12-2019

Online content consumption: Social endorsements, observational learning and word-of-mouth

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Completed Research Paper

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Abstract

The consumption of online content can occur through observational learning (OL) whereby consumers follow previous consumers' choices or social endorsement (SE) wherein consumers receive content sharing from their social ties. As users consume content, they also generate post-consumption word-of-mouth (WOM) signals. OL, SE and WOM together shape the diffusion of the content. This study examines the drivers of SE and the effect of SE on content consumption and post-consumption WOM. In particular, we compare SE with OL. Using a random sample of 8,945 new videos posted on YouTube, we collected a multi-platform dataset consisting of data on video consumption and WOM from YouTube and data on tweet sharing of the video from Twitter. Applying a panel vector autoregression (PVAR) model, we find that OL increases consumption significantly more than SE in the short run. However, SE has a stronger effect on content consumption in the long run. This can be attributed to the impact of SE on WOM signals, which also increase content consumption. While OL and SE leads to similar amount of positive WOM, SE generates significantly more negative WOM than OL. Our results also show that SE is driven by WOM (i.e., likes and dislikes) but not content popularity. We further confirm the effects of OL vs. SE on content consumption and WOM using a randomized experiment at the individual consumer level. Implications for content providers and social media platforms are derived accordingly.

Keywords: Observational learning, social endorsement, word-of-mouth, online content

Introduction

Online content gains its popularity via two modes of diffusion: broadcast that a large number of individuals receive information directly through a single source, and viral propagation wherein any one individual directly affects only a few others (Goel et al. 2016). First, users can discover the content directly via its broadcast on the original content platform. If without much information on the quality of the content and the reputation of the content provider, their consumption of the content is mainly driven by OL, the effect that a consumer's decision is influenced by the choices of other consumers (Hendricks et al. 2012). As digital platforms reveal past consumption information and also use it to prioritize content, consumer content choice is affected by its past consumption number which reveals the actions of previous consumers. Therefore, herding occurs when users follow the action of previous consumers while ignore their own private information of the content (Bikhchandani et al. 1992). Under OL, the prior consumption number of the content positively affects subsequent consumption (Wu and Huberman 2008, Chen et al. 2011).

The second mode, viral propagation, comprises a multi-generational information spreading process where any one node directly affects only a few others. Such information propagation is by social endorsement (SE), the positive sharing of the content with one's social ties on social networking sites. SE can trigger social cascades whereby the endorsing message gets propagated through the social network. For example, users often post links to interesting blogs or videos on their Facebook timeline to share with their friends, and this post can be reposted by their friends on these friends' timeline to share with friends' friends. Consequently, the content could potentially reach far and wide throughout the network (Cha et al. 2009). Consumers have been increasingly engaged in SE activities because of the integration of social media platforms. For instance, YouTube allows users to share watched videos on Facebook, Twitter, Blogger, Tumblr, Pinterest, etc., by simply clicking a button. Following this trend, vast efforts are devoted by individuals and businesses to promote their content and products through online social networks and viral marketing. However, the very large scale of the underlying network makes it difficult to determine their effectiveness. While prior literature has shown the information dissemination effect of SE (Cha et al. 2009, Bakshy et al. 2012), its effect on conversion is still in debate (Banerjee et al. 2013). Furthermore, little is known how OL and SE compare in their effects on content consumption. Such understanding is important for online content platforms to determine how to leverage other social media platforms to promote their content.

In addition to the effects on content consumption, OL and SE can further affect consumers' post-adoption evaluation of the content. For consumers' WOM behavior, researchers have found that consumers adjust their product ratings according to the rating environment. Schlosser (2005) found that consumers lower their ratings after observing prior negative reviews. Generally, a decreasing trend in product ratings is observed (Li and Hitt 2008, Wu and Huberman 2008, Godes and Silva 2012). Moreover, consumers are influenced by strangers and friends differently in their WOM evaluations (Lee et al. 2015). For example, Berger and Heath (2008) found that individuals are more likely to diverge from strangers than from friends. We thus expect the ratings of the users under OL to be different from those of the users following SE.

A clear understanding of SE is not only theoretically meaningful but also provides important managerial implications. Platforms and content providers can leverage SE in combination of OL to achieve wider reach and engagement for their content. First, while it is well known that OL is driven by increased content popularity, it is unclear what content characteristics motivate SE. If SE is similarly driven by popularity, its effect may overlap with or reinforce the effect of OL. If SE is driven by the factors other than popularity, its effect can overcome the limit of OL in diffusing unpopular content to interested audience. Second, given that OL is often within the original content platform, SE can occur across platforms, facilitating the content diffusion beyond its original platform. Lastly, the different effects of SE on content consumption and WOM would in turn change the content diffusion process on the original platform. For example, if SE were driven by interestingness and SE would increase content consumption and WOM, the popularity of the content would gradually reflect its interestingness to audience over time. Such additional dimensions to content popularity need to be accounted for in platform recommender systems.

Therefore, our study examines the motivations for SE of online content and the effects of SE on content consumption and post-consumption WOM compared to the effects of OL. Specifically, we address the following research questions: 1) What drives SE of the online content? 2) Compared to OL information, how effective are SE in increasing content consumption? 3) How does SE influence WOM signals and how does the effect compare with the effect of OL on WOM? To answer these questions, we conduct an empirical study on observational data and a randomized experiment. In the observational study, we gathered a multi-platform dataset from YouTube and Twitter. With YouTube videos as our research subject for content, we randomly sampled 8,945 new videos posted on YouTube on the same day. On a daily basis, we tracked their views and ratings on YouTube and the tweet sharing of these videos on Twitter for approximately a year. In our context, we consider tweet sharing of a video to be SE and the likes and dislikes of the video on YouTube to be WOM, because SE are always positive but WOM can be either positive (i.e., likes) or negative (i.e., dislikes). As SE and OL can be motivated by and in turn influence content consumption/WOM, all the variables of SE, OL, content consumption, and WOM are endogenous. To address this issue, we employ a PVAR model to capture their mutual influence at the video level. We find that while both OL information and SE increase subsequent consumption, OL increases content consumption significantly more in the short run. However, the effect reverses in the long run. The PVAR results also show that SE is driven by WOM volume but not content popularity or provider reputation. In terms of post-adoption evaluation, we derive that while both increase positive WOM similarly, SE leads to more negative WOM than OL. To further validate these results on the relative effects of OL and SE, the randomized experiment is conducted at the individual consumer level. The experiment results are consistent with the empirical findings based on observational data.

