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Modeling the demand and supply of product related information; using evidence from YouTube

Theses of the doctoral dissertation

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Contents

Abstract

Despite the role of product related information in new product launches, our knowledge about its demand and supply in the product reviewer market is very limited. The dissertation aims to fill this gap in the literature by modeling the economy of product information using data from YouTube. The main objective prior to the hypothesis formulation was to explore the product reviewer market on YouTube and identify the role, the demand, and the supply of product related information.

We found that based on the products the videos are reviewing, we can identify different information markets on the platform, and this segmentation significantly differentiates the performance of the videos posted on them as well. However, the topics' effect on the videos is diminishing over time.

Then, we were able to formulate hypotheses regarding the characteristics of the demand and supply on the market and build model extensions aimed to answer them. First, related to the demand, we endogenized the overall interest towards the topic into a current state of satiation and topic awareness. The results indicate that both measures have a significant relationship with the performance of the videos, having positive and negative coefficients, respectively. Second, we also aimed to unfold the supply on the market and move away from the homogenous channels' assumption. We considered two factors that can differentiate these channels, their sizes and their unobserved brand images. We found that the size of the channels has a significant positive impact on the performance of the videos, while it has a negative effect on the above-defined satiation and topic awareness. Our results suggest that the unobserved factors related to the image of the brand also significantly differentiate both the response variable and the topic effects.

Finally, accounting for the long-term incentives of the channels, we aimed to derive a set of models examining their growth. The main hypothesis regarding these models was whether the performance of the videos translates into subscriber counts. We found that the performance positively influences the subscriber gaining process, and outstanding videos provide extra effects for this growth. In addition, we tested if the video-level reactions from the audiences can be related to the process and found that the average ratio of likes to views and dislikes to views are significant predictors of the subscriber count changes over time.

1. Relevance of the topic

1.1. Motivation

Product related information is one of the main drivers of new product launch successes. Therefore, its content, how it is presented, and how it is perceived are key information for managers at firms that launched or plan to launch a product on the market. The literature differentiates three types of medium in which this information is distributed. The owned media, such as the website of the firm, the paid media, such as billboard advertisements, and the earned media, such as amazon reviews or Twitter posts coming from users and experts. While the firms essentially have a very high-level control over owned and paid media, understanding earned media poses a great challenge for them. Nevertheless, marketers cannot simply avoid earned media and focus on the other two if they aim for success, as this medium could have immense effects on the market performance of their products (Erdem and Keane, 1996; Reinstein and Snyder, 2005; Wu et al. 2015; Li and Du, 2017). As Newman (2014) describes in his article:

> *"Earned media [...] hardly ever works alone. You have to make it a part of your marketing ecosystem along with paid and owned media. The truth is: in today's digital landscape, they either work together or they don't work at all."*

Thus, if firms aim to understand how information about their product is going to be reached by consumers, besides controlling paid and earned media, they also need to understand the drivers of earned media.

From the perspective of the firms, this challenge has steadily become even more difficult in recent decades. Along the widespread usage of the internet and social media, new platforms and possibilities emerged for those who aim to post product related information, making the earned media ecosystem increasingly more complex. The information coming from peers who have already bought the item or service now can be reached by almost anyone in the world in various forms. Nowadays, most online ecommerce platforms have a segment for user feedbacks, but there are also websites dedicated completely to such reviews.

However, information about the product can come not only from peers but also from third-party professionals or experts. In the case of this type of review, we can observe that the domain has changed just as much as that of peer reviews. First, the traditional magazine or newspaper segments of product reviews have moved to blogs and websites. Then, with the emergence of organized online attention platforms, such as YouTube, the professional or expert reviews evolved into the complex ecosystem that we can observe today. While the role of blogs and websites remained meaningful, the system, where all the reviewers and consumers share the same platform, has grown to be an integral source of product related information for consumers.

