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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 on 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. Based on this gap, our 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 are diminishing over time.

Then, we were able to formulate hypothesizes 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 used the literature on information search to endogenize the overall interest towards the topic into a current state of topic awareness, which is mostly driven by the satiation of the audience. Our results indicate that both the topic awareness effect and its counterpart, the satiation effect are significant, having positive and negative relationship with the performance of the videos, 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, based on the personal branding literature. We found that the sizes of the channels have significant positive impact on the performance of the videos, while having significant negative effect on the above-defined demand effects. Our results suggest that the unobserved factors related to the image of the brand also significantly differentiates 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. Our main question to these models were whether and how the performance of the videos translates into subscriber counts. We accepted this hypothesis and found that the outstanding videos provide extra effects for the growth. In addition, we tested whether the video level reactions from the audiences can be related to the growth and found that the average ratio of likes to views and dislikes to views proved to be significant.

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 type 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 or experts. While the firms essentially have a very high-level control over the 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 performances 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 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 of the 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. In case of user reviews, the traditional word-of-mouth (WOM) of consumers who already bought the item now can be reached by almost anyone in the world in various forms, such as online ratings, or text-based feedback. Nowadays, most of the online ecommerce platforms have a segment for user feedbacks, but there are also websites dedicated only for such reviews.

The other main type of the product reviews is the feedback that does not come from the companies or users, but from some third-party information intermediary. Due to its function in the consumer learning process, we simplify the notation of this category as expert or professional reviews. In case of this type of reviews, we can observe that the domain has changed just as much as that of user reviews.

First, the traditional magazine or newspaper segments of product reviews has moved to blogs and websites. Then, with the emergence of organized online attention platforms, such as YouTube, the profession or expert reviews evolved into the complex ecosystem that we can observe nowadays. In this system, while the role of blogs and websites remained meaningful, the websites, 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 more the traditional newspaper or magazine model. The centralized supply provides easier access of information from more sources for consumers. Meanwhile, the properties of the platform make the entry to the market accessible for anyone who aim 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 user reviews and its effect on the consumers and the firms are well-documented in the marketing domain. However, our understanding about the expert review ecosystem is very limited in general and our knowledge is especially scarce regarding the modern shared platform reviewer market. Therefore, in the dissertation we aimed to fill this gap in the literature and shed light of the main drivers of this complex market. In addition, we have chosen 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.

Product Reviews

Based on the content of these videos, the dissertation connects to the product review literature which can be divided into two parts in terms of the source of the reviews. The reviews that are coming from the users of the product who already used it and the ones that originates from professionals, defining the product review expertise.

The literature stream on user reviews (e.g. Erdem and Keane, 1996; Zhao et al., 2013, Wu et al. 2015) is mostly focusing on the consumers' learning process when they are facing these feedbacks from other consumers. The results of this category had many implications for the dissertation. For instance, it describes the evolution of the individual and 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. However, we argue, that product reviewers on YouTube fit better to the field of expert reviews.) The relatively narrow literature that is available for this domain are mainly examining the economic impact of the reviews on the firms (such as sales or market value) (e.g. Eliashberg and Shugan, 1997; Basuroy et al., 2003, 2008; Reinstein and Snyder, 2005; Tellis and Johnson, 2007; Terry et al., 2011). Nevertheless, the findings of these domains (both user and expert reviews) have shown that reviews in general play a crucial role in the consumers' quality perception and expectation about goods with uncertain quality. They also highlight the need for firms to understand these processes and acknowledge the role the earned media in this regard as well.