Literature Review

The literature on content diffusion has been growing rapidly in recent years. In particular, several studies have examined the underlying driving forces of the diffusion of online videos. Susarla et al. (2012) found that social interactions are influential in determining which YouTube videos become successful. Goldenberg et al. (2012) examined the role of product networks on YouTube in facilitating content exploration. Qiu et al. (2015) investigated how learning and network effects drive the diffusion of online videos on YouTube. Susarla et al. (2016) explored the impact of WOM structure on the popularity of YouTube videos. Most of these studies have mainly focused on a single social media platform, i.e. YouTube. Our work examines the diffusion of online videos from a different perspective considering the cross-platform impacts between different social media platforms (i.e. YouTube and Twitter). Our results show that without considering the cross-platform effects, we are likely to lose significant leading indicators of the popularity of online content.

Related to the motivations for SE, in general, empirical evidence suggests that useful information (Berger and Milkman 2012; Heath et al. 2001), interesting topics (Chen and Berger 2013), and higher quality brands/products (Lovett et al. 2013) are more likely to be passed on or talked about. Using the social networks and photo favorite markings on Flickr, Cha et al. (2009) found that, while OL is driven by popularity, social links play a different role in transmitting information independent of the popularity of the information. Tracking diffusion events on Twitter, Bakshy et al. (2011) found that URLs rated more interesting and/or eliciting more positive feelings are more likely to spread through SE. However, according to Berger and Schwartz (2011), more interesting products only get talked about sooner after people first experience them. Moreover, Berger and Milkman (2012) found that practically useful, surprising, interesting, positive, and emotionally arousing news articles are more likely to be highly e-mailed. Additionally, Chen and Berger (2013) demonstrated that controversy affects the likelihood of conversation through opposing effects of interest and discomfort.

Prior studies on the effects of SE suggest that they can potentially contribute to content diffusion through information passing and social influence. Results on social influence have been mixed. Most studies found that the online social networks exert significant influence on product purchase (e.g., Aral and Walker 2011, Bapna and Umyarov 2015), content adoption (Bakshy et al. 2009), responses to advertisements (Bakshy, Eckles et al. 2012), product ratings (Lee et al. 2015), cooperative behavior (Fowler and Christakis 2010), and information dissemination (Bakshy, Rosenn et al. 2012, Cha et al. 2009). On the contrary, Banerjee et al. (2013) found that once information passing is accounted for, a user's decision to participate in microfinance is not significantly affected by network neighbors. Second, social influence can potentially affect users' engagement in SE activities such as contribution quantity and sharing behavior. For example, Wikipedia writers' contribution quantity is positively affected by the size of audience (Zhang and Zhu 2011); Twitter users' posting level increases as the number of followers increases (Toubia et al. 2013). According to Barasch and Berger (2014), audience size affects the type of content people share. Shi et al. (2014) also demonstrated that weak social ties are more likely to retweet a message on Twitter than strong social ties. These studies have mainly examined how SE affects consumers' adoption decision but not their post-adoption evaluation.

Our study is also related to literature on consumers' WOM behavior. An individual's online rating of a product is affected by previously posted ratings (Moe and Schweidel 2012; Lee et al. 2015). Such influence includes selection effects on whether to contribute a product rating and adjustment effects on what to contribute. In terms of selection effects, Moe and Schweidel (2012) found that positive ratings environments increase postings, whereas negative ratings environments discourage posting. Both Li and Hitt (2008) and Godes and Silva (2012) demonstrated a negative trend in product ratings and attribute it to dissimilar preferences between early and later buyers. For adjustment effects, Moe and Trusov (2011) found that the posting of positive ratings encourages negative subsequent ratings and that disagreement among prior raters tends to discourage posting of extreme opinions by subsequent raters. Moe and Schweidel (2012) found that less frequent reviewers imitate prior reviewers whereas active reviewers post negative opinions to differentiate themselves. Lee et al. (2015) differentiated prior ratings by friends from those by strangers and showed that friends' ratings always induce herding, whereas ratings by the crowd lead to both herding and differentiation in subsequent ratings. These studies examine how consumers' ratings are affected by ratings from others (friends or public), and none has discussed how consumers adopting the product from different information sources rate the product differently.

Hypothesis Development

Motivations of SE

Content popularity in driving SE

SE may be driven by content popularity similar to OL. The primary value of social broadcasting networks, such as Twitter comes from information provision and consumption (Bakshy et al. 2011, Kwak et al. 2010). According to Berger (2014), people talk about some products and ideas more than others for impression management, emotion regulation, information acquisition, social bonding, or persuading others. Among these motives, impression management and social bonding would likely lead to sharing of popular content, because sharing of popular content can enhance one's image, signal expertise, fill conversational space and increase social bonding. Sharing similar antecedents with other communication channels, microblogs such as tweets are also used to share information, communicate identify, establish social status and connect to others (Buechel and Berger 2018).

As online content differs in both vertical (i.e., quality) and horizontal (i.e., taste) dimensions, popular content receive high consumption in the past because of both high quality and wide positioning, whereas the low consumption of unpopular content can be caused by either low quality or narrow fit (Chen et al. 2011). First, to signal or enhance their perceived expertise, people are more likely to share about popular content, because experts are expected to identify high-quality products better than novices (Lovett et al. 2013). Second, because of wide positioning, sharing of popular content helps establish the common ground in conversational space. The common communal topics better increase social bonding because people feel more socially connected to others with perceived interpersonal similarity (Berger 2014). Therefore, we propose the following hypothesis:

H1: Content with more past consumption is more likely to receive social endorsements.

Content WOM in driving SE

Different from OL, SE may also be driven by interestingness and emotional arousal of the content. Among the aforementioned five motives for information sharing in Berger (2014), emotion regulation and persuasion would encourage sharing of arousing, controversial, and polarized content. First, emotion regulation leads more emotional things to be shared more. For example, movies and new articles with higher emotional intensity (regardless of positive or negative sentiments) are more likely to be discussed (Berger and Milkman 2012, Luminet et al. 2000). People are more willing to talk about urban legends that evoke more disgust, interest, surprise, joy, or contempt (Heath et al. 2001). Second, the persuasion motive predicts that people share things to influence others (Bui et al. 1994, Roskos-Ewoldsen 1997). People have higher persuasion motive for things that are more emotionally polarized or more arousing in nature (Berger 2014).

