International Telecommunications Policy Review, *Vol.22 No.2 June 2015, pp.67-92*

< Special Issue>

Online Brand Community Management for New Products: The Role of Consumer-Specific Social Network Topology

Jungyoun Lee*
Minki Kim**

ABSTRACT

Firms have recently sought to maintain a vibrant brand community by incentivizing consumers to generate and spread word-of-mouth (WOM) about their brands via web-based social media. This effort requires an understanding of how consumers are motivated to share their experiences with other consumers. However, despite the widely recognized role of the social network structure in shaping individual's decisions, there are few studies in the marketing literature examining the association between consumers' structural properties in brand communities and their WOM activities. This study aims to show the impact of time-varying consumer-specific network topology on consumers' decision to generate brand-related WOM. Music fandom, a type of a brand community established around a particular media figure, is chosen along with unique data crawled from online social network platform Twitter. This study finds that consumers' decisions to share brand-related experiences are significantly motivated by the local-level structural properties of a brand community,

---

※ Application received, February 12, 2015; Final version received, March 21, 2015; Accepted, May 14, 2015.

* Korea Advanced Institute of Science and Technology, E-mail: sjlee8867@kaist.ac.kr

** Corresponding author, College of Business, KAIST Business School, SUPEX Hall 304, 85 Hoegiro, Dongdaemun-Gu, Seoul 130-722, Korea, Telephone: 82-2-958-3512 , Fax: 82-2-958-3620. This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2013S1A5A8025321).
E-mail: minki.kim@kaist.ac.kr

suggesting that the formulation and implementation of an effective marketing strategy to maintain a vibrant brand community should involve a comprehensive consideration of the opportunities and constraints embedded in the configuration of consumers' local networks.

Key words: Electronic word-of-mouth, Brand community, Music fandom, Consumer-specific social network topology

Ⅰ. INTRODUCTION

Consumers are increasingly relying on consumer-to-consumer (C2C) communication to obtain product information instead of firm-initiated marketing actions and expert opinions (Trusov et al., 2009; Smith et al., 2005; Stephen & Galak, 2012). In fact, many researchers find that both the volume and the valence of consumer-generated word-of-mouth (WOM) play a significant role in determining product sales (e.g., Chen et al., 2004; Duan et al., 2008; Chevalier & Mayzlin, 2006; Forman et al., 2008). Accordingly, brand communities have arisen as a major source of information for consumers (Kozinets, 1999; Muniz & O'Guinn, 2001), as the community members can easily exchange shared consumption-related concerns and experiences about a particular brand.

Nowadays, the sphere of brand community influence further extends to the online environment, as advancements in information and communication technologies (ICTs) have fundamentally reshaped the way consumers make purchase decisions. Mediated by various web-based social media, they communicate about brands through electronic WOM, and reflect the thus acquired information in their decisions (Godes & Mayzlin, 2004). For instance, on Twitter, approximately 12,600 tweets mentioning at least one brand published every minute, representing 3.6% of its total volume.[1] Most noticeably, such online social network (OSN) platforms have spawned *virtual* brand communities, enabling bidirectional, many-to-many, and non-geographically bound interactions among consumers (Kozinets, 1999;

[1] According to a Brandwatch report, available at (last accessed March 10, 2015). http://www.brandwatch.com/wp-content/uploads/2013/02/The-Twitter-Landscape-2013.pdf

Muniz & O'Guinn, 2001; Brodie et al., 2013). With the increase in consumers' reliance on online brand communities, marketing managers have been interested in keeping the communities vibrant and favorably disposed toward their brands, by encouraging consumers to generate and spread WOM about the brands. Managers' are therefore concerned with understanding the mechanism of how consumers are motivated to share actively their experiences.

This brings our attention to the widely recognized idea that in today's networked environment, behavior should be understood in its social context. Specifically, researchers from various disciplines demonstrate that opportunities and constraints for individual behaviors are largely determined by and embedded in the configuration of the neighborhood, or local network. To name only a few, Haynie (2001) shows that adolescents' level of involvement in delinquent behavior is correlated with peer network density and their position within the network. Reagans & McEvily (2003) explain that social cohesion around a dyadic relationship affects individuals' willingness to invest time and effort in sharing knowledge with others. These studies identify and emphasize the role of individual-specific environments that comprise multiple dyadic relationships with neighbors in shaping decisions. Given this reality, marketers should be well aware of the association between consumer's structural properties and their WOM activities in OSNs to incentivize successfully consumers to generate WOM about their brands and maintain a vibrant brand community.

In terms of properly managing brand communities on OSN platforms, however, there is still a need to delve into the role of consumer-specific network topology in motivating consumers' decisions to share experiences. In fact, the role of network structure in shaping decisions has long been recognized in several different contexts, particularly focused on the association between consumer networks and product diffusion. For instance, Yoganarasimhan (2012) explores the different impacts of various connectivity characteristics reflecting individuals' local network positions on aggregate-level product diffusion. Katona et al. (2011) describe individuals' decision to adopt an online portal as a function of their local network structure formed by already adopted neighbors. However, there is only limited attention on the association between consumers' network structures and their decision to share experiences, or participate in brand-related WOM activities. Among the few studies, Bakshy et al. (2012) investigate the impact of strength of the ties between a pair of individuals, on motivating them to spread information on Facebook, but their study has left room for improvement regarding the consideration of more diverse network attributes that may be responsible for consumers' decisions to spread WOM.

Hence, this study develops an empirical model to examine the impact of network structure on WOM activities within a brand community, focusing on the role of dyadic-level properties, i.e., consumer-specific network topology. This study selected music fandom, a type of a brand community established around a particular media figure, along with unique data crawled from the OSN platform Twitter. Specifically, this investigation features the role of ICT-based interactive music consumers on the success of a new musician debuting via a reality-show singing competition because the widespread diffusion of a reality-show-based musician largely depends on C2C communication acting as a promotional channel for awareness and popularity. Twitter is not only a place where individuals actively express their affection toward media figures, but also a networking platform where users constantly establish and terminate social relations with each other. This feature allows an identification of music fandom in the online space and an observation of the changes in the fans' connectivity structure over time.