Behavior of the media

In contrast to the studies in the field of product reviews, the dissertation aims to model the expert review market itself, and not only examine its impact on the consumers or the firms. This includes the participants with their incentives and the dynamics in the market caused by the product related information. While we identified a gap in the marketing domain regarding to modeling the market of product relation information itself, we can find theoretical models from other disciplines where the agents have similar goals and incentives as in our approach. This stream models the behavior of various types of media. However, the framework of these studies is different compare 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 appliable to our model. (e.g. Mullainathan and Shleifer. 2005; Xiang and Sarvary, 2007; Battagion and Vaglio, 2015; Gabszewicz et al., 2001; 2002; 2004) However, perhaps the most important difference comes from the researchers' methodological choice, as this literature stream is building models on a theoretical level, while our dissertation uses quantitative models tested on data downloaded from YouTube. Nevertheless, this domain also 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 Sarvary's (2013). In their framework, they assume that news providers try to maximize ex ante expected audience size to achieve the optimum. This also means, that they have a fixed rate per viewer advertising and content revenue.

Personal Branding

Online personal branding is one of the trending topics in the marketing literature in the recent years. The main connection point here is the argument that YouTube review channels are creating, building, and managing their own brands as it is defined by this domain. (e.g. Hewer and Brownlie, 2013; Duffy and Hund, 2015; Dion and Arnould, 2016; Scolere et al., 2018). The self-brands' unique property that their faces are the brand itself, it is built around the individual. For instance, we can mention the brands around popular figures such as Gordon Ramsey, LeBron James, or Calvin Klein, but the domain also considers the management of the brand of influencers as well.

From the perspective of the dissertation, the direction of persona-fied brands 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 considers to be connected to the profession of the brand. To successfully manage these types of brands, the channels need to appropriately merge different persona facets, features into a brand image and narrative.

Therefore, thorough the dissertation we consider these channels similarly to the brands in other industries. We develop our model to account for the differences among the channels' brand images, while we also consider the implications of our models to address the above described argument regarding the persona-fied self-brands.

YouTube and the video format

Finally, based on the chosen platform and format of the reviews, our 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, Cha et al., 2009) helps us to understand the unique features that only applies 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 video when we estimate our model. Here, we can build on the studies that already examined the evolution of the views of the videos on YouTube.

The other important aspect of our chosen segment is the video format. As the related studies pointed out, that consumers react differently, they 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

Our approach to model the product reviewer economy is built around the product related information. Thus, our model development process starts by the definition and identification of the information markets on the platform that can be connected to new products on the market. Based on the volume of both new products and product review videos, we choose the smartphone industry to estimate our models. We define an information market in YouTube as the collection of the 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 *products*. Therefore, we can measure the overall demand for information by the number of views the information *products* received in the past.

Making the ground for most of the models in the dissertation, we first hypothesize that the segmentation of the platform to different information markets is indeed significant. More specifically, the topic of the video, which is the product it is reviewing, has meaningful effect on its performance, denoted by the view count changes from one period to another. However, from the information market and product review literature we also know that as the uncertainty of the consumers decrease, the demand for information is decrease as well. Hence, we not only test the presence of the effect on the topic, but we also expect it to decrease over time.

H1:

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

B: The effect of the product on the video is decreasing over time.

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

Besides the individuals' satiation and topic interest effect, the channels are also an integral part of the market and their activity may also affect the performance of all the videos on the market. First, we assume that the channels are competing each other for views. We argue that based on the definition behind competition, it is only possible if there is scarcity regarding the focal resource. Hence, the competition among channels is connected to the satiation effect of the market, since that property shows that the viewers interest is finite. On the other hand, we also argue that as channels are posting videos on the market, they can also raise the overall interest towards the topic. This may work by directing some their unique fanbase to videos on competitor videos with the same topic. Among others, another possibility could be that they are making content such that it is interesting enough for the audience to incentivize them to remain aware and follow up on the topic. Either way, this effect essentially raises the pool of aware views on the market. Therefore, it is connected to our previously described topic awareness.

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 are already satiated.

With this function, we are able to introduce the current state of satiation and topic awareness into the model. Nevertheless, the properties of this function and the estimation of the model poses us a challenge to overcome. Hence, we formulate the following research questions regarding the endogenized topic interest:

RQ1: What is the resultant of the potential positive and negative endogenous topic effects on the YouTube product reviewer market?

RQ2: How can we separate the aggregate effect to represent the satiation and topic awareness of the consumers and the competition among channels?