The different structure of these platforms has multiple consequences compared to that of previous model with separate websites, that resembled the traditional newspaper or magazine model more. The centralized supply provides easier access to information from more sources for consumers. Meanwhile, the properties of the platform make the entry into the market accessible for anyone who aims to pursue a carrier in this expertise. One can also argue that the centralized demand creates a completely different route to success than previous models.

Therefore, if firms and marketers want to understand how consumers access, gather, and ultimately learn about their products, they are facing an increasingly difficult challenge. They need to get a grasp on how product related information flows in the modern reviewer market and understand that reviewers nowadays may have different motives and incentives due to this complex ecosystem.

The literature on the evolution of peer reviews and their effect on the consumers and firms is well-documented in the marketing domain. However, our understanding of the expert review ecosystem is very limited in general, while the knowledge regarding the modern shared platform reviewer market is especially scarce. Therefore, in the dissertation, we aim to fill this gap in the literature and shed light on the main drivers of this complex market. In addition, we chose YouTube, one of the most popular organized online attention platforms to examine and model the expert review system.

1.2. Position in the literature

Examining product review channels on YouTube is a special field in the domain of marketing, as it lies in the intersection of multiple different literature streams. Hence, in this section, we outline the most important connection points of the dissertation with the marketing and economic discipline.

eWOM

Given that the content of the videos is essentially product reviews, the dissertation connects to the literature examining electronic word-of-mouth (eWOM), which is a piece of online information about a given product or firm from a company independent source (Hennig-Thurau et al., 2003).

The main literature streams in this domain that relate to our focal topic are examining the expertise (e.g., Racherla and Friske, 2012; Keh and Sun, 2018; Naujoks and Benkenstein, 2020), credibility and trustworthiness (e.g., Cheung et al., 2008; Filieri et al., 2018), and motivation (e.g., Mackiewicz, 2008; 2010) of the eWOM poster and the impact (e.g., Dellarocas et al., 2007; Chevalier and Mayzlin, 2006; Zhao et al., 2013; Wu et al., 2015) of the information on the economic performance of the product or firm. Based on the literature on expertise, we can divide product reviews into peer and expert reviews. This helps us to understand the position and special features of our focus, expert reviews on YouTube.

The findings of this domain had many implications for the dissertation. For instance, it describes the evolution of the individual and the aggregate level of uncertainty and demand for information regarding a new product. Therefore, we will largely rely on this field during our model development process. Moreover, the findings in this domain (both peer and expert reviews) have shown that reviews, in general, play a crucial role in the consumers' quality perception and expectation about goods with uncertain properties.

Demand for Media Content

Expert reviews distributed on YouTube are different from the more traditional eWOM categories as the demand for these reviews could be driven by similar motivations to the ones behind media content watching.

Therefore, the examination of the demand for reviews in this market essentially leads us to the literature on the demand for media content (e.g., Katz et al., 1973; Shao, 2009; Khan, 2017). Combining these motives with the demand for product related information described above, we can identify product and non-product related motivations to watch the content creator generated product review videos. Among others, non-product related motives include the entertainment, social utility, or mood management needs of the audience.

We rely on this domain when we extend our spectrum with the examination of the supply and suppliers of the reviews. We keep in mind that the reviewer who aims to maximize the viewership of the videos is facing a demand that is not only related to the presented product, in which case the informativeness and credibility are the main defining factors, but it is also driven by non-product related needs, such as entertainment or social needs to interact with other people.

Personal Branding

Online personal branding has been one of the trending topics in the marketing literature in recent years (e.g., Dion and Arnould, 2011; 2016; Scolere et al., 2018; Varga and Sujbert, 2018; Fournier and Eckhardt, 2019; Smith, 2020). The main connection point here is the argument that YouTube product review channels are creating, building, and managing their own brands as it is defined by this domain. The unique, defining aspect of these brands is that it is built around an individual whose face is the brand itself. For instance, we can mention brands around popular figures such as Gordon Ramsey, LeBron James, or Calvin Klein.

