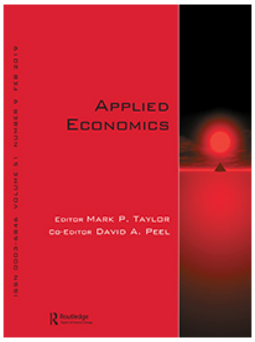

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The more others care, the more you share? – Social contagion as a stardom trigger of social media superstars –

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ABSTRACT
Emerging superstars on social media platforms reshape the media landscape. This research analyses social contagion as a stardom trigger of social media superstars (SMS). We argue that in addition to serving as a quality indicator, the number of observed consumers of SMS performances also indicates the suitability of discussing the SMS performances with others. We experimentally manipulated the number of previous views of a YouTube video and find that a high number of previous views significantly increases the perceived quality and the video's discussion suitability even when holding all objective video characteristics constant. We discuss implications for aspiring SMS and (online) marketers.

KEYWORDS
Social media; superstars; social contagion; discussion suitability; stardom triggers

JEL CLASSIFICATION
C91; M39

I. Introduction

Individuals do not tend to make decisions independently, but rather are influenced by the observed behaviour of others. For example, individuals are more likely to demand a dish when they are given the information that it is one of the most popular dishes (Cai, Chen, and Fang 2009), to download a song that has been also downloaded by others (Salganik, Dodds, and Watts 2006), or to buy mass-market products at Amazon.com with high previous sales (Chen, Wang, and Xie 2011). Such herding behaviour (Banerjee 1992) or social contagion (Dodds 2004) has also been found in the diffusion of new agricultural technology (Conley and Udry 2010), in the microloan market (Zhang and Liu 2012), in the wedding services market (Tucker and Zhang 2011), in the kidney market (Zhang 2010), in the box office movie market (Moretti 2011), and in app stores (Carare 2012), to name just a few examples of the social multiplier effect (Glaeser, Sacerdote, and Scheinkman 2003). Individuals tend to follow the herd because they infer product quality from what their peers have chosen (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992).

This paper studies how social contagion influences the consumption of social media superstar services. Referring to the superstar definition of Rosen (1981), we define social media superstars (SMS) as *persons who disseminate their service over social media platforms, who earn enormous amounts of money and dominate the activities in which they engage*. Social media platforms like YouTube allow content providers to address millions of people at very little cost and enable a few of them to become well-known and wealthy superstars. Felix 'PewDiePie' Kjellberg is a good example of a social media superstar. The young Swedish video-game commentator produces videos that have been viewed more than 17 billion times. His YouTube channel has more than 63 million subscribers and it is estimated that he earns 12 million USD per year (Berg 2015).

Whereas traditional superstars, like tennis star Roger Federer, earn enormous amounts of money because of their superior talent (Rosen 1981), SMS mostly resemble celebrities who are known for being well-known and who can monetize their fame because the social media platforms, such as YouTube, share their advertising revenues with the SMS. Unlike traditional superstars, whose fan communities are often difficult to assess, SMS have fan communities that are easily quantified from the number of clicks, views or subscriptions.

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The conventional explanation of the social multiplier effect is that the number of observed consumers serves as a quality indicator for experience goods whose quality is ex ante uncertain (e.g. Banerjee 1992; Moretti 2011). For the services provided by SMS, previous consumption figures are likely to increase future consumption beyond just serving as a quality indicator: The size of the fan community has a value per se. We argue that watching a highly popular video is more valuable than watching a less popular video because watching the popular video enables the consumer to discuss the video with other consumers who have also watched the video. The more popular a SMS becomes, the more likely that the services provided by this SMS represent common ground that everyone can relate to and comment on. People love talking about common ground topics such as SMS performances because it makes them feel more socially connected (Berger 2014). Given 'the basic human tendency to converse about people known in common' (Shiller 1995, 185), SMS provide a projection screen for all kind of rumours and interpretations. The advantage of such celebrity gossip in comparison to neighbourhood or friendship gossip is that there are no repercussions and no accountability (Franck and Nüesch 2007). Susarla, Oh, and Tan (2012a, 2012b) show that the social interactions are more influential than quality-related video characteristics in determining which YouTube videos become successful.

Whereas Rosen's (1981) superstar theory assumes that a star's objective talent superiority leads to the enormous superstar earnings, Adler (1985) argues that there may be large differences in earnings even where there are no differences in talent. According to Adler (1985) the appreciation of a star performance increases firstly with the amount of star-specific knowledge that has been accumulated through past consumption and secondly by discussion of the performance with other knowledgable individuals. The more popular a star becomes, the easier it is to find other individuals with whom to discuss the performance. Especially in arts where objective measures of a star's talent are lacking, stardom arises because of the consumers' need for a common culture (Adler, 2006).

In our study we test Rosen's and Adler's star theories by presenting experimental data on how and why previous views of a SMS video affect the likelihood of sharing a video. According to Rosen's star theory, the number of previous views serves as a quality signal and thereby increases future star consumption because poorer quality is only an imperfect substitute for higher quality. Because in arts, unlike in sports, there are no objective quality measures of a star performance, the number of previous views may serve as a proxy for the star's talent. According to Adler's star theory, the number of previous views is expected to increase the likelihood of sharing by indicating the performance's suitability for informed discussion with others thanks to the greater number of informed people available to discuss it.

All subjects watch one and the same YouTube video and then answer questions about the video's perceived quality, its suitability for discussions and the likelihood of sharing the video. The subjects are randomly exposed to one of two treatments, i.e. either one with a high number of previous views or one with a low number of previous views in a between-subject design. We find that the larger number of previous views significantly increases the perceived quality of the video and the video's suitability for discussing it with others, even though all objective video characteristics are held constant. The perceived quality of the video and its suitability for discussion in turn significantly increases the likelihood of sharing the video. Thus herding behaviour in the consumption of SMS services has two channels: The number of previous views serves as an indicator of the quality and of the suitability for discussing it with others. In the following, we first present experimental evidence and then discuss theoretical and practical implications.

II. An experimental study

Participants

Participants were recruited via *Prolific Academic*, a provider of online access panels. By tracking the IDs of participants, we prevented multiple submissions. We cleaned the initial sample (N = 700) for participants who did not pass attention and manipulation checks. The final sample (n = 644) exhibits an average age of 31.4 years (SD = 10.8), of whom 48.4% are female.

Procedure

Participants evaluated a short video clip from YouTube via an online survey. All participants watched a humorous video of a man presenting his sneaker collection in a ridiculous manner. Below the video we presented the number of previous views. In the *high previous views treatment*, previous views of the video were 32,779,756 and marked in green. In the *low previous view treatment*, previous views of the video were 827 and marked in red. Due to the between-subject design, each participant was assigned to only one treatment. Figure 1 presents the web page design used in the experiment. We avoided any hints about the importance of the previous view information for the rest of the survey. After watching the video, participants were asked to evaluate the video's perceived quality and its suitability for discussing it with others. Moreover, subjects were also asked to provide information on demographics and social media use.

Measures

The dependent variable is the *sharing likelihood*, as already used by Berger and Milkman (2012). The participants answered to the question 'How likely would you be to share the video with others?' on a seven-point Likert scale varying from 1 ('not at all likely') to 7 ('extremely likely'). The main predictor is the *high previous view* treatment, a dummy equalling one if the participant was randomly assigned to the treatment with high previous views (zero otherwise). To measure the *perceived quality* of the video, we use the four items established by Chakravarty, Liu, and Mazumdar (2010). These four items have a high internal consistency (Cronbach's α = 0.94) and thus were aggregated to a single factor. To measure the video's *discussion suitability* we built on Beersma and van Kleef (2012) and Litman and Pezzo (2005) and introduced eight items (see Appendix A) that include questions like 'The video is suitable for conversations with others.'. Here again, the eight items were aggregated to a single factor due to the high internal consistency (Cronbach's α = 0.95). Besides questions about demographics, we also asked participants how intensely they used social media. All measures were tested for their comprehension in a pilot study of 60 participants recruited via *Prolific Academic*. To avoid an overlapping sample, we did not permit these participants to take part in the final study.

Results

Table 1 shows the means, standard deviations, and Pearson correlation coefficients of key variables. The average age is 31.4, 48.4% are female, 46.5% are employed, and 61.6% possess an education higher than a high school diploma. As for social media use, 89.7% of the subjects are YouTube users, and thus can be considered to be familiar with the social media platform as simulated within this experiment. Moreover, our average subject is active on social media platforms in general, with an average number of 2 posts and shares per day and 7 likes and dislikes on average per day. The vast majority of subjects were unaware of the video prior to participating in this experiment (average value of 6.8 to the statement: 'I have never watched the video before.' on a seven-point Likert scale with 7 denoting 'strongly agree').

