Popularity Determinants of YouTube Videos

Determinantes da popularidade dos vídeos do YouTube

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Abstract
Objective: This article aims to identify and estimate the determinants of YouTube video popularity.

Methodology/procedures: An empirical survey was conducted with 50 Brazilian YouTube channels. The hypotheses pertinent to the model were developed and subjected to the relevant validations.

Originality/Relevance: In the theoretical dynamic model, the number of views of a video depends positively on the video's category, the number of videos per channel, the total number of days online, and the number of likes; it is negatively impacted by the video's duration, the number of subscribers, and the number of comments. As it is a phenomenon that impacts society, the importance of empirical, academic, and technical studies that elucidate comprehensive aspects of the topic is highlighted.

Main results: Empirical results reveal that the most important popularity factors are the number of videos per channel and the total days online. Robustness tests are conducted thru quantile regressions. The audience may vary between content categories in terms of views and responses.

Theoretical/methodological contributions: The study aims to contribute by elucidating general aspects and knowledge gaps in this topic, which can be considered as emerging. It can indeed be considered a potential frontier of research.
Social/managerial contributions: The understanding, discovery, and explanation of this phenomenon are important for decision-making by regulatory sectors, organizations, and society in general.

Keywords: YouTube, user-generated videos, video sharing, popularity, quantile regression

Resumo
Objetivo: Este artigo tem por objetivo identificar e estimar os determinantes da popularidade dos vídeos do YouTube.

Metodologia/procedimentos metodológicos: Foi realizada uma pesquisa empírica, do tipo *survey*, com 50 canais de YouTube brasileiros. Foram elaboradas as hipóteses pertinentes ao modelo, sendo submetidas às validações pertinentes.

Originalidade/Relevância: No modelo dinâmico teórico, o número de visualizações de um vídeo depende positivamente da categoria do vídeo, do número de vídeos por canal, do total de dias online e da quantidade de curtidas; é impactado negativamente pela duração do vídeo, pelo número de inscritos e pela quantidade de comentários. Como se trata de um fenômeno impactante na sociedade, evidencia-se a importância de estudos empíricos, acadêmicos e técnicos, que elucidem aspectos abrangentes do tema.

Principais resultados: Os resultados empíricos revelam que os fatores de popularidade mais importantes são o número de vídeos por canal e o total de dias online. Os testes de robustez são realizados através de regressões quantílicas. O público pode variar entre categorias de conteúdo em termos de visualizações e respostas.

Contribuições teóricas/metodológicas: O estudo pretende contribuir, elucidando aspectos gerais e lacunas de conhecimento, neste tema que pode ser considerado como emergente. Efetivamente pode ser considerado como uma fronteira potencial de pesquisas.

Contribuições sociais/para a gestão: A compreensão, descoberta e explanação deste fenômeno é importante para as tomadas de decisões pelos setores reguladores, pelas organizações e pela sociedade em geral.

Palavras-chaves: YouTube, vídeos gerados por usuários, compartilhamento de vídeos, popularidade, regressão quantílica

Resumen:

Objetivo: Este artículo busca identificar y estimar los determinantes de la popularidad de los videos de YouTube.

Metodología/peocedimientos metodológicos: Se realizó una encuesta empírica con 50 canales brasileños de YouTube. Se desarrollaron hipótesis relevantes para el modelo y se sometieron a las validaciones correspondientes.

Originalidad/Relevancia: En el modelo dinámico teórico, el número de visualizaciones de un video depende positivamente de la categoría del video, el número de videos por canal, el total de días en línea y el número de "me gusta"; se ve afectado negativamente por la duración del video, el número de suscriptores y el número de comentarios. Dado que se trata de un fenómeno de gran impacto social, es evidente la importancia de estudios empíricos, académicos y técnicos que diluciden aspectos integrales del tema.

Resultados principales: Los resultados empíricos revelan que los factores de popularidad más importantes son el número de videos por canal y el total de días en línea. Se realizan pruebas de robustez mediante regresiones cuantiles. La audiencia puede variar entre categorías de contenido en términos de visualizaciones y respuestas.

