

Creator intercept

Creator intercepts as random coefficients were specified and their variance σ^2_{0j} was estimated. The estimate of $\sigma^2_{0j} = 0.1503$ (p-value < .01) indicates that the CCGRs of different creators are not homogenous for the audience.

The estimate of the coefficient suggests that, ceteris paribus, the videos posted by different creators generate daily views which are over 15.03% apart. The magnitude of σ^2_{0j} can be gleaned from the view numbers corresponding to two examples of values showing the distribution of β_{0j}. On average, the reviews of creators from the 25th percentile and the 75th percentile of the distribution of β_{0j} gathered 209 267 and 1 869 586 views, respectively, over the two-week period. This result shows major differences in popularity for the content posted by different creators. Given the significance of the creator intercept, I accept Hypothesis 2. The creator of the video has a significant impact on the viewership of the product review.

Based on the variance in product and creator intercepts, it can be concluded that both content creators and products reviewed are important drivers of CCGR views, and that standard deviation parameters representing differences between content creators and differences between products have similar values.

Conclusions

The growth of social media is accompanied by the increasing importance of earned media. In recent years, a new genre of earned media has emerged on social media platforms, namely the content creator-generated reviews (CCGR). One of the most important contributions of this study is that it offers the first empirical research on this type of media, an already prominent, yet still growing phenomenon, with high relevance to marketing. Prior literature on earned media focused primarily on user-generated content, including the UGR. The phenomena of user-, and content creator-generated reviews are different from one another in several important ways. Most importantly, the generation of the CCGR, in contrast to the UGR, is a profit-seeking enterprise. Moreover, content creators vs. users tend to produce more content, more regularly, and invest more resources per review. This can allow creators to develop a relationship with the audience. Taken together, these differences translate into a different set of incentives underlying the UGR and the CCGR. In this study, I focus on a fundamental aspect of demand for the CCGRs. I seek to establish whether CCGR views are driven by the product being reviewed and by the creator of the review. Based on prior literature, the CCGRs can be conceptualised not only as a source of consumer learning about products but also as an entertainment product. Up to now, the literature has not offered evidence supporting either of these approaches.

I found that the demand for content creator-generated reviews is driven by both the product being reviewed and the creator of the review. This finding has important implications for marketers and content creators.

The finding that the reviewed product featured in a CCGR is a significant driver of its audience size is fundamentally important, because it establishes a clear link between the CCGR and consumers' demand for product information. A prominent stream of research on earned media focuses on the link between earned media and sales (e.g., Chevalier–Mayzlin 2006; Babić Rosario et al. 2016; Moon–Kamakura 2017; Marchand et al. 2017) or purchase intention (Chen–Dermawan 2020; Huang et al. 2022; Silaban et al. 2022; Weinlich–Semerádová 2022). These studies laid the foundation for this field of knowledge by documenting its relevance to marketing. However, these studies did not examine consumers' information consumption , a process which can be expected to mediate the impact of earned media on sales. This study provides evidence regarding earned media consumption, thereby shedding light on what, based on experimental data (Kostyra et al. 2016), appears to be a causal link between earned media and brand sales.

I also found that CCGR views depend on the creator of the review, underscoring the importance of creators and their characteristics. This finding is consistent with prior survey research (Shao 2009) on YouTube audiences, listing non-product information-related audience motivations like entertainment and mood management. In terms of the relationship between the source and the recipient of the message, the CCGRs turn out to be similar to word-of-mouth (WOM) and celebrity endorsements (CE) but different from user-generated reviews (UGR). In the case of WOM and CE, the source-recipient relationship is a core driver of recipient's trust and message transmission efficacy. On the other hand, the literature on the UGR has not reported message recipients developing relationships with the message source. Instead, audiences have been found to rely on hosting platform credentials such as reviewer badges when forming beliefs about reviewer credibility (e.g., Zhu et al. 2014; Langan et al. 2017).

The finding that both the reviewed product and the creator are significant drivers of the demand for the CCGR implies that audiences approach a review with a pre-existing interest in a particular product but are also attracted by specific content creators. This finding, while intuitive, captures the essence of the CCGRs. Marketers eager to maximise sales by venturing to influence content creators or blur the lines between the paid medium of influencer marketing and the earned medium of the CCGR can damage the pillars on which the CCGR seem to rely, namely the relationship between the audience and the creators. This notion is consistent with the findings of Gerrath–Usrey (2021) that reviews by bloggers which are incentivised by brands can harm reviewer's credibility and authenticity.

