9 July 2011

How Did Facebook Outspace Myspace With Open Innovation? An Analysis Of Network Competition With Changes Of Network Topology

Gwangjae Jung
KAIST, indioblu@business.kaist.ac.kr

Byungtae Lee
KAIST, btlee@business.kaist.ac.kr

ISBN: [978-1-86435-644-1]; Full paper

HOW DID FACEBOOK OUTSPACE MYSPACE WITH OPEN INNOVATION? AN ANALYSIS OF NETWORK COMPETITION WITH CHANGES OF NETWORK TOPOLOGY

Gwangjae Jung, Management Engineering, KAIST, Seoul, Republic of Korea, indioblu@business.kaist.ac.kr

Byungtae Lee, Management Engineering, KAIST, Seoul, Republic of Korea, btlee@business.kaist.ac.kr

Abstract

A social network service (SNS) is one of the most prospering social media platforms in the Web 2.0 era. In May 2007, Facebook implemented "Open API," which allows a third-party to create its own APIs and facilitates group interactions. This innovation led to a radical increase in user growth of Facebook and surpassed leading SNS, Myspace at that time. There have been several laws of network value such as Metcalfe's and Reed's law which assume different topology of networks. Borrowing these concepts, we hypothesize the positive relationship between the growth of SNS adoption and "Open API" policy. In other words, this policy revolutionized Facebook's topology from one defined by Metcalfe's law to that of Reed's law. We model the duopoly competition of SNSs and show that the growth of SNS adoption is a polynomial function of time under both Metcalfe's and Reed's law, but the marginal growth under Reed's law is greater than that under Metcalfe's law. We also empirically test the existence of structural change after the adoption of "Open API" policy. The empirical result confirms the structural change in Facebook, which implies that "Open API" transformed Facebook one-to-one communication network into a group forming network.

Keywords: Social Network, Network Value, Laws of Telecommunication, Network Growth, Open API.

1 INTRODUCTION

Since the term Web 2.0 made its introduction into the world, the focus of internet use shifted to social interaction in the internet and introduced the concept of social networking. A social network service (SNS) is an online platform which provides services that enables the user to form social relations in cyberspace. People make anonymous acquaintances with other people, forge new relationships and have according interactions through SNSs. Morgan Stanley announced a report that social networking usage surpassed that of e-mail since November 2011[1]. According to eBizMBA Rank[2], the most popular top 10 SNSs such as Facebook, Myspace, Twitter, and Linkedin each have millions of regular monthly visitors.

Myspace and Facebook are known as the pioneer examples that characterized features of Web 2.0, and have been maintaining this popularity since the beginning of the Web 2.0 era. Myspace and Facebook were the only social networking services that were listed in the "Alexa Top 10 Global Sites[3]" list and they are both boasting with over tens of millions users nowadays. Myspace was launched in August 2003, and over 80 million users had subscribed to Myspace in 2007 (Ahn et. al. 2007). Facebook started its business about six months later, and had to catch up Myspace.

In 2007, Facebook announced "Open API[4]" platform model and brought in a new trend to social networking services. Similar to the "Open source software development" policy in the software industry, this new "Open API" platform allowed third-parties to create applications on the Facebook platform (Arrington 2007). This dramatic innovation encouraged many people to create and use APIs in Facebook. According to the recent statistics in "Facebook Press Room[5]," over 550,000 APIs have been developed by this time, and users of Facebook installed 20 million APIs every day.

After 4 months following the innovation, the Alexa Traffic Rank[6] of Facebook arose by almost 10 steps from 16th. In contrast to this, Myspace's rank gradually fell off. This reverse in ranking defies the open frequently cited law in network, the network externalities. According to the positive network externalities, the larger (leader) network has competitive advantage over the follower. This startling outcome of network growth in Facebook raises the question of how "Open API" innovation affects social network characteristics than in turn result in the growth of networks. There are three well-known statements of the network value – Sarnoff's, Metcalfe's, and Reed's law. They assume topologies of the network (Dohler et. al. 2008; Westland 2010). For example, Metcalfe's law is applied to one-to-one communication networks, in which users interact by link-formations. On the other hand, in a network under Reed's law, each new group that is formed contributes to the value. Therefore, we hypothesize that "Open API" may have changed characteristics of network, that is, network topology. The network topology is related to the logical and physical structure of the network[7]. If the social network structure (topology) is changed, it alters the mechanism of interactions, and values of networks are determined by the number of interactions that may be governed by newly introduced interaction mechanisms. Based on this context and the amazing growth of Facebook, it is important to find out whether Facebook's open innovation has really changed the fundamentals of its network and the rule of game.

To address this question, the main objective of our research is to find the relationship between the growth of SNS adoption and the network topology which is linked to the value of a social network.

[1] Internet Trends, Morgan Stanley, April 12, 2010,
[2] http://www.ebizmba.com/articles/social-networking-websites
[3] http://www.alexa.com/topsites, the above ranking was recorded on April 10th 2010.
[4] http://en.wikipedia.org/wiki/Open_API
[5] http://www.facebook.com/press.php
[6] http://www.alexa.com
[7] http://en.wikipedia.org/wiki/Network_topology

Adoption of “Open API” somehow alter the environment of Facebook, and it is expected to be a proliferation of new tools and activities for users, who were priorly only limited to just making online connections (Stone 2008). It is crucial to find out how this policy changes the way of interactions in the network and eventually increases the number of users. From an academic perspective, these network value functions are only invented by the statement and not analytically or empirically verified (Metcalfe 1995; Reed 1999). As a result, verification of these network value functions and application to our analysis is one of the important issues of this study. Previous studies in social networks were mainly focused on the behavioural issues in social networks (Boyd & Ellision 2008).

The second objective is to analyze the effect of network value to the adoption of SNSs in a duopoly situation. After the announcement of “Open API”, Facebook experienced a radical increase of users, and shortened its gap with Myspace. The analysis of the impact “Open API” may suggest insights to newly entered SNS about how to take over the leading SNS. In a previous research, competition of two technologies under the existence of network effect was handled with a similar concept with our model (Arthur 1989). However, most of previous studies assumed that the network effect is linear to the adoption size, without any changes in network characteristics (Swann 2002).