From the perspective of the dissertation, the direction of persona-fied brands (Dion and Arnould, 2016) has the most relevant consequences. Essentially, we can conclude from these studies that the image of the brand, the persona, is a performed role by the individual who is the face of the brand. She (He) is doing this to meet the expectation that she (he) or her (his) advisors consider being connected to the profession of the brand. To be successful in the market, channels need to appropriately merge different persona facets, features into a brand image and narrative.

Therefore, we consider these YouTube channels similar to brands in other industries and develop our model to account for the differences among the channels' brand images in attracting product and non-product related demand.

Behavior of the media

In contrast to the studies in the field of eWOM and product reviews, the dissertation aims to model the market of reviews itself, and not only a specific aspect of the information, such as its credibility or impact on the consumers or the firms. Besides the demand for reviews described above, the supply side of the market consists of the information suppliers with their own incentives to post the reviews. While there is a literature stream in the eWOM domain that examines the motives behind the posting decision of peer reviews, expert reviewers on YouTube have different, financial incentives to provide these reviews.

From this perspective, the incentives of the reviewers resemble the goals of media firms and agents who aim to maximize their viewership. In this way, the dissertation connects to the theoretical literature on the behavior of the media. However, the framework of these studies is different compared to ours.

First, only a few studies examine similar decision variables of the actors in the market. Most of these studies investigate the decision regarding the objectivity, accuracy, political orientation, price, or programming variety of their content, which is not applicable to our model (e.g., Mullainathan and Shleifer. 2005; Xiang and Sarvary, 2007; Battagion and Vaglio, 2015; Gabszewicz et al., 2002; 2004). However, perhaps the most important difference lies in the researchers' methodological choice, as this literature stream is building models on a theoretical level, while the dissertation uses quantitative models tested on data downloaded from YouTube. Nevertheless, this domain still points out important details for the dissertation as it unfolds the theories behind the different revenue models of the media. Based on this aspect, we can conclude that our approach builds on the model derived by Falkinger (2007) and Xiang and Soberman (2014). In their framework, they assume that news providers try to maximize the ex ante expected audience size to achieve the optimum revenue. This also means that they have a fixed rate per viewer advertising and content revenue. This domain also serves as a background to the dissertation's final set of models, which examines the long term growth of the channels through their incentives to maximize their revenue coming from the viewership of all the videos.

YouTube and the video format

Finally, based on the chosen platform and format of the reviews, the dissertation also connects to the literature on YouTube and video content. However, important to note that the relation here is only methodological in its nature.

The literature on YouTube (e.g. Li et al., 2016) helps us to understand the unique features that only apply to this platform and can significantly alter our model if we do not account for them. The best example could be the control for the lifetime of the videos when we estimate our model. Here, we can build on the studies that have already examined the evolution of the views of the videos on YouTube.

The other important aspect of our chosen segment is the video format. The studies in this domain pointed out that consumers can be more influenced if they can actually see the product in someone's hand when they are using it, which strengthens our arguments regarding the product related elements of the video. In addition, we argue that this format enables more room for personal brand building than traditional text based expert reviews.

2. Research objectives, hypotheses, and structure

Given the motivation of the research and the available literature in this area, the broad objectives prior to the research were the following:

1. Explore the role of product related information in the reviewer market.
2. Identify the key characteristics of the demand and supply in the market.
3. Examine the relationship between these characteristics and the information *"product",* which is the video containing the information.

The first building block of our approach to model the product reviewer economy is the product related information aspect of the reviews. Thus, our model development process starts with the definition and identification of the information markets on the platform that can be linked to new products on the market. Based on the volume of both new products and product review videos, we selected the smartphone industry to estimate our models. We define an information market on YouTube as the collection of videos providing information about a given product on the market, and the demand for information as the audience's interest towards these videos, which we refer to as the information contents. Therefore, we can measure the overall demand for information by the number of views the information content received in the past.

Using these definitions, we first examine the relationship between the aspect of the videos that it contains product related information, and the demand coming from the audience. Thus, we hypothesize that the above described segmentation of the platform to different information markets is indeed significant, which also establishes the baseline model for the product review economy in the dissertation.