Finally, an additional novel aspect of the study is the focus on a "visual" social network, i.e., YouTube. Prior research has mostly focused on text-based social networks, such as Twitter. Meanwhile, in recent years, visual social networks, such as TikTok, Instagram and YouTube, have been growing in prominence (Babić Rosario et al. 2020).

Limitations and future research

This study has several limitations that set the stage for new research. First, the data is aggregated across consumers, which allows us to include a broad set of creators, products, and a long sample period. However, it does not look at the video-watching histories and click streams of individual audience members. While individual data on what people watch on YouTube is not in the public domain, future research should seek to access such data to produce a more granular picture of demand drivers for the CCGRs. Second, the data does not include information about the (YouTube) platform behaviour, in particular, the platform's content choices. Such choices are driven by the platform's recommender system. Future research should seek to include additional data capturing the key aspects of the platform's behaviour in order to shed light on how CCGR demand drivers emerge from an interaction of viewer preferences, social interaction and platform behaviour. Third, prior research explored the direct link between the properties of earned media, such as the valence of the UGR, and sales, while this study documents that the demand for earned media can also be associated with other motives than product interest. Altogether, this implies that the relationship between earned media consumption and sales is complex, hence, future research should study earned media, information consumption and sales jointly.

References

Babić Rosario, A.–de Valck, K.–Sotgiu, F. 2020. Conceptualizing the electronic word-of-mouth process: What we know and need to know about eWOM creation, exposure, and evaluation. *Journal of the Academy of Marketing Science* 48(3), 422–448.

Babić Rosario, A.–Sotgiu, F.–De Valck, K.–Bijmolt, T. H. 2016. The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research* 53(3), 297–318.

Banerjee, S.–Bhattacharyya, S.–Bose, I. 2017. Whose online reviews to trust? Understanding reviewer trustworthiness and its impact on business. *Decision Support Systems* 96, 17–26.

Chen, J. L.–Dermawan, A. 2020. The influence of YouTube beauty vloggers on Indonesian consumers' purchase intention of local cosmetic products. *International Journal of Business and Management* 15(5), 100–116.

Chen, Y.–Liu, Y.–Zhang, J. 2012. When do third-party product reviews affect firm value and what can firms do? The case of media critics and professional movie reviews. *Journal of Marketing* 76(2), 116–134.

Chen, Y.–Xie, J. 2005. Third-party product review and firm marketing strategy. *Marketing Science* 24(2), 218–240.

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.

Colicev, A.–Malshe, A.–Pauwels, K.–O'Connor, P. 2018. Improving consumer mindset metrics and shareholder value through social media: The different roles of owned and earned media. *Journal of Marketing* 82(1), 37–56.

Decker, R.–Trusov, M. 2010. Estimating aggregate consumer preferences from online product reviews. *International Journal of Research in Marketing* 27(4), 293–307.

Figueiredo, F.–Almeida, J. M.–Gonçalves, M. A.–Benevenuto, F. 2014. On the dynamics of social media popularity: A YouTube case study. *ACM Transactions on Internet Technology (TOIT)* 14(4), 1–23.

Gerrath, M. H.–Usrey, B. 2021. The impact of influencer motives and commonness perceptions on follower reactions toward incentivized reviews. *International Journal of Research in Marketing* 38(3), 531–548.

Google Help, https://support.google.com/youtube/answer/3399767?hl=en, downloaded: 09.02.2022.

Haridakis, P.–Hanson, G. 2009. Social interaction and co-viewing with YouTube: Blending mass communication reception and social connection. *Journal of Broadcasting & Electronic Media* 53(2), 317–335.

Hoiles, W.–Aprem, A.–Krishnamurthy, V. 2017. Engagement and popularity dynamics of YouTube videos and sensitivity to meta-data. *IEEE Transactions on Knowledge and Data Engineering* 29(7), 1426–1437.

Hu, N.–Bose, I.–Koh, N. S.–Liu, L. 2012. Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems* 52(3), 674–684.

Huang, T. Y.–Chen, W. K.–Chen, C. W.–Silalahi, A. D. K. 2022. Understanding how product reviews on YouTube affect consumers' purchase behaviors in Indonesia: an exploration using the stimulus-organism-response paradigm. *Human Behavior and Emerging Technologies* 2022, 1–19.

Khan, M. L. 2017. Social media engagement: What motivates user participation and consumption on YouTube? *Computers in Human Behavior* 66, 236–247.