Contribuciones teóricas/metodológicas: Este estudio pretende contribuir a dilucidar aspectos generales y lagunas de conocimiento en este tema, que puede considerarse emergente. Se puede considerar, en efecto, una posible frontera de investigación.

Contribuciones sociales/para la gestión: Comprender, descubrir y explicar este fenómeno es importante para la toma de decisiones de los sectores reguladores, las organizaciones y la sociedad en general.

Palabras clave: YouTube, vídeos generados por usuarios, compartición de vídeos, popularidad, regresión cuantílica

1. Introduction

YouTube is the largest video platform with a global audience of over two billion viewers from over 100 countries each month (www.youtube.com/yt/press/statistics.html) and an ad revenue of $4.04 billion as of the first quarter of 2020 (Spangler 2020). According to The Diffusion Group (TDG), the percentage of minutes per online video visualization will increase from 17% in 2015 to 38% in 2025; over 80% of internet traffic is projected to be driven by video consumption. TDG's forecast of continued growth in–video echoes claims by digital marketing experts that "video content is the future"[i] and the increasing attention marketers are giving to social media channels and video sharing platforms with predominantly user-generated content (e.g. YouTube) for advertising brands, products and services and attempting to influence electronic-word-of-mouth (eWOM)[ii] (van Noort et al. 2012).

With video advertising generating billions of dollars per year, it pays for marketers, who are already exploring ways to leverage and incorporate user-generated content into marketing efforts and campaigns (Thompson and Malaviya 2013), to understand video popularity determinants on YouTube, and then replicate those elements that contribute to video success. The present study's exploration of specific elements driving a video's public success using relevant industry data and data-mining tools contributes to bridging the research and practice gap identified in the digital, social media, and mobile marketing (DSMM) context by Lamberton and Stephen (2016).

This paper analyzes the determinants of video popularity of Brazilian channels on YouTube along with viewer behavior. Our objective is to provide a theoretical model identifying the key variables that influence video visualization and to estimate the model to ascertain which of these have the greatest effect on a video's popularity. Additionally, we aim to pinpoint what content leads to video success as well as gain greater insight on public reaction to these favored videos. As a relevant and timely inquiry, this study also provides evidence-

based justification for decision makers who need to allocate marketing budgets and resources for creating and integrating consumable content across user-generated video platforms.

The internet, according to Zwass (2010), allows consumers to create value, which is an elusive concept in marketing (Gronroos & Voima 2013). The YouTube platform facilitates customer use and transformation, providing feature and performance recommendations, and consequently co-creation of value (Moller 2008). Video success depends on the viewer's use value captured by social interactions (including variables such as comments, likes and number of subscribers) as content creators and consumers become co-creators of value; they also become the driving force of the YouTube video industry (Vargo & Lusch 2004, 2008a, 2008b).

This paper illuminates how video "value" is created, and a distinctive feature of our approach is to offer a simple theoretical model of the determinants of video popularity with empirical evidence obtained through an original database. As a pioneering paper, it uses the lag structure of the model as an important component of our theory. The hypothesis derived by the model is that the number of views of a video depends positively on the video category, the amount of videos per channel, the number of days online and number of likes; it is negatively impacted by video duration, number of subscribers and comments.

YouTube facilitates data gathering. For this study, we selected data from the top 50 Brazilian YouTube channels as of September 2018. We test the hypothesis derived by the model. The empirical results show that the most important popularity factors are the total amount of videos per channel and the number of days online. Robustness tests are carried through quantile regressions that assess whether the effects of popularity determinants vary along different quantiles. The audience may vary across video content categories in views and responses, such as in the case of music videos, which receive the most views but have a low level of engagement.

2. Relevant Literature

As the predominant video sharing platform, YouTube is featured in studies on video user-generated content in marketing and in much of the literature analyzing video popularity dynamics and characteristics. According to Chen's (2103) qualitative study of YouTube content

creators, individual personal brands are crafted through a three-stage process (extract, exude, and express) and has implications for consumer empowerment. Verhellen et al. (2013) explore the advertising potential of YouTube's online video-sharing content capability and find positive effects of brand placement and integration—measured by prominence and endorser expertise (celebrity vs. amateur)— on viewer response (brand recognition and purchase intention).