More specifically, we investigate whether the topic of the video, which is the reviewed product, significantly impacts the demand for the video, denoted by the view count changes from one period to another. However, from the studies on new product diffusion processes and consumer learning, we also know that as the uncertainty of the consumers decreases, the demand for information decreases as well. Hence, we not only test the presence of the effect on the topic but also expect it to decrease over time.

H1:

A: The reviewed product has a significant effect on the performance of the video.

B: The product's effect on the video's performance is decreasing over time.

This approach aimed to grab the exogenous effect of the topic on the videos. We argue that while this is a crucial aspect of the model, endogenous effects should also be represented. Thus, we aim to derive endogenous measure(s) of topic interest from the aggregate behavior of the market participants. First, relying on information economics, we assume that the individuals' interest towards a topic decreases over time due to their information satiation. Therefore, after the point when they join the market, they gradually lose interest. However, we do not assume that every viewer would become more and more satiated at the same rate.

Given the satiation of consumers, we can also infer that the YouTube channels on the supply side of the market may face a limited demand from the audience, which could induce competition among them. Overall, this effect would suggest a negative relationship between the performance of the videos reviewing the same product. However, we also argue that the increasing viewership of competitor video(s) may also increase the performance of the focal video. First, competitor product reviewers may bring new audience members to the market, which induces a spill-over effect for other videos on the same topic. Second, the potential viewers may use the aggregate demand and/or the number of videos on the topic as a signal of topic attractiveness. Third, as the viewership of the topic increases, the potential viewers may enter the market to have a sense of belonging to the social network and don't miss out on something important. Either way, these effects essentially raise the pool of audience that is not satiated yet. Instead, they are still aware and following up on the topic.

Based on the probabilistic properties of finding already satiated or still interested viewers, we derive a function that separates the viewership of the topic to recent views, representing the share of audience that is still interested, and to views that happened earlier, showing us the share that is already satiated. With this function, we are able to introduce the current probabilistic state of satiation and topic awareness into the model. Therefore, we hypothesize the following statement regarding the endogenized topic interest:

H2: Recent topic views have a positive, while the ones that happened earlier have a negative impact on the performance of the videos.

In our model, we differentiate three levels. The level of the videos, the level of the product, which is the collection of the videos on the same topic, and finally, the level of the channel, which is the collection of the channels' videos on multiple topics. So far, we modeled the relationship between the video and topic level, but we did not account for the channel level. Thus, in the following, we shift our focus from the demand corresponding to a specific topic to the supply side of the market and examine the reviewers' role in the market.

As we outlined in the previous section, the personal branding literature shows us that we should not handle the supply on the market as a set of homogenous actors, as there could be heterogeneity in the channels' capability to attract product and non-product related demand as well. First, corresponding to the non-product related demand, we can approach the reviewers' brands as a buffer in terms of the performance of their videos. In other words, the channels with more attractive brand images have a competitive advantage compared to other channels. This means that consumers may have a perception about the channels' capability to fulfill their non-product related needs, and they take this consideration into account when they choose a video to watch. Second, corresponding to the product related demand, we also test the possibility that the brand image is not independent of the topic effects in the model. Meaning, that we test whether a channel with a more attractive brand image has a different relation to the topic information market than channels with a worse image. Therefore, we hypothesize the following:

H3:

A: The unique channel characteristics have a significant effect on the performance of the videos.

B: The unique channel characteristics significantly differentiate the topic effects for the channels

The other differentiating factor among channels that we account for to resolve the homogenous supply assumption on the market is the aspect that they have different sizes. Here, we are building on studies examining size dependent market power and the possibilities of being a *"niche"* topic creator. Similarly to the previous differentiation, we test the size's effect from two perspectives. It may be a separate buffer to the performance of the videos, but it can also alter the relations that are already present in the model. As an example, we may expect that bigger channels can facilitate the topic awareness effect better and benefit more from a trending topic. Since we denote the size of the channels with the number of subscribers they have at the moment, we outlined the following hypotheses:

H4:

A: The channel's subscriber count has a significant impact on the performance of the videos.