This study finds that the structural properties of a brand community at both the individual and aggregate levels affect consumers' decisions to share experiences. Specifically, the adding egocentric network variables to the model led to a statistically significant improvement in the model fit, implying that the variables play a critical role in explaining consumers' WOM activities in the brand community. Also, this study reiterates the widely recognized idea that individuals' decisions should be understood not only in the context of their personal attributes, but also according to the structure of their social network and position in it, which together reflect the opportunities and constraints available in terms of decision-making.

The rest of this paper is organized as follows. Section 2 provides an overview of the industry. The process of collecting music consumption activities from Twitter is introduced in Section 3. Section 4 presents the relevant topological characteristic measures of social networks and an empirical model that describes the impact of the structural properties of an individual's social network on WOM activities related to a brand within brand community. Section 5 reports the estimation results. Finally, Section 6 concludes the paper and discusses the implications of the findings.

Ⅱ. BACKGROUND

1. ICT and Music-related Brand Communities

Today's music consumers are inundated with new songs and artists daily, which makes them notoriously capricious. Indeed, two-thirds of Internet users engaged in some digital music activity in the second half of 2012 (IFPI 2013). More than 20 million music consumers conveniently learn about new releases via music subscription services, while approximately 200 million are instantly offered updated music through personalized radio stations.[2] Consumers also learn about new music by watching music videos on video-sharing websites, or by interacting online with others with similar musical tastes (Kim et al., 2013). With increasing avenues to find and consume music at a very low search cost, consumers may no longer linger on a particular piece of music or a musician. Their shortened attention span in turn threatens musicians' market survival.

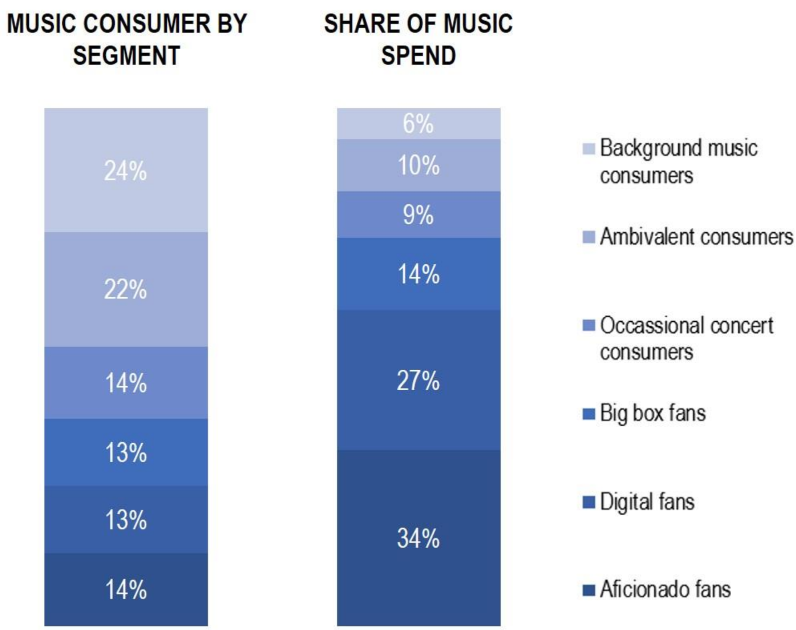
In hopes of increasing awareness for their artists, major record labels typically invest the largest portion of their expenses in marketing and promotions (IFPI, 2014). Yet, it is challenging for labels to expect how long the fickle public will talk about their artists. Even chart-topping artists with selling millions of albums carry the burden of being labeled a one-hit wonder. After all, the most challenging yet indispensable strategy is to build a vibrant fan base, which translates into establishing a brand community around a musician. Indeed, music fandom possesses the three characteristics of brand communities suggested by Muniz & O'Guinn (2001): consciousness of kind, shared rituals and traditions, and a sense of moral responsibility. Fans are clearly aware of the boundary between fans and non-fans (Fiske, 2002), share becoming-a-fan stories with each other to proclaim their affiliation to the community (Cavicchi, 1998), and actively produce and circulate artist-specific texts (e.g., tribute videos uploaded on YouTube) to ensure the community's long-term survival (Fiske, 2002). For musicians, building a fan base means having people who will remember and talk about them.

Keeping a fan base brings financial benefits to musicians as well. Figure 1

[2] According to a PC Magazine article, available at (last accessed March 10, 2015). http://www.pcmag.com/article2/0,2817,2417568,00.asp

describes the financial benefits created by music fans.[3] In the US, 40% of the consumers categorized as fans accounted for 75% of all music expenditures, spending between $20 billion and $26 billion on music in 2011 and 2012, respectively. They not only purchase current and future album releases, but are also willing to “pay even more for exclusive extras, such as in-studio updates, real-time emails, pre-orders, limited editions, autographed copies, vinyl records, and lyric sheets handwritten by the artist.” Moreover, fans promote music across neighbors via positive WOM (Buttle, 1998). Clearly, musicians’ recourse against the plethora of competitors is a stable fan base.

<Figure 1> Share of music fans and their spending (Nielsen, 2013)



Notes: In the Nielsen study, fans are segmented based on spending behaviors. The classification scheme defines aficionado fans as top-tier devotees of music, who consume all formats of music, including merchandise and concert tickets. On the other extreme are background music consumers who do not generally invest much money in entertainment.

[3] According to a Nielsen study, available at (last accessed March 10, 2015). http://www.nielsen.com/us/en/newswire/2013/turn-it-up--music-fans-could-spend-up-to--2-6b-more-annually.html

Benefitting from advances in ICT, musicians and record labels can now use cost-effective marketing strategies to raise awareness through various web-based social media. For instance, the recent success of Psy, a Korean pop singer, was initiated by conversations among a small group of music consumers who had discovered his music video on YouTube and spontaneously spread the word. The effectiveness of such e-WOM in grabbing public attention is widely recognized among industry practitioners. Being one of them, Billboard announced plans to include YouTube streaming data in its determination of the Billboard Hot 100.[4]

2. Music Consumers as Interactive Audiences

Since the early 2000s, the sphere of consumer influence has extended to producing music, as music consumers are mediated by interactive technologies in their selection of musicians. The music industry used to be defined by a conventional business model, the so-called "Star System," which relies on centralized promotion through mass media and the professional selection of artists by major or independent labels (Bourreau et al., 2012). Still dominant, this structure leads to the unilateral provision of products from suppliers to consumers and does not facilitate interaction between them.