Several studies on online video content popularity identify initial popularity as an indicator of long-term success. In Szabo and Huberman's (2010) popularity model, predictions are based on linear correlation between the logarithms of the early and later stages of the content's popularity. Further developing this model, Pinto, Almeida and Gonçalves (2013) use data analytics collected from the video (the number of likes, the amount of comments and how many times it was favorited) along with the video creator's data (number of friends and subscribers) to estimate YouTube popularity trends using multivariate linear regression. They find three patterns of users' reactions to videos: instant hits, videos that attract increasing attention over time, and videos with a limited audience.

Cha et al. (2007) use data from YouTube and Daum to analyze video popularity cycles and identify a pattern—content popularity is established at the early stage of video lifecycle. Over 70% of the video requests are comprised of videos older than one month while 80% of viewed videos, on any given day, were posted at least one month prior, with the most recently posted ones viewed the most. Figueiredo, Benevenuto and Almeida (2011) also investigate popularity predictors finding that the most viewed videos experience popularity peaks after their initial posting, while random videos and videos with image copyright experience lower levels of peaks in popularity. Zhou et al. (2016) similarly identifies the video discovery mechanisms on YouTube (related video recommendation system, keyword-based search engine, and highlights) as influencers of view rates; recommendations and search are the two consistent long-term drivers of video views.

Cheng, Dale and Liu (2008), with data on more than three million videos present a statistical study on video duration, access patterns, growth trend and "active life period," (the period of time in which videos remain popular). They conclude that social interactions (likes and comments) have the least impact on video popularity when compared with the other video

characteristics; they do not demand a user's account or login to access the platform. Employing a panel data framework, Yoganarasimhan (2012) observes factors impacting YouTube video consumption and find that viewership is not greatly impacted by the number of ratings (unless there are none), the average rating received, having honors or daily comments, while being favorited does positively impact viewership.

Zink et al. (2009) investigates geographical characteristics in relation to popularity of YouTube videos finding little correlation between the global popularity and local video popularity. Studying a one-year sample of over 20 million YouTube videos, Brodersen, Scellato, and Wattenhofer (2012) identify geographic locality as a constraining influence on video popularity accounting for focus location, view focus and view entropy. Of the global online video consumption analyzed, the U.S. accounted for 37.7% of the fraction of video focus location with Brazil coming in second at 6.6%. Castañón (2017) focused on the popularity of YouTube channels in general. His regression results suggest strong behavioral patterns captured by the correlation between entertainment and music as well as between the total number of views and the number of likes and comments.

Currently there is limited research that takes full advantage of data extracted from YouTube's API (Application Programming Interface). For example, Kamiyama and Murata (2019) use a time-series model and API to analyze the number of daily views, their finding conforms to the lognormal distribution and is consistent with a previous study by Borghol et al. (2011). Examining meta-data (views, ratings, and comments) on over one million YouTube videos over the course of eight months, the study finds viewing rates of user-generated videos change over time - designated as the popularity dynamics or popularity evolution - and that current popularity of a video is not a reliable predictor of future popularity. Schwenner and Ziewiecki (2018) analyze product promotion by social media influencers on the most popular 100 YouTube channels in Germany; the study uses the number of channel subscriptions as an accepted indicator of popularity and extracts basic information and statistical data for videos from 2007 - 2019 using YouTube API. Findings suggest that monetized content in product promotion videos by social influencers (via both referral links and oral advertisement) has an increasing influence in the fashion and beauty spheres.