The emotional intensity or polarized opinions of the content can be measured by the extreme opinions towards the content. On many platforms, WOM in the form of customer reviews and ratings summarizes both extreme and moderate opinions. However, in the context of YouTube, content WOM captured by likes and dislikes reflects extremely positive and extremely negative attitudes without moderate opinions. As such, more WOM discussion, regardless of likes or dislikes, would lead to increased SE, according to the emotion regulation and persuasion motives. Therefore, we propose the following hypotheses:

H2a: Content with more positive WOM discussion (i.e., likes) is more likely to receive social endorsements.

H2b: Content with more negative WOM discussion (i.e., dislikes) is more likely to receive social endorsements.

Effects of SE

Effects of SE on content consumption compared to OL

OL information such as past sales volume or rank, reveals the actions of other consumers but not the reasons behind their actions (Bikhchandani et al. 1992). According to theories on information cascade, with limited information available, people observing the purchase actions of previous consumers will follow their predecessors' actions (Banerjee 1992). SE is public and positive sharing of a product or content on social networking sites such as liking the brand on Facebook, posting the content in tweets or retweets on Twitter, advocating the product in videos on YouTube (Bernritter et al. 2016). Under SE, users of social networking sites are exposed to products or content via status updates from their contacts. Oftentimes, these updates consist of messages simply quoting or forwarding others' messages and may imply information free-riding without sharing private information (Han and Yang 2013).

OL information may be more influential in affecting consumers' content consumption than SE for the following reasons. First, whereas OL information such as past sales or views comes from anonymous users who have consumed the product or content, endorsements such as Tweets and Facebook posts come from social ties who may not necessarily have done so (Li 2018). Anonymous but consumption-based information is more effective than the social but non-consumption-based information for user conversion, because actions speak louder than words (Chen et al. 2011). Essentially, SE could be "cheap talk" if reputation of recommender is not taken into account. Therefore, OL information, signaling prior consumers' choices, primarily reduces quality uncertainty (Tucker and Zhang 2011), while SE primarily increases product awareness by virtue of information passing effect (Banerjee et al. 2013, Li and Wu 2018). Quality uncertainty reduction increases the expected utility, whereas awareness does not change consumer preference for the product. For example, Banerjee et al. (2013) find that informed network neighbors only spread information of a microfinance program but not affect a user's decision to participate; Tirunillai and Tellis (2012) demonstrate that positive chatter on Twitter has no significant effect on stock returns. Second, OL information implies higher consumer utility than SE because of network externalities, whereby a consumer's consumption utility increases with the user base. While learning is an information-based process, network externalities are utility based such that purchasing products with large customer base often offers benefits of inter-operability, availability of accessories, and, for online content specifically, social interaction with others (Katz and Shapiro 1985, Qiu et al. 2015). Since both learning of product quality and network effects that increase the consumption of the popular content are present in OL but not SE, we propose the following hypothesis:

H3: Past consumption information (OL) increases subsequent content consumption more than social endorsement does.

Effects of SE on content WOM compared to OL

As both OL and SE increase content consumption, they are likely to increase content WOM volume. However, they may have differential effects on positive versus negative WOM. Numerous studies have documented that an individual's publicly expressed opinion can be influenced by the opinions of others and does not necessarily reflect the individual's unbiased and independent product evaluation (e.g., Godes and Silva 2012, Li and Hitt 2008, Moe and Trusov 2011). On one hand, users tend to follow the ratings of the crowd when they rate a popular product (Lee et al. 2015). Therefore, consumers viewing the content due to the influence of OL information are more likely to rate the content positively, as overwhelmingly positive product ratings are posted online (Chevalier and Mayzlin 2006). However, the influence of others' ratings is reduced by the presence of social networking (Lee et al. 2015). As such, consumers viewing the content following SE are less likely to rate the content positively, compared to those under OL. In other words, the increased content consumption due to OL would result in more positive WOM than that due to SE.

On the other hand, consumers also demonstrate a differentiation behavior in their ratings after viewing what others have posted (Schlosser 2005). Lee et al. (2015) showed this differentiation effect in evaluating unpopular movies but not popular movies. As consumptions are driven by content popularity under OL, consumers following OL information would demonstrate less differentiation effect in their ratings, resulting in less negative and more positive WOM. For SE, Ryu and Han (2009) found that tie strength between the opinion recipient and the opinion provider increases the recipient's WOM likelihood but decreases his WOM valence when his opinion is incongruent with the opinion provider. Accordingly, SE encourages more WOM postings than OL without social ties. And when consumers following SE do not think as highly of the content as the endorser, they rate it more negatively than consumers under OL. As such, the increased content consumption due to SE would result in more negative WOM of the content than the increased content consumption due to OL. We hence propose the following:

H4a: Past consumption (OL) information increases positive content WOM more than social endorsement does.

H4b: Social endorsement increases negative content WOM more than past consumption (OL) information does.

Data and Descriptive Analyses

YouTube and Twitter are currently the leading websites of online videos and short messages, respectively, in most countries. Each has millions of monthly active users worldwide. Unlike other products or innovations, UGC, especially user-created online videos, often comes with limited marketing efforts, and relies mostly on WOM or social sharing to spread. From YouTube, we randomly sampled 20,106 new videos posted on December 26, 2017. For each video, we collected data on its diffusion from YouTube and on tweet sharing of it from Twitter on a daily basis. The observation period consists of 52 weeks from December 27, 2017 to December 25, 2018. The final sample consists of 8,945 videos after deleting the videos that were private or blocked by YouTube. The YouTube data for the video itself include number of views, number of likes, number of dislikes, and the video category; and data for the video provider are number of subscribers, number of videos posted, total views of all videos posted, and tenure of the provider. The Twitter data include all tweets containing a hyperlink to the video. In the main analysis, retweets are not included. As a robustness check, we re-estimate the model with retweets included.