However, the development of interactive technologies has transformed the nature and behavior of music consumers, who have transformed from distant spectators to an interactive audience. Reality television encourages ordinary people to participate in music production via media such as the Internet, iTV, and smartphones (Holmes, 2004). For instance, the viewers of American Idol, a US-based televised talent show, determine the show's outcome by voting for their favorite contestants or joining real-time conversations about the show on Twitter. The show thus consistently provides its viewers with opportunities to accumulate a contestant-specific narrative. As a result, the audience develops a sense of responsibility for the contestants as their "chief care-providers" (Cowell, 2003) and are stimulated to become further involved in the show.

Consumers' responsibility and affection for musicians may affect the musicians positively, as consumers voluntarily serve as a promotional channel. One example

[4] According to Billboard website, available at (last accessed March 10, 2015). http://www.billboard.com/biz/articles/news/1549766/billboard-charts-add-youtube-views

is the English-Irish group One Direction, who greatly benefited from fan-driven promotional activities on OSN platforms. The band built a large fan base while appearing on the British reality television show *The X Factor* in 2011. Fans served as “effective ambassadors for the band” on various OSN platforms such as Twitter and VEVO, in which they engaged in 21 million daily digital interactions per year (IFPI, 2013). As a result, the band’s debut album topped the Billboard 200 chart and charts in fifteen other countries in its first week of release, selling more than three million copies worldwide.

Ⅲ. DATA

We constructed a unique data set from Twitter by identifying fans and their communities. The data set covers the two-month period, from the day of debut of a sample musician. As the main source of data, Twitter is a popular online social networking and microblogging platform full of music-related activities. In fact, 50 % of all active Twitter users, approximately over 100 million, follow at least one musician’s account, four of the Top 5 most-followed accounts are musicians, and two million Twitter users sent 114 million music-related tweets in 2012.[5] In this study, various topological characteristics of a social network are measured based on relationships with other Twitter users.

A distinguishing feature of Twitter is that it is a directed network where relationships between any two nodes are not necessarily bilateral. Unlike most OSN services, such as Facebook, Twitter allows a user to follow other users without their confirmation, and observe their Twitter activities via a timeline. Furthermore, users can freely stop following, or unfollow, an account to terminate the relationship without their permission. However, the unilateral follow relationship in Twitter tends to be unstable. They are twice more likely to be broken than the reciprocated relationship, as only passive interactions are possible and users cannot achieve a sense of emotional closeness (Kwak et al., 2011). Thus, to identify the impact of an interaction with neighbors resulting from the structural characteristics of his social

[5] According to a Mashable article, available at (last accessed March 10, 2015).
http://mashable.com/2012/12/20/music-ruled-twitter-2012
According to a Mashable article, available at (last accessed March 10, 2015).
http://mashable.com/2012/09/14/social-music-sharing

network, this study focuses on reciprocal relationships.

Before examining the role of social network structures in generating musician WOM, we outline the four kinds of Twitter interactions to consider: tweeting, re-tweeting, mentioning, and replying. Users *tweet*, or publish short messages, to make a statement, and these tweets are displayed in the timelines of other users who follow the publisher (called "followers"). A *re-tweet* is a direct quote and re-broadcast of another user's tweet, sometimes with additional comments. This feature is commonly used by Twitter users to disseminate information to their followers. The *mention* and *reply* features allow a user to address and/or converse with another user. Among the four types, this study focuses on tweets and re-tweets. The followings were collected to measure various topological characteristics of social networks based on Twitter users' relationships with other users: (1) all tweets and re-tweets mentioning the name of the sample musician and (2) social network information about the authors of the tweets and re-tweets (i.e., fans).

It is worth noting that Twitter users generate WOM by publishing a tweet or re-tweet that contains the musicians' names. Since the focus is on how the fans engage in WOM activity as their consumer-specific network topology changes over time, their social network information was collected. Specifically, tweets mentioning the names of the sample musicians were identified amid the authors' entire music-related Twitter activity, as well as the tweets' publication time. These "music-related activities" refer to the act of posting a tweet or re-tweet that contains the name of any of the musicians. The data set also includes the author's social network information available at the time of publication. Each author's social network is constructed based on reciprocal relationships with other authors who mentioned the same artist in their tweets or re-tweets over the previous week; accordingly, each user's network is updated weekly. This provides information about the formation of the authors' network with other authors at the time each tweet is published, and how the changes in the network influence their activities. Section 4.1 provides greater detail about the variables reflecting the topological characteristics of the network.

One new musician who successfully debuted via a reality show singing competition was selected to examine the role of ICT-based interactive music consumers because C2C communication as a promotional channel for awareness and popularity largely influence the widespread diffusion of such a reality show-based musician. The musician selected participated in a reality singing competition similar to *American Idol* and ended as a runner-up through a public vote in 2011.

Ⅳ. METHODS AND ESTIMATION

1. Social Network Analysis: Variable Construction

Any social network can be represented as a graph consisting of a set of nodes (individuals) and a set of edges connecting pairs of edges (relationships). Let $G = \{N, E\}$ denote a network, where *N* is the set of nodes and *E* the set of edges. An edge connects a pair of nodes in N, or $E = \{(i, j) | \, i \text{ and } j \text{ are connected}\}$ for all $i, j \in N$. The number of other nodes to which a given node is linked is called the "degree" of the node. In this study, the degree of a node is measured based on its reciprocal relationships with other nodes. All network-based variables are time-varying, as the follower-following relationships between any two nodes are updated weekly.

The network can be analyzed in two dimensions: the egocentric network of node *i* and the complete network to which node *i* belongs. An egocentric network is the consumers' local network, composed of their dyadic ties with neighbors who generated WOM for the same musician. A complete network aggregates the dyads of all consumers who generated WOM for the same musician. The egocentric network variables include local clustering coefficient, degree centrality, and average second degree; the complete network variables are global clustering coefficient and network size.

1) Egocentric Network Variables

(1) Local clustering coefficient (*LOCLC*)

The local clustering coefficient measures the level of cohesion between a node's neighboring nodes (Watts & Strogatz, 1998). Consider a simple graph of *i* = *1*, … , *N* nodes. The local clustering coefficient of node *i* is defined as the number of existing edges divided by the maximum number of possible edges among *i*'s neighbors:

$$LOCLC(i) = \frac{t_i}{k_i(k_i - 1)/2} \tag{1}$$

where k_i is the degree of node i, and t_i is the number of edges among its neighbors. In other words, it is the probability that a user's friends are also friends. If positive network externalities exist in the network, consumers' local clustering coefficient may be positively correlated with their activities in the network.

(2) Average second degree (*AVGSD*)

The average second degree of node *i* is the average degree of its adjacent nodes.

$$AVGSD(i) = \frac{|F\big(F(\{i\})\big) - F(\{i\}) - \{i\}|}{\sum_j a_{ij}} \tag{2}$$

where $F(\{i\}) = \{j|(i,j) \in E\}$. Second-degree neighbors have more marginal product diffusion benefits than first-degree neighbors have, especially in the later stages of the spread (Yoganarasimhan, 2012).

(3) Degree centrality (*DGCNT*)

The degree centrality of node *i* refers to the level of its communication activity, or the ability to communicate directly with others (Freeman, 1979). It is the degree of node *i* normalized by the maximum possible degree:

$$DGCNT(i) = \frac{\sum_j a_{ij}}{n - 1} \tag{3}$$

where n is the total number of nodes in the network, and $a_{ij} = 1$ if i and j are connected and $a_{ij} = 0$ otherwise.

2) Complete Network Variables

(1) Global clustering coefficient (*GLBC*)

The global clustering coefficient gauges the aggregate level of clustering in a network, and is the average of the local clustering coefficients over all nodes (Watts & Strogatz, 1998):

$$GLBC = \frac{1}{n}\sum_i c_i \tag{4}$$

where n is the total number of nodes in the network, and c_i is the local clustering coefficient of node *i*. Networks with higher global clustering coefficients can be characterized by higher interconnectivity among nodes and a higher probability of clique formation.

(2) Network size (*SIZE*)

Network size refers to the number of nodes in the network. In this study, it measures the number of users who mentioned the sample musician within the study period. The literature on network externalities suggests that the size of a market is positively correlated with the size of the network externalities enjoyed by the consumers (e.g., Yang & Mai, 2010). In particular, a significant portion of utility for consumers comes from the possibility of building and developing social relationships with other consumers (Lin & Lu, 2011).

2. Descriptive Statistics of Network Variables

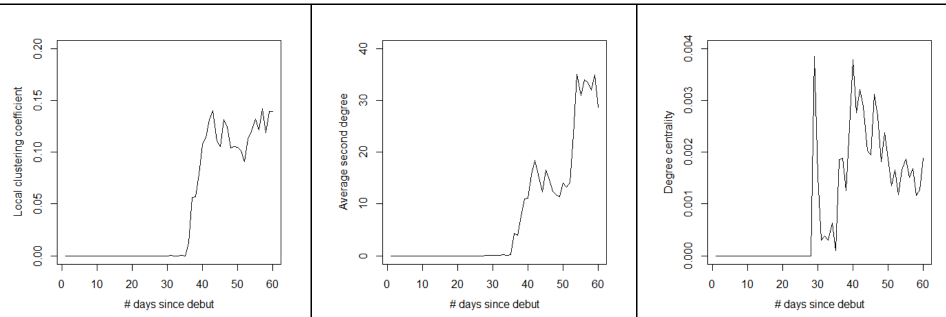
Table 1 presents the descriptive statistics of the variables. As mentioned earlier, the data covers the two-month period starting from the day of the musician's debut. The mean of each variable is measured as the average value over the study period. The number of observations for the egocentric network variables indicates the number of authors who published tweets and re-tweets containing the name of each musician within the study period. There were 60 observations for the complete network and non-network variables, as the variables represent the characteristics of the entire consumer network centered on the musician and they are updated daily.

Additionally, information about the musicians' media exposure (*MEDIA*), traditionally a major strategy for raising awareness and generating WOM, was collected. The data were augmented by combining each sample musician's daily media coverage on television, cable television, radio, and online news.

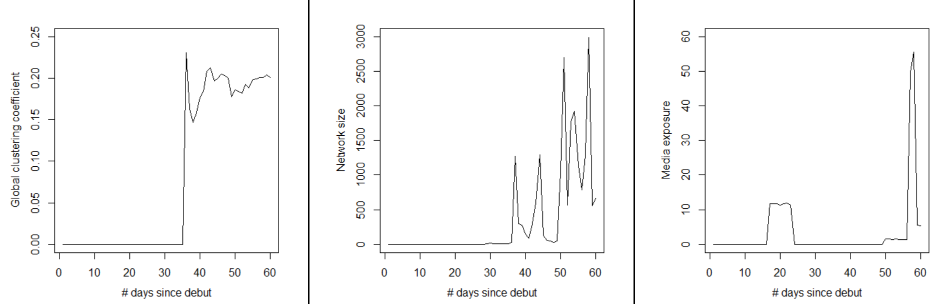
<Table 1> Descriptive statistics

	Obs.	Mean	Min	Max
Egocentric network variables				
LOCLC	35,713	.046	0	.14
AVGDG	35,713	7.70	0	35.01
DGCNT	35,713	.001	0	.004
Complete network variables				
GLBC	60	.08	0	.23
SIZE	60	334.03	11	2,987
Non-network variable				
MEDIA	60	5.42	0	55.57

<Figure 2> Dynamics of variables



(a) *LOCLC* | **(b) *AVGSD*** | **(c) *DGCNT***



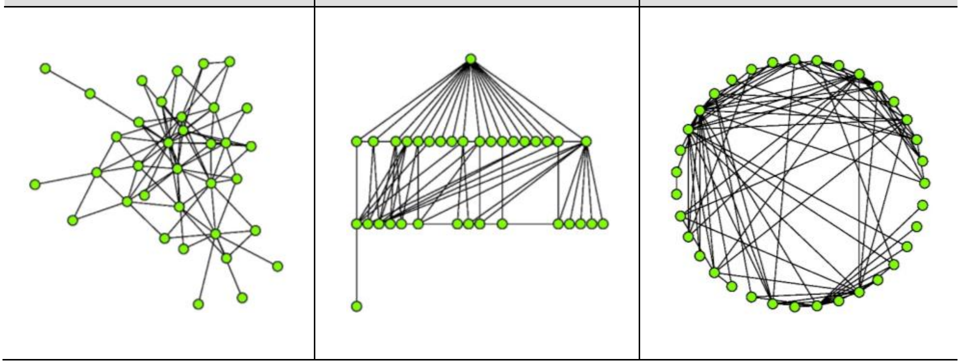
(d) *GLBC* | **(e) *SIZE*** | **(f) *MEDIA***

Figure 2 describes the changes in the average value of each variable over time. The network variable values remain extremely low and stable for about the first thirty days, during which audience voting had not yet begun. This may reflect the encouragement of between-consumer conversations as consumers learn about the candidates and develop responsibilities toward them. Unlike the network variables, the level of media exposure exhibits some fluctuations during the first month. This momentary increase in media coverage may be because the sample musician's performance was prominently featured in the singing competition during the second week of the show, which was followed by the publication of a number of online news articles reiterating the performance.

