Ilmenau University of Technology
Institute of Economics

Ilmenau Economics Discussion Papers, Vol. 24, No. 112

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Januar 2018

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ISSN 0949-3859

The Economics of Social Media Stars: An Empirical Investigation of Stardom, Popularity, and Success on YouTube

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Abstract: The economic literature on the superstar phenomenon provides empirical evidence on different types of stars, above all athletes and musicians. A new and, to our best knowledge, unexplored area of this star theory arouse with the development of social media markets. In this paper, we analyse a unique sample of 200 YouTube stars out of four different video categories to address the research gap. By employing econometric methods from panel data analysis, we contribute to answering the following research questions: (i) Are the classic theoretical concepts of popularity and superstardom by Rosen, MacDonald and Adler applicable? (ii) Can social media stars actively influence their popularity by employing special upload strategies? We find empirical evidence that former success positively and significantly influences the current success of social media stars, as theoretically presumed by MacDonald. Furthermore, the results support Adler's assumptions that the most popular stars snowball into superstardom due to higher growth rates. Finally, our investigation shows that social media stars can actively influence their popularity with distinctive upload strategies and market behaviour.

Keywords: social media, digital media, popularity, superstar theory, cultural economics, media economics

JEL-Codes: L82, Z10, D31, D83

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× We thank the participants of the 49th Hohenheimer Oberseminar (Ilmenau, October 2017), the participants of the Research Platform meeting (TU Ilmenau, December 2017) as well as Sonja Rinne for valuable comments on earlier versions of the paper. Furthermore, we thank Milan Lange and Mona Bader for valuable editorial assistance.

1. Introduction

Different terms are used to describe the phenomenon of *social media stars,* inter alia, micro-celebrities, celebrity endorsers, influencers, or online stars. For the purpose of our analysis, *social media stars* are content providers on social media platforms such as YouTube, Instagram or Twitter whose "fame is native to social media" (Marwick 2015: 337). Some of them are reaching truly superstar status, for instance, in terms of income the YouTube-Gamer Felix Kjelberg earned approximately 15 million USD in 2016 (Berg 2016). His star position can be emphasised by up to 79 million views per video and 50 million subscribers by 2016 (Socialblade 2017).

So far, the theoretical and empirical literature on the economics of superstars has, to our best knowledge, not addressed the phenomenon of social media stars. We want to extend the understanding of the social media star phenomenon and provide first insights into star strategies in the digital world. We operationalise classic popularity approaches by MacDonald (1988) and Adler (1985, 2006) and complement these with novel concepts of attention economics like audience building and maintenance. Our general research questions are: Are the classic popularity concepts applicable? Can social media stars actively influence their popularity by upload strategies?

To investigate these aspects, this paper provides an empirical analysis of 200 YouTube stars out of four different video categories. The findings support the assumptions of MacDonald and Adler, showing that important elements of classical superstar theory remain applicable in the social media world. Moreover, we show that novel aspects like distinctive upload behaviour influence success in social media markets.

The paper is structured as follows. Section 2 reviews relevant literature on the economic theory and outlines our hypotheses. Section 3 contains the data description, estimation methods and econometric analysis. In section 4 we present and discuss our results. The preliminary conclusion in section 5 summarises and gives a brief overview.

2. Economic Theory of Offline and Online Superstars

The modern economic theory of stardom relates to the seminal paper by Rosen (1981). He first identifies the principal economic phenomenon of superstars: relatively small differences in talent generate significantly over-proportional differences in income. Rosen argues that imperfect substitution of different levels of talent drives the effect. Lesser talent is a poor substitute for greater talent. In the words of Rosen (1981: 846) "hearing a succession of mediocre singers does not add up to a single outstanding performance." This imperfect substitution goes along with scale effects, so that those artists who enjoy superior talent become superstars and can reap monopoly-like rents as a consequence.

Superior talent is certainly a factor in generating superstars. However, popularity is empirically found to play an important role in the explanation of stardom as well (inter alia, Budzinski & Pannicke 2017) and superior talent alone does not suffice to explain popularity. Therefore, we focus on extensions of Rosen's seminal thoughts by referring to popularity theories brought forward by MacDonald (section 2.1), Adler (section 2.2) as well as attention economics (2.3).

2.1 MacDonald Popularity

MacDonald (1988) emphasizes the importance of former success as a factor of explanation for current popularity. Consumers are assumed to be risk adverse and to prefer known qualities over unknown ones. If consumers have experienced a given artist in the past and enjoyed the experience, then this artist represents a *known quality*. Even though the quality of an artist may vary over time, the consumer expects a relatively similar quality and will be satisfied if the artist meets this expectation. In contrast, newcomers represent unknown qualities. They may provide a better experience than incumbent stars but there is a substantial risk that they will perform worse. Thus, risk-adverse consumers will choose incumbent stars as long as they do not deviate too much from their known quality. MacDonald offers an explanation why consumers may be conservative in their consumption in the course of time and stick with their heroes. Due to the risk adversity of consumers, past success predetermines future success.

The driving-force of the model dynamics is an informational deficiency on the side of the consumers. Due to the experience good character of the artists' products, consumers can assess quality only after the consumption. The inherent dynamics of the model imply that artists are not 'born to be stars' (by natural superior talent) but instead 'rise to become stars'. Since past achievements explain future success due to the combination of the experience good character of the artistic goods and the risk adversity of the consumers, entry barriers for newcomers emerge. Newcomers with the same or slightly superior talent than incumbents will find it difficult to draw consumers away from the established stars. They need extraordinary talent (considerably in excess of the incumbents' talent) in order to capture the risk-adverse consumers' attention and rise to stardom.

Applying MacDonald's theory to social media stars implies that artists being longer in the market (incumbents) should enjoy an advantage over newcomers. Moreover, particularly successful incumbents should be able to stay at the top or even increase their advantage. Thus, we derive the first two hypotheses:

H1: The duration in the market significantly and positively influences the current success.

H2: Successful stars of previous periods can maintain their top position within their category.

2.2 Adler Popularity

Next to the artist's talent and former success, superstars may attract fans by their high profile and celebrity status (see also Boorstin 1961; Franck and Nüesch 2007). Adler (1985) addresses this issue by referring to the 'consumption capital' model (Stigler & Becker 1977). The accumulation of star-specific 'consumption capital' drives a special type of a bandwagon effect (Leibenstein 1950): the more consumers know about the art and the artist, the more enjoyment they derive from consuming more art of this type or respectively more from this artist. Thus, the marginal utility of consumption increases. Adler (1985, 2006) refers to three ways of accumulation of ‘consumption capital’:

(1) exposure to the art itself (Stigler & Becker 1977),
(2) through communication about the art with friends and acquaintances (commonality effect), and
(3) through media coverage of the art/artist (Adler 2006).

According to Adler, the only consumption costs for consumers is time, divided into ‘actual time’ (of consumption, communication, etc.) and the time for searching suitable conversational partners (Adler 1985: 209) and media contents. In order to minimize searching costs the consumer chooses the most famous artist because there is more information available and more knowledgeable conversational partners to find. “When the artist is popular, it is easier to find discussants who are familiar with her or to find media coverage about her. This is why consumers prefer to consume what others also consume” (Adler 2006: 898).

The results are positive network effects that create path-dependency and snowball effects, since an individual consumer maximizes its marginal utility by joining the majority and following the same artist. The more members the network has, the higher is the probability of finding suitable conversation partners. Media presence supports the artist’s popularity by circulating and enhancing the flow of information (Adler 2006).

Effectively, the most popular stars snowball into superstardom due to higher growth rates in a self-reinforcing process. With respect to social media stars, consumers ‘choose’ the most successful personality as it is easier to find information and other people to talk to (other fans/ online communities). This leads to the third hypothesis:

H3: Stars in top positions have higher growth rates than stars in mediocre positions.

2.3 Attention Economics

A relevant prerequisite for starting Adler's snowball effect as well as for conquering MacDonald's entry barriers for newcomers is to grasp the attention of the audience, or at least, of a sufficiently large part of the audience. This has become particular peculiar in the times of the internet where the amount of potentially available artistic content has virtually exploded. On YouTube alone one billion hours of content is watched daily (YouTube 2017), however, 10-30 percent of the videos have fewer than ten views, depending on the video category (Chowdhury & Makaroff 2013). Moreover, Ding et al. (2011: 363) find that among all content providers the most popular 20 percent receive 97 percent of the views. This phenomenon of information overflow implies an increasing importance of access to the audience and active audience-building in order to be perceived in the first place. This is a precondition of any rising-to-stardom process, regardless whether it is built upon superior talent or network effects.