Because of the scarcity of daily tweet sharing, we aggregate both YouTube and Twitter data by week as the unit of our period. For video i in week t, the key variables, their descriptions, and summary statistics are presented in Table 1. The distribution of our key variables is highly skewed. For example, half of the sample videos received no likes, dislikes, or tweet mentioning during our study period. However, deleting these observations would cause severe selection bias. Instead we use the log transformed variables with "+1" to retain the zero observations in empirical analyses. We measure OL and SE quantitatively as the number of video views and the number of tweets containing the video URL. The correlation matrix is shown in Table 2.

Table 1. Summary Statistics

Variable	Description	Mean	Median	Std. Dev.	Min	Max
$Views_{it}$	Increased video views	934	4.43	15,826	0	4,464,880
$Likes_{it}$	Increased video likes	9.082	0	148	0	36,663
$Dislikes_{it}$	Increased video dislikes	0.627	0	12.140	0	4550
$Twts_{it}$	Tweets containing the video URL	0.018	0	2.210	0	1894
$Subs_{it}$	Increased subscribers for i's provider	3,519	114	18,591	0	2,473,982
$Videos_{it}$	New videos posted by i's provider	48	4.43	164	0	52,187
$CAge_{it}$	Weeks since i's provider registered on YouTube	237	211	152	1	705

Table 2. Correlation Matrix							
	1	2	3	4	5	6	7
1. $\mathrm{LogViews}_{it}$	1.000						
2. $\mathrm{LogLikes}_{it}$	0.795	1.000					
3. $\mathrm{LogDislikes}_{it}$	0.586	0.760	1.000				
4. $\mathrm{LogTwts}_{it}$	0.106	0.150	0.163	1.000			
5. $\mathrm{LogSubs}_{it}$	0.423	0.337	0.231	0.036	1.000		
6. $\mathrm{LogVideos}_{it}$	-0.071	-0.092	-0.045	-0.014	0.528	1.000	
7. $\mathrm{LogCAge}_{it}$	-0.044	-0.042	-0.047	**-0.001**	0.122	0.123	1.000

Notes. All the pairwise correlations (except for the bold coefficient) are significant at p<0.001 level.

Empirical Model and Estimation Procedure

We employ a PVAR model to examine the impacts of OL and SE on content consumption and WOM. PVAR models have been widely used in Macroeconomics (Love and Zicchino 2006), and increasingly adopted in the Information Systems (IS) area (Chen et al. 2015, Dewan and Ramaprasad 2014, Luo et al. 2013). A VAR model, wherein each dependent variable (DV) is affected by its own past values and the past values of all other DVs, offers several advantages. First, it captures the bi-directional relationship between content consumption/WOM on YouTube and SE of the content on Twitter, accounting for time trends, serial correlation, and reverse causality (Luo 2009). Second, it flexibly considers both the immediate and lagged-term impacts among the key variables. Third, it captures the dynamics of carryover effects over time through the generalized impulse response functions (IRFs), which is robust to the assumptions of causal ordering of the DVs. With VAR in panel settings, panel VAR models also control for unobserved individual heterogeneity by including video fixed effects. We specify the following baseline model:

$$
\mathrm{Y}_{\mathrm{it}} = \begin{pmatrix} LogViews_{it} \\ LogLikes_{it} \\ LogDislikes_{it} \\ LogTwts_{it} \\ LogSubs_{it} \end{pmatrix}
= \sum_{s=1}^{p} \emptyset_s \begin{pmatrix} LogViews_{it-s} \\ LogLikes_{it-s} \\ LogDislikes_{it-s} \\ LogTwts_{it-s} \\ LogSubs_{it-s} \end{pmatrix} + \beta_1 \mathrm{LogVideos}_{\mathrm{it}} + \beta_2 \mathrm{LogCAge}_{\mathrm{it}} + \delta_{\mathrm{t}} + \mu_{\mathrm{i}} + \varepsilon_{\mathrm{it}}, \tag{1}
$$

where $\emptyset_s$ is a 5 x 5 matric of slope coefficients for s-lagged endogenous variables; $s = 1,2,\dots,p$, where p is the number of lags included, indicating number of past periods that affect the DVs of current period. β_1 and β_2 are five-element column vectors of coefficients for exogenous variables of $\mathrm{LogVideos}_{\mathrm{it}}$ and $\mathrm{LogCAge}_{\mathrm{it}}$. It is intuitive to take LogCAge as exogenous. LogVideos is considered as exogenous because the number of videos produced is largely predetermined as video providers develop their regular video-posting patterns. Nevertheless, in a robustness check, we include LogVideos as an additional endogenous variable and find no significant change in our results. μ_{i} is a column vector of unobserved video fixed effects, capturing the influence of videos' time-invariant attributes; δ_{t} is a vector of time specific effects, applicable to all videos; and $\varepsilon_{\mathrm{it}}$ is a vector of error terms.

We estimate the PVAR model using GMM estimation, which makes no distributional assumptions on the data and controls for heteroscedasticity and temporal autocorrelation in the error terms. GMM is selected instead of the within-group estimator for the fixed effects model because the latter will yield biased estimations for dynamic panel models (Arellano 2003, Chen et al. 2015). To select the optimal lag length ("p"), we specify the model with a reasonably long length of lags (i.e. 4 weeks) and conduct a downward model selection test according to consistent moment and model selection criteria (MMSC) (Andrews and Lu 2001), namely the Akaike information criteria (AIC) (Akaike 1969), the Bayesian information criteria

(BIC) (Rissanent 1978, Schwarz 1978), and the Hannan-Quinn information criteria (HQIC) (Hannan and Quinn 1979). According to MMSC-BIC, which outperforms MMSC-AIC and MMSC-HQIC in post-selection GMM estimators (Andrews and Lu 2001), we set the optimal lag length to be one week.

With $p = 1$, we estimate the other parameters with GMM estimation. We then conduct Stationarity and unit root tests to examine the stability of the statistical properties of the dependent variables. These tests show that all the endogenous variables are stationary and that there is no unit root. We also use the Granger causality tests to test for Granger causality (Granger 1969). The results are the same as the significance tests of the parameter estimates. Next, IRFs and cumulative IRFs (CIRFs) are calculated to derive the dynamic effects of one endogenous variable on another. IRFs are commonly used to model the dynamics among the endogenous variables and are not sensitive to the causal ordering of the variables. The IRFs use the PVAR estimates to trace the effect of a unit shock (of one standard deviation) in one variable on all other endogenous variables over subsequent periods. The confidence intervals of the IRFs and CIRFs are calculated with Monte Carlo simulations.