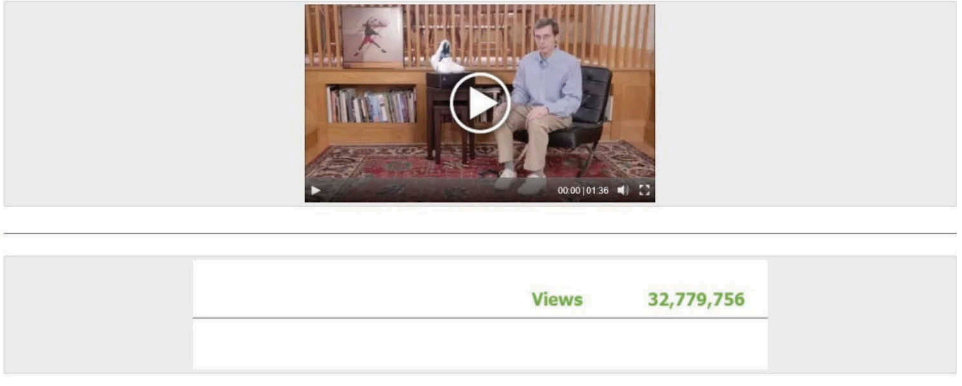

Figure 1. Sample web page. Note: Video displayed in the experiment, here in the *high previous views* treatment. Source: Brad Hall, YouTube, URL: https://youtu.be/PrgPlfNwByQ.

Table 1. Means, standard deviations, and bivariate correlations.

Variables	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
(1) Sharing likelihood	2.959	2.128	1.000											
(2) High previous views treatment	0.492	0.500	0.064	1.000										
(3) Discussion suitability[a]	0.000	0.970	0.627***	0.078*	1.000									
(4) Perceived quality[a]	0.000	0.963	0.687***	0.088*	0.617***	1.000								
(5) Age	31.416	10.772	−0.134**	−0.029	0.009	−0.095*	1.000							
(6) Female	0.484	0.500	−0.163***	−0.028	−0.014	−0.139***	0.238***	1.000						
(7) Employment	0.465	0.499	−0.034	−0.004	0.036	0.021	0.138***	0.023	1.000					
(8) Education	0.616	0.486	−0.087*	−0.003	0.041	−0.028	0.257***	0.151***	0.320***	1.000				
(9) YouTube user	0.897	0.303	0.136**	0.005	0.042	0.080**	−0.195***	−0.246***	−0.064	−0.077*	1.000			
(10) Daily posts and shares	2.032	8.532	0.081*	−0.018	0.058	0.045	0.075	0.062	−0.046	−0.012	0.044	1.000		
(11) Daily likes and dislikes	7.107	11.759	0.142***	−0.023	0.093*	0.043	−0.105**	0.045	−0.069	−0.106***	0.099*	0.100*	1.000	
(12) Prior non-awareness	6.832	0.731	−0.057	0.035	−0.007	−0.076	0.023	0.040	−0.011	0.046	−0.050	−0.025	0.004	1.000

*$p < .05$.
**$p < .01$.
***$p < .001$.
[a]Denotes a factor. Notes: n = 644.

Table 2. Results of mediation tests predicting sharing likelihood: indirect effects high previous views.

			BC 95% CI	
	Estimates	SE	Lower	Upper
Indirect Effects	Predictor: High previous views treatment			
Total indirect effect of high previous views	**0.2869**	0.1222	0.0472	0.5227
1. Discussion suitability	**0.1176**	0.0590	0.0108	0.2412
2. Perceived quality	**0.1692**	0.0786	0.0157	0.3252

Table 2 shows the results of mediation tests of the *high previous view* treatment predicting the *sharing likelihood* through the mediators *discussion suitability* and *perceived quality*. In line with Preacher and Hayes (2008), we test each indirect effect while simultaneously controlling for the other. As recommended, we show bootstrap estimates from 5,000 bootstrap samples given a bias-corrected 95% confidence interval. Table 2 shows that the total indirect effect is 0.29, significantly above zero. The perceived quality of the video contributes 59% and the video's *discussion suitability* 41% to the total indirect effect. As we assign treatment status randomly, we do not have to include control variables to prevent biased estimates. However, we still control for age, gender, employment, education (dummy equalling 1 if education is higher than a high school diploma), the intensity of social media use (dummy for YouTube use, the number of daily posts and shares, the number of daily likes and dislikes, and a dummy equalling 1 if the participant already knew the video) to increase the model's goodness-of-fit measures.

The path coefficients (illustrated in Figure 2) are shown in Table 3. In the *high previous views* treatment participants perceive the video to be more suitable for discussion and of higher quality. Both effects are statistically significant at the 5% level. Both the *discussion suitability* and the perceived quality then significantly increase the *sharing likelihood*.

III. Discussion

Our experiment shows that individuals perceive the content to be not only of higher quality, but also more suitable for conversations with others. Our results have both theoretical and practical implications. The theoretical implication is that in the context of SMS performances, a high number of previous consumers not only serves as a quality indicator for services whose quality is ex ante unknown, but also has a value per se, because a popular service becomes common ground topic that consumers can talk about with others. This implies that unlike traditional superstars, who possess some kind of superior talent, SMS could theoretically be mere celebrities who are just known for being well-known.

