The Analysis of Advertising Pricing Based on the Two-Sided Markets Theory in Social Network

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Abstract. The mushroom development of social networks has brought opportunity to the analysis of social ad pricing. On the one hand, compare with traditional ad pricing, social networks advertising pricing (SNAP) enables greater consumer surplus and profits to social network companies; On the other hand, reasonable SNAP can provide guidance to network users and advertisers and coordinate the interests between bilateral participants to maximize their behavior. In this regard, using the methodology of bilateral market, this paper firstly analyzed the conduct of bilateral participants to maximize the benefits of social network companies. Secondly, the paper investigates the characteristics of bilateral markets and social networks comprehensively and proposes the Relation-Intensity Model (R-I model) to measure the strength of social relation to optimal ad asking price. Finally, the paper draws a conclusion that the SNAP increases along with the growth of the number of users at first and performs a downward trend after the number of users comes to a certain value (threshold). Thus, the paper explains that after exceeding certain amount of users (a higher network clustering coefficient), the price elasticity of demand of advertising is relatively large, lower price for the enterprise can realize higher profits, i.e. the scale effect of advertising exceeds its price effect.

Keywords: Bilateral market; social network; social relationships intensity; online advertising pricing; cross-network externality.

1 Introduction

On basis of the 33th "Statistical Report on Internet Development in China", the scale of China's Internet users has reached 618 million, the Internet penetration rate has been 45.8% relatively, and social networking users in the overall utilization rate has come to 45.0% by December 2013 [1], and according to the latest report of iResearch, the scale of Online Advertising in China reaches 110 billion Yuan with an increase rate of 46.1% [2]. In addition, a consuming psychology test of U.S. shows that the differences of the impact power between online advertising and friends' recommendation is 12 times. DCCI also shows that 75% of people are willing to buy

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products from a friend's recommendation [3]. Obviously, the value of social commerce basis of the social relationship is that making the transactions among strangers turns to be the market of acquaintances, so as to strength the confidence and improve the efficiency. Therefore, taking the background above as a starting point to analyze the issues of SNAP is reasonable and necessary both in theory and in practice.

The analysis of social network advertising is mainly reflected from its profit model and the way of ad pricing. On the one hand, online advertising is the main profit model of Chinese social network, social ad pricing contains mainly brand advertising, product placement and precision marketing advertising [4]. Brand advertising in social network is China's main social network advertising presently. However, compared with the portal sites, social brand advertising is not dominant. On the other hand, online advertising pricing has remained mostly on the traditional way of ad pricing, such as flat-rate model, the cost per mille (CPM), cost per click (CPC) and so on[5]. Facing with the demand analysis of SNAP, they are difficult to form a unified, flexible and efficient pricing way. Thus, based on the environment of big data, this paper try to seek a more convincing pattern of ad pricing accordingly.

According to relative data of iResearch, the consuming behavior of social network users in China is still conservative in 2011: the proportion of social network users that paid fees is only 47.3 percent, and most of them consume very less [4]. This suggests that the spread of advertising is still relatively low among social users, analysis of user behavior or content services are not in place for social network platform. Thus, the SNS focusing on enhancing the experience of social network users is necessary to improve the value of social network advertising, which is mainly reflected from the marketing value and the path of promotion [4].

2 Literature Review

2.1 Summary of Research on Social Network

Social networks (Social Network Service) refers to online relationship net that is based on the real social interpersonal relationships, which comes into being from social users' friends of friends (Friend of a friend) [6] [7]. Lu [8] points out that social network is a huge network system that is woven of a large number of interrelated user nodes, which can be described with a network diagram indicated data sets of heterogeneous relationship [8]. Watts and Strogatz [9] believe that, the increase randomness among users will make the social network topology tend to be random network [9]. After studying the impact of network structure on the spread behavior, Centola [10]. reckons that a larger cluster of (strong ties) network topology will impact great effects on the spread of behavior, comparing to random network (weak ties) [10]. Borgatti et al. [11] also suggests that, more centralized network structure (such as star structure) is more excellent than decentralized structure (such as a circle) both in the rate and efficiency [11].

Vaughn [12] creates a FCB grid model to describe the behavior characteristics of consumer purchase decisions by quantifying the user's perception. Lee et al. [13] exploits a theoretical model of online brand community to analyze the impact of brand community to users' behavior. Meng and Cui [7] [14] measure the ad price of social network by using the linear fitting of several traditional ad prices. These methodological analyses of advertising still does not walk out of the plight of traditional online advertising, which consider the effects of social users on ad pricing sufficiently.

2.2 Summary of Research on Bilateral Market

Through the middle layer or platform, two kinds of participants conduct a transaction, and the benefits of a group of participants that joint the platform depends on the number of participants in another group, this kind of market is called bilateral market [15] [16] [17]. