Modeling of the evolution of third-party product reviewer market on YouTube

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Abstract
In recent years, we could observe a boom in the number of reviewers and influencers in the product reviewer market. The number of participants on the supply side of the product reviewer market is an important factor for both firms and consumers as few participants could control the narrative around the product. The rise in the number of reviewers could signify that the market is heading in the opposite direction, towards perfect competition. In contrast, the product reviewer market is a unique type of earned media for firms because the reviewers have profit incentives to provide information about the firms' products. The underlying financial drivers incentivize the reviewer to differentiate their content and accumulate market power for long-term benefits, indicating a market structure that goes towards a monopolistic competition. Thus, we aimed to explore the current trends in the market of tech product reviews on YouTube by investigating the drivers behind the growth of the reviewers. We found evidence that big channels grow faster, implying a multiplicative growth process for the participants. In addition, our models suggest that the growth of the channels has a strong positive connection with the average revealed valence towards their content.

Keywords: product review, earned media, YouTube

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1. Introduction

The role of product-related information is crucial in case of consumer uncertainty that is present on the market due to the consumers’ lack of sufficient knowledge about the quality of a given product or service (OREN – SCHWARTZ, 1988; ROBERTS – URBAN, 1988; ERDEM – KEANE, 1996; IYENGAR et al., 2007; NARAYANAN – MANCHANDA, 2009; ZHAO et al., 2013). Third-party or expert reviews have a unique place in the available product-related information sources for consumers. The supply in this market is not (only) driven by the desire to inform or increase purchase intention but the direct revenue of providing these reviews. Thus, the suppliers’ profit incentives could influence the consumers’ learning process about the products. Given the impact of product-related information on consumers’ purchase intention, firms need to understand their earned media, which includes the third-party reviewer market. This market has undergone a substantial evolution since the offline era. Professional reviews were distributed by printed media first, then TV and radio stations started to have segments dedicated to these professionals.

The consequence of expert reviews being published or broadcasted in an offline medium was that becoming a professional reviewer had high entry costs. It was not a profession that anyone can immediately start to pursue. This barrier has changed with the internet. While some offline media, containing expert reviews, launched an online extension or fully moved to an online format, the most significant difference was that now everyone could become a professional reviewer by creating websites or blogs dedicated to reviewing typically one or just a couple of product categories.

The professional review market has developed even further in the recent decade with the widespread usage of social media and organized online attention platforms, such as YouTube (SMITH, 2020). These websites essentially give a shared platform for the demand and supply of information to meet each other. This means that it is easier to become a reviewer on the supply side, making entry to the market even more accessible for anyone aiming to pursue a carrier in this expertise. However, it could also be beneficial for the consumers, as it is easier to get information from multiple sources from various reviewers. Hence, the expert review system has been evolving from a simple, more segmented market to a more complex ecosystem where all the reviewers and consumers share the same platform. As a result, it is easier to become a reviewer on the supply side in this platform and easier to get information from more reviewers on the demand side. In contrast, the older, more traditional sources (e.g., user ratings, advertisements, etc.) still play an important role in consumer decisions. In recent years, we could observe a boom in the number of individual product reviewers and influencers in various social media platforms, which highlights the shift in marketing communication nowadays.

From the perspective of the firm, the number of participants on the supply side of the third-party product reviewer market is important due to the mixture of the arguments, that 1. firms do not have control over these media, 2. the product reviewers have their financial incentives by providing these reviews. One can argue that an increase in the number of independent reviewers is essentially good for the firm. It reduces the variance across the valence of the narrative towards the product. Thus, the fact that the firm does not have control over these narratives becomes more predictable, which is crucial for the firm. From this perspective, the increase in the independent suppliers of product-related information can signify that the market is going towards perfect competition, which is favorable for firms. However, the reviewers profit incentives over this activity can highlight an opposite direction in the evolution of the product review market. Similarly to every other market -where possible- the suppliers are interested in differentiating their product, grab more market share and grow faster than other participants which result in more profit in the long term. If possible, their incentives can highlight the evolution of the market structure that goes towards monopolistic competition in the long term. Therefore, the main goal of this study is to shed light on the drivers behind the growth of third-party product reviewers and explore where the market structure is progressing in the long term by using data collected from YouTube.

We approach the drivers behind the growth of YouTube reviewers (denoted by the change in their corresponding subscriber count) with three point-of-view. First, we examine whether the channels can successfully translate their viewership success into subscribers. Since we know that channel size has a positive impact on the viewership of the videos from prior studies (YOGANARASIMHAN, 2012; DIWANJI et al., 2014; LIIKKANEN – SALOVAARA, 2015; WELBOURNE – GRANT, 2016; BURGESS – GREEN, 2018), with this question, we aim to explore whether the channels with higher view count changes on their videos can grow faster. If they can successfully translate their views into subscribers, we found evidence of a multiplicative growth process. A higher subscription number results higher viewership, which translates to even more viewership in the long term. Therefore, we hypothesize the following.

H1. The view count changes of the channels’ videos have a significant positive effect on its subscriber number changes.

However, one of the limitations of this hypothesis is that it does not differentiate the impact of the content on the size of the channel from the perspective of the audience’s opinion or preference towards the videos. Multiple questions can arise from this limitation. Are the channels with positively rated content going faster? Or only the engagement from the audience is that what matters for them? Or, there is no such connection, and channels with low engagement can also grow fast if they make content desirable for a specific set of viewers.

Thus, the second hypothesis of the study aimed to approach the growth of the channels by examining the audience’s valence or engagement towards the channel. In other words, we are interested whether we can find patterns that outline the connection between what the audience thinks about or how they reach them and their growth. Along these goals, we are using the video-level audience reactions, namely, the number of likes, dislikes, and comments, to test the following hypothesis.

H2. We can explain the channel growth better if we use the channels’ audience reaction metrics.

Using data downloaded from YouTube, we derived empirical models to test the above hypotheses. We found evidence that the performance of the channels (denoted by the view count changes of their videos) indeed have a strong positive connection with the growth of the channels, confirming our first hypothesis and highlighting a multiplicative growth across creators. The outlined process also shows that the big channels, on average grow faster than smaller channels. Then, we tested the connection between the audience reaction to the videos and the subscriber count changes of the channel. We found that out of the average audience metrics, likes and dislikes positively and negatively connect with the new subscriber count of the channels, respectively.

The remainder of the paper is organized as follows. The Literature review and methodology section describes the most critical theories from the related disciplines. This includes the literature on product reviews and earned media, the domain of modeling news, firms and agents, and the literature stream of personal branding. The Data and methods section outlines our data collection procedure and derives the models for the corresponding hypotheses, while the Results and conclusion section concludes the results of our analysis.

2. Literature review and methodology

The literature on professional or expert consumer reviews is relatively small in the marketing domain compared to that of on other sources of product-related information (e.g., ERDEM – KEANE, 1996; CHEVALIER – MAYZLIN, 2006; IYENGAR et al., 2007; NARAYANAN – MANCHANDA, 2009; SZYMANOWSKI – GIJSBRECHTS, 2012, 2013; ZHAO et al., 2013;

WU et al., 2015). Moreover, the studies in this literature stream only focus on reviews from a handful of industries. The most researched area examines the reviews’ effect on the sales performance in the motion picture industry (PRAG – CASAVANT, 1994; ELIASHBERG – SHUGAN, 1997; BASUROY et al., 2003, 2008; REINSTEIN – SNYDER, 2005; BOATWRIGHT et al., 2007; GEMSER et al. 2007; TERRY et al., 2011; HENNING-THURAU et al., 2012), while HILGER et al. (2011) and COX (2015) showed similar effects in case of the wine and the video game industry, respectively.

Other approaches showed the effects of the reviews on the firm strategy in the case of printers and running shoes (CHEN – XIE, 2005) or the effect on firm value in the movie (CHEN et al., 2012) and consumer electronics (TELLIS – JOHNSON, 2007) industry. One exception is KIM et al.’s (2019) paper, examining the reviewer’s psychological trade-off between being objective or helping the brands. However, these studies focus on some economic impact on the firms (such as sales or market value) or the product (purchase intention) and not the supply of the product information or the product review market itself.