From an economic point of view, attention can be described as a scarce resource in an information-rich society (Falkinger, 2008). The trick is to find access to this scarce resource without over-using it. This is particularly true for social media stars who directly compete in the information-richest media where alternative contents are 'just a click away'. Thus, attention is both scarce and volatile: it is both difficult to receive attention and to retain it – at least as long as the self-reinforcing effects of superstardom have not fully kicked in.

As a consequence, social media audience building consists of two elements: (i) audience attraction and (ii) audience maintenance. *Audience attraction* relates to the first contact. The task is to surface in the ocean of information/contents and receive initial attention in order to get the chance to convince consumers. Here, three avenues are of particular importance:

(1) platform specific optimisation relates to the art of adapting the own account and contents to the platform's algorithms, so that more potential consumers find them highly-placed in their recommendations, for instance (but not only)

by strategically cross-referencing the own content to successful contents and stars.

The platform immanent algorithms are not published by its' operators and thus are unknown. Yet, this does not mean they are completely unanticipatable. Through experience, sophisticated market players, such as professional content providers, agencies, and multichannel networks, have built up competences with managing the algorithms. It is possible to (imperfectly) anticipate the algorithms "behaviour" and iteratively improve uploading strategies and networking concepts. This leads to learning and experience effects. Essentially, algorithm management matters and stars are able to outdo amateurs. Algorithms fuel the snowballing effects, as successful posts get pushed and recommended. Positive network externalities can be used by successfully engaging with algorithm management. Hence, it is possible to initiate the Adler/bandwagon effect and multiply upload success (Leibenstein 1950, Adler 1985, 2006).

(2) electronic word-of-mouth (Jansen, et al. 2009; Jin & Phua 2014), i.e. accidental discovery by few consumers à la Adler kick starts the self-reinforcing effects.
(3) presence in opinion-leading contents of others, for instance, being referenced by incumbents, mentioned in relevant blogs, or strategically placed by agencies, etc.

Audience maintenance and development requires direct activity of social media content providers vis-à-vis their consumers. A special element of social media stars is their direct access to consumers via the social media accounts that serve as media to transmit the star's contents. As far as we know, most social media stars either manage these accounts on their own or with the help of a personal management. Nothing like a traditional mass media with its editorial departments (selecting the content and which star to promote e.g. in magazines, channels, broadcasts, etc.) is put in between.[1] Therefore, social media stars must actively manage the frequency of new contents that is provided to "their" audience. The content providers need to invest time and personal resources to create content and generate traffic on their social media pages, i.e. investment into audience building. While other stars need to put effort into self-marketing as well (Meisenberg 2014), we expect the personal behaviour, and especially the upload behaviour, to be a key attribute of audience attraction and maintenance in the social media world. The issue of self-disclosure and self-presentation seems to be omnipresent in this market and more direct than in traditional media markets.

On the one hand, social media stars must actively seek audience attention and offer new content with a sufficient frequency or (attention-volatile) consumers will be detracted to other contents. A social media account where nothing new is uploaded for some time quickly loses the attention of the consumers. On the other hand, information overload can be tiring and overstraining for (attention-scarce) consumers. If more content is uploaded, i.e. the frequency of uploads is too high, then consumers may feel stressed and annoyed – with the consequence of withdrawing their attention.

Regarding the *upload activity*, the frequency, regularity, the time of day as well as technological features (e.g. video length, image size) play a role. Many recipients have consumption habits. Periodical uploads (for instance, two videos a week on Thursday and Sunday at 3 pm on YouTube) conveys consistency, reliability, and can be anticipated by the consumers. The fans can include this in their consumption routine. As mentioned above a certain upload frequency is necessary to gain popularity and connect with people. That is why we conclude that a star's upload activity influences his success.

H4: The frequency of content uploads significantly and positively influence the social media success.

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[1] Note that an editorial selection does exist in the area of attracting new consumers (see above the opinion-leading outlets).

But, in addition, it has to be considered that most of the regular consumers subscribe to more than one account on their social media platforms. If the stars provide too much information, their fans might not have the time and attention resources to consume all content. So, as consumption capacities per unit of time are limited (attention as a scarce resource), this could lead to information overload and dissatisfaction. Hence, we expect content uploads to have a positive impact on success, but, within a given time period, further supply of information has negative impact. The functional relationship between new uploads and success is thus inversely U-shaped. As time reference for the estimation within a given period, we use monthly data.

H5: The monthly video uploads significantly and positively influence the short-term success until a turning point is reached, where further uploads have negative impact.

Both hypotheses relate to audience maintenance and the further increase of audience as fuelled by snowball effects (including electronic word-of-mouth) but limited by information overflow effects. Further hypotheses focusing more on the area of (initial) audience attraction need to analyse strategic investments of content providers into (i) advertising budgets, (ii) access to gatekeepers, opinion-leaders, and major influencers, and (iii) optimisation of (search) ranking positions. Unfortunately, so far, we do not have data to analyse these aspects.

3. Econometric Analysis

3.1 Data and Descriptive Statistics

In our paper, we analyse stars, whose popularity is native to social media. This excludes personalities such as actors, musicians or athletes etc., who are very successful on social media platforms, but gained their fame outside of this system. The available data is limited, hence we have to stick to the platform, which grants the richest data set: YouTube. Webpages like *Socialblade* and *statfire* provide secondary data for a variety of YouTube accounts. We used both platforms and complementing information from YouTube to collect a unique dataset.[2] For our analysis, we chose 200 YouTube stars out of four categories: *Comedy*, *Gaming*, *Howto & Style*, and *People & Blogs*. These categories are selected because the majority of the stars within are originally YouTubers and not primarily famous in other media sectors. Categories in which external stars can be found most e.g. *Music* are not suitable for our analysis since here traditional stars are mixed with the stars inherent to the platform. Moreover, some other categories are simply not useful for the analysis of stardom due to the nature of their content, such as *Trailers* or *Pets & Animals*. We have data for the top 25 (Top25) stars out of each category as well as the ranks 50-74 (50^{+}). Unfortunately, the data for the positions in between is not available. However, the two groups may serve to compare the top stars with those in mediocre ranking positions. It is the very nature of the superstar phenomenon that the top ranks display huge gaps to the lower ranks (Rosen 1981). Therefore, the top25 should be sufficient to analyse the major relevant aspects in those cases where the research question does not benefit from comparing the two groups. See Figure 1 for the distribution of subscribers within the sample, which also visualises the superstar phenomenon.[3] This distribution makes it also unlikely that the missing positions in the top74 (26-49) considerably distort the data.

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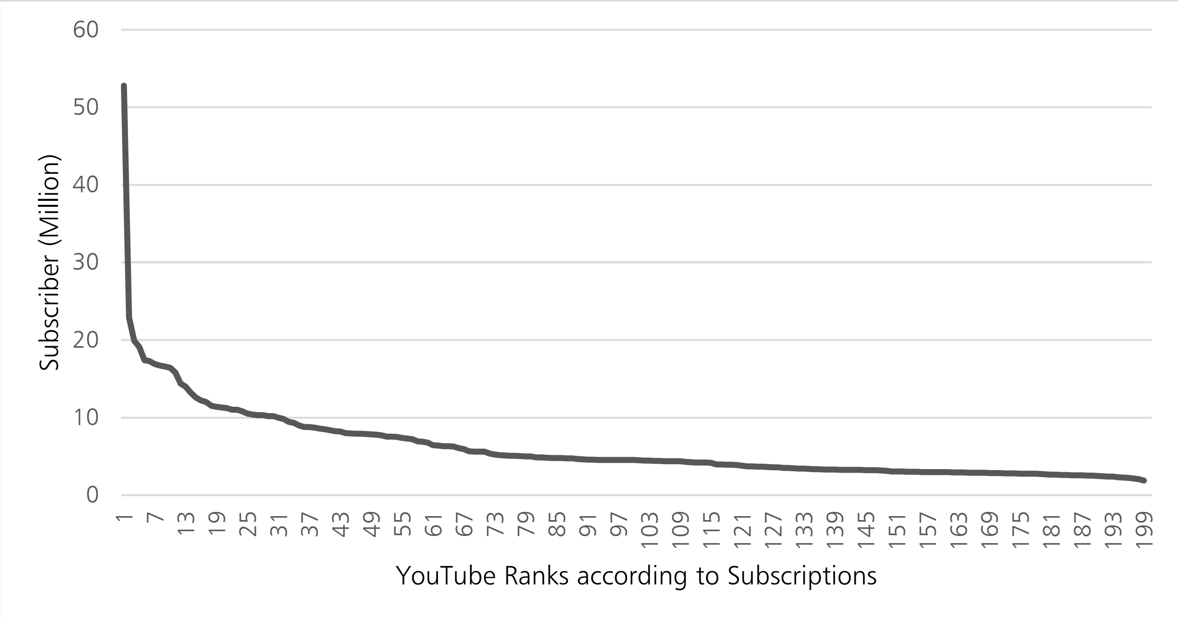
2 Some of the public websites were withdrawn by *statfire* after the information was collected. Thus, some parts of the data set are not publicly available anymore.

3 The distribution of views and subscribers for each category can be found in the appendix.

Figure 1: **Distribution of Subscribers**



We use unbalanced panel data from January 2016 to April 2017.[4] Based on the popularity of the investigated account, the availability of data varies. The platform *statfire* started to collect information of successful accounts earlier. This is why the Top25 mainly represent the period from January 2016 to February 2017 and the 50^{+} the time from March 2016 to April 2017. We have a total of 2457 observations and thus 12.285 on average per account. As the data is collected monthly, this translates into an observation period of one year on average for each account.

Table 1 shows an overview of the different categories in the sample. The category Gaming, is most favoured with a mean of 7.9 million subscribers and 2.4 billion views. In this YouTube section gamers play video games and (humorously) comment on them. YouTube-Comedians are also quite popular with a mean of 5.7 million subscribers, although the difference in mean views (1.0 billion) compared with the leading category is considerable. Last in the ranking are the categories Howto & Style and People & Blogs. The Howto & Style content mainly focuses on make-up and fitness tutorials, whereas YouTubers of People & Blogs usually broadcast their private lives in so-called "vlogs" (video-blogs). Interestingly, the mean number of subscribers of

[4] Newer data is not available.

Howto & Style accounts is higher (4.2 million) than People & Blogs (3.4 million), but the latter has more views.

Table 1: **Descriptive Statistics Categories**

Category	Obs.	Subscriber		Views		Videos	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total	2457	5.3m	4.5m	1175.6m	1555.9m	1719.0	8813.9
Comedy	607	5.7m	3.9m	1007.0m	880.9m	288.0	319.0
Gaming	618	7.9m	6.7m	2400.2m	2415.8m	5058.0	16874.2
Howto & Style	610	4.2m	2.7m	593.0m	602.9m	913.1	3011.3
People & Blogs	622	3.4m	2.0m	694.8m	759.3m	588.2	567.9

As presented in Table 2 the majority of the accounts in the sample are operated by men. Only the category Howto & Style contains more female accounts. Especially Gaming seems to be male territory. The description “mixed” is used for accounts starring two people (male and female).

Table 2: **Descriptive Statistics Gender**

	Comedy	Gaming	Howto & Style	People & Blogs
Female	117	13	488	222
Male	463	566	122	361
Mixed	27	39	0	39

Moreover, the majority of the sample prefers English, even if it is not always the operator’s native language. Spanish and Portuguese are also found quite often. A lot out of these have South-American origin.

Table 3: **Descriptive Statistics Language**

Language	Frequency	Percent
Arabian	14	0.57
English	1,615	65.73
French	88	3.58
German	25	1.02
Japanese	14	0.57
Portuguese	277	11.27
Russian	126	5.13
Spanish	298	12.13

3.2 Methods and Variables

The hypothesis H1-H5 raise different questions, which correspondingly need different methods to solve. In H1, H4 and H5 one continuous dependent variable and a number of explanatory variables allow an estimation by linear methods like ordinary least squares (OLS) regression. Moreover, we compare the OLS results to the panel models: fixed-effects and random-effects. For random-effects we use the GLS (generalised least squares) estimator and for fixed-effects the within regression estimator. The hypotheses H2 and H3 need to be solved differently. That is why other statistical methods are implemented here.

Regressions

H1: The duration in the market significantly and positively influences the current success.

H4: The frequency of content uploads significantly and positively influence the social media success.

H5: The monthly video uploads significantly and positively influence the short-term success until a turning point is reached, where further uploads have negative impact.

The interesting factor and thus the depending variable in our analyses is the popularity and the success of the stars. The controversial question is how this success can be measured. Evidently, the economic approach would be measuring the revenue. Due to non-disclosure agreements (Döring 2014: 27), a YouTuber's income can only be estimated and varies between 0.25 and 4 USD per 1,000 clicks (Detel: 2017: 291). This makes the available data limited and imprecise. According to Socialblade, the No. 1 YouTuber in the sample receives between 604k and 9.7m Euro yearly (in September 2017) (Socialblade 2017). The wide range leads to very vague and unreliable results. Furthermore, a German study revealed that professional YouTubers receive additional money from various sources, such as product placement (38 percent), product sponsoring (19 percent) and other activities e.g. books, songs or performances (10 percent) (Zabel & Pagel 2017: 140). Reliable data on the income is thus not available for all sources and a representative sample.

As an income variable is not feasible, we use proxies for social media success. According to the scientific literature there are different indicators to be considered including aspects like *comments* and *ratings* (interaction/participation) (Chatzopoulou et al. 2010) or *content unrelated* (Borghol et al 2012). However, the most common and fundamental as well as better measurable indicators for popularity are the *views* (scope/reach) (Chatzopoulou et al. 2010; Borghol et al. 2012) and *subscriptions* (fans/main audience) (Burgess & Green 2009: 59-60; Wattenhofer et al. 2012: 358; García-Rapp 2017: 233). We follow the literature by using the two proxies *views* and *subscribers* to measure the success, while implementing case discrimination: we differentiate between short-term and long-term success. Usually, users will subscribe to a channel after they have watched several videos and if they happened to like them, since YouTube videos can be categorised as experience goods (MacDonald 1988). Furthermore, subscribing to a channel represents a commitment to the star since it reflects the recipient's interest in future content. Therefore, along with the literature, we interpret subscriptions to represent sustainable long-term success (García-Rapp 2017: 234).

A more instant and direct feedback to a video-upload is given by the *number of views*. After a video is online, it spreads and "collects" views, which indicates its' scope or reach as in other mass media measurements (Burgess & Green 2009). The prompt reaction makes it a good proxy for short-term success. Moreover, this factor is also connected to monetary success, as YouTubers get paid for the recipients' consumption of advertising on their page. While the precise interrelation of views, placing of in-stream and other advertising and remuneration of the content provider is complex and secret to the public, more views will generally also generate more income (Döring 2014: 26). As a consequence, we follow the mainstream of the literature by defining

$$Y_{long} = f(Subscriber)$$
$$Y_{short} = f(Views).$$[5]

To measure the MacDonald popularity (H1), which continues over one or more periods, we take the long-term proxy of subscribers into account. The corresponding independent variables used for the linear regression are: the *duration* in the market and the *views* the star has received to gain subscribers. The duration means the time span between the foundation of the account and the time of observation, so the time the star has spent on the platform. The dependent and independent variables are logged. As control variables we use the information of the *category*, *gender* and *language* of each account (see descriptive statistics and (Tables 1-3).

$$lnY_i^{Subscriber} = \alpha + \beta_1 \cdot lnDuration_{i1} + \beta_2 \cdot lnViews_{i2} + x_1 \cdot Controls_i + \varepsilon_i \qquad (1)$$

The short-term success of views is expected to be a result of video-uploads and activity in H4. That is why the independent variables in the following regression are *uploads* and *duration*. For this equation the dependent and independent variables are also logged. Again, the control variables are *category*, *gender*, and the *language*, included as indicator variables.

$$lnY_i^{Views} = \alpha + \beta_1 \cdot lnUploads_{i1} + \beta_2 \cdot lnDuration_{i2} + x_i \cdot Controls_i + \varepsilon_i \qquad (2)$$

In the third regression, the non-linear relationship between video-uploads and short-term success within a given time period is being investigated (H5). We focus on a monthly time unit and add the squared upload-variable to the equation. The control variables stay unchanged to prior procedures.

$$Y_i^{Monthly\ Views} = \alpha + \beta_1 \cdot Monthly\ Uploads_{i1} + \beta_2 \cdot Monthly\ Uploads_{i2}^2 + x_1 \cdot Controls_i + \varepsilon_i \qquad (3)$$

$\alpha = intercept$

$\varepsilon = error\ term$

[5] Obviously, this definition does not capture deviating behaviour like continuously watching videos of the same without subscribing to the channel or inactive subscriptions (no views). We follow the literature by assuming that this deviating behaviour remains exceptional.