B: The channel's subscriber count has a significant interaction effect with the topic effects in the model.

The result of Hypothesis 4A could have another important implication for channels as it could lead to a multiplicative relationship between the size of the channels and the performance of the videos of the channel. The process in which this can work relies on the argument that the relationship outlined in this hypothesis could be present in both directions.

If we find evidence that not only the channel size affects the views of the videos, but the views could also translate into subscribers, the channel size has a multiplicative effect on the revenue of the channels. In this process, the channel size affects the number of views the videos receive, then the views translate into subscribers, which causes an even higher number of views in long term. Due to this potential connection and long-term incentives of the channel to maximize their revenue, our second set of models is built to explain the growth of the channels.

We derive the base model representing the discussed relationship where the performance of the videos can translate into subscribers. Then, we extend this approach in two directions. First, we argue that if the channels make videos such that it reaches outside of the usual viewership of the channel, it can generate a boost for the subscriber gaining process. Second, we attempt to explain this process by using the reactions from the audience towards the videos to have a better understanding of the role of valence and audience engagement in the growth of the YouTubers. Here, we use two different methodologies, representing different consideration processes behind the subscribing decision. We derive a model with an underlying assumption that the videos' properties are essentially the manifestations of the channels' overall properties. Hence, with the aggregation of the audience reactions across the videos, we can derive an average view for the channel. We can use three reactions for these models: the number of likes, dislikes, and comments. Our second approach considers the role of valence and audience engagement in the growth process on a video contribution level. This implies a more direct effect between a better-perceived video and the subscriber number of the channel, meaning that if a new video is perceived better by the audience than the average perception of other videos, the channel will experience a spike in the subscriber count, while with the previous approach, the impact is much more conservative.

Finally, for the overall set of models, we formulated four hypothesizes, highlighting different aspects of the growth of the channels:

> *H5: The view count changes of the channels' videos have a significant positive effect on the subscriber number change of the channel.*
>
> *H6: The videos with outstanding view counts compared to the channel's other videos have a significant additional positive effect on the subscriber number changes of the channel.*
>
> *H7: We can explain the channel growth better if we use the channels' average audience reaction metrics.*
>
> *H8: We can explain the channel growth better if we use video contribution audience reaction metrics.*

We summarized the hypotheses and research questions in Table 1, which provides a hierarchical ordering of the model effects relating to our statements and questions.

Table 1: Structure of the dissertation

Category	Chap-ter	Response variable	Code	Represented Effect	Variable	Direction
TOPIC EFFECTS	Ch. 4	VIEWS	H1: A-B	Popularity	$Random\ Intercept$	Direct
				Age	$age\ of\ topic_i$	Direct
	Ch. 5		H2	Total Past Views	$\sum_{l}^{N}\sum_{t}^{\bar{T}}\Delta\, Views_{l,i}$	Direct
				Satiation	$\sum_{l}^{N}\sum_{t}^{\bar{T}} w_{\bar{T}}(t)\,\Delta\, Views_{l,i}$	Direct
				Topic Awareness	$\sum_{l}^{N}\sum_{t}^{\bar{T}}(1 - w_{\bar{T}}(t))\,\Delta\, Views_{l,i}$	Direct
CHANNEL EFFECTS	Ch.6		H3: A-B	Persona	$Random\ Intercept$	Direct
					$S_{j,t}$	Direct
					$TA_{j,t}$	Direct
			H4: A-B	Size	$Subscription_{k,t}$	Direct
					$(S_{j,t} * Subscription_{k,t})$	Interaction - Topic
					$(TA_{j,t} * Subscription_{k,t})$	Interaction - Topic
CHANNEL GROWTH	Ch. 7	SUBSCRIPTION	H5	Performance	$\sum_{i}^{N_{kt}}\Delta\, Views_{it}$	Direct
			H6	Reach	$\sum_{i}^{N_{kt}}\Delta Views_{it}{}^{\overline{Views}_{it}}$	Direct
			H7-8	Audience Reactions	$\frac{\sum_{i}^{N_{kt}} Audience\ Reaction\ Metric}{\sum_{i}^{N_{kt}} Views_{it}}$	Indirect
					$\sum_{i}^{N_{kt}}\frac{\sum_{i}^{N_{kt}} Audience\ R.M.}{Views_{it}}\Delta Views_{it}$	Direct