For these ends, our research consists of two approaches. First we use well-known laws of the network value – Metcalfe’s and Reed’s law - and model the duopoly competition of social network adoption by the functional form of the network value. We use a simulation method to derive the growth of SNS adoption in multi-periods. In the simulation, we mainly discuss the effect of network values to the SNS adoption. The second part is for the empirical analysis. We collected the daily web traffic data of Facebook and Myspace including the date Facebook adopted “Open API.” policy. By applying the growth functions of our model, we test the difference of growth patterns between, before and after “Open API” policy

The rest of the paper is organized as follows. In section 2, we review research on social network adoption and network value. In section 3, we suggest our model and simulation. The result of simulation is discussed in Section 4. Section 5 is for the empirical analysis to enhance the result of the analytical model. Section 6 discusses about the implication of our findings both from the analytical model and the empirical test. Finally, we discuss the managerial implications, future research directions, and contributions.

2 LITERATURE REVIEW

While most of literatures argue the important role of interaction and group forming activity in SNS, previous studies of SNSs are mainly about the static features of social network service. The value of the network itself was not covered in this research area. In early studies, behaviour of impression management (Skog 2005), the network structure of SNSs (Kumar et. al. 2010), and the privacy issues (Acquisti & Gross 2006; George 2006) were examined. However, in this case of Facebook, previous studies are limited in providing explanations about this phenomenon. In addition, Facebook was originally a follower in the SNS market and outpaced Myspace later. It is a unique case that opposes the first move advantage in traditional network research and e-business. Thus, the relationship between characteristics of SNS and the impact of Open Platform seems to be a worthwhile subject to investigate.

There are three well-known statements of the network value –Sarnoff’s law, Metcalfe’s law, and Reed’s law (Reed 1999). Each model is classified by the main way of interaction among people (Mayfield 2005). Metcalfe’s law states that the value of a network is proportional to the square of the network size (Metcalfe 1995). It is generally applied to a telecommunication network such as telephone, internet, or social network. In a telecommunication network, the main interaction is one-to-one communication. As a result, the number of possible connection in a network of a number of nodes is asymptotically proportional to the square of the network size. Under Metcalfe’s law, the marginal network effect is equal to the network size. Reed’s law states that the value of a network is proportional to the exponential of the network size (Reed 1999). It is generally applied to "Group Forming Networks (GFNs)." In GFNs, people consider collaboration and group facilitation as an important value. News groups or chat groups in the internet are examples of GFNs. In a group forming network, the number of possible subgroups determines the value of a network.

Generally, social networks are considered as either a one-to-one communication network or a group forming network (Reed 2001). A social network usually contains various functions such as instant messaging or online chatting. To identify the topology of a social network, it is important to focus on what kinds of functions the network has. In that sense, our analysis assumed a typical social network that focuses on functions that facilitates one-to-one communication such as messaging. Our analysis also considers that each application (API) in a social network can be a trigger for making subgroups in the network. In that sense, we assume that the adoption of "Open API" activates the characteristic of group formation in a social network.

Various studies examined the network effect and its implementation. The network effect rises when the value of a product to one user depends on how many other users exist. Technologies that are generally subjected to strong network effects tend to exhibit long lead times following by explosive growth in the result of positive feedbacks. Kats and Shapiro (1986) examined the technology adoption in the presence of network externalities. They argued that the pattern of adoption depends on whether technologies are sponsored and they suggested strategic advantages in a two firm competition situation. Saloner and Shepard (1995) econometrically tested the existence of the network effect through the empirical examination of adoption of automated teller machines. Farrell and Saloner (1986) examined the dynamics of installed base competition. Arthur also has emphasized the role of positive feedback in the economy (Arthur 1989) Network effects were more recently popularized by Robert Metcalfe. In our research, we mainly incorporate Arthur's model of technology adoption to the analytical model.

3 MODEL

The main purpose of the model is to show growth patterns of social network adoption by different mechanisms of user interactions in a social network. For this issue, our study models two social network services that are in a competition with the purpose of adopting potential users. Our analysis basically employs a basic structure of Arthur's (1989) model. Arthur's model handled the adoption of two competing technologies under the pre-existence of the network effect that occurred by previous adoptions. Instead of technology, we consider a social network as an online social network site (SNS), such as Facebook or Myspace. We also regard the network effect in the model as the value which is induced by interactions among existing members of the network. The main difference between our model and previous studies is the functional form of the network value. We apply two different rules of interactions – Metcalfe's and Reed's law – and derive how growth patterns of SNSs change by different functional forms of the network value.

3.1 Social Network Services

Our model assumes two different online social network services – A and B. In each period, users in each SNS make interactions with each other and the amount of interactions among users leads to an increase in the network value of each SNS. In our model, it is assumed that interactions in a SNS are sharing information with other users in that SNS. Finding out trends or getting information is one of the important reasons that people use social network services on the internet (Ellison et. al. 2006; Weaver & Morrison 2008; Shi et. al. 2010). Therefore, the network value of a SNS j at time t (NV_{jt}) is assumed to be the total amount information which is created at time t in SNS j. The network value of a SNS is determined by the total number of existing users at the previous period, and the network value law (law_j) that decides the rules of interactions in SNS j. There are two types of network value laws, Metcalfe's and Reed's law. The main difference between these two laws is the unit of interaction. If a SNS follows Metcalfe's law (law_j=M), the rule of interaction is based on one-to-one communication, which implies that the unit of interaction is a node / a user in the network. On the other hand, if SNS j follows Reed's law (law_j=R), users interact by group communication. This implies the unit of interaction under Reed's law is a group. We will describe the details of how users interact with each other in the other section.

3.2 Potential Users

There are N potential users in the model. At every turn, potential users observe expected utilities of adopting each SNS and choose the one that provides the most benefit to the user. Similar with the Arthur (1989), the model assumes a preferred SNS for each user (f_i=A or B). This implies that each user is initially given one SNS that he prefers over the other one. Therefore, if the expected utilities of adopting A and B are the same, a user chooses to adopt the preferred one. User i's expected utility of adopting SNS j at time t is as follows

$$U_{ijt} = wtp_{ij} + \alpha NV_{jt-1} \qquad (1)$$

U_{ijt} consists of user i's willingness to pay for adopting SNS j (wtp_{ij}) and the network value of j at time (t-1) ($NV_{jt\text{-}1}$). wtp_{ij} means each user i's perceptive value to SNS j. For the preferred SNS, user i's willingness to pay for adoption (wtp_{if_i}) is normally distributed with mean of μ[8] variance of σ^2. For the non-preferred one, willingness to pay for adoption is ($wtp_{if_i} - \Delta$). Our model does not assume switching cost of SNS adoption.

3.3 Rules of Interactions in a Social Network

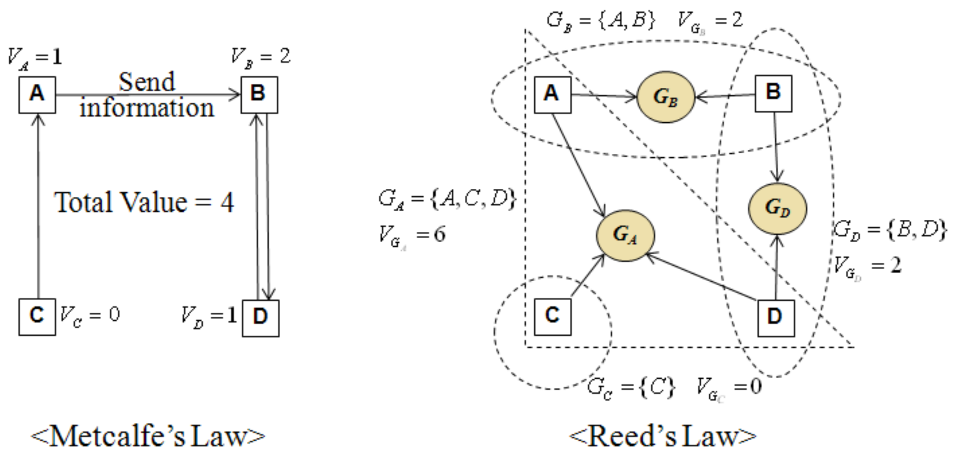

Figure 1. Rules of Interactions and the network value of a SNS

Under Metcalfe' law, users make interactions by sending information to other users. Sending information under Metcalfe's law is like writing comments on other users' Myspace profile pages or posting on walls in Facebook. At every period, each user of SNS j can send information to other users up to p_j times. Hence, if the number of users in SNS j at time t is n_{jt}, the network value NV_{jt} is $n_{jt}p_j$. Metcalfe's law states that the network value is proportional to square of the network size, but this

[8] μ generally gets negative value, which means that most people are reluctant to adopt a new product or technology (Lee and Lee 2006)

holds only when all links in the network are activated. Prior studies criticized over-estimation of the network value under Metcalfe's law (Odlyzko and Tilly 2005; Yoshikai 2005; Briscoe et. al. 2006). Considering the cost of sending information[9], our model complies with the method of interactions under Metcalfe's law but limits the amount of interaction per user to p_j. The number of interactions in SNS j (p_j) is assumed to be equivalent to all users in the same SNS. Users spend all possible number of interactions, because they have to maximize their benefit.

Under Reed's law, on the other hand, users interact by group communication. In a SNS following Reed's law (law_j=R), each user joins several groups in the SNS and send information to the affiliated group. A group in our model is like an API in Facebook. In Facebook, people play games with other users through API. Considering active uses of APIs and cost of API uses[10], our model limits that the total number of groups in a SNS is same as the number of existing users. Moreover, we assumed that a user in SNS j can join q_j number of groups at one period. If a SNS follow Reed's law, each user in the SNS creates an API when he/she adopts the SNS. G_A in Figure 1 represents the group created by user A. Before the joining process occurs, each group has only one member. After joining groups, each user stocks information to the groups he/she belongs to. A user can send one unit of information to each group. The value of each group in a SNS is defined as the multiplication of the size of group and the amount of information in the group. The network value of SNS under Reed's law is the sum of total value of groups in the SNS. Figure 1 shows the graphical representation of interactions in a SNS by its network value law, explains how the network value is calculated. Under Metcalfe's law in Figure 1 assumes the number of information each user can send (p_j) is 1. Likewise, under Reed's law in Figure 1, each user can join one other group (q_j=1), and share one unit of information in each group. In that case, the total value of networks in Figure 1 are 4 and 10 respectively.

3.4 The Procedure of Simulation

Based on the set up for SNSs, potential users, and the rules of interactions, we perform a simulation to derive the growth patterns of SNS adoption in a duopoly competition. The procedure of simulation organizes with three major parts. In the initialization part, the network value law is assigned to SNS A and B, and wtp_{ij} and f_i are assigned to potential users. After the initialization, the model iterates adoption and interaction procedures. The iteration basically performs 50 times but stops when there is no more new adoption (including switch to the other SNS) in this period. In the adoption process, each potential user observes the network values of SNS A and B at the previous period and chooses one that gives the most benefit. In the interactions process, adopted users make interaction with others in each SNS. The amount of interaction affects the network value of a SNS.

4 RESULTS AND DISCUSSION

For the simulation, several variables in the model are set by certain values. The number of potential adopters in the market is set by 1000 (N=1000). wtp_{ij} is assumed to follow normal distribution with mean value -50 and a variance of 30 ($\mu = -50, \sigma^2 = 30$). The gap of willingness to pay for adoption between a preferred and a non-preferred SNS is 55 ($\Delta = 55$). Under Metcalfe's law, the default value of the amount of interaction per user is 5 ($p_j = p_{j'} = 5$). Under Reed's law, the number of groups that a user can join at one period is also set to 5 ($q_j = q_{j'} = 5$). As mentioned in section 3, these values are assigned in the initialization process. Adoption and interaction processes are iterated until 50 periods or until no more new adoptions occur. The results are obtained by 1000 times of simulation. In this

[9] Generally, it is impossible to interact millions of Facebook users at a given time.
[10] In fact, Facebook has over millions of API, but only tens of them occupy the most interaction (active uses of API).

section, we mainly discuss the growth patterns of SNS adoption and marginal growth under Metcalfe's and Reed's law.

