Smash that subscribe button! The evolution of the third-party product reviewer market on YouTube

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THE AIM OF THE PAPER
In recent years, we could observe a boom in the number of reviewers in the third-party product reviewer market. The structure of this market is an important factor for both firms and consumers as few strong participants could control the narrative around the products. Thus, the main goal of our study is to explore the market structure of this market by shedding light on the drivers behind the growth of the reviewers.

METHODOLOGY
We collected daily data on English language technology product reviewer channels from YouTube API over a 106-day time window to measure how product reviewers grow over time and estimated hierarchical regression to explore the drivers of the growth process.

MOST IMPORTANT RESULTS
We found that (1) big channels grow faster, implying a multiplicative growth process, (2) breakthrough videos boost this process, and (3) the audience's average revealed valence has a significant connection with the subscriber count increase.

RECOMMENDATIONS
Given the known impact of product reviews on consumers' decisions, understanding the size and structure of this earned media is key for marketers. Thus, our results and implications are most applicable for firms with products that attract significant demand and supply of product reviews.

Keywords: product review, earned media, YouTube

INTRODUCTION

Product-related information from external sources plays a crucial role in consumers' decision-making process when they lack sufficient information about a given product or service (Erdem and Keane 1996, Narayanan and Manchanda 2009, Zhao et al. 2013). For instance, this situation could arise in the case of new product launches when the consumers do not have first-hand experiences with the product. Third-party or expert reviews have a unique place in consumers' available product-related information sources. 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. This market has undergone a substantial evolution since the offline era when becoming a professional reviewer had high entry costs. It was not a profession that anyone could immediately start to pursue. This barrier has changed with the internet, where everyone can become a reviewer by creating websites or blogs dedicated to reviewing products.

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 product-related information, making the market entry even more accessible for anyone aiming to pursue a carrier in this expertise and helping consumers to get information from more reviewers on the demand side. In recent years, we could observe a boom in the number of individual product reviewers and influencers in various social media platforms, highlighting the shift in modern marketing communication.

Given the impact of product reviews (Tellis – Johnson 2007, Chen et al. 2012) and the financial incentives of the reviewers, understanding the size and structure of the market is key for marketers. One can argue that the increase in the number of reviewers is beneficial for the firm. It reduces the variance in the valence of product-related narratives. It becomes more predictable, which is crucial for the firm. From this perspective, the increase in the number of product reviewers can signify that the market is going towards perfect competition, which is favorable for firms. In contrast, the reviewers' profit incentives can implicate an opposite trend in the evolution of the product review market, similarly to every other market – where possible – the suppliers are interested in differentiating their product, grabbing more market share, and growing faster than other participants which result more profit for them in the long run. In this way, their incentives can implicate that the market structure goes towards monopolistic competition in the long term. The market structure in this framework is essentially dependent on the distribution of the reviewers' sizes as product review providers. Thus, the long-term structure can be unveiled by examining the evolution of this distribution, which depends on the market participants' different growth processes over time. From the firm's perspective, this distribution conveys crucial information. In a balanced market, the number of potential consumers the reviewers can reach is balanced as well. Thus, the valence of one reviewer is less impactful on the economic performance of the product they are reviewing. In contrast, in case of a skewed distribution, a few giants can dominate the narrative, while the small reviewers will be marginal. This is a factor the firm should consider during the planning of the product's marketing mix strategy.

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.

The remainder of the paper is organized as follows. The Literature review section describes the most critical theories from the related disciplines. The Hypothesis development section presents the hypotheses of the study. The Data and methods section outlines our data collection procedure and derives the models for the corresponding hypotheses, while the Results section describes the results of the model estimations. Finally, the Conclusions and limitations section concludes the results of our analysis.

LITERATURE REVIEW

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, 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 (Eliashberg – Shugan 1997, Basuroy et al. 2003, Reinstein – Snyder 2005, Gemser et al. 2007, Henning-Thurau et al. 2012), while Hilger et

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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. 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. These studies highlight how different these markets are from traditional markets with a clear demand and supply definition coming from the fact that YouTube channels, media firms, or similar information mediation entities aim to attract the audience's attention (Falkinger 2007, Smith 2020). 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. 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 consists 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.