Aspiring SMS may benefit from the insights that a large fan base frames contents to be of higher perceived quality and renders them more suitable for gossip. Even the currently most successful SMS 'PewDiePie' spends a lot of time interacting with fans in the comments sections beneath his videos on YouTube to form 'a community of 'bros'' (Jacobs 2014). Our findings are

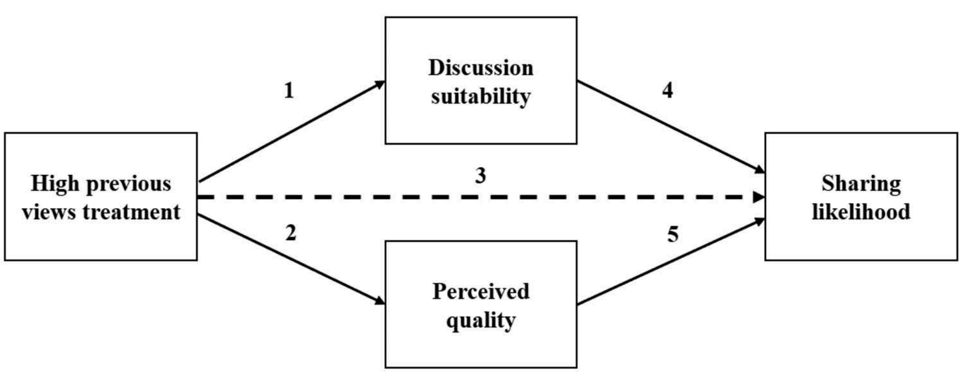

Figure 2. A multiple mediator model of the effects of a high views treatment on sharing likelihood.

Note: Results from the analyses of indirect effects are displayed in Table 2 and path estimates are displayed in Table 3.

Table 3. Path coefficients of the multiple mediator model.

Paths as Represented in Figure 2		Results High previous views
1. High previous views	→ Discussion suitability	0.15*
2. High previous views	→ Perceived quality	0.16*
3. High previous views	→ Sharing likelihood	−0.01
4. Discussion suitability	→ Sharing likelihood	0.74***
5. Perceived quality	→ Sharing likelihood	1.00***
Model R^2		0.56***

*$p < .05$.
**$p < .01$.
***$p < .001$.

also relevant for all marketing efforts to attract the attention of consumers, particularly young people. Not surprisingly, the world's largest traditional entertainment company, *GroupM*, which is responsible for one in three ads globally, announced in January 2016 a partnership with *Fullscreen*, a multi-channel network (MCN) and entertainment company that represents some of the most popular SMS on YouTube and other social media platforms, an alliance aiming to match brands with young target audiences using SMS as ephemeral celebrities. Other big entertainment companies, such as Disney and Hearst, have already invested in MCNs, showing that SMS are growing in importance in the battle for consumer attention (Kuchinskas 2016).

We encourage future studies to test the generalizability of our findings on other social media platforms such as *Facebook* or *Instagram* and for various types of contents. Because our experiment models a one-shot decision of only one video, it does not consider a series of recommendation situations and cannot test how an updating of the perceptions of the *discussion suitability* and *quality* affects the consumption behaviour of SMS services over time. Additionally, as our predictor *high previous views* is a binary variable, we are not able to calculate the *sharing likelihood* as a function of the number of previous views. We therefore encourage future studies to test the marginal benefits of previous consumption figures at various levels. The importance of this is demonstrated, for example, by Wu and Wu (2016) finding that the effect of review volume on consumers' willingness to pay for TVs on eBay is non-linear. A 'tipping point' (in the sense of Gladwell 2001) may exist where the number of an aspiring YouTuber's viewers explodes from a slow linear increase into a star-creating boom. The knowledge of this 'critical mass' of consumers may be decisive in becoming a SMS.

The experimental results presented in this study indicate that the number of previous views of a *YouTube video* increases the likelihood of sharing the video with others. Social contagion thus serves as a stardom trigger. Mediation analyses identify two underlying channels: The number of previous consumers increases the perceived quality and discussion suitability of SMS performances with others. Confirming audience size as a key metric, aspiring social media superstars should channel their efforts into fostering their audience (size).

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix A

Table A1. Measures

Construct	Scale items	Answer scale(s)	Cronbach's α	Based on
Perceived quality	Please evaluate the content quality of the video.	1 ('very unfavourable/ negative/ dislike/ very bad') to 7 ('very favourable/ positive/ like/ very good')	0.94	Chakravarty, Liu, and Mazumdar (2010)
Discussion suitability	I think that the video contributes to a good conversation with others. I could talk about this video with others. I can easily talk about this video with others. The video is suitable for trivial conversations with others. The video is suitable for conversations with others. The video is suitable for 'chatty conversations' with others. The video is suitable for small talk with others. The video is suitable for gossip.	1 ('strongly disagree') to 7 ('strongly agree')	0.95	Beersma and Van Kleef (2012); Litman and Pezzo (2005)