4.1 Growth Patterns of SNS Adoption

The growth patterns of SNS adoption under Metcalfe's and Reed's law can be mathematically derived to an approximate functional form. Assuming two firms are symmetric[11], user i will adopt SNS j at time t only if wtp_{ij} is lower than $-NV_{jt-1}$. This implies that SNS j's number of users at time t (n_{t-1}^{j}) is affected by the standard normal cumulative distribution function of wtp_{ij}. Therefore, it can be expected that the number of users is $\frac{1}{2}\Phi({}^{NV_{jt-1}-\mu}/_{\alpha_j \sigma})$. Therefore, by Taylor approximation of the normal cumulative distribution function (Marsaglia 2004), it can be speculated that the growth of SNS adoption is an odd degree polynomial function of time t with a given number of initial adopters (n_0^j). We empirically test the relationship between the number of adopters and time using the data of the simulation[12]. Assuming two SNSs are symmetric, the result verifies that the growth of SNS adoption takes the form of an odd degree polynomial function of time t (Under Metcalfe's law β_1=11.88, β_2:-0.003, all $ps<0.01$; Under Reed's law β_1=29.01, β_2:-0.027, all $ps<0.01$).

Proposition 1. *If the number of interactions per user is far lower than the network size, the growth of SNS adoption under both Metcalfe's and Reed's law is approximately an odd polynomial function of time with a given number of initial adopters.*

Figure 2 shows the growth patterns of SNS adoption under Metcalfe's and Reed's law. Both growth patterns can be explained with three parts – the number of adopters in the equilibrium, the critical mass that converts marginal growth into an increasing trend, and the time that it takes to reach the equilibrium. It can be observed that the number of adopters in the equilibrium under Reed's law is higher than the one under Metcalfe's law, and the equilibrium also reaches faster. This shows that the network value per unit of interaction under Reed's law is greater than the one under Metcalfe's law.

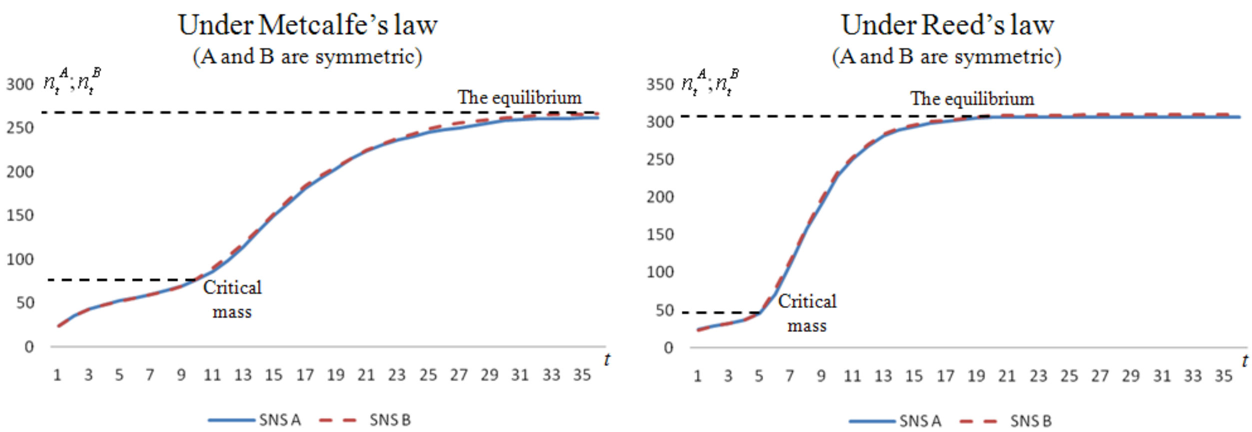

Figure 2. Growth of SNS adoption under Metcalfe's and Reed's law

---

[11] This means that *A* and *B* follow the same network value law with the same number of initial adopters and interactions per user.

[12] Considering the rest terms as an error, we set up the model to $n_t^j = C + \beta_1 t + \beta_2 t^3 + \varepsilon_t$ for regression analysis.

4.2 The Marginal Growth of SNS

There are three main factors affecting the marginal growth of SNS adoption – the initial adopters (n_0^j), the number of interactions per user (p_j, q_j), and the mechanism of interaction (Metcalfe's or Reed's law). The number of initial adopters means whether the SNS takes a first-mover advantage. The number of interaction per user refers to the question of how many interactions are activated in the SNS. The mechanism of interaction determines if the SNS is facilitated to one-to-one communications or group communications. Generally, these three factors affect the amount of interaction and eventually increase the growth of SNS adoption.

In perspective of the marginal growth, the number of interactions per user gives more effect to the growth of SNS adoption than the initial adopters. In the model, we perform simulations by altering SNS *A*'s number of interactions per user or the number of initial adopters. Figure 3 show the result of simulation. Regardless of the network value law, as the number of interaction increases, not only the maximum number of adopters but also the marginal growth of adoption increases. It can be shown that adoption of SNS *A* grows more rapidly as p_A increases, even when *B*'s initial adopters are higher than *A*'s. This implies that the first-mover advantage can be overcome by facilitating the interactions in a SNS, which leads to increase in the marginal network value.