Figure 3 provides samples of the local networks of Twitter users who generated WOM for the sample musician. To enable a ready inspection and comparison of the network structures, the constructed networks were arranged with three algorithms: Fruchterman-Reingold, Reingold-Tilford, and Circle. Each sample network, consisting of 35 users, is based upon the follower-following relationships established two months after the debut.

<Figure 3> Structure of the consumer WOM network on Twitter

(1) Fruchterman-Reingold	(2) Reingold-Tilford	(3) Circle



Notes: The snowball sampling method was used to preserve the structure of the network whose degree distribution follows a power law.

3. Model

This section presents an econometric model to measure the impact of consumer-specific network topology on their promotion of musicians, i.e., decision to publish a tweet or re-tweet about musicians. One concern regarding the data is that it contains the possibility of right-censored observations. That is, there is limited knowledge about the time of sample users' tweeting activities beyond a certain time point, as the data covers only the period of a defined length. Since all music-related tweets published by each user within a given window are treated as separate observations, the data would then necessarily include one right-censored observation per user at the upper bound of the window (i.e., the timing of the publication since the last observed publication). Another issue is that the probability of any user publishing a promotional tweet may depend on the length of time elapsed since the last publication.

To address these concerns, this study adopts a parametric hazard model that considers the conditional probability that an event of interest would occur at a time point given that it has not occurred so far, as it introduces the *hazard* and *survivor* functions in the likelihood construction (explained in Section 4.3.2). This feature allows a distinction between the probabilities of uncensored and censored observations. The role of inter-publication time in determining users' decision to publish a new tweet is addressed by assuming a specific functional form to describe the intrinsic rate of publication as a function of time elapsed since last publication while controlling for the effects of covariates. This results in a parametric hazard model that can investigate how each user's structural properties influences the decision to publish a promotional tweet about musicians at different times.

1) Hazard models

The hazard model describes an occurrence of the event of interest as a function of the underlying temporal pattern of the event, called *baseline hazard*, in addition to a set of covariates affecting the baseline hazard. For instance, a household's purchase timing decision is often influenced by both the product's consumption rate and the price at the time of purchase. Different assumptions on the association between the baseline hazard and the covariate functions give rise to different types of hazard models (see Table 2).

One of the most frequently used models is Cox's (1972) Proportional Hazard Model (PHM), which assumes a multiplicative relationship between the baseline hazard and the covariate function. Thus, in the model, a unit increase in a covariate is associated with the multiplicative change in the hazard (i.e., hazard ratio). Contrary to the PHM, Aalen's (1980) Additive Risk Model (ARM) incorporates the covariate effects on the baseline hazard additively. Another type of hazard models is the Accelerated Failure Time Model (AFTM), proposed by Prentice & Kalbfleisch (1979), which specifies the scale parameter of the baseline hazard as a function of covariates and time *t*, thereby allowing covariates to directly accelerate or decelerate the time to the event.

<Table 2> Hazard functions by model type

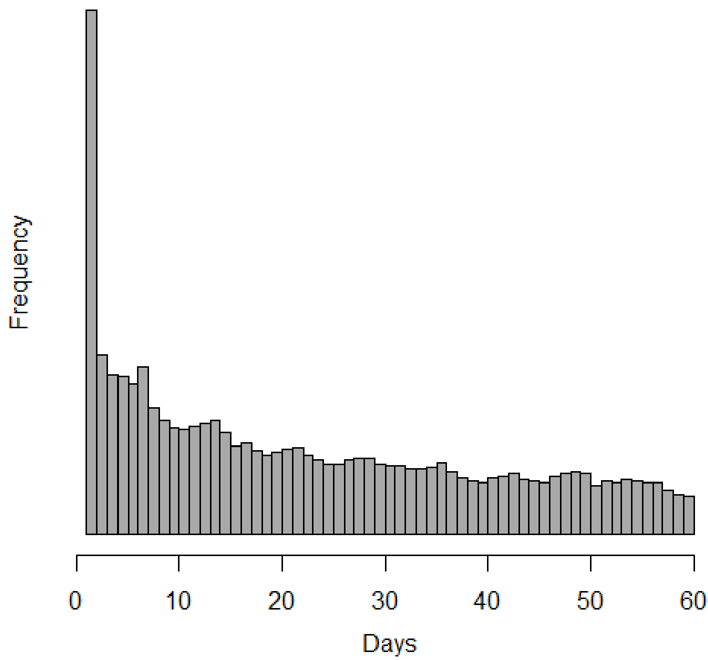
Model	Association between baseline hazard and covariates	Hazard function
PHM	Multiplicative	$h(t\|X) = h_0(t) \cdot \gamma(X(t) \cdot \beta)$
ARM	Additive	$h(t\|X) = h_0(t) + \gamma(X(t) \cdot \beta)$
AFTM	Multiplicative	$h(t\|X) = h_0(t \cdot \gamma(X(t) \cdot \beta)) \cdot \gamma(X(t) \cdot \beta)$

Notes: The terms $h(t|X)$, $h_0(t)$, and $X(t)$ denote the hazard function, the baseline hazard, and a set of covariates affecting the hazard rate, respectively. A functional form $\gamma\big(X(t)\big) \equiv exp(X(t) \cdot \beta)$, also used in this study, is typically adopted to assure the non-negativity of the hazard function.

2) Accelerated Failure Time Model (AFTM)

Users' decision to publish a tweet about a musician is modeled using the AFTM with log-logistic specification. Among some commonly used distributions to characterize the baseline hazard (e.g., exponential, Weibull, Erlang-2, and Gompertz), the log-logistic distribution is chosen for its flexibility in allowing for various shapes for the baseline hazard, as well as the availability of closed-form expressions for the density and survivor functions (Chintagunta & Prasad, 1998). As shown in Figure 4, the flexible log-logistic distribution properly reflects patterns in the data.