Based on the answers to these questions, we can now hypothesize the main statement regarding the goals of these models:

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 levels 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 modelled the relation between the video and topic level, but we did not account for the channel level. As we outlined in the previous chapter, the personal branding literature shows us that we should not handle the supply on the market as a set of homogenous actors. Instead, we assume that we can observe heterogeneity among them from multiple aspect. First, we can understand the brands of the channels as a buffer in terms of the performances of their videos. In other words, the channels with more attractive brand images have a competitive advantage compare to other channels. Second, we also test the possibility that the brand image may not be independent from other factors of the model. This includes the topic effects we derived before. Meaning, that we test whether a channel with more attractive brand image have different relation to the topic information market than channels with 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 differentiates the topic effects for the channels

The other differentiating factor among channels that we account for in this dissertation is the aspect that they have different sizes. Here, we build on the consideration that relies on the arguments of size dependent market power and possibilities of being a *"niche"* topic creator. Similarly to the previous differentiation, we test the effect of the size of channel from two perspective. It may be a buffer to the performance of the videos, but it can also alter the relations in the whole model. As an example, we may expect that bigger channels can facilitate the topic awareness effect better and grab more share from the common effect of the trending topic. Since we denote the size of the channels with the number of subscribers they have at the moment, we outlined the following hypothesizes:

H4:

A: The number of subscribers of the channels has a significant impact on the performance of their videos.

B: The number of subscribers of the channel has a significant interaction effect with the topic effects in the model.

The result of the Hypothesis 4A has another important implication for the channels. This is due to the aspect that the size of the channel could have multiplicative benefits for the channel if it is proven to be significant. The process in which this can work relies on the argument that there could be a relationship between the channels' size and the performance of their videos for both directions. If we find evidence that not only the channel size affects the views of the videos, but the views of the channel's videos also translates into subscribers at later periods, the channel size have multiplicative effect for the revenue of the channels. In this process the channel size affects the number of views its videos get, then the views translate into subscribers that causes even higher number of views in long term. Due to this potential connection and long-term incentives of the channel, our second set of models are 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 into 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 try to explain this process by using the reactions from the audience towards the videos of the channels to understand some of the motives of the subscribers. Here, we use two different methodology, representing different consideration process 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 number of audience reactions across 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 takes the number of new view counts of the videos of the channel from period to period and assumes a process on a video contribution level. Thus, 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 has a significant positive effect on its subscriber number changes.

H6: Outlier videos of the channel in terms of their view counts have significant positive extra 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 the video contribution audience reaction metrics.

We summarized the system of hypothesizes 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	Chapter	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; RQ1-2	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 this dissertation can be investigated on many different sets of observations, coming from reviews on different categories of products. The only condition which the chosen product category must fulfill, is the presence of enough product reviewer channels to obtain sufficient number of observations to derive reliable results.

Notwithstanding, there are multiple products that can serve as 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 hypothesizes 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 be also 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 modelling (Bates et al. 2004).

This modelling 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 is 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 was aimed to define and identify the markets corresponding to information about different products on YouTube. We denoted the collection of the 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 who posted the content, while the demand comes from the audience that seeks for 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 hypothesis on every common significance level. This implicates that our framework of information segmentation on the platform was supported by the data, which made us 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 parts 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 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 that comes from outside of the platform.

To endogenize this effect, on one hand, we relied on the information search and consumption 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 towards the topic. Finally, we derived a weighting function in the model which can separate the views in 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 the parameters of the function and estimating the 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. For RQ1, we found that the resultant of the effects is only significantly different from zero at a 10% confidence level. Regarding the function form, we observed both function form, the linear and the multiplicative inverse, to be significant. 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 have shown that both the satiation and the topic awareness effect are significant, having negative and positive coefficient, respectively. Thus, we accepted H2.