Kostyra, D. S.–Reiner, J.–Natter, M.–Klapper, D. 2016. Decomposing the effects of online customer reviews on brand, price, and product attributes. *International Journal of Research in Marketing* 33(1), 11–26.

Lacy, S. 1989. A model of demand for news: Impact of competition on newspaper content. *Journalism Quarterly* 66(1), 40–48.

Langan, R.–Besharat, A.–Varki, S. 2017. The effect of review valence and variance on product evaluations: An examination of intrinsic and extrinsic cues. *International Journal of Research in Marketing* 34(2), 414–429.

Lee, J. E.–Watkins, B. 2016. YouTube vloggers' influence on consumer luxury brand perceptions and intentions. *Journal of Business Research* 69(12), 5753–5760.

Li, C.–Liu, J.–Ouyang, S. 2016. Characterizing and predicting the popularity of online videos. *IEEE Access* 4, 1630–1641.

Lovett, M. J.–Staelin, R. 2016. The role of paid, earned, and owned media in building entertainment brands: Reminding, informing, and enhancing enjoyment. *Marketing Science* 35(1), 142–157.

Marchand, A.–Hennig-Thurau, T.–Wiertz, C. 2017. Not all digital word of mouth is created equal: Understanding the respective impact of consumer reviews and microblogs on new product success. *International Journal of Research in Marketing* 34(2), 336–354.

McCracken, G. 1989. Who is the Celebrity Endorser? Cultural Foundations of the Endorsement Process. *Journal of Consumer Research* 16(3), 310–321.

Moon, S.–Kamakura, W. A. 2017. A picture is worth a thousand words: Translating product reviews into a product positioning map. *International Journal of Research in Marketing* 34(1), 265–285.

Mullainathan, S.–Shleifer, A. 2005. The market for news. *American Economic Review* 95(4), 1031–1053.

Neuberger, C.–Nuernbergk, C. 2010. Competition, complementarity or integration? The relationship between professional and participatory media. *Journalism Practice* 4(3), 319–332.

Pfeuffer, A.–Lu, X.–Zhang, Y.–Huh, J. (2021). The effect of sponsorship disclosure in YouTube product reviews. *Journal of Current Issues & Research in Advertising* 42(4), 391–410.

Shao, G. 2009. Understanding the appeal of user-generated media: a uses and gratification perspective. *Internet Research* 19(1), 7–25.

Silaban, P. H.–Silalahi, A. D. K.–Octoyuda, E.–Sitanggang, Y. K.–Hutabarat, L.–Sitorus, A. I. S. (2022). Understanding hedonic and utilitarian responses to product reviews on YouTube and purchase intention. *Cogent Business & Management* 9(1), 2062910.

Sokolova, K.–Kefi, H. 2020. Instagram and YouTube bloggers promote it, why should I buy? How credibility and parasocial interaction influence purchase intentions. *Journal of Retailing and Consumer Services* 53(C).

Stephen, A. T.–Galak, J. 2012. The effects of traditional and social earned media on sales: A study of a microlending marketplace. *Journal of Marketing Research* 49(5), 624–639.

Tellis, G.–Johnson, J. 2007. The Value of Quality. *Marketing Science* 26(6), 758–773.

Tirunillai, S.–Tellis, G. J. 2012. Does chatter really matter? Dynamics of user-generated content and stock performance. *Marketing Science* 31(2), 198–215.

Weinlich, P.–Semerádová, T. (2022). Product Endorsement by Opinion Leaders: The Case of YouTube Community. In *Achieving Business Competitiveness in a Digital Environment* 207–239. Cham: Springer.

Welbourne, D. J.–Grant, W. J. 2016. Science communication on YouTube: Factors that affect channel and video popularity. *Public understanding of science* 25(6), 706–718.

Wu, C.–Che, H.–Chan, T. Y.–Lu, X. 2015. The economic value of online reviews. *Marketing Science* 34(5), 739–754.

Zadeh, A. H.–Sharda, R. 2014. Modeling brand post popularity dynamics in online social networks. *Decision Support Systems* 65, 59–68.

Zhao, Y.–Yang, S.–Narayan, V.–Zhao, Y. 2013. Modeling consumer learning from online product reviews. *Marketing Science* 32(1), 153–169.

Zhu, L.–Yin, G.–He, W. 2014. Is this opinion leader's review useful? Peripheral cues for online review helpfulness. *Journal of Electronic Commerce Research* 15(4), 267–280.