<Figure 4> Frequency distribution of intervals between fan tweets



Notes: The graph describes the time interval between successive fan tweets about the new musician.

To derive the conditional probability of an event given its non-occurrence, or the hazard function, let random variable t denote the time until an event of interest occurs, i.e., the number of days elapsed since the last publication of a tweet or re-tweet about the sample musician. The probability density function for the log-logistic distribution is given by:

$$f(t) = \frac{\alpha \cdot \lambda \cdot (\lambda t)^{\alpha-1}}{\{1 + (\lambda t)^{\alpha}\}^{2}} \tag{5}$$

where α is a shape parameter and λ is a scale parameter. Accordingly, the cumulative distribution function *F(t)* is given by:

$$F(t) = \frac{(\lambda t)^{\alpha}}{1 + (\lambda t)^{\alpha}}. \tag{6}$$

From Equations 5 and 6, the baseline hazard function is obtained as:

$$\begin{aligned} \mathrm{h_o}(t) &= \lim_{\Delta t \to 0} \frac{P[t < T \le t + \Delta t | t < T]}{\Delta t} \\ &= \lim_{\Delta t \to 0} \frac{P[T \le t + \Delta t] - P[T \le t]}{\Delta t} \cdot \frac{1}{P[t < T]} \\ &= \frac{f(t)}{1 - F(t)} \\ &= \frac{\alpha \cdot \lambda \cdot (\lambda t)^{\alpha - 1}}{1 + (\lambda t)^{\alpha}}. \end{aligned} \tag{7}$$

The term *1-F(t)* can also be denoted by *S(t)*, or the *survivor function*, indicating the probability of non-occurrence of the event by time *t*.

As the AFTM incorporates the influence of covariates into the baseline hazard by multiplying it to the scale parameter λ, the hazard function, or the likelihood that a user publishes a tweet that mentions the sample musicians is given by:

$$\begin{aligned} \mathrm{h}(\mathrm{t}|X) &= \frac{\alpha \cdot \lambda\gamma(X) \cdot (\lambda\gamma(X) \cdot t)^{\alpha-1}}{1 + (\lambda\gamma(X) \cdot t)^{\alpha}} \\ &= \frac{\alpha \cdot \left(\lambda\gamma(X)\right)^{\alpha} \cdot t^{\alpha-1}}{1 + (\lambda\gamma(X) \cdot t)^{\alpha}} \end{aligned} \tag{8}$$

where γ(X) denotes the covariate function, and $\alpha, \lambda, \gamma(X) > 0$.

Hence, an AFTM with a log-logistic specification shows how each time-varying covariate influences the time interval between a user's consecutive promotional activities, and thus reveals which factor accelerates or decelerates the decision to publish a tweet or re-tweet about the musician. Specifically,

$$\gamma(X) = \exp\left(\sum_{h_1=1}^{H_1} X_{ih_1}(t)\beta_{h_1} + \sum_{h_2=1}^{H_2} X_{h_2}(t)\beta_{h_2} + \sum_{h_3=1}^{H_3} X_{ih_3}\beta_{h_3}\right) \tag{9}$$

where X_{ih_1} are the egocentric network characteristics specific to user *i* at time *t*, X_{h_2} are the complete network characteristics and media exposure of the sample musicians at time *t*, and X_{h_3} indicates user *i*'s time-invariant characteristic, such as intrinsic level of interest in music. The likelihood function for user *i* is thus:

$$\mathrm{L_i} = \prod_{r_i=1}^{R_i} f(t_i, X_t)^{\delta_{r_i}} \cdot S(t_i, X_t)^{1-\delta_{r_i}} \tag{10}$$

where R_i is the total number of music-related tweets or re-tweets published by user i during the study period. $\delta_{r_i} = 1$ if the r_i^{th} tweet is about the sample musician, while $\delta_{r_i} = 0$ otherwise. By construction, the first term in the above function, $f(t_i, X_t)$, captures the probability of uncensored observations, whereas the second term, $S(t_i, X_t)$, describes the probability of censored observations. The parameters are estimated using a maximum likelihood estimation on the sample likelihood:

$$\mathrm{L} = \prod_{i=1}^{N} \prod_{r_i=1}^{R_i} f(t_i, X_t)^{\delta_{r_i}} \cdot S(t_i, X_t)^{1-\delta_{r_i}}. \tag{11}$$

Ⅴ. RESULTS AND DISCUSSION

Table 3 presents the estimation results. As this study focuses on the role of egocentric network variables in explaining Twitter user's WOM activities, there are two model specifications: with and without the egocentric network variables. The likelihood ratio test is used to examine if an increase in the likelihood associated with the addition of egocentric network variables is large enough to conclude that the variables are significant in explaining the WOM activities.

Specifically, the bottom of the table shows the log-likelihood values of the two specifications, which form the basis of the assessment of the explanatory power of each model. The likelihood ratio statistic is computed as twice the difference in the log-likelihoods between the unrestricted (*with* egocentric network variables) and the restricted (*without* egocentric network variables) models, which is 586.976. The resulting test statistic is approximately chi-square distributed with the degrees of freedom equal to the number of constrained parameters, which is 4 in this case. As the test statistic is larger than 14.860, the critical value of chi-square at the .5% significance level, adding egocentric network variables together results in a statistically significant improvement in model fit.

<Table 3> Parameter estimates of covariates (obs.=450,083, n=80,060)

	Without egocentric network variables	With egocentric network variables	
Parameters	**Estimates**	**Estimates**	**Elasticities**
$LOCLC_t$	—	.528 (.076)**	69.486
$AVGDG_t$	—	.455 (.056)**	57.571
$DGCNT_t$	—	1.481 (.045)**	339.784
$DGCNT_t \times MUSIC$	—	-.001 (.036)	-.141
$GLBLC_t$	.457 (.001)**	.463 (.005)**	58.938
$SIZE_t$	.033 (<.001)**	.030 (.004)**	2.989
$MEDIA_t$	-.164 (.001)**	-.164 (.001)**	-15.086
Shape parameter	-2.589 (<.001)**	-2.588 (.002)**	
Scale parameter	-4.988 (.001)**	-4.988 (<.001)**	
Log-likelihood	-182,153.990	-181,860.502	

Notes: (1) Results highlighted with ** and * indicate significance at 99% and 95% confidence levels, respectively. (2) The figures in parentheses are the standard errors of the coefficients.