After testing for heteroscedasticity (Breusch-Pagan test), all panel regression models are calculated with robust standard errors.

Further Methods

H2: Successful stars of previous periods can maintain their top position within their category.

The ranks of the stars, according to their subscribers and views, give us ordinal data, which can be used to perform a Spearman rank correlation. This non-parametric test calculates the relationship between two variables. So we check the relation between the ranks on different dates: May 2016 and July 2016, May 2016 and October 2016, and in the long-run May 2016 and January 2017.

$$r_s = \frac{6 \sum_i d_i^2}{n \cdot (n^2 - 1)}$$

$r_s = Pearson\ correlation\ coefficient$

$d_i^2 = squared\ difference\ between\ ranks$

$n = number\ of\ observations$

If the results show that the ranks stay nearly unchanged and especially the top positions have little fluctuation, it will support our hypothesis.

H3: Stars in top positions have higher growth rates than stars in mediocre positions.

To investigate if the accounts of top stars grow more rapidly on average, we perform a t-test. We compare the mean growth of the Top25 to the mean growth of the ranks 50^{+}. Again, the dependent variables of views and subscribers are being checked. To maximise the available observations we take a 10 month period.

4. Results and Discussion

4.1 MacDonald Popularity

The results from the linear models support our hypothesis based on MacDonald's assumptions. The duration of a star in the social media market and his success in previous periods positively influences his long-term success measured in the number of subscribers (H1). Table 4 displays the most notable estimates for the OLS and GLS regression (Model 1 and 2) and the fixed-effects model (Model 3). The complete regression tables (including all control variables) can be found in the appendix. The variable "duration" is significant and positive over all three models. As the estimation results are consistent between our models, it underlines their robustness. The second exogenous variable "views" also influences the subscriber success positively and significantly. This supports the idea of YouTube videos as experience goods, which the consumers watch before subscribing to a channel.

The controls, which were integrated as indicator variables, are omitted in the fixed-effects model (Model 3). In Model 1 and 2, however, one variable stays significant. It seems that female stars have higher probability to succeed because male and mixed groups are significantly negative compared to the basis female = 0.

Table 4: Extract: Empirical Results MacDonald Popularity

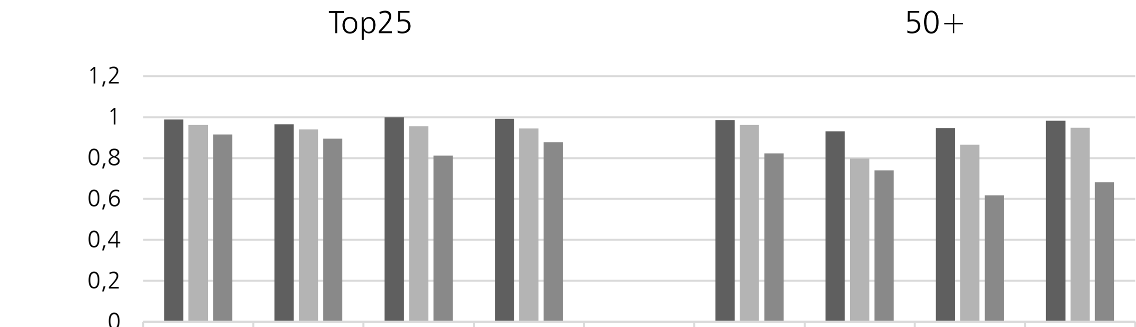
	Model 1 Log (Subscriber)	Model 2 Log (Subscriber)	Model 3 Log (Subscriber)
Log Views	0.439***	0.422***	0.356**
	(10.78)	(4.17)	(3.25)
Log Duration	0.243**	0.877***	1.314***
	(3.04)	(4.71)	(5.23)
1. Female	0	0	0
	(.)	(.)	(.)
2. Male	-0.179*	-0.358**	0
	(-2.25)	(-3.21)	(.)
3. Mixed	-0.391**	-0.485*	0
	(-2.70)	(-2.17)	(.)
_cons	4.152***	0.163	-1.945
	(4.36)	(0.10)	(-1.11)
N	2457	2457	2457

t statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

MacDonald assumes that success is transferred from one period to the next. Successful stars survive different periods and establish their position in the market. Those stars will prevail in the long-run. That is why it is interesting to observe if YouTube stars can maintain their top position in the ranking. To test whether the stars in our sample maintain their top position within their respective category (H2), we use the Spearman rank correlation and compare the Top25 stars to the 50^{+} of mediocre rank. Again, the same proxies for success (number of subscribers and views) are being used and compared.

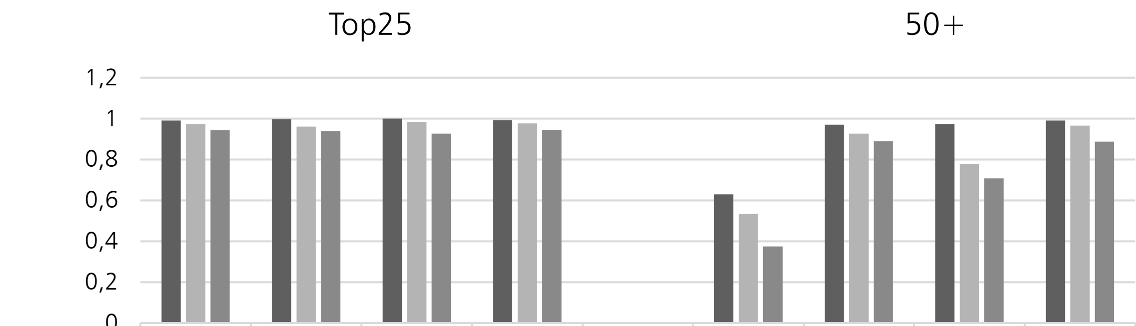
Figure 2 and 3 show the results of the Spearman rank correlation within the YouTube categories. The Spearman coefficients ($-1 \leq r_s \leq 1$) are listed below each figure. A r_s of $+1$ indicates a perfect association of ranks, as it occurs in the category Howto & Style (Figure 2, Top25) after an observation period of three months (May-July). So in this case all of the ranks stayed unchanged. It is noticeable that for both proxies (views and subscriber) there is less fluctuation within the group of the Top25 than among the less successful ones of the ranks 50^{+}. This supports the hypothesis of the top stars staying in dominant positions. As it can be expected, the correlation decreases over time, but especially the long-term success of subscriber ranks remains remarkable stable. Regarding the views, the category "Comedy" stands out. Among the Top25 the ranks stay almost unchanged, whereas, among the 50^{+} the correlation is the lowest in the sample. So the leading comedians are very successful and stay on top of the list, while the lower ranks fight for attention and short-term success. This could be interpreted in Rosen's favour, as a few talented and witty star-comedians "dominate the activities in which they engage" (Rosen 1981, 845). This aspect is not observable within the subscriber ranks of comedy. Maybe, people only subscribe to a comedy channel, if they like the content and humour – and not just based on a one-off impression. That is why there is more consistency and a smoother process.