The literature on online reviews and opinions channels is extensive**.** Online comments provide evaluative/descriptive statements about a video, include positive/negative personal opinion, and incorporate advice-giving and information about quality (Mangold et al., 1999). Baumeister et al. (2001) argue that people react more strongly to negative information than to positive, and perceived negative emotions reduce usefulness of the review (Yin et al. (2013). Hair and Ozcan (2018) study the effects of profanity on perceptions of online reviews; in negative reviews, profanity reduces usefulness while in positive reviews, it increases review helpfulness. Hu et al. (2009) observe that the majority of online reviews are favorable. Hsieh et al. (2012) attribute a higher propensity for sharing or forwarding content (generating positive eWOM in the process) to how strongly it influences consumer affective response. Positive video reviews are in turn more likely to be shared than negative ones, according to Bi et al. (2019), thus marketers should give focused attention to negative third-party reviews as these opinions and experiences often inform others beliefs and attitudes about companies and their products or services.

A novel approach to studying this data is through data mining and sentiment analysis, which focuses on the users' behavior and the particular content that attracts their attention. Data mining exploits large datasets with the objective of identifying repeated clusters and patterns allowing an analysis of information in an efficient manner (Liu and Zhang, 2012). Sentiment analysis refers to the natural language process [NLP], text mining and computational linguistics, which identify, extract, quantify and study subjective information, not observed in the form of data. Pak and Paroubek (2010) remark that more efficient language programming and greater users' exposure to social networks generate valuable behavioral sources with regards to a given subject, product, or service.

3. Model

In this section, we develop a dynamic theoretical model in which time lags embody a number of hypothesis implicit in marketing literature and closely follows the discussion put forward by Kuppelwieser, Simpson and Chiummo (2013) on co-creation of value between

producer and consumer on YouTube. However, for the sake of the empirical estimation, we focus on the steady state solution of the model.

The number of views of a YouTube video *V*, is a function of comments *C*, likes *L*, number of subscribers *S*, and days online *D*, plus the category *Q* and duration *M* of the video, which are constant:

$$V_t = \alpha C_t + \beta L_t + \gamma S_t + \delta D_t + Q - M \qquad (1)$$

Equation (1) assumes that longer videos get less audience, so the impact of *M* on *V* is negative. The number of likes is a linearly increasing function of views:

$$L_t = aV_t \qquad (2)$$

More people enjoying a video per period of time triggers the popularity of the channel; if a channel has many followers, in the subsequent period, it gathers less followers:

$$S_t = -b_1 V_t + b_2 V_{t-1} \qquad (3)$$

Comments depend on the number of people that think videos that deserve comments are the important ones; if a video had many previous comments, it gets less comments over time. So we assume the number of comments is a function of past views:

$$C_t = -c_1 V_{t-1} + c_2 V_{t-2} \qquad (4)$$

Note that Equations (2), (3) and (4) refer to social interactions along time between customers [viewers]. They essentially capture value co-creation by customers at YouTube as hypothesized by Kuppelwieser, Simpson and Chiummo (2013). The number of days a video remains online depends on the number of views:

$$D_t = qV_t \quad (5)$$

Plugging Eqs. (2)-(5) into (1) yields:

$$V_t = [1 + \gamma b_1 - a\beta - q\delta]^{-1}[Q - M - (\alpha c_1 - \gamma b_2)V_{t-1} + \alpha c_2 V_{t-2}] \quad (6)$$

The long run equilibrium, i.e., the steady state is found by $V_t = V_t = V^*$:

$$V^* = \frac{[Q-M]}{[1+\gamma(b_1-b_2)+\alpha(c_1-c_2)-a\beta-q\delta]} \quad (7)$$

According to Equation (7), the equilibrium number of views of a video depends positively on the specific video category [such as music, gaming, and entertainment], the number of days online [captured by the term $q\delta$], and the amount of likes [given by $a\beta$]. The number of views depends negatively on video duration and, assuming that the following inequalities $(b_1 > b_2), (c_1 > c_2)$ hold, on the number of subscribers and comments. The next sections present the data set and the tests of the above model.