Proposition 2. *Both under Metcalfe's and Reed's law, the marginal growth to the number of interactions per user is higher than that of the initial adopters if other conditions are hold.*

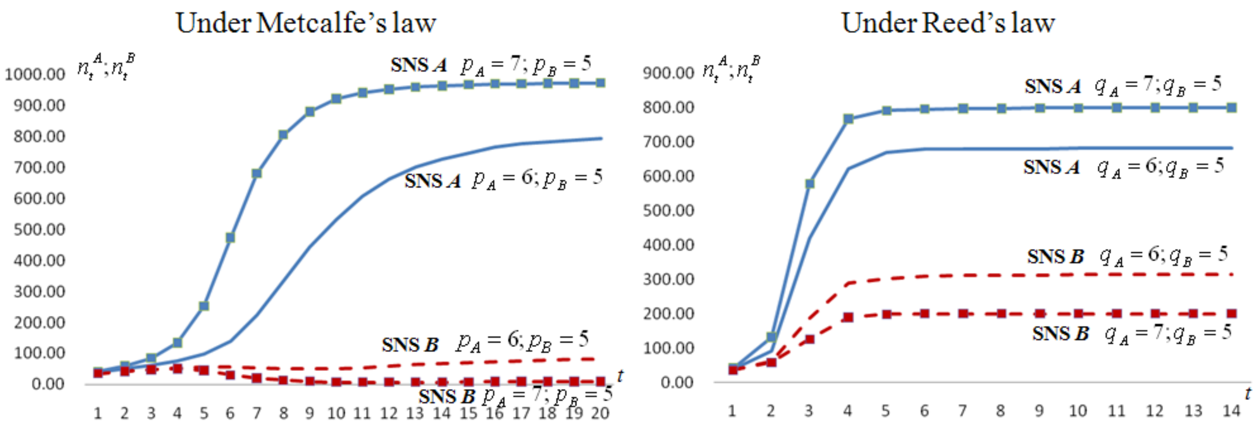

Figure 3. Growth of SNS adoption under Metcalfe's and Reed's law (the variables except p_A and p_B get the same values as those that were set up in the beginning of Section 4)

The result shows that the most effective factor that increases the marginal growth of SNS adoption is a change in the mechanism of interaction – from one-to-one communication to group communication. The change of interaction mechanism, from one-to-one to group communications, transforms the network value per unit of interactions. Even when *A* has higher initial adopters and higher number of interactions per users, the SNS adoption under Reed's law outgrows that under Metcalfe's law. This means that the change of interaction mechanism in a SNS is the most effective way that increases the number of its adoption.

Proposition 3. *The effect of the network value induced by group communications dominates that by one-to-one communications in perspective of marginal growth of SNS adoption.*

Applying the case of Facebook, we regard *A* and *B* as Myspace and Facebook respectively, and derive growth patterns of *A* and *B*. For this issue, both *A* and *B* are assumed to follow Metcalfe's law at the start of the simulation, but *B* changes to follow Reed's law after the 10th period. This is the application of "Open API" case into the model. SNS *A*, which is assumed to be Myspace, has 150 initial adopters to allow the first-mover advantage to *A*. Figure 4 shows the result. As mentioned in the propositions, the change of interaction mechanism dramatically increases the network value of SNS *B*. The number of adopters of *B* eventually overgrows that of *A* after 14th period.

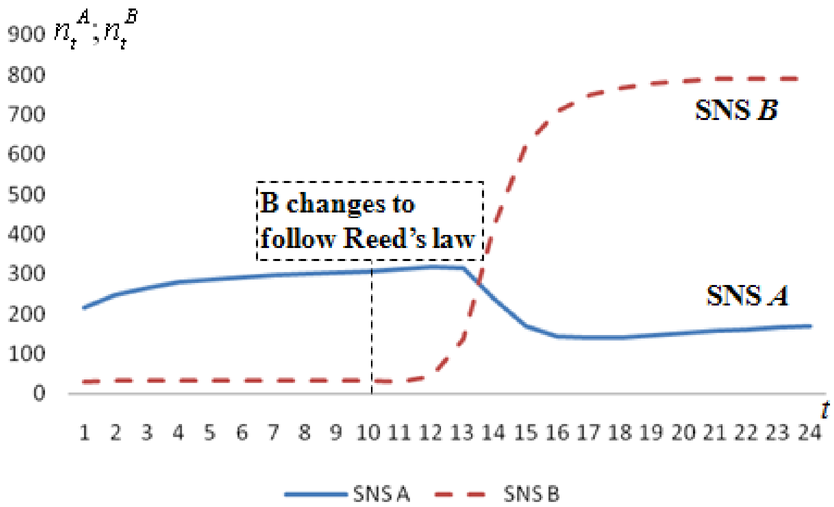

Figure 4. The change of interaction mechanism (from Metcalfe's to Reed's law) in SNS B (α_A=0.03, α_B=0.002)

5 EMPIRICAL ANALYSIS

In this section, we use traffic data of Facebook and Myspace to verify whether the "Open API" policy prospered group interactions in Facebook and increased the marginal growth of its users. For this issue, we first test the relationship between the amount of interaction in a SNS and its adoption. We also perform the Chow breakpoint test (Chow 1960) on data that lies between the period of before and after "Open API." This test verifies that there occurs a structural change in the relationship between the network value and the new adoption after introducing "Open API."

For the empirical analysis of growth of social network, we use the traffic data from "Alexa.com." Alexa is a representative company which provide online measure of all websites' historical traffic. For the traffic ranking, it mainly provides two types of measurements – reach and pageviews. By the definition from Alexa[13], reach measures the number of unique Alexa users (out of million samples) who visit a site on a given day. Pageviews are the total number of URL requests for a site. Despite the concern that there might be some biases, the traffic data from Alexa is one of the most critical indicators of the viability of websites[14]. This data is usually considered that the more traffic a site receives, the more reliable its traffic data is. Actually, Alexa's traffic data is used as a proxy for measuring the marketing potential of a website or a good tool for search engine optimization[15]. In our analysis, both Facebook and Myspace steadily ranked less than 50th (out of millions of websites).

[13] http://www.alexa.com/faqs/?p=134 , "How are Alexa's traffic ranking determined?"
[14] http://news.jornal.us/article-5607.How-to-use-Alexacom-to-Make-Money.html
[15] http://www.avangate.com/articles/alexa-ranking-99.htm

Therefore, traffic data of these two SNS seem reliable for the empirical analysis. In our analysis, we collected both types of daily traffic data over a period of November 11th 2006 to January 19th 2011 (1541 daily samples and 220 weekly samples). These two traffic data are plotted in Figure 5.