The most closely related literature stream that aims to account for the motives of the reviewers explores the behavior of media firms, news providers, and other entities that aim to attract the audience’s attention. This domain consists of studies with multiple different assumptions regarding the goals and incentives of the entities modeled by them. Hence, we can also observe that the decision variables of the information mediators derived from these assumptions are also different in these papers.

There is a considerable number of studies focusing on the objectivity, accuracy, or political orientation of the presented content (e.g., MULLAINATHAN – SHLEIFER 2005; XIANG – SARVARY, 2007; BATTAGION – VAGLIO, 2015; GABSZEWICZ et al., 2001, 2002, 2004), but there are also studies concerning the decision of the information mediators with respect to the price to access information (GODES et al., 2009), programming variety (GAL-OR – DUKES, 2003) and presented information signal (FALKINGER, 2007; XIANG – SOBERMAN, 2014). However, these models are not only different in the perspective of the information mediators’ decision variables but also in terms of their source of revenue. While GAL-OR – DUKES (2003) assume only advertising revenue, GODES et al. (2009) assume content and advertising revenues as well. Our approach in this regard is most closely related to FALKINGER’S (2007) and XIANG – SOBERMAN’S (2014) study, assuming that news providers try to maximize ex-ante expected audience size to maximize their revenue.

The last segment of this domain that we are building on during the development of our models is the studies concerning attention economies partly (SMITH, 2020) or entirely (FALKINGER, 2007). These studies highlight how different these markets are from traditional markets with a clear demand and supply definition, based on the approach that YouTube channels, media firms, or similar information mediation entities are trying to attract the audience’s attention. Assuming different attention capacities for every audience member and competing information signal sellers, with their decision to choose the strength of the signal, FALKINGER (2007) could derive the equilibrium audience sizes. His findings rely on the theorems proved on a theoretical model that may be applied to platforms and fields where the supply side aims to attract attention from the audience members. Therefore, FALKINGER’S (2007) model can be easily translated to the case of YouTube. The “family of information signal sender” -FALKINGER (2007) is essentially the supply of information, which equals to the set of YouTube channels in this platform. The set of information signal receivers is the set consisting of individual audience members, in other words, the aggregate audience. Nonetheless, there is a key difference between this domain and this study. Besides SMITH’S (2020) paper, the results of the studies discussed above were derived from theoretical models without empirical data. In contrast, we aim to explore the research questions and hypotheses by developing empirical models using data downloaded from YouTube.

3. Data and methods

The overall goals set up by this study can be investigated on many different sets of observations, coming from reviews on different categories of products. The only condition that the chosen product category must fulfill is the presence of enough product reviewer channels to obtain a sufficient number of observations to derive reliable results. Driven by this condition, technology product reviewers have been chosen for estimating our models. First, a list of channels was collected using the channel search option of YouTube API with combinations of the following tech product reviewer-related keywords: tech/technology, phone/smartphone, and product review/unboxing. These searches resulted 1,642 channels as potential subjects for our research. However, the distribution of the subscriber count of these channels is highly skewed, as we observe exponentially more channels as the channel size decreases. Hence, we use a cutoff value on the channels' subscriber counts to decide which channels will be included in the dataset. In Table 1, we divided the channels into five groups according to their subscriber counts. Based on this table, we decided that the threshold value for channels will be 10,000 subscribers.

Table 1
Number of channel search results per subscriber count groups

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

Source: own elaboration based on data from YouTube API

After manually checking the results of the search results, we noticed that some of the channels are incorrectly labeled as English language channels. Thus, we filtered out these channels and ended up with 78 YouTubers overall. Second, the next step is to gather the information products they posted on the platform, which could be done by collecting all the video IDs the given channel posted from a given date. We had chosen to start collecting the video IDs from 01 May 2020, which meant a 47-day time window between the date when the first videos in the dataset were posted and when the daily observation began. The final step of the data gathering process then collects both the video and channel-related variables daily. Hence, every day we checked whether new video(s) was/were posted on the market compared to the previous observation day. If there was/were, we added it/them to the list of videos, then repeated the downloading process for every channel ID and the updated list of video IDs. The download process took place from 16 June 2020 to 01 October 2020. The final result contained two datasets – a sample with 8,320 observations about the channel-related variables and 294,890 observations about the video-related variables.