4. Methodology and Data

The determinants were estimated using linear regressions. The main hypothesis is that the average effect of each regressor, controlled by the other variables, on the dependent variable is constant. The parameters were estimated by OLS. In this way, we are assuming the conditional mean is:

$$E[y|x_1, x_2, \dots] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots$$

The parameters and model inference were performed using the t and F tests at the 5% significance level. As an exercise of robustness/sensitivity, we also estimate quantile

regressions for the deciles of the dependent variable, that is, the linearity for the conditional quantiles is such that:

$$Q[y|x_1, x_2, \dots] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots$$

Therefore, it was possible to test the effect changes of determinants through dependent variable distribution. In this case, the estimation process is performed by minimizing a function of the predicted error using linear programming and standard errors are calculated by bootstrap. Models were estimated using Stata.

YouTube has a list of videos that are highly viewed on a daily basis, the so-called "top trending." According to *Variety* magazine, to determine which videos make this list, YouTube's algorithm uses a combination of factors related to user interactions on the platform, such as the number of views, comments, likes and shares. The procedures used to assemble the database described in an API, Application Programming Interface, is a set of programming instructions that gives access to a specific software application. Data was obtained using the YouTube API, created by Google Developers, which allows the incorporation of normally performed functions on video platforms of third-party websites or applications. The structure of this API is based on resources, which are individual data entities that can be extracted by the user with 11 types of resources available.

Bearing in mind that the objective of the paper is to analyze the determinants of popular videos, our focus was on Brazilian channels and their videos. Therefore, channel (channel) and video (video) resources were used. Within each resource, there are numerous properties that can be extracted by the user and each of them represents specific data. The following properties were used: (1) Channel: title, publishedAt, viewCount, videoCount, subscriberCount, keywords; (2) Video: title, viewCount, likeCount, dislikeCount, commentCount, channelId, channelTitle, categoryId, publishedAt, duration, definition, tags.

Auth 2.0 is an authentication protocol widely used by developers at large companies, such as Google, Twitter and Facebook. It allows applications to obtain limited access to an HTTP service by creating an approval interaction between the resource owner and the end user,

without the user directly manipulating usernames and passwords, ensuring the security of the data worked on. The Google Developer APIs use the OAuth 2.0 protocol for authentication and authorization of data extraction; therefore, it was necessary to adjust these settings for the design of the project. Within the Google API Console, it was necessary to initially obtain the ID credentials and then obtain an access token to the Google Authorization Server API.

Python was used to organize, extract and analyze the generated base. Based on the SocialBlade ranking, the best-known platform in the market for statistical data from various social networks (e.g. YouTube, Instagram and Twitter), the list of videos of the 50 largest Brazilian channels was established as an initial sample on September 17, 2018. Each channel has a unique ID, used to identify it in certain applications and other services, such as the YouTube API. From the list of 50 channels, a Python script was generated to extract the variables.

Table 1
Variable Description

Variable	Description
c_title	Channel name
days_active	Number of channel days since availability
c_view_count	Number of channel views
c_video_count	Number of Channel videos
c_subs_count	Number of channel subscribers
c_keywords	Channel Tags
video_id	Video Identification number
video_title	Video title
view_count	Video views number
Like	Video likes number
Comment	Video comments number
category_id	Video Category ID
category_description	Video Category name
Music	Music Dummy
Entert	Entertainment dummy
Gaming	Gaming Dummy
days_online	Days since video was posted
duration	Video duration (seconds)

The list of variables used in Table 1 has a final sample of 51,677 videos. Dummies were created for categories such as games (gaming) and music (music). Chosen variables and their qualitative effects are inspired by the theoretical model developed in Section 2.

5. Results

Preliminary Description

From the selected sample, the most representative information belongs to the Gaming. Entertainment and Music categories. These categories, as shown in Table 2, constitute 84.10% of all videos. This fact is reiterated by other works: Castañon (2017) and Wu et al. (2018); according to Chatzopoulou et al. (2010), these categories are the most interesting for data analysis because of their relative importance.