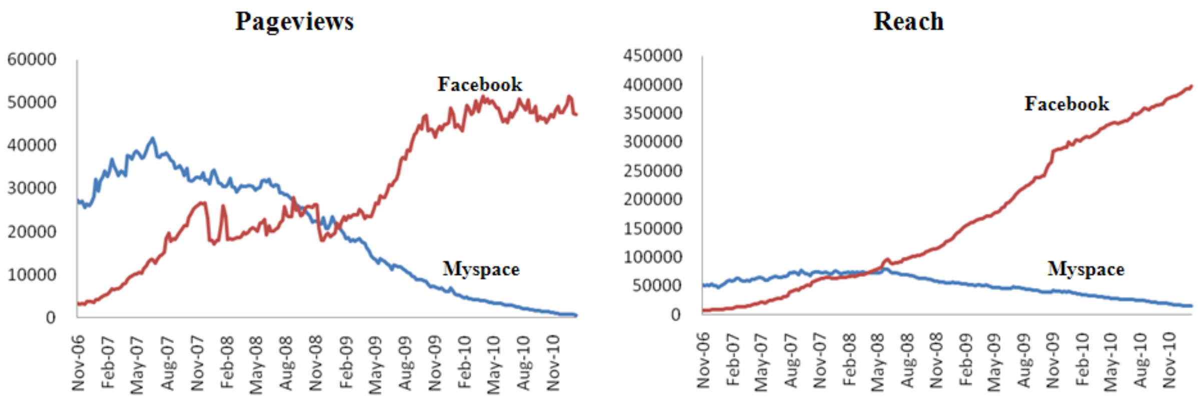

Figure 5. Reach and Pageviews data of Facebook and Myspace

According to the definitions of traffic data in prior studies, reach data is used to measure the audience market share (Kozberg 2001), and pageviews data is a measurement of how many times a particular web property has been seen (Demers and Lev 2001). Therefore, it can be interpreted that reach data of a SNS is a proxy for the total number of active users, and pageviews data is the amount of interactions that occur in a SNS. The number of actual users of Facebook and Myspace increased 125% and 19% respectively during the period of our data sample[16]. The traffic data of Facebook and Myspace show similar trends of growth in the number of users.

Regression models for the empirical analysis are based on the growth patterns in the results of the simulations. We basically hypothesize that the amount of interactions at a previous period positively affects the new adoption in a SNS. In the regression model, we use reach data ($R_{f,t}$) as a dependent variable and pageviews ($PV_{j,t}$) as an independent variable as shown in equation (2). We will observe whether there are changes in β_i before and after "Open API (2007.05.24)." However, we discover that all reach and pageviews data have unit roots. For that reason, Durbin-Watson statistics is a value of 2.018 when using equation (2). Moreover, there are high correlations between reach and pageviews data in both Facebook and Myspace. In that case, there are two alternatives – use I(1) series of each variable or apply a vector error correction model (VECM) (Hansen 2002). Both alternatives use the difference of each variable instead, but VECM considers long-run effects in the model. In the analysis, we first use VECM (Equation (3)) for the test of the weekly data of Facebook and Myspace. We also use operating years of Facebook and Myspace as a control variable.

$$\begin{pmatrix} R_{f,t} \\ R_{m,t} \end{pmatrix} = \begin{pmatrix} C_1 \\ C_2 \end{pmatrix} + \begin{pmatrix} \beta_1 & \beta_2 \\ \beta_3 & \beta_4 \end{pmatrix} \begin{pmatrix} PV_{f,t-1} \\ PV_{m,t-1} \end{pmatrix} + \begin{pmatrix} \beta_5 & \beta_6 \\ \beta_7 & \beta_8 \end{pmatrix} \begin{pmatrix} PV_{f,t-1} \\ PV_{m,t-1} \end{pmatrix}^2 + \begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix} \quad (2)$$

$$\begin{pmatrix} \Delta R_{f,t} \\ \Delta R_{m,t} \end{pmatrix} = \begin{pmatrix} C_1' \\ C_2' \end{pmatrix} + \begin{pmatrix} \alpha_1 & 0 \\ 0 & \alpha_2 \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \gamma_t \end{pmatrix} + \begin{pmatrix} \alpha_3 & 0 \\ 0 & \alpha_4 \end{pmatrix} \begin{pmatrix} \Delta R_{f,t-1} \\ \Delta R_{m,t-1} \end{pmatrix} + \begin{pmatrix} \alpha_5 & \alpha_6 \\ \alpha_7 & \alpha_8 \end{pmatrix} \begin{pmatrix} \Delta PV_{f,t-1} \\ \Delta PV_{m,t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_t' \\ \nu_t' \end{pmatrix} \quad (3)$$

Before "Open API (2007.05.24)," there are 30 samples out of 220. Descriptive statistics show that both reach and pageviews increase twice as much after "Open API." In case of Myspace, on the other

[16] http://brainstormtech.blogs.fortune.cnn.com/2007/11/15/nielsen-facebook-growth-outpaces-myspace/

hand, the data shows s slight decrease in reach data, but in pageviews the amount of interaction drops by almost half after "Open API."

SNS		Pageviews	Δ%	Reach	Δ%
Myspace	Before "Open API"	32774.1	1.22	57314.6	0.58
	After "Open API"	17693.1	-2.04	50227.2	-0.70
Facebook	Before "Open API"	6397.0	4.50	13090.5	3.86
	After "Open API"	32058.5	0.94	190022.5	1.55

Table 1. The data before and after "Open API (2007.05.24)"

The result of VECM confirms that there are significant time trends in both Facebook and Myspace. Facebook shows a positive time trend (0.157, p<0.001), but Myspace shows a negative trend (-0.071, p<0.001). However, both SNSs do not show a significant structural change after "Open API." This may be caused by the fact that the most of samples are after "Open API" (86.4% of samples). Therefore, we pick daily data from 2006.11.01 to 2007.10.31 (365 samples) to balance the extent of data between before and after "Open API." It is not necessary to check long-run effects in this case, we use I(1) series of each variable to test the structural change. Therefore, we use equation (4) in this case. Because daily data was used in this case, the day of the week effect must be considered (Trusov et. al. 2009). Therefore, Monday, Saturday, and Sunday are used as control variables.