In terms of the parameter estimates for egocentric variables, to assist interpretation of the model parameters, the unit-less elasticities are presented in the far right column of Table 3. The elasticities indicate the percentage change in the hazard rate for a unit increase in the value of the covariates, or the relative impact of the covariates on the interval between consecutive promotional activities. In general, the structural properties of a user's local network were positively correlated with the WOM activities. Specifically, a unit increase in the local clustering (*LOCLC*) and the average second degree (*AVGDG*) hastened tweeting activities by 69.49% and 57.57%, respectively. In other words, a user is more likely to publish a tweet about the sample musician, as an additional tie is created among neighboring fans, or among neighboring fans and their neighbors.

The degree centrality (*DGCNT*) had the largest elasticity of 339.78. As degree centrality is typically associated with the level of interconnectedness with neighbors, or level of activity in the community, this result suggests that as consumers become more active in communicating with other members of the community, they become more motivated to generate and spread WOM about the musician. The model also includes an interaction term between *DGCNT* and *MUSIC*. *MUSIC* is a time-invariant variable that describes the level of each consumer's general interest in music. This variable is computed as the number of tweets and re-tweets that contained the names of a selection of other musicians[6] published by each user during the month before the study period. However, the coefficient for the interaction term was small and not statistically significant, suggesting that the impact of degree centrality on WOM activities did not vary significantly by consumers with differing levels of general interest in music.

In terms of the complete network variables, they remained significant after controlling for the egocentric variables. Based on the estimated parameters for global clustering (*GLBLC*) and the network size (*SIZE*), consumers were encouraged to participate in WOM activities when the brand community becomes densely connected at the aggregate level, and when it becomes larger in size. Also of note is the way in which media exposure affects WOM activities. Fans tweeted about the musician less frequently as the musician's media coverage increased. Although this finding may seem counterintuitive at first, this could be explained by referring to the audience's role as care-providers (Cowell, 2003). Through media exposure, the musician raises public awareness and popularity, thereby allowing fans to feel less responsible for the musician.

An additional data set was constructed based on the conventional industry business model to provide further managerial insights. Controlling for the time effects, we selected another musician who released a debut album the same year as the sample musician. The main difference is that unlike the reality show-based musician, this musician was supported by specialists in the artists and repertoire (A&R) department of a major record label and promoted through mass media. While this does not provide a generalization to all cases of a new musician's debut, or to other industries, it reaffirms the role of local network structures in shaping consumer's behavioral decisions.

[6] The top twenty ranked musicians in terms of digital music sales during the month before the study period were selected. Digital music sales consisted of various components including downloads, streaming, ringtones, background music, and karaoke sales.

<Table 4> Parameter estimates of covariates (Star System) (obs.=352,661, n=57,842)

	Without egocentric network variables	With egocentric network variables	
Parameters	**Estimates**	**Estimates**	**Elasticities**
$LOCLC_t$	—	-.112 (.557)	-10.617
$AVGDG_t$	—	.047 (.028)	4.783
$DGCNT_t$	—	.883 (.257)**	143.580
$DGCNT_t \times MUSIC$	—	.028 (.014)*	2.853
$GLBLC_t$	.144 (.002)**	.146 (.098)	15.733
$SIZE_t$	-.030 (.003)**	-.003 (1.610)	-.299
$MEDIA_t$	-.147 (.005)**	-.150 (.033)**	-13.900
Shape parameter	.896 (.006)**	.898 (.026)**	
Scale parameter	-4.991 (.077)**	-4.958 (.245)**	
Log-likelihood	-17,699.732	-17,663.124	

Given in Table 4, the model fit was repeatedly improved by adding the egocentric network variables. The chi-square test statistic, 146.432, exceeds the critical value of chi-square at the .5% significance level. This again supports the idea that the local network configuration plays an important role in shaping the decision to share experiences.

Overall, the signs of the estimated coefficients are generally similar to those estimated in the case of the reality show-based musician. For the major label-sponsored musician, however, the interaction between the degree centrality (*DGCNT*) and interest in music (*MUSIC*) was positive and statistically significant. This finding is intuitive and suggests that consumers who are generally highly interested in music are more likely to generate WOM about the musician, as they become more connected to neighboring fans. This further implies that providing music devotees with opportunities to become acquainted and communicate with each other would lead to increased WOM about the musician.

This study's results confirm that, concerning proper management of brand communities on OSN platforms, managers should pay attention to the role of consumer-specific network topology to encourage consumers' WOM activities effectively. Although the role of network structure in shaping decisions has long been recognized in several different contexts, particularly the association between consumer networks and product diffusion, only limited attention has been paid to the association between consumer network structure and decisions to share experiences, i.e., participate in brand-related WOM activities. Hence, this study attempted to investigate how consumers are motivated differently by various brand community configurations at the individual level, while controlling for the effects of the global structure of brand communities and traditional marketing strategies. Based on the analysis, this study finds that diverse individual-level structural properties are responsible for encouraging consumers' WOM activities on OSN platforms, and thereby keeping the brand community vibrant.

Ⅵ. CONCLUSION

Brand success and survival in any industry largely depends on the ability to retain the consumers' attention for a long period of time—thus, to establish a vibrant brand community. Accordingly, web-based social media, where consumers share opinions and experiences, are attractive platforms through which managers wish to enhance consumer awareness of their brands and stimulate consumer-generated WOM for their products. However, what motivates consumers to share their experiences has remained insufficiently explored.

This study focused on the impact of consumers' individual-level topological characteristics on WOM activities in the context of music consumption. Musicians are regarded as brands, and it is crucial that they build a stable fan base that will keep their consumer network vibrant and spread positive WOM to a wider audience. In fact, major record labels are aware of the significance of fandom and fan's WOM activities, and typically invest the largest portion of their expenditures on marketing and promotion. An empirical model that examines how consumers are motivated differently by various structural properties of their local social network to generate and spread WOM about a brand was developed to investigate the impact of network structure on WOM activities within a brand community.