HYPOTHESIS DEVELOPMENT

We approach the drivers behind the growth of YouTube reviewers (denoted by the change in their corresponding subscriber count) from three point-of-view. First, we examine whether the channels can successfully translate their viewership success into subscribers. Prior studies have shown that a channel's subscription count is a significant predictor of the number of views the channel's videos are attracting (Welbourne and Grant 2016, Hoiles et al. 2017), meaning that bigger channels, on average, have higher performance on the market. Thus, we aim to explore if channels with higher view count changes on their videos can grow faster. We found evidence of a multiplicative growth process if they successfully translate their views into subscribers. A higher subscription count results in 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 their subscriber number changes.

The above hypothesis was formulated by not differentiating among the audience of the channels' videos. It only shows the viewership's effect on the channel's growth on average. Hence, we extend our previous approach with effects that differentiate the videos from two different perspectives. First, we investigate whether the videos that reached a wider audience than the usual viewership of the channel act as a booster in the growth process, relying on the following classification of the audience. From the channel's point of view, we can categorize the audience into three groups:

1. The viewers that already subscribed to the channel.
2. The audience that watched at least one video but decided not to subscribe (yet).
3. The viewers who are not familiar with the channel thus have not considered subscri bing yet.

In the first case, the channel's primary goal is to keep these viewers in the follower base and prevent a potential unsubscribe. In the case of the second group, the channel can assume that there is a possibility that they will eventually become subscribers in the future. Hence, they aim to provide evidence through their videos, incentivizing them to subscribe eventually. In the third group, the viewers are not familiar with the content creator; they have not seen any content posted by the channel. Thus, they have not considered subscribing yet. This group could contain viewers who would subscribe immediately and viewers who would go to the second group after watching the channel's content, so the probability of a viewer becoming a subscriber is higher in the third group than in the second group. The study's second hypothesis builds on this higher probability. Based on the higher chance of converting the viewers into subscribers, we expect higher growth if the channel reaches the third group. In other words, we assume that if channels can reach out from their usual audience, they may realize higher growth. Therefore, we hypothesize that the videos with a significantly higher view count than the usual view count of the channel's videos have an extra positive impact on the new subscriber count of the channel compared to the new subscriber count suggested by the view count of the video.

H2. The videos with outstanding viewership compared to the channel's other videos have a significant positive extra effect on the subscriber number changes of the channel.

If the hypothesis is accepted, that shows us that breakthrough videos could act as a booster in the channels' growth process. Combined with the first hypothesis, they can be a difference-maker for small channels to step into a path to long-term success.

While the second hypothesis differentiated the channel's content by the audience size it reaches, the final 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 if we can find patterns that outline the connection between what the audience thinks about the videos and the growth of the channel. Along these goals, we use the video-level audience reactions, namely the number of likes, dislikes, and comments, to test the following hypothesis.

H3. We can better explain the channel growth by using the channels' audience reaction metrics.

DATA AND METHODS

While the goals set up by the study could be investigated on many different sets of observations, due to the high number of product reviewers on the market, we selected the technology genre to test our hypothesizes. The data collection procedure consisted of three steps.

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 the research. The distribution of the subscriber counts of these channels is highly skewed, as we observe exponentially more channels as the channel size decreases (Table 1). Hence, a minimum 10 000 subscriber count requirement was determined for the channels to be included in the data download process.

Then, we manually screened all the channels and filtered out the ones with non-English and non-product review-related content, ending up with 78 reviewers. Finally, we collected all the video IDs from these channels from 01 May 2020 and refreshed them on a daily basis until the end of the download process, which took place from 16 June 2020 to 01 October 2020. During this interval, the channel and video-related measures were retrieved, which resulted two panel datasets – a sample with 8,320 observations about the channel-related variables and 294,890 observations about the video-related variables.

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

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 performances 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 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:

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

where β_{0k} is the trend component of the model and β_1 is the average 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 model a constant performance ratio across all the channels. Finally, we used the lme4 and lmer R packages (Bates et al. 2014, Kuznetsova et al. 2017) to estimate the hierarchical model.