Table 2
Videos Distribution by Categories

Categories	**Nº Videos**	**Videos %**
Gaming	20572	39.81
Entertainment	16970	32.84
Music	5915	11.45
Film & Animation	2266	4.38
People & Blogs	2161	4.18
Comedy	2077	4.02
Science & Technology		2.62
Travel & Events	189	0.37
Shows	113	0.22
Sports	33	0.06
Education	8	0.02
Pets & Animals	8	0.02
News & Politics	5	0.01
How to & Style	3	0.01
Nonprofits & Activism	3	0.01
Total	**51677**	**100**

Although they encompass the majority of videos, Gaming, Entertainment and Music does not necessarily hold the top average views. The top average likes or even the best engagement (the rate between likes and views). Table 3 shows that videos classified as Music and Films/Cartoons present average views of about three times the sample's average. This observation is understandable considering that users are much more likely to watch music or animation videos more than once as opposed to singular or less repetitive views for gameplay or for videos that address current issues. Furthermore, users of different profiles are more likely to access videos in these categories than specific videos on science, technology, or travel.

The high average views of Film/Cartoons is explained in part by the target audience of YouTubers who tag their videos in this category. About 70% of them belong to channels like "TotoyKids," "Erlania e Valentina," "Turma da Mônica," "Galinha Pintadinha" and "Bela Bagunça," known to be watched by children ages 0 to 7 years old. This group usually watches the same programs frequently, and this repetition (or habit) strongly contributes to elevating the mean value of this category.

Another curious point is the production pattern of certain video categories. About 80% of the videos included in Entertainment, Gaming, People & Blogs, Comedy, Science & Technology and Travel & Events are almost created in the same way: the content creator speaks directly to the camera, other videos are exhibited, and there is video editing. All these categories obtained a similar engagement rate, except the outlier "Comedy," which is consistently superior to the sample's average (Table 3).

Table 3
Views, likes e engagement

Categories	**Nº Videos**	**Views average**	***Likes* average**	**Engagement**
Gaming	20572	1005797	44710	4.4%
Entertainment	16970	2004286	109188	5.4%
Music	5915	9592573	96441	1.0%
Film & Animation	2266	9445444	79961	0.8%
People & Blogs	2161	2640881	125812	4.8%
Comedy	2077	3574384	314406	8.8%
Science & Technology	1354	1349050	58247	4.3%
Travel & Events	189	1285598	67081	5.2%

Shows	113	432102	40642	9.4%
Sports	33	1324024	74933	5.7%
Education	8	3343800	98966	3.0%
Pets & Animals	8	3107589	202111	6.5%
News & Politics	5	971076	109616	11.3%
How to & Style	3	1073616	89563	8.3%
Nonprofits & Activism	3	1015668	141815	14.0%
	51677	**2847430**	**87465**	**3.07%**

On the other hand, Music and Animation videos have a really low like engagement at approximately 1%. There are two possible reasons for this low engagement: (1) the content creator does not issue a "call to action" or ask the spectators to like the video using the classic phrase: "don't forget to like and subscribe"; and (2) the impossibility of liking the same video twice, considering that videos from these categories tend to be watched more than once.

Econometric Analysis

The OLS regression was estimated using dummy variables for three main YouTube categories: Music, Entertainment and Games. Furthermore, robust standard errors were used to deal with hereroskedascity. The results are shown in Table 4. It is worth mentioning that both dependent and independent quantitative variables are in logarithmic scale. Therefore, the significant parameters can be directly interpreted as elasticities.

Table A (see Appendix) presents the Variance Inflation Factor (VIF) of each variable and the average VIF. The results suggest that potential problems associated with the presence of multicollinearity are not important.

Based on the regression analysis, the adherence of the model is almost 88%. The model is significant (F-test). Each variable is significant at least at a level of 5%. Concerning the channel's features, the number of videos has a positive effect on the number of views; whereas, the total number of views, number of days since the channel has been created and number of subscribers have a negative effect on the videos' popularity. These results are generally supported by the theoretical description (Section 2). For example, increasing the number of channel days availability by 1% reduces, on average, popularity by 0.19%. Also, increasing the

total number of channel videos by 1%, increases, on average, the views number by 1.15%. The YouTube page format is, as noted before, helpful with this. Related videos, which are often from the same author or have similar subjects, appear at the right side of the page (in the case of smartphone/mobile viewing). The more videos a channel holds, the higher probability of its videos appearing in this section.