So far in the dissertations, our approach to the suppliers of the information could be described by a set of uniform, homogenous agent. In contrast, in the next parts, based on the personal branding literature, we aimed to resolve this assumption and account for individual heterogeneity across YouTubers. This also defined us the third level of our overall model. First, the video level measures, second, the product level, consisting the videos posted on the same topic by different creators and finally the channel level, which includes the videos posted by the same channel on various topics.

We considered two aspects which differentiates channels in terms of the performances of their videos, posted on the different information markets. First, the personal branding literature, second, the sizes of the channels. We tested the brand related elements of the model first. From the available literature we inferred that the brand images of the channels may have multiple different roles in the model of product review economy. First, it can act as a buffer for the performance of the videos of the channel. Meaning, it provides a fixed amount of views for the channels over time, so it is not dependent on other aspects of the model. In contrast, our second approach resolves this assumption and enables cross-effects with the topic effects defined before. In conclusion, these two outlined approaches defined two models aimed to answer the third hypothesis of the dissertation. Since our results supported both the buffer and the topic cross-effects, we accepted H3-A and B.

The other channel differentiating factor we examined is the sizes 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 to that of brand images. Hence, we first assumed a direct relationship, representing the effect as an independent variable in the model. Second, we tested cross-effects between the topic effect as well. Here, we assumed that based on the subscriber counts, channels may moderate or boost the positive or negative effect of the current state in the market in terms of the demand or supply of information, which was motivated the fourth hypothesis. Our results have shown that both approaches are significant in the model, hence we accepted hypothesis 4-A and B.

From these effects, we obtained a model with the above described three layers: videos, topics, channels. However, channels when making decisions not only interested in short term benefits but rather to maximize their revenue on the long term as well. 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 described 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 that the two aspects can be related through a process in which viewers 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 a potentially multiplicative benefits for channels. From this process, we can infer that as channel size grows, it positively impacts all the videos of the channel, which result higher growth rate, resulting a multiplicative process. These considerations motivated our second set of models, modelling the growth of the channels.

Besides our main objective in this segment, which is to examine the effect between the performance and the 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 into 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 which was aimed to show whether outstanding videos of the channel provides 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 channels' growth. 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 metric of the videos into an average 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 rather than handling all the videos equally, 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 certain 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 hypothesis 5 and 6. However we can only partly accept hypothesis 7, as only the average likes per views and the average dislikes per views have proven to be significant. Based on the results, we found no evidence, that the framework derived for hypothesis 8 would be appropriate to model the connection between the audience reactions coming to the videos and the growth of the channels.

5. Future research directions

The dissertation outlined a base framework for examining the role, the demand, and the supply of product related information in the platform of YouTube. A straightforward continuation research direction from this point could be the introduction of model extensions that could unfold even more aspects of the information market.

First, one can argue that similarly to other markets, the demand and supply of the information about a given product could be dependent on information on other product(s). Therefore, introducing cross-market dependencies and elasticities to the model could give valuable information for firms, marketers, and the information mediators as well.

Second, as we mention thorough the dissertation, one can argue that comments of the videos can contain information about the consumers valence towards the information *products*. However, retrieving this information lied outside of the limits of the dissertation as it would require the application of highly sophisticated natural language processing (NLP) designed to YouTube comments on product reviews. Nevertheless, we consider this direction a relevant and interesting potential future research area, as it may provide more depths about the information consumers revealed preference about the information *product*.

The potential extensions above described directions to extend the framework corresponding to YouTube. In contrast, there could be other similar platforms in which these information markets could be identified. Therefore, from the perspective of the firms, extending the literature about the economy of product related information in other platforms could be a significant future research direction.

Finally, we estimated our models on data collected from product reviewers in the tech genre. Nonetheless, there are many other industries where the corresponding market of product related information provides us the opportunity to apply our framework. Hence, repeating our methodology to other products' information markets could highlight important structural differences among consumers and/or providers caused by or related to the different genres of product reviews.

References

Basuroy S, Chatterjee S, & Ravid S.A. (2003). How critical are critical reviews? The box office effects of film critics, star power and budgets. Journal of Marketing 67(4): 103–117.