Based on the analysis, this study finds that the structural properties of a brand community at both the individual and the aggregate levels affect consumers' decisions to share their experiences. For instance, in the case of both the reality show-based musician and the major label-sponsored musician, the fan's level of communication activity with other fans, reflected in the fan's degree centrality, was positively associated with the decision to generate and spread WOM about the brand. Manager may use the results to devise potential marketing strategies to facilitate consumers' WOM, e.g., to offer frequent opportunities to interact with other consumers who share an interest in a particular brand. In this specific case, record label mangers could arrange events in which fans could gather and become acquainted with as-yet unconnected neighbors, thereby helping individual fans' increase their level of activity within the community. This would allow managers to develop a long-lasting brand community centered on their musicians by encouraging fans to share stories about the artists. Overall, this study reiterates the widely recognized idea that individuals' decisions should be understood not only in the context of their personal attributes, but also according to the structure of their social network and position in it, which together reflect the opportunities and constraints available in making decisions.

REFERENCES

Aalen, O. (1980). A model for nonparametric regression analysis of counting processes. In *Mathematical statistics and probability theory* (pp. 1-25). Springer New York.

Bakshy, Eytan, Itamar Rosenn, Cameron Marlow, Lada Adamic. (2012). The role of social networks in information diffusion. *Proceedings of the 21st International Conference on World Wide Web*. ACM, 519-528.

Bourreau, Marc, Michel Gensollen, Francois Moreau. (2012). The impact of a radical innovation on business models: Incremental adjustments or big bang? *Industry and Innovation*, *19(5)*, 415-435.

Brodie, Roderick J, Ana Ilic, Biljana Juric, Linda Hollebeek. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research* , *66(1)*, 105-114.

Buttle, F. A. (1998). Word of mouth: understanding and managing referral marketing. *Journal of Strategic Marketing*, *6(3)*, 241-254.

Cavicchi, Daniel. (1998). *Tramps like us: Music & meaning among Springsteen fans*. New York: Oxford University Press.

Chen, Pei-Yu, Shin-yi Wu, Jungsun Yoon. (2004). The impact of online recommendations and consumer feedback on sales. *ICIS 2004 Proceedings*.

Chevalier, Judith A, Dina Mayzlin. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43(3),* 345-354.

Chintagunta, P. K., & Prasad, A. R. (1998). An empirical investigation of the "dynamic McFadden" model of purchase timing and brand choice: Implications for market structure. *Journal of Business & Economic Statistics*, *16(1)*, 2-12.

Cowell, Simon. (2003). All together now! publics and participation in american idol. *Invisible Culture: An Electronic Journal for Visual Culture 6*.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, 187-220.

Duan, Wenjing, Bin Gu, Andrew B Whinston. (2008). The dynamics of online word-of-mouth and product sales: an empirical investigation of the movie industry. *Journal of Retailing*, *84(2)*, 233-242.

Fiske, John. (2002). *The adoring audience: Fan culture and popular media*, chap. The cultural economy of fandom. London: Routledge.

Forman, Chris, Anindya Ghose, Batia Wiesenfeld. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research, 19(3)*, 291-313.

Freeman, Linton C. (1979). Centrality in social networks conceptual clarification. *Social Networks, 1(3)*, 215-239.

Godes, David, Dina Mayzlin. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, *23(4)*, 545-560.

Haynie, D. L. (2001). Delinquent peers revisited: Does network structure matter? 1. *American Journal of Sociology*, *106(4)*, 1013-1057.

Holmes, Su. (2004). But this time you choose! Approaching the interactive audience in reality TV. *International Journal of Cultural Studies*, *7(2)*, 213-231.

IFPI. (2013). IFPI digital music report 2013: Engine of a digital world. Accessed: 2015-03-10.
http://www.ifpi.org/content/library/DMR2013.pdf.

____ (2014). Investing in music- how music companies discover, nurture and promote talent. Accessed: 2015-03-10.
http://www.ifpi.org/content/library/investing_in_music.pdf.

Katona, Z., Zubcsek, P. P., & Sarvary, M. (2011). Network effects and personal influences: The diffusion of an online social network. *Journal of Marketing Research, 48(3)*, 425-443.

Kim, M., Go, G., & Cho, S. (2013). To Tweet or Not to Tweet? Social Media Marketing for Digital Music Contents. *Entrue Journal of Information and Technology, 12(1)*, 45-58.

Kozinets, Robert V. (1999). E-tribalized marketing?: The strategic implications of virtual communities of consumption. *European Management Journal, 17(3)*, 252-264.

Kwak, Haewoon, Hyunwoo Chun, Sue Moon. (2011). Fragile online relationship: A first look at unfollow dynamics in twitter. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1091-1100.

Lin, K. Y., & Lu, H. P. (2011). Why people use social networking sites: An empirical study integrating network externalities and motivation theory. *Computers in Human Behavior, 27(3)*, 1152-1161.

Muniz, Albert M Jr., Thomas C O'Guinn. (2001). Brand community. *Journal of Consumer Research, 27(4)*, 412-432.

Prentice, R. L., & Kalbfleisch, J. D. (1979). Hazard rate models with covariates. *Biometrics*, 25-39.

Reagans, R., & McEvily, B. (2003). Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly, 48(2)*, 240-267.

Smith, Donnavieve, Satya Menon, K Sivakumar. (2005). Online peer and editorial recommendations, trust, and choice in virtual markets. *Journal of Interactive Marketing, 19(3)*, 15-37.

Stephen, A. T., & Galak, J. (2012). The effects of traditional and social earned media on sales: A study of a microlending marketplace. *Journal of Marketing Research, 49(5)*, 624-639.

Trusov, Michael, Randolph E Bucklin, Koen Pauwels. (2009). Estimating the dynamic effects of online word-of-mouth on member growth of a social network site. *Journal of Marketing, 73(5)*, 90-102.

Watts, Duncan J, Steven H Strogatz. (1998). Collective dynamics of small-world networks. *Nature, 393(6684)*, 440-442.

Yang, J., & Mai, E. S. (2010). Experiential goods with network externalities effects: An empirical study of online rating system. *Journal of Business Research, 63(9)*, 1050-1057.

Yoganarasimhan, Hema. (2012). Impact of social network structure on content propagation: A study using Youtube data. *Quantitative Marketing and Economics, 10(1)*, 111-150.