Estimation Results

Parameter Estimates of Direct Effects

Table 3 presents the parameter estimates for the baseline model. Considering that some videos are uploaded by the same provider, we report the robust standard errors clustered by providers. The coefficients of $LogViews_{it-1}$ measure the influence of video popularity as OL information, while the coefficients of $LogTwts_{it-1}$ reflect the impact of tweet sharing as SE. Positive and negative WOM of the content are measured by $LogLikes$ and $LogDislikes$, respectively. According to the $LogViews$ equation in Column (1), the significant and positive coefficients of both $LogViews_{it-1}$ and $LogTwts_{it-1}$ confirm that both OL information and SE increase content consumption significantly. The coefficient of $LogTwts_{it-1}$ is much small than that of $LogViews_{it-1}$ ($p<0.001$). This suggests that the same level of OL information increases content consumption more than social endorsement, supporting H1. Although we are most interested in the mechanisms of OL and SE in driving content consumption, this equation also controls for the impacts of WOM and provider reputation. We find both likes and dislikes significantly increase video views. This can be explained by that viewers with extreme opinions (e.g., like or dislike) are more willing to express and share their opinions with others than those with moderate views (Hu et al. 2009). Such sharing raises the awareness of the video regardless of the valence (positive or negative) of the shared opinions (Berger et al. 2010; Qiu et al. 2015). Provider reputation measured by the number of its subscribers also positively affects subsequent content consumption.

Table 3. Parameter Estimates

Independent variable	**Dependent Variable**				
	$LogViews_{it}$ (1)	$LogLikes_{it}$ (2)	$LogDislikes_{it}$ (3)	$LogTwts_{it}$ (4)	$LogSubs_{it}$ (6)
$LogViews_{it-1}$	0.763*** (0.004)	0.105*** (0.003)	0.022*** (0.001)	-0.0002 (0.0003)	0.029* (0.013)
$LogLikes_{it-1}$	0.088*** (0.003)	0.623*** (0.004)	0.082*** (0.002)	0.003*** (0.0005)	0.040*** (0.007)
$LogDislikes_{it-1}$	0.033*** (0.004)	0.143*** (0.006)	0.583*** (0.007)	0.008*** (0.001)	-0.020* (0.009)
$LogTwts_{it-1}$	0.069*** (0.017)	0.127*** (0.019)	0.074*** (0.018)	0.308*** (0.039)	-0.032 (0.020)
$LogSubs_{it-1}$	0.034*** (0.004)	0.004 (0.002)	-0.002 (0.001)	-0.0002 (0.0002)	0.689*** (0.012)
$LogVideos_{it}$	-0.006 (0.004)	-0.016*** (0.003)	0.001 (0.001)	-0.0002 (0.0002)	0.084*** (0.025)
$LogCAge_{it}$	0.020 (0.027)	0.046* (0.018)	-0.013 (0.010)	0.0003 (0.002)	0.317*** (0.088)

*Notes. Numbers in parentheses are robust standard errors clustered by provider. Video fixed effects and time specific effects are included in the estimation. *p<0.05; **p<0.01; ***p<0.001.*

The LogTwts equation (Column (4)) shows how the tweet mentioning of the video is driven by the diffusion of the video, video likes and dislikes, and the provider's subscribers. The insignificant coefficients of $LogViews_{it-1}$ and $LogSubs_{it-1}$ suggest that tweet sharing of the video on Twitter is not affected by either the video or the provider's popularity. H1 is not supported. Instead, significant and positive coefficients of $LogLikes_{it-1}$ and $LogDislikes_{it-1}$ show that SE is driven by the WOM of the content, especially the negative WOM. Therefore, both H2a and H2b are supported. According to this finding, unlike popularity-based OL, SE is driven by WOM volume. That is, the widely-discussed content is more likely to be recommended by consumers to their social ties.

The results for the LogLikes and LogDislikes equations (Columns (2) and (3)) are very similar. Increased video views and tweets lead to more likes and dislikes of the video in the following week. And both video views and tweets lead to more likes than dislikes. To examine the relative influence of OL information and SE on content WOM, we test the difference between the coefficients of $LogViews_{it-1}$ and those of $LogTwts_{it-1}$. The results show significant difference in their impacts on $LogDislikes_{it}$ ($p<0.01$) but not in their impacts on $LogLikes_{it}$ ($p>0.1$). Therefore, OL information has a similar positive effect in increasing positive WOM as SE, and H4a is not supported; social endorsement has a stronger impact on negative WOM than OL information, and H4b is supported.

Lastly, the LogSubs equation (Column (5)) describes how a video contributes to users' subscription to the video provider, reflecting how one-time consumers of the video are converted to long-term consumers of the video provider. Intuitively, we find that the number of subscribers increases as video views and likes increase and decreases as video dislikes increase. Although video dislikes, increase video views and tweet sharing similar to video likes, they significantly reduce the popularity or reputation of the video provider.