Figure 2: **Spearman Rank Correlation: Subscribers**



	Top25 Comedy	Top25 Gaming	Top25 Howto & Style	Top25 People & Blogs	50+ Comedy	50+ Gaming	50+ Howto & Style	50+ People & Blogs
(May-Jul)	0,9885	0,9654	1	0,9915	0,9854	0,9308	0,9462	0,9817
(May-Oct)	0,9623	0,94	0,9554	0,9454	0,9615	0,7977	0,8646	0,9478
(May-Jan)	0,9146	0,8946	0,8123	0,8769	0,8231	0,74	0,6185	0,6826

Figure 3: **Spearman Rank Correlation: Views**



	Top25 Comedy	Top25 Gaming	Top25 Howto & Style	Top25 People & Blogs	50+ Comedy	50+ Gaming	50+ Howto & Style	50+ People & Blogs
(May-Jul)	0,9908	0,9962	0,9992	0,9915	0,6287	0,97	0,9738	0,9908
(May-Oct)	0,9738	0,9608	0,9838	0,9769	0,5339	0,9262	0,7785	0,9654
(May-Jan)	0,9438	0,9392	0,9269	0,9454	0,3739	0,8885	0,7069	0,8877

The overall results of this chapter emphasise the aspect of continuous work to create long-term success and stay on top. In MacDonald's model the success continues over more than one period. The exact time span of these periods is unknown. Here, the observation period is approximately one year for each account. It would be interesting to study a longer time span, as it might take one to three years to grow a sustainable fan-base. On the other hand, so far youtubing has been a very volatile and short-run business, so that one year actually is already some time. Moreover, it could be questioned if there is a critical mass the content provider needs to achieve to reach star status and disproportional growth.

4.2 Adler Popularity

According to Adler's approach of the superstar theory, the most successful star with initial advantage snowballs into stardom (see section 2.2). So it can be expected that the most successful star grows faster than the second best. Translated into the social media system, we expect the stars of the top positions (Top25) to grow faster than those of mediocre ranks (50^{+}) (H2). To investigate the increase in subscribers and views, we calculate the difference in numbers (Delta-Subscriber and Delta-Views) after ten months. Subsequently, a paired t-test allows us to compare the medium growth of one group to the other. Table 5 and 6 display the results of the t-test, showing that the means of one group are statistically different from the other. The initial success of views and the long-term success of subscribers are both significantly higher for the top group.

Table 5: **Paired T-Test Delta-Subscriber**

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Top25	99	1.67m	0.16m	1.59m	1.35m	1.99m
50^{+}	99	0.79m	0.57m	0.57m	0.68m	0.91m
diff	99	0.88m	0.16m	1.61m	0.55m	1.20m

mean(diff) = mean(Top25 - Top50^{+})   t = 5.4212
Ho: mean(diff) = 0   degrees of freedom = 98

Ha: mean(diff) < 0   Ha: mean(diff) != 0   Ha: mean(diff) > 0
Pr(T < t) = 1.0000   Pr(|T| > |t|) = 0.0000   Pr(T > t) = 0.0000

Table 6: **Paired T-Test Delta-Views**

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Top25	98	431m	54m	535m	324m	538m
50^{+}	98	147m	24m	239m	99m	195m
diff	98	284m	51m	510m	181m	386m

mean(diff) = mean(Top25 - Top50^{+})   t = 5.4984
Ho: mean(diff) = 0   degrees of freedom = 97

Ha: mean(diff) < 0   Ha: mean(diff) != 0   Ha: mean(diff) > 0
Pr(T < t) = 1.0000   Pr(|T| > |t|) = 0.0000   Pr(T > t) = 0.0000

Whereas a further t-test of the growth rates showed no significant difference between the groups, the Top25 increase their distance regarding total numbers. To further underline this argument, we were able to observe no changes for the No. 1

star of each category after ten month, except for Peoples & Blogs were No. 1 and No. 2 swapped places regarding the views. So as assumed, the most successful social media stars are able to grow fast and increase their fame. They do not only maintain their top positions (see chapter 4.1), but expand their lead.

4.3 Attention Economics: Upload Activity

Extending the classic superstar approach in respect to attention economics and audience building, we checked the upload behaviour of our sample. The results of the linear regressions regarding the independent variables are outlined in Table 7 (for complete regression tables see appendix Table 11). Model 1 shows the estimates of an OLS regression, Model 2 those of the GLS regression and in Model 3 we used fixed-effects. In this case, we study the influence of video uploads on the short-term success of "views" (H4). The duration in the market has positive and significant impact in Model 2 and 3. Moreover, the key aspect of this section, the video uploads, are statistically significant and positive in the first two models.

Table 7: **Extract: Empirical Results Upload Activity I**

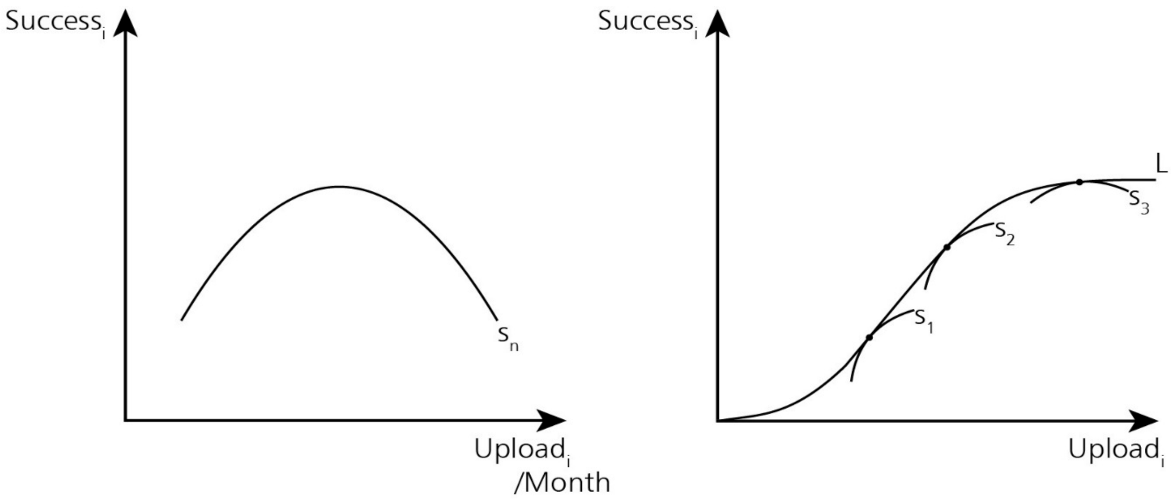
	(Model 1) Log (Views)	(Model 2) Log (Views)	(Model 3) Log (Views)
Log Uploads	0.526^{***}	0.640^{***}	0.663
	(7.95)	(4.01)	(1.97)
Log Duration	0.219	1.426^{**}	1.836^{**}
	(1.78)	(3.28)	(3.28)
_cons	16.18^{***}	7.401^{*}	2.318
	(20.42)	(2.38)	(0.58)
N	2457	2457	2457

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Thus it can be expected that a certain activity over time is beneficial in the YouTube market, however, the empirical evidence of a positive influence is not robust over all three models. Therefore, we extend the model towards attention economics and the aspect of information overload. In regard to attention as a scarce resource, we not only assume that uploads have a positive impact on success, but that further supply of information (beyond the optimal level and within a limited time period) has negative impact (H5). Figure 4 illustrates the relationship between uploads and success over time. So far, we used the total numbers of subscribers, views and uploads to see the big picture and sustainable effects. As a monthly optimum is strategically reasonable for YouTubers and provided by the data set, we use this as limited time interval for the analysis. The graph on the left shows the inversely U-shaped characteristic for a given month (short-term) S_n. The one on right illustrates the long-term progression including the curve L, which encloses the short-term curves. The tangent points show the optimal upload level each month. Due to the slope of the curve, it is harder to oversaturate the market in the beginning (S_1 and S_2). Note that due to the relatively young state of the market and the limited time period of our dataset, we cannot estimate the long-run s-curve (right side of fig. 3). Still, we can estimate whether our data is consistent to the left side.

Figure 4: **Upload and Success**



Hence, a non-linear relationship of an inverse U-shape is expected to describe the connection between monthly uploads and monthly views. The short summary regression statistics for Equation 3 and this U-shape theory are listed in Table 8 (full table see appendix Table 12). The estimated parameter $\beta_1$is clearly positive, whereas the squared term β_2 is negative. These results, (with varying levels of significance) consistent over Model 1 (OLS), Model 2 (GLS) and Model 3 (fixed-effects), are robust and suggest that an inverse U-shaped progression cannot be rejected.