$$\begin{pmatrix}\Delta R_{f,t}\\ \Delta R_{m,t}\end{pmatrix}=\begin{pmatrix}C_1''\\ C_2''\end{pmatrix}+\begin{pmatrix}\gamma_1 & 0\\ 0 & \gamma_4\end{pmatrix}\begin{pmatrix}\Delta R_{f,t-1}\\ \Delta R_{m,t-1}\end{pmatrix}+\begin{pmatrix}\gamma_5 & \gamma_6\\ \gamma_7 & \gamma_8\end{pmatrix}\begin{pmatrix}\Delta PV_{f,t-1}\\ \Delta PV_{m,t-1}\end{pmatrix}+\begin{pmatrix}\gamma_9 & \gamma_{10}\\ \gamma_{11} & \gamma_{12}\end{pmatrix}\begin{pmatrix}\Delta PV_{f,t-1}\\ \Delta PV_{m,t-1}\end{pmatrix}^2$$
$$+\gamma_{13}Mon_t+\gamma_{14}Sat_t+\gamma_{15}Sun_t\begin{pmatrix}\varepsilon_t''\\ \nu_t''\end{pmatrix} \qquad (4)$$

F-statistics of the Chow breakpoint test between before and after "Open API" is 2.88, which rejects the assumption that no structural change exists after "Open API." The result confirms that there are significant effects of interaction at the previous period to new adoptions in both Facebook and Myspace. In Facebook, it can be observed that there are positive effects on Monday and Sunday, but negative effects on Saturday. Out of seven days of the week, we only use Monday, Saturday and Sunday, which show significance in the model, as control variables.

variable	Myspace		Facebook	
	before	after	before	after
$\Delta R_{f,t-1}$	-	-	-0.390***	-0.136
$\Delta R_{m,t-1}$	-0.297***	-0.214**	-	-
$\Delta PV_{f,t-1}$	-0.055	-0.081	-0.009	0.036*
$\Delta PV_{f,t-1}^2$	0.002	0.006	-0.004	0.006*
$\Delta PV_{m,t-1}$	-0.009	-0.211***	-0.220***	-0.001
$\Delta PV_{m,t-1}^2$	0.007**	0.011***	0.012***	0.009***
Monday	0.636	-2.087**	5.287***	6.426***
Saturday	-1.081	-0.274	-3.225***	-6.486***
Sunday	0.569	1.197	2.894***	3.673***
Adjusted R^2	0.154	0.383	0.317	0.463

Table 2. The result of regression from 2006.11.01 to 2007.10.31 (breakpoint: 2007.05.24)[17]

6 IMPLICATION

Our model mainly investigates the growth patterns of SNS adoption according to laws of network value. If a user cannot make all interactions possible in the SNS, which implies the number of interactions per user is limited, the growth of SNS is an approximate odd polynomial function of time t with a given number of initial adopters of SNS. This usually shows an S-shaped curve. The model characterizes three factors which affect the network value law. These three factors are: a number of initial adopters, which is associated to the first-mover advantage, a number of interactions per user, and the network value law that is determined by the mechanism of interactions in a SNS. The result in the model shows that the change in the network value law from Metcalfe's to Reed's law increases marginal growth and gives a chance for the follower SNS to overtake the leader.

Applying the result of the model to the case of Facebook, it can be said that the "Open API" platform altered the mechanism of interactions to a group communication one. At the beginning of its service, Facebook had a lower number of adopters than Myspace. This means that the gap of the number of adopters between Facebook and Myspace hindered the growth of Facebook. Moreover, users in Facebook did not interacted sufficiently enough with others users to overcome Myspace's first-mover advantage. "Open API" can be considered as a signal when user interactions in Facebook were transformed from one-to-one communications to group interactions. This change means two important things. First, as shown in the model, a unit of interaction creates more network value in group communication than one-to-one communication. Second, as mentioned in the Morgan Stanley Research[18], the method of interaction shifts from one-way (asynchronous) to multi-way (synchronous), which is one of the important features of Web 2.0 (Mannes 2006). These two characteristics attracted more interactions in Facebook than before, and eventually overtake Myspace and allowed Facebook to take the leading position in the market. According to "Alexa.com," Facebook was ranked in the 2nd place, and Myspace ranked in the18th place in the amount of web site traffic in 2010[19]. By letting users freely create and use APIs in the social network, each API can play a role of a subgroup in Facebook. In API statistics in Facebook, six out of top ten APIs are social network gaming such as "FarmVille (www.facebook.com/FarmVille)" or "Mafia Wars (www.facebook.com/MafiaWars)," which let massive number of users interact with each other in one environment[20].

The empirical analysis applies the result of the simulation model to the real data. The analysis verifies that Facebook had a structural change after "Open API" in terms of the network value and growth of adoption. This can be seen as evidence that Facebook started to activate group formation after "Open API." In the beginning of SNSs, people usually utilized them as self-representation and self-broadcast in the network (Boyd 2004). As the number of user increases, the network value shifted to one-to-one communications such as instant messaging. Nowadays, APIs become a kind of catalyst that increases subgroups in the social network nowadays.

7 CONCLUSION

This paper mainly investigated the growth of social network services adoption using the functional form of network value. We apply the generally accepted laws of the network value and derive the model of competition between two SNSs. The results derived by simulation show that social network

[17] *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively.
[18] Internet Trends 2010 by Morgan Stanley Research,
[19] http://www.alexa.com/topsites, the above ranking is the recorded on April 10th 2010.
[20] http://statistics.allfacebook.com/applications

adoption is a polynomial function of previous adoption, and a SNS under Reed's law gets higher marginal growth of adoption than the one under Metcalfe's law. We may apply this result to other network or standard competition. As mentioned above, often winner-takes-all phenomena in IT are attributed to network externalities or network effects but disruptions have been observed in those markets as well. Such disruptions may be caused by fundamental changes in network characteristics. Our approach may be used to model such more general distruptions.