Source: own elaboration

3. Data and Methodology

The overall goals set up by the dissertation 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.

Notwithstanding, there are multiple products that can serve as a potentially suitable category for our research, for instance, beauty products, technology, board games, sneakers, headphones, or speakers. Motivated by our prior knowledge about the category, we decided to test our hypotheses on the technology, more specifically, the smartphone subcategory of product reviews. Thus, we collected data about product review channels and videos from YouTube API on a daily basis from 16 June 2020 to 01 October 2020.

In previous sections, we highlighted how our framework builds up from multiple literature streams. This property has an important manifestation to our methodology as well, as there could be underlying hierarchical or nested structure(s) in the dataset. For instance, based on the personal branding literature, we can assume that the videos are nested by the unique characteristics of the corresponding posting channels, while based on the consumer learning literature, one can argue that the unique characteristics of the topic of the videos, which is the products they are reviewing could also be a nesting factor.

From the perspective of building and estimating models with regressions, this nesting structure, in general, is caused by unobserved factors that sort the examined variables into separate groups with significantly different estimated regression equation(s). This creates a hierarchical system of regression equations, which can be estimated by hierarchical mixed effects modeling (Bates et al. 2004).

This modeling methodology, we define the coefficients as random variables and estimate the properties of their probability distributions rather than handling them constant. Hence, the effects are denoted as random intercepts and random slopes for the grouping variables, while fixed effects denote the non-random coefficients.

As the above example highlighted, we identified two potential nesting structures in the dissertation. First, the videos could be nested in a product related information market. In this case, the characteristics of the given topic could contain the products' and the brands' exogenous popularity or historical perception. Second, the videos could be nested by their corresponding content creators. The unobserved factors here could be the channels' presentation or title giving style, but we can list all the factors that are part of the channels' persona and we do not measure it.

4. Results

Along the objectives described in the previous chapters, the first part of the dissertation aimed to define and identify the markets corresponding to information about different products on YouTube. We denoted the collection of videos posted on the same topic, which is a new product on the market, as an information market. Relating to this, the supply of the market consists of the channels that posted the content, while the demand comes from the audience that seeks information. Building on this denotation, we were able to examine the baseline effect of the topic on the videos and answer our first hypothesis. Based on the model estimations, we found that we can accept both H1-A and B on every common significance level. This implies that our framework of information segmentation on the platform was supported by the data, which made it possible to further develop the model.

Hence, in the next chapters, we examined the demand and supply on the market more thoroughly. In the previous part of the thesis, we argued that the estimated effect of the topic could highlight the overall topic interest towards the demand for information about a certain product. However, this effect was estimated in a way that it represents the topic's interest in an exogenous fashion. Thus, we argued that if we aim to examine the dynamics of the demand and supply of information on the market, we need to endogenize a part of this effect, while we should also keep an exogenous part, accounting for effects coming outside of the platform.