Table 8: **Extract: Empirical Results Upload Activity II**

	(Model 1) Monthly Views	(Model 2) Monthly Views	(Model 3) Monthly Views
Monthly Uploads	664564.2**	709660.2*	731371.1*
	(2.85)	(2.16)	(2.13)
Monthly Uploads^2	-809.2**	-516.6*	-513.1*
	(-2.69)	(-2.13)	(-2.08)
_cons	44425338.8***	40385940.5***	28631231.5***
	(6.59)	(5.72)	(4.36)
N	2253	2253	2253

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Thus, our empirical analysis supports the theory that upload activity matters for the success of social media stars in a non-linear, inverted U-shape way. Increasing the frequency of uploads from low levels c.p. gains views and subscribers, thus contributing to attracting and maintaining audience. A certain frequency of uploading new content is required to keep attention-volatile consumers on board. However, further increasing the frequency of uploads from already high levels c.p. deters views and subscribers, crowding out attention-scarce (information overloaded) consumers by 'spamming' them with too much content.

There are further aspects, which would be interesting to observe in this area. This dataset does not allow the analysis of constant behaviour, as in frequent upload and periodical upload. We have only monthly totals, rather than the exact day and time of the upload. That is why it is not possible to study certain time zones or regular uploads on specific days. Furthermore the length of the videos is unknown. The link between frequency and video length might be interesting. More attention and time is required to watch long videos than short clips. So the frequency might correlate with the video length. Eventually, we cannot measure the quality of the content. It is possible that the mass production of new content (high frequency of uploads) asks too much of the creativity of the artists so that quality drops.

5. Conclusion

This paper aims to extend the understanding of superstars in social media markets. For reasons of data availability, we restrict our empirical analysis to the platform YouTube. We find support for traditional superstar effects like the popularity concepts of Adler and MacDonald. This demonstrates that a new media – social media platforms – do not erode well-known economic mechanisms from the traditional world. Fundamental economic concepts from the 'classical' economics of superstars like the experience good character and network effects apply to social media stars as well.

Notwithstanding, new markets and new media additionally offer new avenues for stardom. The times of the internet are rightfully hailed for the almost non-existing technological barriers to provide content. This does not imply, however, that all content has the same chance to grasp the attention of the audience. Information overflow means that building and maintaining audience becomes an important prerequisite to enter 'the market for social media stars' (attention economics). With respect to social media platforms like YouTube, the underlying algorithms of ranking and recommending contents to users play an important role. While they are not published and not known, neither to content providers nor to users, the market participants can learn to imperfectly anticipate underlying mechanisms and to (imperfectly) use them to promote their content. The combination of algorithm management and upload-frequency strategies may be a relevant success factor. In our empirical analysis, we find support for the relevance of social media specific upload behaviour. An inverted U-curve between upload frequency and (short-term) success proxies is supported by our data.

Table 9 shows an overview of the paper's hypotheses, methods and empirical evidence.

Table 9: **Overview: Hypotheses and Results**

Hypothesis	Method	Empirical Evidence	Critics
H1: The duration in the market significantly and positively influences the current success.	Linear Regressions	✓	Only one year observable with this sample. A longer time span would be useful.
H2: Successful stars of previous periods can maintain their top positon within their category.	Spearman Rank Correlation	✓	(see above)
H3: Stars in top positions have higher growth rates than stars in mediocre positions.	Paired T-Test	✓	
H4: The frequency of content uploads significantly and positively influence the social media success.	Linear Regressions	(✓)	More information on the content required to enable more detailed analysis
H5: The monthly video uploads significantly and positively influence the short-term success until a turning point is reached, where further uploads have negative impact.	Regressions with squared term	✓	(see above)

Our paper represents a first contribution to analyse social media stars from the perspective of the economics of superstars. Further research on differences and similarities on other platforms is needed. This includes both the further development of the economic theory of social media stardom, in particular in the areas of algorithm management and upload behaviour, and further empirical analysis with broader and longer-running datasets (if available).

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Appendix

Table 10: Empirical Results MacDonald Popularity

	Model 1 Log (Subscriber)	Model 2 Log (Subscriber)	Model 3 Log (Subscriber)
Log Views	0.439^{***} (10.78)	0.422^{***} (4.17)	0.356^{**} (3.25)
Log Duration	0.243^{**} (3.04)	0.877^{***} (4.71)	1.314^{***} (5.23)
1. Comedy	0 (.)	0 (.)	0 (.)
2. Gaming	0.0302 (0.35)	0.107 (0.85)	0 (.)
3. Howto & Style	-0.161 (-1.60)	-0.317^{*} (-2.36)	0 (.)
4. People & Blogs	-0.213^{*} (-2.29)	-0.0894 (-0.73)	0 (.)
1. Female	0 (.)	0 (.)	0 (.)
2. Male	-0.179^{*} (-2.25)	-0.358^{**} (-3.21)	0 (.)
3. Mixed	-0.391^{**} (-2.70)	-0.485^{*} (-2.17)	0 (.)
1. Arabian	0 (.)	0 (.)	0 (.)
2. English	0.552^{***} (7.18)	0.149 (1.09)	0 (.)
3. French	0.593^{***} (4.34)	0.141 (0.57)	0 (.)
4. German	0.293 (0.91)	-0.0107 (-0.02)	0 (.)
5. Japanese	-0.264^{*} (-2.39)	-0.508^{**} (-3.17)	0 (.)
6. Portuguese	0.571^{***} (5.06)	0.364^{**} (2.76)	0 (.)
7. Russian	0.467^{**} (3.08)	0.353^{*} (1.99)	0 (.)
8. Spanish	0.637^{***} (6.01)	0.279 (1.85)	0 (.)
_cons	4.152^{***} (4.36)	0.163 (0.10)	-1.945 (-1.11)
N	2457	2457	2457

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Empirical Results Upload Activity I

	(Model 1) Log (Views)	(Model 2) Log (Views)	(Model 3) Log (Views)
Log Uploads	0.526^{***} (7.95)	0.640^{***} (4.01)	0.663 (1.97)
Log Duration	0.219 (1.78)	1.426^{**} (3.28)	1.836^{**} (3.28)
1. Comedy	0 (.)	0 (.)	0 (.)
2. Gaming	-0.333 (-1.64)	-0.443 (-1.33)	0 (.)
3. Howto & Style	-0.917^{***} (-5.11)	-1.285^{***} (-5.06)	0 (.)
4. People & Blogs	-0.825^{***} (-5.95)	-0.671^{**} (-2.93)	0 (.)
1. Female	0 (.)	0 (.)	0 (.)
2. Male	0.0337 (0.23)	-0.322 (-1.30)	0 (.)
3. Mixed	0.164 (0.63)	0.00662 (0.02)	0 (.)
1. Arabian	0 (.)	0 (.)	0 (.)
2. English	-0.266^{*} (-2.22)	-1.114^{***} (-3.31)	0 (.)
3. French	0.0129 (0.05)	-0.796 (-1.78)	0 (.)
4. German	-0.445 (-0.96)	-1.124 (-0.91)	0 (.)
5. Japanese	-0.233 (-1.07)	-1.066^{*} (-2.17)	0 (.)
6. Portuguese	-0.826^{***} (-5.00)	-1.307^{***} (-4.79)	0 (.)
7. Russian	0.275 (0.86)	0.0704 (0.17)	0 (.)
8. Spanish	-0.157 (-0.87)	-0.933^{**} (-2.69)	0 (.)
_cons	16.18^{***} (20.42)	7.401^{*} (2.38)	2.318 (0.58)
N	2457	2457	2457

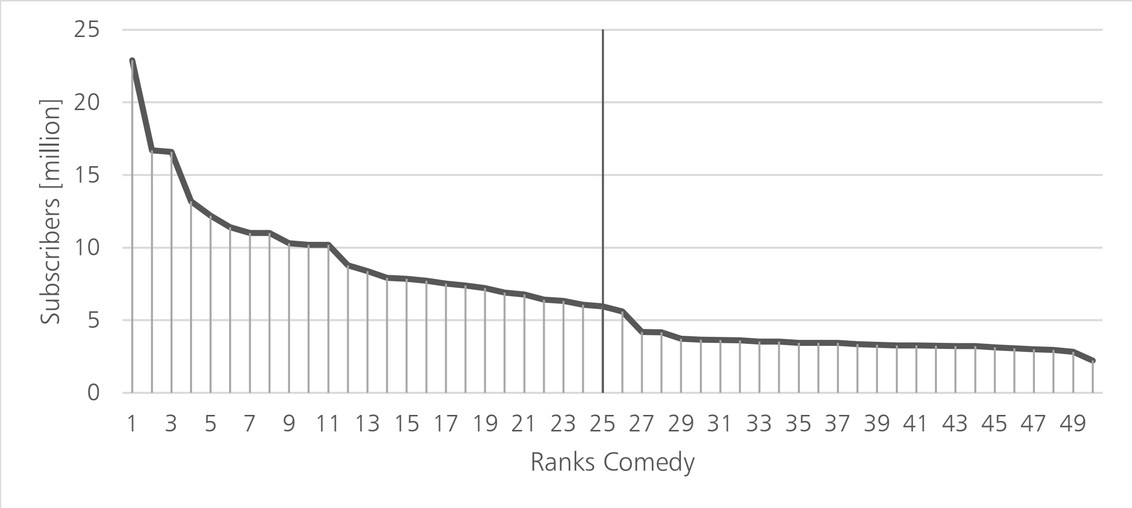
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