Deriving the reach effect

The reach of a video is defined to show how far the channel's videos can spread on the market beyond the regular follower base, while the channel's reach is the aggregated measure based on the reach of the videos. The underlying assumption behind the effect is based on the argument that channels may get more subscribers if they make a video that can reach outside of the channel's usual audience compared to the number of subscribers that the number of views would suggest. Hence, we expect an extra amount of growth if one or more videos of the channels are getting unusually high views compared to the regular view counts. However, before defining the overall effect represented in the regression, we should first derive the video level reach metric. Based on the arguments, the video's reach effect should only be notable if the performance is an outlier compared to the channel's other videos' performances. This can be achieved if we derive the metric so that it attains exponentially higher values if the performance of the video stands out from the usual performances. Finally, we need to grab the property of this effect that the video is only an outlier in the set of the channel's videos. It does not have to be an outlier in the full dataset. This can be accomplished by normalizing the videos' performances the channels have for each content creator separately. In this way, every channel will have its own reference system of performances, while our metric in the regression will denote the same effect for every channel. Without the channel level normalization, this method would result a biased metric, led by the sizes of the channels across all the creators. Therefore, we calculate the defined reach metric in the following way:

$$r_{it} = \Delta Views_{it}^{\overline{Views}_{it}} \ ,$$

where $\overline{Views}_{it}$ is the normalized value of the view counts of channel k (with i = 1…N_k) in the scale of all channel videos. Then, we can aggregate the reach metric for each channel across all the videos to get the channel's total reach at time t, which can be represented in the regression equation.

$$R_{kt} = \sum_{i}^{N_{kt}} \Delta Views_{it}^{\overline{Views}_{it}}$$

Important to note that this is the only term in the regression that is represented without the logarithmic transformation. The lack of conversion is to keep the exponential connection with the formula. If we took the logarithm of it, we would lose some level of this exponentiality in the model, and it would not be capable of sufficiently denoting the hypothesized connection.

Using audience reactions

The model extension corresponding to the third hypothesis aims to explore the connection between the audience reactions and the subscriber gaining process. Modeling this relationship, we examine whether a significant portion of the variance in the channel growth can be explained 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 to the growth of the channel that posted that video, the most valuable assets for us are the observations that reveal the audience's valence towards the videos. Therefore, we can use the number of likes and dislikes a given video received as a good measure of revealed valence. However, simply introducing these measures to the regression would result a biased relationship due to the positive connection between the number of views and the audience reactions a given video receives, so we divided 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 if we do not handle them separately. Meaning the audience's overall valence towards a video may lie in comparing the number of likes to the number of dislikes at a given period. Hence, we represent the absolute number of likes and dislikes and the relative measure expressed by the ratio of these two variables.

The last audience reaction measure has a unique role in the model, as it does not reveal the audience's valence. While the comments of the videos may contain information that shows both positive and negative valence (even at the same time) towards a video, the resource requirement for retrieving reliable information from the comments (e.g., with sophisticated natural language processing (NLP) and sentiment analysis techniques) was beyond the limits of the research. Nevertheless, the number of comments can still provide extra information about the audience. The 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.

This is even more accurate if we consider that a significant part of the comments is replied to other comments, suggesting that the viewer spent more time with the particular video. Thus, the number of comments may show higher engagement from the audience than the number of likes or dislikes. This argument holds regardless of the valence of the comment. Therefore, we represent the number of comments as an extra measure of engagement from the audience. However, we expect that as the video's viewership grows, the number of comments increases as well. Hence, we 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 the independent variables in the model:

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

RESULTS

Based on the objectives we set up in this paper, we estimated three models and summarized the results in Table 2. Analyzing the first model, we can observe that the coefficient corresponding to the performance of the channels is significant. Therefore, we found evidence that the aggregated number of view count changes has a significant positive impact on the channel's growth. In other words, we should reject the hypothesis that the coefficient is zero, and we can accept hypothesis 1. This means that besides a unique performance-independent element, we could also observe performance-dependent effects in the model. The implication of this result is crucial for channels on the market. With the evidence on a performance-dependent growth, we can confirm the performance's multiplicative effect on the channel's revenue. This process essentially shows that higher performance leads to even higher performances through the follower base building of the channel.