To endogenize this effect, on the one hand, we relied on the information economics literature, which showed how the individual information need evolves, how the audience becomes satiated over time. On the other hand, we also used arguments regarding the competition among channels and the topic awareness of the audience that is still interested in the topic. Finally, we derived a weighting function in the model that can separate the views of the topic according to its recency. Based on the properties of this function, the most recent views represented a certain share of interested views, while the views that happened earlier showed us a certain share of satiated views. Then, we optimized the properties of the function by iteratively changing both the form and parameters of the function and estimated a model with the variables created by the function. Based on the results of this model setup, we were able to answer the first two research questions and the second hypothesis of the dissertation. Regarding the function form, both the linear and the multiplicative inverse functions resulted in significant model specifications. Based on the slight favor towards the multiplicative inverse function, we found that the optimal exponent of this function is 0.9. Then, using this weighting function, the estimated model has shown that both the satiation and the topic awareness effects are significant, having negative and positive coefficients, respectively. Thus, we accepted H2.

In the previous part of the dissertations, our approach to the suppliers of the information could be described by a set of uniform, homogenous agents. However, motivated by multiple literature streams, we may observe differences among the channels in their capability to attract product and non-product related demand. Overall, we considered two aspects that differentiate channels in terms of the performances of their videos posted on different information markets. These are the brand and the size of the channels. We tested the brand related elements of the model first. From the personal branding, we inferred that the brand images of the channels might have multiple different roles in the model of product review economy. First, corresponding to the non-product related demand of the audience, it can act as a buffer for the performance of the videos. Meaning, it can directly provide extra views for the channels over time, independently from other aspects in the model. Second, corresponding to the product related demand, it could be connected to the topic effects in the model as well. Since our results supported both the buffer and topic cross-effects, thus we accepted H3-A and B.

The other channel differentiating factor we examined is the size of the channels. This aspect relied on the literature of size-dependent market power across firms or brands. To investigate the effect of this aspect on the performance of the videos, we followed similar logic that in case of the brand images. Hence, we assumed a direct relationship, representing the effect as an independent variable in the model, and we also tested cross-effects with the topic effect as well. Here, we assumed that based on the subscriber counts, channels might moderate or boost the positive or negative effect of the current state of topic interest on the market, which motivated the fourth hypothesis. Our results have shown that both approaches are significant in the model. Hence, we can accept hypothesis 4-A and B.

From these effects, we obtained a model with three layers: videos, topics, and channels. However, channels are not only interested in the short-term benefits but also in maximizing their revenue in the long term. From this perspective, channels may be more interested in building their follower base. This consideration also arises when we examine the correlation between the two aspects, the performances of the videos and the growth of the channel. In the previous segment, we have shown the effect of subscriber count on the performance of the videos, here, we consider the relationship in the other direction. In other words, we assume a process in which viewers can eventually become subscribers. Therefore, the performances of the videos could translate to the growth of the channel, resulting long term benefits. If this connection is proven to be right, it has important implications for the channel as it highlights potentially multiplicative benefits for channels. From this process, we can infer that as channel size increases, it positively impacts all the videos of the channel, which leads to a higher growth rate, indicating a multiplicative process. These considerations motivated our second set of models, modeling the growth of the channels.

Besides our main objective in this segment, which is to examine the effect between performance and growth, we also aimed to investigate other drivers that can have important implications for the channels in terms of their growth. This extends our baseline framework in multiple directions. First, we argue that channels may achieve higher growth if they can reach the audience that is not familiar with their content. Motivated by this consideration, we derived a metric that was aimed to show whether outstanding videos of the channel provide extra benefits for them. Second, we also aimed to explain the phenomenon better by assuming that valence and audience engagement can be connected to the growth of the channels. Here, we assumed and tested two different approaches. First, we tested the *average subscribing image,* which assumes that in the eyes of the audience, the properties of the videos are the manifestations of the overall image of the brand. Therefore, we can aggregate the available feedback metrics of the videos into an average subscribing image of the channel. These metrics are the likes to views, dislikes to views, comments to views, and likes to dislikes. The other approach took a different path and instead of handling all videos equal, it tried to explain the growth on the video contribution level. Hence, the main driver of this methodology was the number of new views the videos received compared to the previous period, weighted by the audience reaction metrics mentioned above. Therefore, in this segment, we estimated four models to answer the final four hypotheses of the dissertation. Our results unambiguously suggest that we can accept both hypotheses 5 and 6. However, we can only partly accept hypothesis 7, as only the average likes per views and average dislikes per views have proven to be significant. In addition, based on the results, we found no evidence that the framework derived for hypothesis 8 would be appropriate to model the relationship between the audience reactions coming to the videos and the growth of the channels.