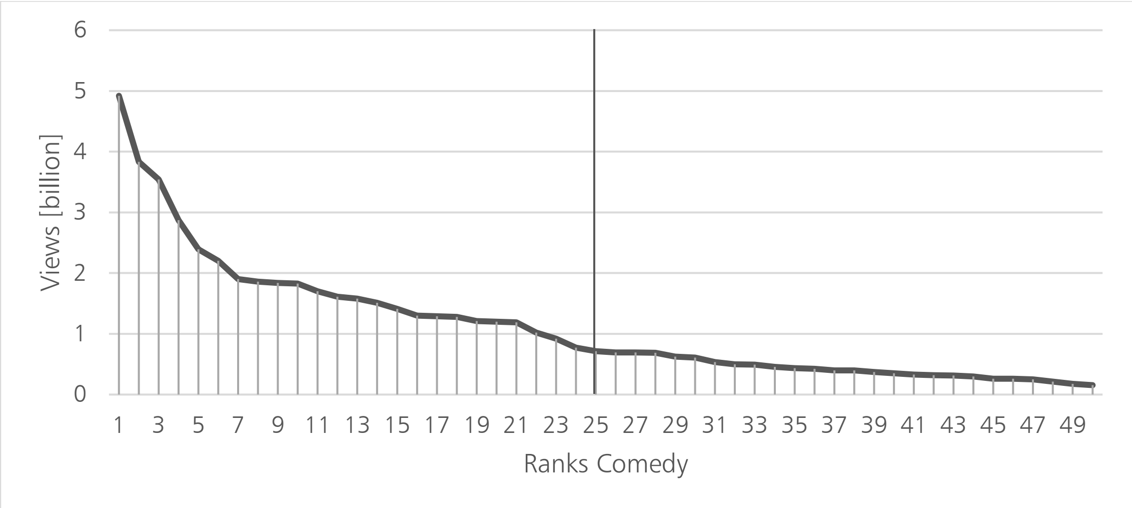
Table 12: Empirical Results Upload Activity II

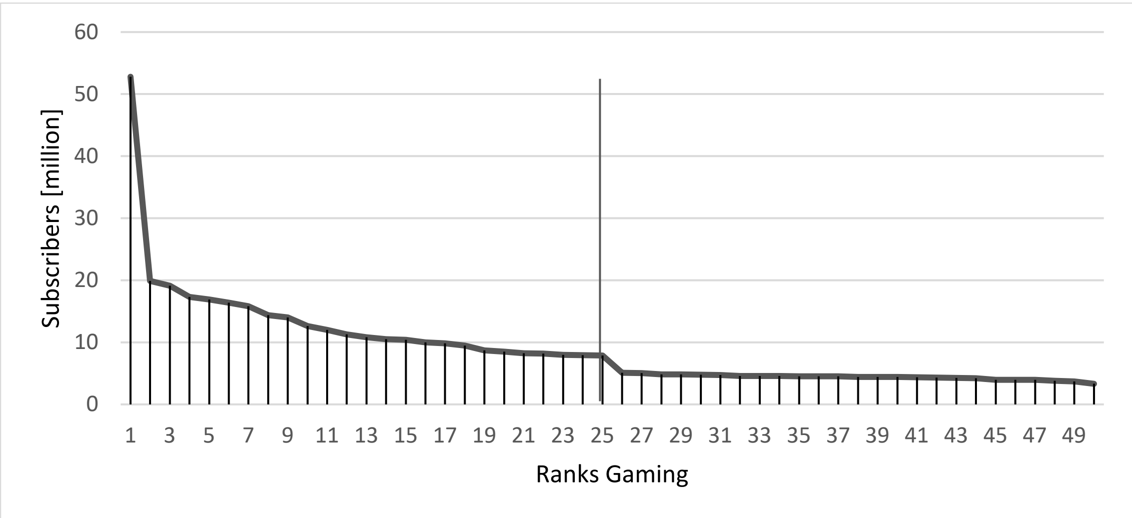
	(Model 1) Monthly Views	(Model 2) Monthly Views	(Model 3) Monthly Views
Monthly Uploads	664564.2**	709660.2*	731371.1*
	(2.85)	(2.16)	(2.13)
Monthly Uploads^2	-809.2**	-516.6*	-513.1*
	(-2.69)	(-2.13)	(-2.08)
1. Comedy	0	0	0
	(.)	(.)	(.)
2. Gaming	21848082.8	18497293.7	0
	(1.75)	(1.17)	(.)
3. Howto & Style	-19171119.6**	-15655179.2*	0
	(-2.98)	(-2.52)	(.)
4. People & Blogs	-7792735.6	-5923138.5	0
	(-1.11)	(-0.84)	(.)
1. Female	0	0	0
	(.)	(.)	(.)
2. Male	887940.7	614875.4	0
	(0.14)	(0.10)	(.)
3. Mixed	17229281.5	15731411.1	0
	(0.73)	(0.71)	(.)
1. Arabian	0	0	0
	(.)	(.)	(.)
2. English	-14569779.2***	-14020182.4***	0
	(-4.45)	(-3.85)	(.)
3. French	-32774673.6***	-29357522.8***	0
	(-3.98)	(-3.50)	(.)
4. German	-55820350.4	-53625484.6	0
	(-1.86)	(-1.72)	(.)
5. Japanese	24246338.9**	26481476.7**	0
	(2.95)	(2.76)	(.)
6. Portuguese	-31072132.3***	-29152685.5**	0
	(-3.45)	(-3.09)	(.)
7. Russian	10073948.2	13534380.5	0
	(0.46)	(0.62)	(.)
8. Spanish	5508869.7	6478852.5	0
	(0.54)	(0.64)	(.)
_cons	44425338.8***	40385940.5***	28631231.5***
	(6.59)	(5.72)	(4.36)
N	2253	2253	2253

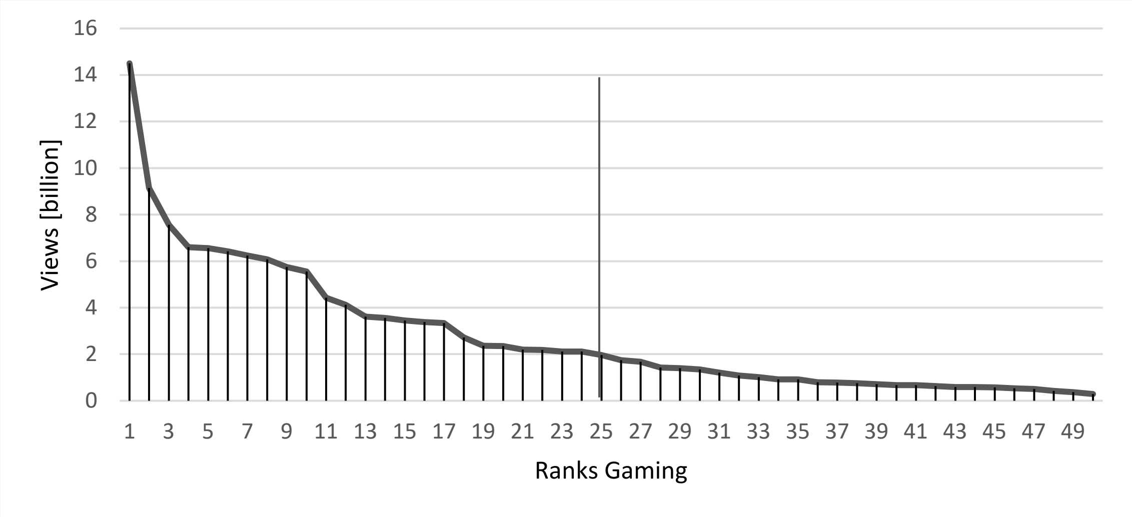
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