3.1 Base model with the performance of the channel

Let denote the channels' sizes at a given period by their measured subscriber counts at that period. Hence, our response variable through the study:

$$\Delta Subscribers_{k,t} = Subscribers_{k,t} - Subscribers_{k,t-1}$$

Since we assume that nonlinearity could be present in the connection between the subscriber gaining process and our independent variables, we use the logarithmic transformation of our variables. Then, to answer our first hypothesis, we start building the base model by assuming both performance independent and dependent growth factors. We denote the performance of the videos at a given period as the number of views gained compared to the previous period, and we define the performance of the channel as the sum of the performance of the videos:

$$\sum_{i}^{N_{kt}} \Delta\, Views_{it} \ = \sum_{i}^{N_{kt}} (Views_{it} - Views_{i,t-1})\,,$$

where N_{kt} is the number of videos the channel k has at time t. For the performance independent growth, we assume that every channel has a unique growth rate separate from the views of the videos. Then, we use hierarchical mixed-effects modeling to define a random intercept for the channels on the market and define the following model with both performance dependent and independent factors:

$$\Delta Subscription_{kt} = \beta_{0k} + \beta_1 \sum_{i}^{N_{kt}} \Delta\, Views_{it} + \varepsilon_{kt},$$
$$\beta_{0k} \sim N\big(E(\beta_{0k}), \delta^2_{\beta_0}\big),$$

where β_{0k} is the trend component of the model and β_1 is the rate in which the performance of the channels translates to subscribers. Thus, the trend component in the model is unique for the channels, but we are interested in modeling the constant performance ratio across all the channels. Finally, for the estimation of the hierarchical model, we used the lme4 and lmer R packages (BATES et al., 2014; KUZNETSOVA et al., 2017).

3.3 Using audience reactions

The second hypothesis's model extension aims to explore the connection between the audience reactions and the subscriber gaining process. Modeling this relationship, we ask whether we can explain a significant part of the variance of the growth among channels by introducing the audience's revealed valence, opinion, or engagement to the model.

From the perspective of connecting the audience's opinion about a given content on the market and the growth of the channel that posted that video, the most valuable asset for us is the observations that reveal the audience's valence towards the focal video. Therefore, we can use the information about the number of likes and dislikes a given video received as a good measure of the revealed valence.

Implementing these measures to truly show the valence towards the video is facing an obstacle as simply introducing it to the regression would result a biased relationship. This is due to the positive connection between the number of views and audience reactions a given video receives. Therefore, to achieve an appropriate measure, we divide both the number of likes and dislikes at a given period with the number of views in that period.

Finally, one can also argue that these valence metrics still contain unfolded information that can be examined if we handle them together. Meaning, the overall valence towards a video from the audience may lie in comparing the number of likes to the number of dislikes at any given period. Hence, we not only represent the absolute number of likes and dislikes but also a relative measure expressed by the ratio of these two variables.

Our last audience reaction measure has a unique role in our model, as it does not reveal the audience's valence. While one can argue that comments for the videos can contain information that can show both positive and negative valence (even at the same time) towards a video, retrieving this information would require too much resource in the model development process. Hence, the reason is only due to a technical limitation since it would require highly sophisticated natural language processing (NLP) and sentiment analysis techniques. Nevertheless, the number of comments can still provide extra information about the audience. Our underlying assumption that motivates the representation of this variable is based on the consideration that posting a comment requires more effort from the viewers than clicking on the like/dislike function of the platform. Thus, we argue that the number of comments may show higher engagement from the audience than that of likes or dislikes. This argument holds regardless of the valence of the comment. Therefore, we are representing the number of comments as an extra measure of engagement from the audience. In the case of this variable, we can apply the same assumption regarding its correlation with the number of views as in the case of the likes and dislikes. Meaning, we expect that as the video's viewership grows, the number of comments is increasing as well. Hence, once again, we should divide the number of comments by the number of views before representing it in the regression. The above-defined variables are video-specific metrics, while our methodological approach requires us to define channel-specific variables. Thus, we summarize all audience reactions across all the videos a given channel has at a certain period and divide it by the aggregate number of views to achieve the audience reaction variables introduced to the regression. Then, consistently to our previous models, we take the logarithmic transformation of this variable to get our independent variables in the model:

$$\begin{aligned}\ln \Delta Subscription_{kt} &= \beta_{0k} + \beta_1 \, ln \sum_i^{N_{kt}} \Delta Views_{it} + \beta_2 \, ln \, \frac{\sum_i^{N_{kt}} Likes_{it}}{\sum_i^{N_{kt}} Views_{it}} + \beta_3 \, ln \, \frac{\sum_i^{N_{kt}} Dislikes_{it}}{\sum_i^{N_{kt}} Views_{it}} \\ &+ \beta_4 \, ln \, \frac{\sum_i^{N_{kt}} Comments_{it}}{\sum_i^{N_{kt}} Views_{it}} + \beta_5 \, ln \, \frac{\sum_i^{N_{kt}} Likes_{it}}{\sum_i^{N_{kt}} Dislikes_{it}} + \varepsilon_{kt} \ , \\ &\qquad where\colon \beta_{0k} \sim N\left(E(\beta_{0k}), \delta^2_{\beta_{0,}}\right)\end{aligned}$$

4. Results and conclusion

Based on the objectives we set up in this paper, and the methodology to achieve these goals we estimated four models. The results of these models examined the channels' growth from different perspectives to answer our hypothesizes. We summarized the results in Table 2.
Analyzing the results of the first model, we can observe that the coefficient corresponding to the performance of the channels is significant. Therefore, based on the methodology behind this independent variable, we found evidence that the aggregated number of view count changes has a significant positive impact on the channel's growth. In other words, as the model indicates, we should reject the hypothesis that the coefficient is zero, and we can accept hypothesis 1, meaning, besides a unique performance-independent element, we can observe performance-dependent effects in the model. The implication of this result is crucial for channels in this market. With the evidence of a performance-dependent growth, we can also confirm the multiplication effect of the performance on the revenue of the channel. This process essentially shows that a higher performance leads to even higher performances through the follower base building of the channel.
However, important to keep in mind that the valence of the videos could also matter in terms of the growth, which may prevent the overall positive resultant of the experimenting process.
Thus, the follow-up models were aimed to explore the connection between the audience reactions and the subscription growth of the channels. Our results indicate that we can explain a significant part of the variances in the growth process of the channels with the usage of the likes to views and dislikes to views ratio on a 5% significance level. However, we have not found evidence that the number of comments or the like to dislike ratio would be related to our response variable. In terms of the directions of the effects, we can conclude that the results meet our prior expectations, as we can observe a positive regression coefficient corresponding to the overall like ratio of the channel, while there is a negative coefficient for the overall dislike ratio.
In conclusion, we found that despite the growing number of market participants, the tech reviewer market on YouTube is not heading towards perfect competition. It rather shows signs of a long-term monopolistic competition market structure. In addition, we found that the growth

of the channels has a strong positive connection with the average revealed valence towards their content, which can be a signal for both small and big channels about the long-term growth potential of their current content.