Short- and Long-Term Overall Effects

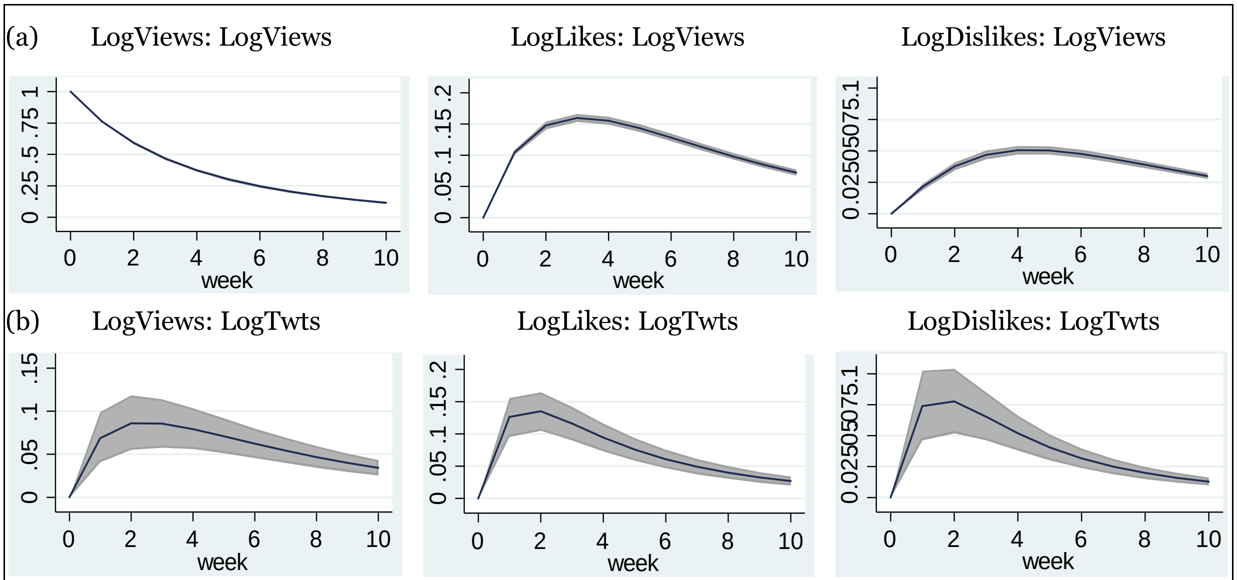
Under VAR models, IRFs are commonly used to trace the dynamic change in the response variable over time given an exogenous one standard deviation shock in the impulse variable only. To calculate the impulse responses, we simply assume an infinite-order vector moving-average (VMA) representation of the vector of DVs by rewriting y_t as follows (Chen et al. 2015, Hamilton and Susmel 1994):

$$y_t = \partial + \theta_t + \omega_1\theta_{t-1} + \omega_2\theta_{t-2} + \cdots, \tag{2}$$

Where ∂ represent a five-element vector of constants, θ is a vector of white noise process with $E(E(\theta_t) = 0, E(\theta_t\theta_t') = \sigma^2 I$ and $E\,(\theta_t\theta_s) = 0$ for $t \neq s$. $\omega_{j,k}^s$, representing impulse responses of y_j to s_{th}-lagged shock of $\theta_k$as shown in equation (3). Hence, ω can be recursively determined as equation (3), given the parameter estimates results such that $y_t = \partial + (1 + \omega_1 + \omega_1{}^2 + \cdots) * \theta_t$. 95% non-parametric confidence intervals are estimated using Monte Carlo simulations.

$$\frac{\partial y_{j,t+s}}{\partial\theta_{k,t}} = \frac{\partial y_{j,t}}{\partial\theta_{k,t-s}} = \omega_{j,k}^s \qquad j, k = 1,2,3,4,5 \tag{3}$$

Figure 1 shows the IRFs of subsequent LogViews, LogLikes, and LogDislikes in response to a one-standard-deviation shock in LogViews and LogTwts of the current period. We find that, consistent with our main findings, the increase in subsequent views following a one-standard deviation shock in OL information is much higher than that following a one-standard deviation shock in SE, in support of H3. And moreover, the responses of likes to a one-standard deviation shock in OL and that to a one-standard deviation shock in SE are very similar, whereas the reactions of dislikes to a shock in SE are much higher than those to a shock in OL, supporting H4b.



Note. Impulse variable: Response variable
The center lines correspond to the estimates, and the shaded areas are the 95% confidence intervals.

Figure 1. IRFs: Responses in LogViews, LogLikes, and LogDislikes to a one-standard-deviation shock in LogViews (a) and LogTwts (b)

While IRFs measure the per-period influence, cumulative IRFs (CIRFs) sum the IRFs over time, measuring the total impact of the one standard deviation shock in a number of periods. We define the long-term impact as the CIRF that reaches its asymptote. According to the results, most of the CIRFs reach their long-run (asymptotic) levels within 7 weeks. Hence, in effect, we take the long-term duration as a period of 10 weeks. Because CIRFs are functions of time, they can measure the long-term cumulative effects in percentage terms, as the dependent variables are log transformed. Table 4 presents both the short- and long-term effects calculated from CIRFs.

Table 4. Short- and Long-Term Cumulative Effects

	Response variable				
Impulse variable	**LogViews**	**LogLikes**	**LogDislikes**	**LogTwts**	**LogSubs**
LogViews					
1 Week	0.689***	0.041***	0.039***	-7.819e-5	0.011*
10 Weeks	7.832***	0.472***	0.157***	0.003***	0.176***
LogLikes					
1 Week	0.082***	1.518***	0.077***	0.003***	0.037***
10 Weeks	0.979***	2.875***	0.576***	0.017***	0.366***
LogDislikes					
1 Week	0.074***	0.320***	3.541***	0.018***	-0.045**
10 Weeks	1.349***	2.414***	5.832***	0.072***	-0.011
LogTwts					
1 Week	0.821***	1.512***	0.881***	15.571***	-0.381
10 Weeks	7.476***	9.036***	4.929***	17.286***	-0.524
LogSubs					
1 Week	0.010***	0.001	-0.0006*	-6.135e-5	0.518***
10 Weeks	0.127***	0.038***	0.006*	-6.135e-5	0.983***

*Notes. Estimates from the CIRFs are converted into CIRFs/σ_{lnX}. *p<0.05; **p<0.01; ***p<0.001.*

Since CIRFs report the responses to one-standard deviation of the impulse variable ($\sigma_{\ln X}$), we divide CIRFs by $\sigma_{\ln X}$ to derive the percentage changes in response to one-percent changes in the impulse variables, given that all the endogenous variables are log transformed. We find that the increase in subsequent views due to one-percent increase in views is comparable to the increase in subsequent views due to one-percent increase in tweet sharing. This is because CIRFs include both the direct effects of the impulse variable on the response variable and the indirect effects via the effects of the impulse variable on other endogenous variables. That is, the overall influence of tweet sharing and that of past video views are very similar. According to Table 3, tweet sharing increases video views both directly and indirectly via video likes and dislikes. Therefore, although the direct effect of SE on content consumption is much less than OL, its stronger effects on content WOM make the overall effect of SE very much comparable to that of OL. Table 4 also shows that, including both the direct and indirect effects on content WOM (i.e., likes, and dislikes), the overall effect of SE is still stronger than that of OL.