The result of empirical analysis confirms that there exist significant structural changes in both Facebook and Myspace. Based on the regression of two types of traffic data, reach and pageviews, Facebook showed a rapid growth of traffic data after implementation of the "Open API" policy. On the other hand, the web traffic of Myspace showed a decreasing trend. By applying the analytical model to the empirical analysis, we can conclude that "Open API" drives the change in the method of interaction in the social network, which facilitates group formation in the network. This implies the significance of open/peer innovations.

Eventually, it can be said that "Open API" activates a transformation of the ways of interaction in the social network. APIs let users to create subgroups in the social network, and increase the network value. For Facebook, which was the follower at that time, it was important to accelerate group formation functions and to increase the network value more rapidly.

Several limitations of our research exist in both the simulation model and empirical analysis. We derive the growth patterns of SNS adoption by performing simulations under various assumptions for simplicity of analysis. In empirical analysis, we use traffic data as proxies for the network adoption due to limitations of data access. Nowadays, most of SNSs let users develop APIs in the social networks (Warren 2007). There are many other social networks but we model a duopoly competition. It is possible to include more SNSs in addition to Facebook and Myspace, and empirically test our hypotheses with the panel data. Detailed data of API statistics such as the number of API adoptions or use lead the analysis of what kinds of APIs attract users more.

References

Acquisti, A. and R. Gross. (2006). Imagined communities: Awareness, information sharing and privacy on the Facebook. Springer, p. 36-58.

Ahn, Y. Y. et. al. (2007). Analysis of topological characteristics of huge online social networking services. In *Proceedings of ACM*, p. 835-844.

Arrington, M. (2007). Facebook Launches Facebook Platform; They are the Anti-MySpace. *TechCrunch, May* 24.

Arthur, W. B. (1989). Competing technologies, increasing returns and lock-in by historical events. *The economic journal* 99, p. 116-131.

Beck, T. (2009). The United States Social Networking Market. http://content.grin.com

Boyd, D. M. (2004). Friendster and publicly articulated social networking.

Boyd, D. M. and Ellison, N. B. (2008). Social network sites: Definition, history and scholarship. *Journal of Computer Mediated Communication* 13, p. 210-230.

Briscoe, B. et. al. (2006). Metcalfe's law is wrong-communications networks increase in value as they add members-but by how much?. *Spectrum, IEEE* 43, p. 34-39.

Dohler, M. et. al. (2008). Kumar's, Zipf's and other laws: how to structure a large-scale wireless network?. *Annals of Telecommunications* 63, p. 239-251.

Dwyer, C., S. R. Hiltz and K. Passerini. (2007). Trust and privacy concern within social networking sites: A comparison of Facebook and MySpace. In *Proceedings of AMCIS* 2007.

Farrell, J. and G. Saloner. (1986). Installed base and compatibility: Innovation, product preannouncements and predation. *The American Economic Review* 76, p. 940-955.

George, A.. (2006). Living online: The end of privacy. *New Scientist* 2569.

Goth, G.. (2008). Are Social Networking Sites Growing Up?. *Distributed Systems Online*.

Groth, D. et. al. (2005). *Network Plus Study Guide.* Sybex Inc.

Katz, M. L. and Shapiro, C. (1986). Technology adoption in the presence of network externalities. *The Journal of Political Economy* 94, p. 822-841.
Kumar, R. et. al. (2010). Structure and evolution of online social networks. *Link Mining: Models, Algorithms and Applications*, p. 337-357.
Lee, E. and J. Lee. (2006). Reconsideration of the winner-take-all hypothesis: Complex networks and local bias. *Management science* 52, p. 1838-1848.
Maness, J. M. (2006). Library 2.0 theory: Web 2.0 and its implications for libraries. *Webology* 3.
Marsaglia, G. (2004). Evaluating the normal distribution. Journal of Statistical Software 11, p. 1-7.
Mayfield, R. (2005). Social network dynamics and participatory politics. *LEBKOWSKY, Jon e RATCLIFFE, Mitch, Extreme Democracy*, p. 116-132.
Metcalfe, B. (1995). Metcalfe's Law: A network becomes more valuable as it reaches more users. *Infoworld* 17, p. 53-54.
Odlyzko, A. and B. Tilly. (2005). A refutation of Metcalfe's Law and a better estimate for the value of networks and network interconnections. *Manuscript, March* 2, 2005.
Reed, D. P. (1999). That Sneaky Exponential--Beyond Metcalfe's Law to the Power of Community Building. *Context magazine* 2.
Reed, D. P. (2001). The law of the pack. *Harvard Business Review* 79, p. 23-25.
Saloner, G. and A. Shepard. (1995). Adoption of technologies with network effects: an empirical examination of the adoption of automated teller machines. *The RAND Journal of Economics* 26, p.479-501.
Shi, N. et. al. (2010). The Continuance of Online Social Networks: How to Keep People Using Facebook?. *Hawaii International Conference on System Sciences* (IEEE Computer Society, p. 1-10.
Skog, D. (2005). Social interaction in virtual communities: The significance of technology. *International Journal of Web Based Communities* 1, p. 464-474.
Stone, B. (2008). Facebook expands into MySpace's territory. *The New York Times. http://www. nytimes. com/2007/05/25/technology/25social. html. Retrieved*, March 08.
Swann, G. (2002). The functional form of network effects. *Information Economics and Policy* 14, p. 417-429.
Trusov, M. et. al. (2009). Estimating the dynamic effects of online word-of-mouth on member growth of a social network site. Journal of Marketing 73, p. 90-102.
Warren, C. (2007). Facebook API to open up to other social networks. *Downloadsquad*, http://www.downloadsquad.com/2007/12/12/facebook-api-to-open-up-to-other-social-networks/.
Weaver, A. C. and B. B. Morrison. (2008). Social networking. *Computer* 41, p. 97-100.
Westland, J. C. (2010). Critical mass and willingness to pay for social networks. *Electronic Commerce Research and Applications* 9, p. 6-19.
Yoshikai, N. (2005). A Network value model and its application to technology evaluation for the on-line community. In *Proceedings of APSITT 2005*, p. 399-404.