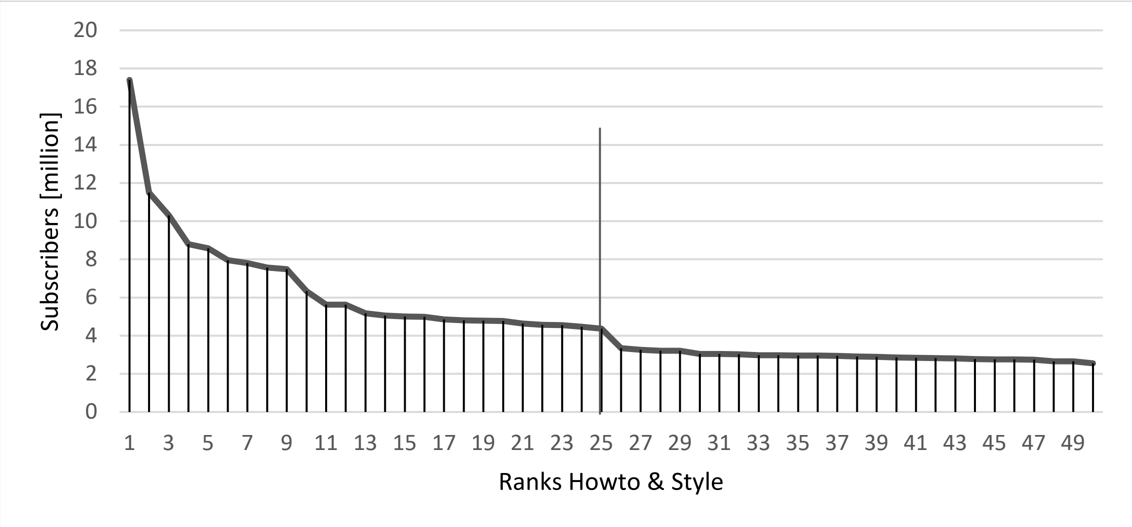
Figure 5-12: Distribution of Subscribers and Views per Category

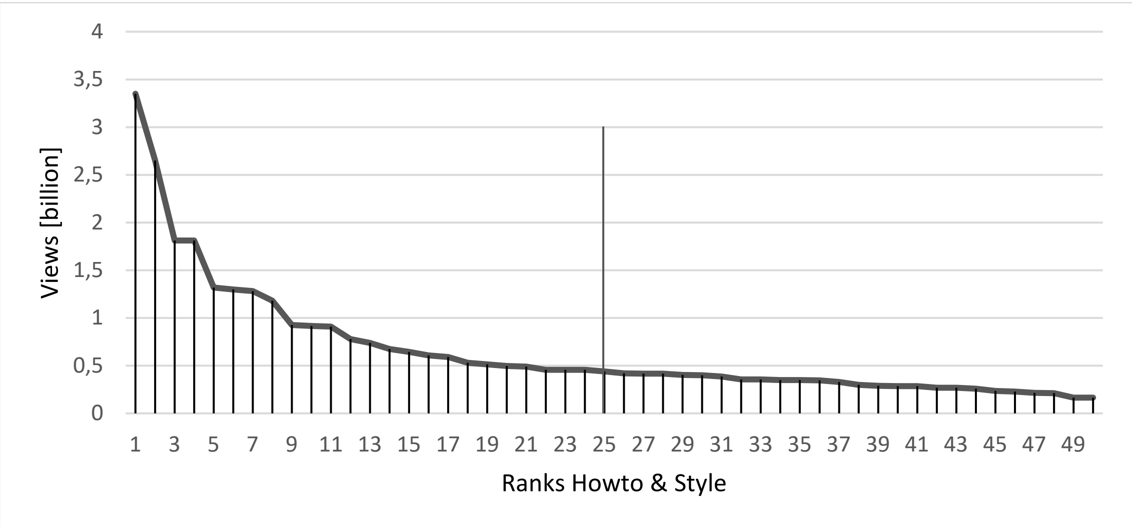


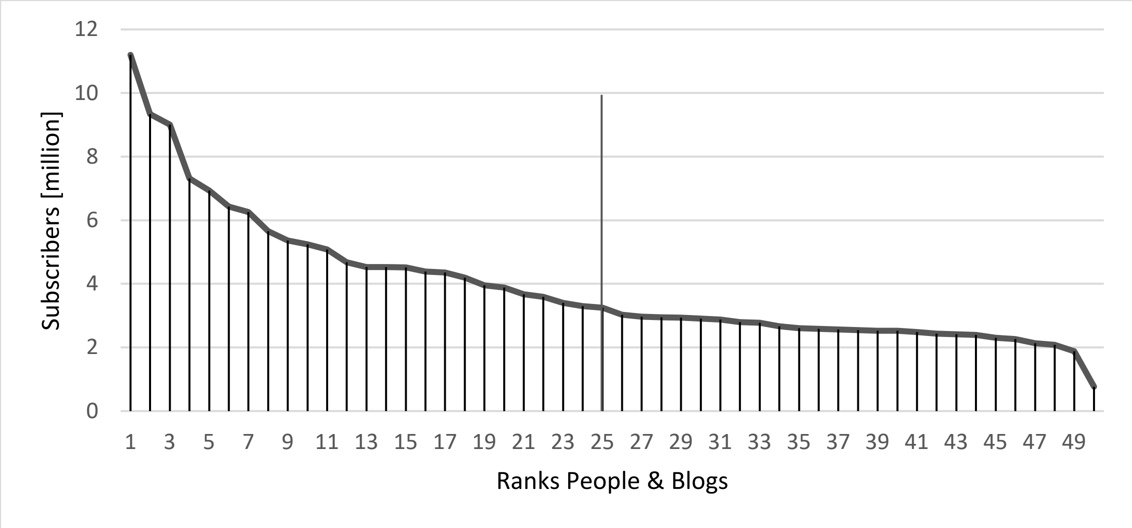





16
14
12
10
8
6
4
2
0
Views [billion]
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49
Ranks Gaming


20
18
16
14
12
10
8
6
4
2
0
Subscribers [million]
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49
Ranks Howto & Style


4
3,5
3
2,5
2
1,5
1
0,5
0
Views [billion]
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49
Ranks Howto & Style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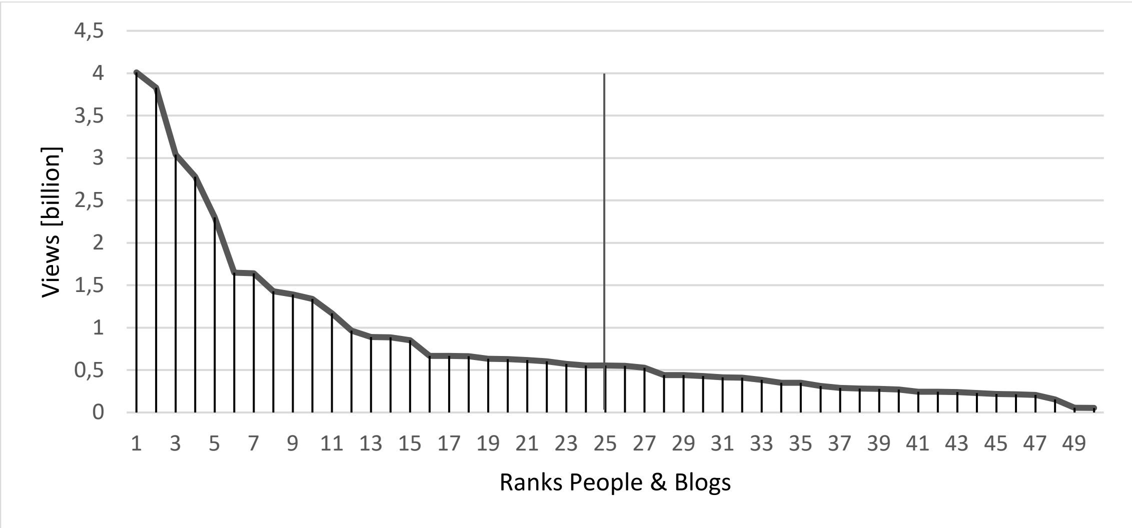
Ranks People & Blogs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Ranks People & Blogs

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