Basuroy, S., & Chatterjee, S. (2008). Fast and frequent: Investigating box office revenues of motion picture sequels. Journal of Business Research, 61(7), 798-803.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). Fitting linear mixed-effects models using lme4. *arXiv preprint arXiv:1406.5823*.

Battaggion, M. R., & Vaglio, A. (2015). Pin-ups and Journalists: A Model of Media Market with News and Entertainment. Journal of Media Economics, 28(4), 217–245. doi:10.1080/08997764.2015.1094078

Cha, M., Kwak, H., Rodriguez, P., Ahn, Y. Y., & Moon, S. (2009). Analyzing the video popularity characteristics of large-scale user generated content systems. *IEEE/ACM Transactions on networking*, *17*(5), 1357-1370.

Dion, D., & Arnould, E. (2016). Persona-fied brands: managing branded persons through persona. *Journal of Marketing Management*, *32*(1-2), 121-148.

Duffy, B. E., & Hund, E. (2015). “Having it all” on social media: Entrepreneurial femininity and self-branding among fashion bloggers. *Social Media+ Society*, *1*(2), 2056305115604337.

Eliashberg J, Shugan SM (1997) Film critics: Influencers or predictors? J. Marketing 61(2):68–78.

Erdem, T., & Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing science*, *15*(1), 1-20.

Falkinger, J. (2007). *Attention economies. Journal of Economic Theory, 133(1), 266–294.* doi:10.1016/j.jet.2005.12.001

Gabszewicz, J. J., Laussel, D., & Sonnac, N. (2001). *Press advertising and the ascent of the “Pensée Unique.” European Economic Review, 45(4-6), 641–651.* doi:10.1016/s0014-2921(01)00139-8

Gabszewicz, J. J., Laussel, D., & Sonnac, N. (2002). Press Advertising and the Political Differentiation of Newspapers. Journal of Public Economic Theory, 4(3), 317–334. doi:10.1111/1467-9779.00100

Gabszewicz, J. J., Laussel, D., & Sonnac, N. (2004). Programming and Advertising Competition in the Broadcasting Industry. Journal of Economics Management Strategy, 13(4), 657–669. doi:10.1111/j.1430-9134.2004.00027.x

Hewer, P., & Brownlie, D. (2013). Spaces of hope, enlivenment and entanglement: Explorations in the spatial logic of celebrity culinary brands. *Journal of Consumer Culture*, *13*(1), 46-63.

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

Li, F., & Du, T. C. (2017). Maximizing micro-blog influence in online promotion. *Expert Systems with Applications*, *70*, 52-66.

Mullainathan, Sendhil, and Andrei Shleifer. 2005. "The Market for News." American Economic Review 95 (4) (September): 1031–1053. doi:10.1257/0002828054825619.

Newman D. (2004). [online] The Role Of Paid, Owned And Earned Media In Your Marketing Strategy: https://www.forbes.com/sites/danielnewman/2014/12/03/the-role-of-paid-owned-and-earned-media-in-your-marketing-strategy/?sh=6e93544b28bf

Reinstein, D.A., Snyder, C.M., 2005. The influence of expert reviews on consumer demand for experience goods: a case study of movie critics. J. Ind. Econ. 53 (1), 27–51.

Scolere, L., Pruchniewska, U., & Duffy, B. E. (2018). Constructing the platform-specific self-brand: The labor of social media promotion. *Social Media+ Society*, *4*(3), 2056305118784768.

Tellis, Gerard and Joseph Johnson (2007), "The Value of Quality," Marketing Science, 26 (6), 758–73.

Terry, N., Butler, M., & De'Armond, D. A. (2011). The determinants of domestic box office performance in the motion picture industry. Southwestern Economic Review, 32, 137-148.

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

Xiang Y, Sarvary M (2007) News consumption and media bias. Marketing Sci. 26(5):611–628

Xiang Y, Sarvary M (2007) News consumption and media bias. Marketing Sci. 26(5):611–628

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