Robustness Tests

Next we carry out several tests to ascertain the robustness of our results. First, as aforementioned, new videos posted ($\mathrm{LogVideos}_{it}$) is treated as exogenous in our model (1) as we believe that most providers, especially established ones, have developed their regular new video posting patterns. A concern is that for some providers, new providers in particular, may change their posting patterns according to the popularity or ratings of their videos and channels, which would make $\mathrm{LogVideos}_{it}$ no long exogenous. In this robustness test, we include $\mathrm{LogVideos}_{it}$ as the sixth endogenous variables that influences and is influenced by other endogenous variables. The results are qualitatively the same as Table 3.

Second, given that fixed effects can be correlated with the regressors, we use forward orthogonal mean deviation (the Helmert procedure) to remove video-specific fixed effects following Love and Zicchino (2006) in the main estimation (Table 3). As a robustness check, we adopt first differences to remove fixed effects instead and find that all hypotheses are supported. Besides, in the main analyses, we consider robust standard errors clustered by video provider as some videos are uploaded by the same provider. Alternatively, we cluster standard errors by video categories and also re-estimate the model with retweets included. The results are generally unchanged.

Lastly, we also test whether our results are subject to alternative orders of endogenous variables. As the current order of variables assumes that users first view and vote (like or dislike) for the video on YouTube, then decide whether to tweet about the video, followed by possible subscription to the video provider in the end. Instead of assuming tweet sharing happens between voting of the video and subscribing to the video provider, it may occur before voting of the video or after subscribing to the video provider. We re-estimate our model under these alternative orders of events and find none would change our main findings.

Randomized Experiment

As noted in prior studies using PVAR models, the findings from PVAR models are mainly predictive or Granger-casual relationships (Granger 1969) instead of the casual relationships typically examined in econometrics and statistics literature. Moreover, the estimation based on observational data captures the influence of OL and SE on content consumption and WOM at the video level. To derive more valid causal inferences, we conducted laboratory experiments using between-subject designs to understand how content consumption and WOM behaviour are affected by OL and SE at the individual user level.

We recruited 270 college students as our study subjects. The subjects were randomly assigned into two groups: an OL group and a SE group. Subjects in the OL group were presented a video described as "popular video recommended by YouTube", whereas subjects in the SE group were shown a video described as "video shared by someone you follow on social media platforms (e.g., Twitter, Instagram, Blogs)". Such qualitative conceptualizations of OL and SE can well complement the quantitative measures of OL and SE (i.e., number of views and number of tweets) used in the observational study. Both groups are asked to indicate their tendencies of watching the video and are then asked to watch the video. In fact, the same video was shown to both groups to control for video-related factors (i.e., topic, quality, etc.). After watching the video, subjects were asked to indicate their tendencies of liking or disliking, and tweeting of the video as well as the likelihood of subscribing to the video provider. All the watching, liking, disliking, tweeting, and subscribing tendencies are measured using the scale of 1 (extremely unlikely) to 7 (extremely likely). We also collected data on the subjects' demographic information and experience with YouTube and Twitter. They are used for balance check and as control variables in the analysis. Students are reasonable study subjects for our study because they are also the main users of social media websites. Among the 270 subjects, 172 (64%) were males and the remaining were females. Their age ranged from 18 to 29, with an average of 21. Our subjects can well represent actual YouTube users, given that 62% of YouTube users are males[1] and 95% of 18- to 34-year-old internet users use YouTube.[2] Our manipulation check shows no significant differences across the two experimental conditions in terms of their demographic dimensions.

We specify the following baseline model to conduct data analyses:

$$\text{likelyWatch}_i = \alpha_0 + \alpha_1 * \text{GroupOL}_i + \Psi * \text{Control}_i + \varepsilon_i \quad (4)$$

The dependent variable likelyWatch_i measures how likely a subject will watch the recommended video on the scale of 1 (extremely unlikely) to 7 (extremely likely). GroupOL_i is an indicator, which equals 1 if subject i was assigned to the OL group, and 0 otherwise. Variables in Control_i include how many hours in a week a subject watches videos on YouTube (YouTubeUse_i), how many hours in a week a subject spends on Twitter (TwitterUse_i), how often a subject votes likes for a YouTube video (VoteLikeUse_i), how often a subject votes dislikes for a YouTube video (VoteDislikeUse_i), how likely a subject watches a YouTube video recommended by someone s/he follows on Twitter (FWTwYouTube_i), whether a subject has watched the video before (watchedBefore_i), gender, respectively. ε_i is the error term.

The results from column (1) are consistent with those in the main analyses. Recommendations from YouTube drive more intentions to watch the video than Twitter sharing does, confirming our H1 that past consumption increases subsequent content consumption more than SE does. We then use $VoteLike$ and $VoteDislike$ as DVs in column (2) and (3), respectively, which measure whether a subject is likely to vote (dis)likes after s/he watches the video. The results are consistent with the main analyses, that is, there is no difference in voting likes between YouTube recommended videos and tweets mentioning videos, but tweets mentioning videos drive more individuals to vote dislikes than YouTube recommendations do, validating our H3 that SE increases negative content WOM more than past consumption does.

Table 5. Experiment Results

	Dependent Variable		
	(1) $View$	**(2) $VoteLike$**	**(3) $VoteDislike$**
$GroupOL_i$	0.562 (0.189)**	-0.090 (0.091)	-0.099 (0.050)*
$YouTubeUse_i$	0.144 (0.109)	-0.131 (0.052)	-0.165 (0.028)***
$TwitterUse_i$	0.906 (0.096)***	-0.030 (0.046)	-0.022 (0.025)
$VoteLikeUse_i$	0.002 (0.098)	0.065 (0.047)	-0.042 (0.026)+
$VoteDislikeUse_i$	0.321 (0.187)+	-0.025 (0.090)	-0.013 (0.049)
$FWTwYouTube_i$	0.096 (0.103)	-0.041 (0.050)	-0.071 (0.027)**
$gender_i$	0.165 (0.189)	0.149 (0.091)	-0.059 (0.049)
$watchedBefore_i$	0.354 (0.116)**	0.212 (0.056)***	-0.003 (0.030)