Table 2
Model estimations

Regression Results

	Dependent variable:			
	ln ΔSubscriptions			
	(1)	(2)	(3)	(4)
Performance: $\ln \sum_{i=1}^{N_k} \Delta Views_{it}$	0.121^{***} (0.010)	0.119^{***} (0.010)	0.122^{***} (0.011)	0.123^{***} (0.011)
Likes: $\ln \frac{\sum_{i=1}^{N_k} Likes_{it}}{\sum_{i=1}^{N_k} Views_{it}}$		1.645 (1.043)	3.325^{**} (1.488)	3.080^{**} (1.560)
Dislikes: $\ln \frac{\sum_{i=1}^{N_k} Dislikes_{it}}{\sum_{i=1}^{N_k} Views_{it}}$		-26.246^{**} (13.285)	-33.140^{**} (13.976)	-35.206^{**} (14.532)
Like Ratio: $\ln \frac{\sum_{i=1}^{N_k} Likes_{it}}{\sum_{i=1}^{N_k} Dislikes_{it}}$			-0.030 (0.019)	-0.029 (0.019)
Comments: $\ln \frac{\sum_{i=1}^{N_k} Comments_{it}}{\sum_{i=1}^{N_k} Views_{it}}$				1.283 (2.437)
Constant	5.820^{***} (0.108)	5.836^{***} (0.109)	5.845^{***} (0.109)	5.840^{***} (0.110)
Random Effects				
Intercept/Channel				
Standard Deviation	0.1984	0.1965	0.1962	0.1968
Likelihood ratio	820.096^{***}	805.121^{***}	803.428^{***}	804.272^{***}
Observations	7,928	7,928	7,928	7,928
Log Likelihood	-6,146.188	-6,139.672	-6,141.464	-6,139.516
Akaike Inf. Crit.	12,300.380	12,291.340	12,296.930	12,295.030
Bayesian Inf. Crit.	12,328.290	12,333.210	12,345.770	12,350.860
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Source: own elaboration

5. Discussion

This study aimed to shed light on the drivers behind the growth of third-party product reviews and explore where the market structure is progressing in the long term by using data collected from YouTube. Our research goals have arisen from the evolution of the professional review market in recent decades due to the widespread usage of the internet, social media, and the appearance of online attention platforms, such as YouTube. These platforms make it easier to become a reviewer on the information supplier side and get information from more reviewers on the demand side, highlighting the changing structure of the third-party product reviewer market. First, in recent years, we could observe a boom in the number of individual product reviewers and influencers in various social media platforms, which could result a more balanced market structure in the long term, where the narrative around the product is less and less centralized. Second, professional or third-party reviewers’ main incentives are to achieve profit by providing product-related information. Thus, the reviewers are also incentivized to make their *product* unique and grab more market share than their competitors, highlighting an opposite trend. This market structure is more and more centralized despite the growing number of suppliers. Thus, by examining the growth of the information providers on the market, we aimed to explore the long-term trends in the market.

First, we aimed to examine if channels can translate their viewership success into subscribers. Building on previous results showing the positive impact of the channel size on the viewership of the videos, we aimed to explore if we find a multiplicative growth process, where a higher subscription number results higher viewership, which translates to even more viewership in the long term. Then, we introduced the audience reactions into the model to explore if we can explain more variance among the different channel growth by using the audiences’ revealed opinions about the channels’ content.

The estimation of the above-described models showed that the aggregated number of view count changes has a significant positive impact on the channel’s growth. This evidence on performance-dependent growth also supports the multiplicative process argument of the study in which higher performances lead to even higher performances through the follower base building of the channels. We also found that a significant part of the variance of the growth of the channels can be explained by the introduction of likes per views and dislikes per views, having a positive and negative association with the growth, respectively.

Our results suggest that despite the growing number of market participants, the tech reviewer market on YouTube is not going towards a more balanced structure. On the contrary, we found that prominent reviewers can grow faster, accumulating more market share over time. In addition, our results show that the revealed valence of the audience has a strong connection with the growth of the channels that can help both small and big suppliers to recognize their long-term growth process.

The majority of the available literature aims to examine the effect of product-related information on some economic metric behind the success related to the product or the firm, such as sales, firm value, purchase intention, or quality perception. Therefore, this research can be considered a novel attempt to understand the product reviewer market itself in the modern marketing communication era. However, our attempt is not comprehensive nor without limitations. First, we estimated our models on data collected from product reviewers in the tech genre on YouTube. Hence, as a natural extension, follow-up research is needed to validate our findings for both other topics on YouTube and the same or different issues outside of YouTube. Second, in this study, we also considered the importance of representing the revealed valence of the audience in our model. However, due to the limitations of our scope in this research, we used the sheer number of available audience reactions in the model. One can argue that a more sophisticated approach could be achieved by mining the audience’s comments on the content of the channels. This highlights a research direction of extending our framework with the application of natural language processing (NLP) and sentiment analysis on the audience’s comments.

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