Analyzing the variables that refer to the video itself, there is a significant and positive effect of number of likes, days since it has been online and entertainment. A 1% percent increase in likes, for example, increases the popularity by 0.97%. The number of comments and the length of video duration in the music and gaming categories have a statistically significant and negative effect. When video duration increases by 1%, the number of views decreases, on average, by 0.08%.

Table 4
OLS Regression

Variable	OLS (Robust)
channel_days_active	-0.1948***
channel_video_count	1.1535***
channel_view_count	-0.4186***
channel_subs_cout	-1.4948***
like_count	0.9738***
comment_count	-0.0594***
days_online	0.2280***
duration	-0.0814***
music_dummy	-0.0217*
entertainment_dummy	0.0253**
gaming_dummy	-0.1147***
cons	6.8035***
N	51677
F	29681.5564
R2_a	0.8791
legend: * p<0.05; ** p<0.01; *** p<0.001	

From these results, an additional question arises: do the previous explanatory variables estimated effects on the conditional mean of the dependent variable stay valid over the dependent's distribution? In other words, does the duration have the same impact on the first decile of views and the ninth decile of popularity? To address this inquiry, we present quantile regressions (Tables 5 and 6)

Table 5
Quantile Regressions - Deciles 1 a 5

Variable	q1	q2	q3	q4	q5
channel_days_active	-0.1368***	-0.1487***	-0.1534***	-0.1440***	-0.1440***
channel_video_count	0.6313***	0.7082***	0.7686***	0.8009***	0.8420***
channel_view_count	-0.1989***	-0.2127***	-0.2423***	-0.2600***	-0.2762***
channel_subs_cout	-0.7401***	-0.8370***	-0.8933***	-0.9275***	-0.9796***
like_count	0.9695***	0.9885***	0.9912***	0.9876***	0.9936***
comment_count	-0.0725***	-0.0859***	-0.0874***	-0.0830***	-0.0865***
days_online	0.0519***	0.0760***	0.0948***	0.1070***	0.1196***
Duration	-0.0196	-0.0269**	-0.0284**	-0.0205**	-0.0186**
music_dummy	0.1495***	0.0934***	0.0613***	0.0707***	0.0563***
entertainment_dummy	0.1130***	0.0815***	0.0676***	0.0742***	0.0590***
gaming_dummy	0.1076***	0.0681***	0.0362*	0.0375*	0.0201
Cons	3.4131***	3.4545***	3.2892***	3.1347***	3.1467***
N	51677	51677	51677	51677	51677

legend: * p<0.05; ** p<0.01; *** p<0.001

Table 6
Quantile Regressions - Deciles 6 a 9

Variable	q6	q7	q8	q9
channel_days_active	-0.1552***	-0.1659***	-0.1680***	-0.1687***
channel_video_count	0.8645***	0.8799***	0.8967***	0.9049***
channel_view_count	-0.2847***	-0.2950***	-0.3043***	-0.3078***
channel_subs_cout	-1.0100***	-1.0247***	-1.0487***	-1.0621***
like_count	0.9957***	0.9952***	0.9949***	0.9926***
comment_count	-0.0863***	-0.0863***	-0.0863***	-0.0849***
days_online	0.1321***	0.1395***	0.1466***	0.1526***
Duration	-0.0163**	-0.0134*	-0.0111*	-0.0083
music_dummy	0.0487**	0.0485***	0.0561***	0.0563***
entertainment_dummy	0.0495***	0.0529***	0.0526***	0.0485***
gaming_dummy	0.0081	0.0034	-0.0004	-.0090
Cons	3.2384***	3.2743***	3.3629***	3.4257***
N	51677	51677	51677	51677