*Notes. +p<0.1; *p<0.05; **p<0.01; ***p<0.001.*

Findings and Contributions

In this study, we aim to understand the motives for SE and its effects on content consumption and post-consumption evaluation compared to OL. Figure 2 summarizes our basic findings. First, we find that while the content with more WOM discussion is more likely to receive SE, content popularity (or provider reputation) does not affect SE of the content, supporting hypothesis H2a and H2b but not H1. This results support the findings of prior literature that interesting topics are more likely to be passed on (Chen and

[1] https://www.omnicoreagency.com/youtube-statistics/

[2] https://www.statista.com/statistics/296227/us-youtube-reach-age-gender/

Berger 2013) and that popularity of the content has no significant effect on SE likelihood (Cha et al. 2009). Second, our findings based on both observational data and randomized experiment show that both OL and SE increase content consumption and WOM significantly. Regarding hypotheses comparing OL with SE, OL information is more effective in increasing the views of content than SE, while consumers following SE are more likely to generate negative WOM than those under OL, confirming our hypotheses H3 and H4b. In terms of positive WOM, the effect of SE and that of OL information are very similar. Therefore, H4a is not supported. In addition, we find that unlike OL which is driven by content popularity, SE is more likely for content with more WOM, either positive or negative. Consistent with Berger and Schwartz (2011) which found that products need to be interesting to spur discussion, our result suggests that consumers tend to endorse widely-discussed content that provides social currency (Hughes 2005). Although the direct effect of SE on content consumption is much less than that of OL, the long-term overall effect of SE on content consumption is not any less than that of OL because of a stronger indirect effect of SE via content WOM. Our research has several limitations. First, in our research design, we investigate only two platforms (i.e. YouTube and Twitter) because of data availability. Certainly, there are other important content and social networking platforms, such as Facebook, Instagram, Weibo, etc. Second, we use only quantifiable metrics (e.g. the number of likes/dislikes; the number of tweets) for content. Such metrics can be enriched with more content characteristics extracted from titles and scripts.

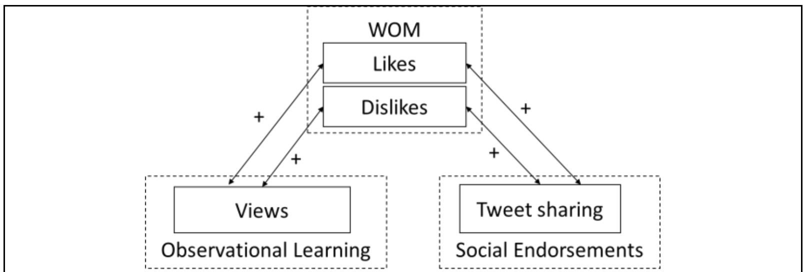


Figure 2. Summary of basic findings

Our study makes several contributions to the literature. First, to the best of our knowledge, this paper is among the very few to examine and compare the effects of both OL and SE on content consumption. Prior research has investigated content diffusion from the perspective of either OL or SE and found that both OL and SE can facilitate the diffusion of online content (e.g., Qiu et al. 2015, Sastry et al. 2009, Susarla et al. 2012). However, none of these studies has compared the differences between these two types of information. Li and Wu (2018) show the complementary effect of OL and SE. However, they do not compare the relative effect of these signals. Further, they show that the primary mechanism for SE is creating awareness. We show that OL information affects consumers' content adoption more than the SE in the short run because this publicly observed information outweighs their own private information in shaping users' beliefs that the product has high quality (Chen et al. 2011). Our findings also provide a more nuanced view of the overall effect of SE as compared to OL. We show that SE can also increase WOM which in turn, leads to a stronger effect of SE on content consumption in the long run.

Second, this study advances the understanding of how OL and SE affect consumers' post-consumption evaluation differently. After consumers view the content, both OL and SE lead to similar level of positive WOM of the content. However, SE result in more negative WOM of the content than OL. This finding suggests that dissatisfied consumers following SE are more likely to rate the content and to rate it more negatively than dissatisfied consumers under OL, consistent with (Ryu and Han 2009). The insignificant difference in positive WOM between SE and OL could be due to increased consumer WOM likelihood under social influence of SE (Ryu and Han 2009, Lee et al. 2015) . We add to the literature on social influence on WOM behavior by studying the effects of SE relative to OL on both WOM likelihood and valence. Finally, we demonstrate that the negative WOM positively affect content consumption and SE. Berger et al. (2010) found a positive effect of negative WOM in raising product awareness. We extend this work by illustrating an additional positive effect of negative WOM in encouraging product recommendations among social ties.

Managerial Implications

This study also provides important managerial implications for social media platforms on better understanding the value of cross-platform strategy. First, content-centric platforms like YouTube and Flickr may devise different cross-platform strategies for different types of content providers. Specifically, they may as well encourage their content providers, especially those new or less popular providers, to get their content propagated through social network such as Twitter via sharing their content to that platform, because these providers are less likely to be viewed by consumers or be recommended by the platform. By sharing their content to other platforms, they can at least receive more views, likes, and dislikes; moreover, dislikes are also helpful in increasing views of the content. However, for popular providers with content being viewed by many viewers, they are better to be cautious with cross-platform strategy. This is because although sharing content to other platforms can trigger followers to view and rate the content in the short term, it cannot trigger subscriptions of content providers and moreover, the increased dislikes are detrimental to content subscription. Second, cross-platform strategy may also be a solution to the current severe under-contribution issues. With the prevalent rich-get-richer problem (Meer 2011), attention-getting videos will attract more views from less popular videos, which may demotivate some providers and in the long run, these providers become less likely to contribute videos. Our finding implies that quality rather than popularity is much important for content cross-platform sharing, because our results show that tweet sharing of the video on Twitter is not affected by either the video or the provider's popularity and it is driven by the WOM of the content. Therefore, social media platforms may consider cross-platform sharing to alleviate the rich-get-richer issues.

Conclusion

We study what drives SE and how its impacts on content consumption and post-consumption evaluation compare with the impacts of OL. According to our results, content consumers are more likely to share with their social ties the content with more WOM regardless of the WOM valence, and content popularity does not affect SE likelihood. Contradict to the note of social influence via social ties, SE are not as persuasive as OL for content consumption. Moreover, while consumers following SE are more likely to rate the content negatively, they are equally likely to rate the content positively as consumers under OL. Therefore, SE need to be used with caution for promoting online content, although negative WOM also increases the content diffusion.

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