The second model aimed to explore if we can observe extra growth for channels that have videos with outstanding viewership compared to the viewership of the channel's other videos. Our results suggest that the presence of a video with exceptional viewership is a significant predictor of the channel growth and implicate that the reach of the videos is an important growth potential for the channels. Thus, we accept hypothesis 2. As the channels have outstanding videos, they – on average – receive an extra number of subscribers compared to what our previous model would have suggested. As a result, the channels on the market, especially the small ones that have not had explosive videos yet, may derive the implication that it is worth experimenting with the content of the video since a groundbreaking video's effect can outweigh the ones with poor performances. Hence, it could have an immense multiplicative impact on future revenues. However, important to keep in mind that the valence of the videos could also matter, which may prevent the overall positive resultant of the experimenting process.

Thus, the follow-up model was 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 portion of the variance in the growth process among 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. 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.

CONCLUSIONS AND LIMITATIONS

In conclusion, despite the growing number of market participants, the tech reviewer market on YouTube is not heading towards perfect competition. The multiplicative growth process implicates that big channels get even bigger over time, which leads to monopolistic competition in the long term, where there are a couple of reviewer giants while you can find plenty of small reviewers trying to break out. We have also found that these smaller channels still have a chance to step on the path that leads to catching up with large channels if they make videos that reach outside of their usual audience. Moreover, we also 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.

The unveiled trajectories on the market structure highlight potential threats for the firm. The growing concentration essentially means that the economic performance of the firm's product will be largely dependent on a small number of reviewers. Thus, marketers need to identify the key figures on the market and use this information during the product's marketing strategy.

Our research can be considered a novel attempt to describe the structure of the product reviewer market and the trajectory of this structure by examining the growth processes of the market participants (on the supply side). However, our approach is not comprehensive nor without limitations. First, we estimated our models on data collected from product reviewers in the tech genre on YouTube. As a natural extension, follow-up research is needed to validate our findings on other product categories or other platforms. Second, while we considered the importance of representing the revealed valence of the audience in the model, due to the limitations of the scope of this research, the usage of these measures could be improved. One can argue that a more sophisticated approach could be achieved by mining the audience's comments on the channels' content. 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.

Table 2. Model estimations

Regression Results

	Dependent variable:		
	ln ΔSubscriptions		
	(1)	(2)	(3)
Performance: $\ln \sum_{i=1}^{N_k} \Delta \mathrm{Views}_{it}$	0.121^{***} (0.010)	0.114^{***} (0.010)	0.115^{***} (0.011)
Reach: $\Delta \mathrm{Views}_{it}{}^{\overline{\mathrm{Views}}}$		0.828^{***} (0.158)	0.820^{***} (0.158)
Likes: $\ln \frac{\sum_{i=1}^{N_k} \mathrm{Likes}_{it}}{\sum_{i=1}^{N_k} \mathrm{Views}_{it}}$			3.012^{**} (1.487)
Dislikes: $\ln \frac{\sum_{i=1}^{N_k} \mathrm{Dislikes}_{it}}{\sum_{i=1}^{N_k} \mathrm{Views}_{it}}$			-33.722^{**} (14.088)
Comments: $\ln \frac{\sum_{i=1}^{N_k} \mathrm{Comments}_{it}}{\sum_{i=1}^{N_k} \mathrm{Views}_{it}}$			1.072 (2.385)
Like Ratio: $\ln \frac{\sum_{i=1}^{N_k} \mathrm{Likes}_{it}}{\sum_{i=1}^{N_k} \mathrm{Dislikes}_{it}}$			-0.028 (0.019)
Constant	5.820^{***} (0.108)	5.884^{***} (0.106)	5.907^{***} (0.108)
Random Effects			
Intercept/Channel			
Standard Deviation	0.1984	0.1749	0.1742
Likelihood ratio	820.096^{***}	483.707^{***}	481.108^{***}
Observations	7,928	7,928	7,928
Log Likelihood	-6,146.188	-6,134.571	-6,128.066
Akaike Inf. Crit.	12,300.380	12,279.140	12,274.130
Bayesian Inf. Crit.	12,328.290	12,314.030	12,336.930
Note:	*p<0.1; **p<0.05; ***p<0.01		

Source: own elaboration

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