legend: * p<0.05; ** p<0.01; *** p<0.001

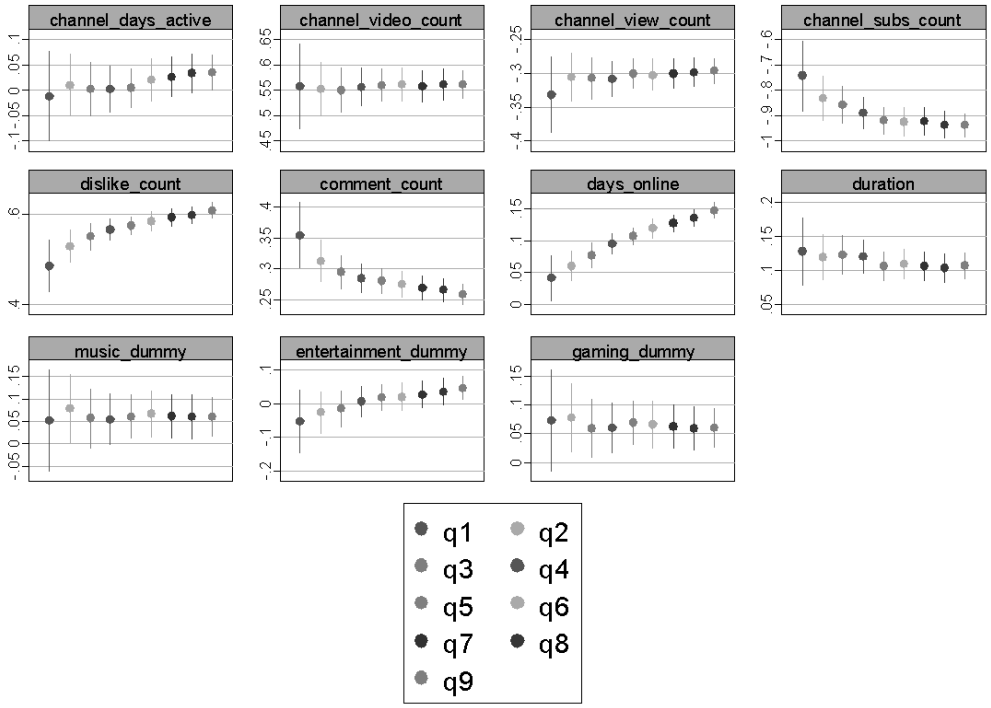

Figure 1 – Quantile Regressions Estimated Parameters

Estimated parameters are significant at 5% for all deciles, except video duration (first decile) and games (fifth to ninth decile). The duration does not affect the popularity of those videos belonging to the 10% least watched. The estimated coefficients by variable and by decile of the dependent variable are plotted in Figure 1. Likes has a stronger (positive) effect on popularity for larger popularity deciles. Something similar happens to the number of views and days on line. The negative effect is stronger in higher deciles of popularity for the activity period of a channel as well as for the number of views and subscribers. The duration has its negative effect increasing from the third popularity decile. Comments seem to follow a similar effect from the second view decile.

6. Conclusion

We conclude with our research findings. OLS results show, for the analyzed sample, that the variables that present positive effects on popularity include the number of videos, likes,

and days the video is online. In addition, entertainment videos are more popular, on average, than any other category of videos. The variables that negatively affect video popularity are the length of time the channel has existed, the total number of channel views, the total number of subscribers as well as the number of comments and video duration. In addition, music videos and games are less viewed than the other categories. Quantile regressions suggest that estimated effects vary over the deciles of the views. This curious phenomenon of old successful videos, after a duration of low viewing, has potential of attracting a new audience and reascending to former levels of popularity. Future research could consider an analysis of the dynamic model presented in this paper with the potential to generate viewing cycles.

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Notes

[i]. For support of our study's immediate relevance to current marketing practice, refer to Neil Patel's YouTube video "How Digital Marketing Will change in 2019"; his sixth tip for marketers (4:36) is to leverage video content for increased viewership, engagement and competitive advantage: https://www.youtube.com/watch?v=b-gwbVJqi9Y. Patel is regarded as "one of the most successful, ubiquitous digital marketers" by Inc.com (https://www.inc.com/larry-kim/9-unique-facts-about-neil-patel.html)

[ii]. eWOM, regarded as "one of the most significant developments in contemporary consumer behavior" (Rosario et al., 2016 p. 297); it evolved from word-of-mouth (WOM) (Thoumrungroje 2014).