5. Discussion

Concluding our findings, we found that the demand for content creator generated reviews is driven by both product and non-product related needs of the audience. Our finding that the reviewed product is a significant driver of its audience size is fundamentally important. It establishes a clear link between the reviews 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 and Mayzlin, 2006; Moon and Kamakura, 2017; Marchand et al., 2017). These studies do not study information consumption by consumers. Our 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.

Our next set of findings refers to the nature of competition between reviews of the same product. We found that the reviews of the same products are predominantly complements in the short run and predominantly competitors in the long run. These findings shed light on the dynamic nature of the product review market. A creator can opt to post their review early to capture the information demand before the other reviews appear. However, such a strategy can involve risk that the product will not be picked by other reviewers and, as a consequence, will not garner much attention. On the other hand, posting a review late exposes the video to the negative, competitive effects.

The evidence regarding the complementarity and competition between content creators has implications for creators and brand managers. Audience's attention to the product is a common good which is of value to brands and content creators. Our findings suggest that prior consumer attention to the product contributes to subsequent attention, but only up to a point. For content creators, this has implications for review topic choice and publication timing. The dissertation does not derive optimal decisions of the actors involved. It could be that the incentives for creators are to publish their content as early as possible. This could maximize the positive effects of complementarity and minimize the effects of competition. Such incentives for creators could lead to mixed outcomes for marketers. On the one hand, they could lead to buzz right after product launch. Moreover, they could also give marketers a tool to influence creators, for example, they could select which creators receive review units before product launch. On the other hand, such incentives could also shorten the burst of the public's product attention. This could, ultimately, lead to a smaller reached audience compared with a scenario when product attention is stimulated over a longer period of time.

We also find that there is heterogeneity across YouTube channels in their capability to attract the product and non-product related sources of demand for videos. Thus, the views of the review depend on the creator of the review, underscoring the importance of the creators and their characteristics. This finding is consistent with the literature on para-social interaction and personal branding, implicating that the audience can develop a relationship with the creator. This finding sets content creator generated reviews apart from reviews coming from peers. In the case of peer reviews, the audience does not seem to develop such a relationship but instead, relies on extrinsic cues such as review helpfulness rating to assess message credibility (e.g., Forman et al. 2008). In contrast, we find that for the reviews on YouTube, the creator's identity is important to the audience.

Finally, we also identified a multiplicative process in the long-term growth of the reviewers on the market. This implies that big channels get even bigger over time. However, we have also found that 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, 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 whose product is being reviewed. The growing concentration could essentially mean that the economic performance of the 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 model the market of product reviews. 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, our data is aggregated across consumers. Such aggregate data allow us to include a broad set of creators, products, and a long sample period. However, we do not observe video watching histories and click streams of individual audience members. While individual data on YouTube watching is not in the public domain, future research should seek to access such data to produce a more granular picture of drivers of demand for, and competition between the reviews. Third, our data does not include information about the platform behavior, in particular, platform's content choices. Such choices are driven by the platform's recommender system. Future research should seek to include additional data capturing key aspects of the platform's behavior. Such research could shed light on how the drivers of the demand and competition emerge from an interaction of viewer preferences, social interaction, and platform behavior. Regarding the model on the growth of the reviewers, 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.

Finally, future research should further our understanding of the link between earned media consumption and sales. Prior research has explored the direct link between properties of earned media, such as the valence of reviews and sales. We document that the demand for earned media can be associated not just with product interest but also for entertainment or social reasons. We also document that audiences' interest in the product depends on earned media popularity. Taken together, this implies that the relationship between earned media consumption and sales is complex. Future research should study earned media, information consumption, and sales jointly.

Publications and Conferences:

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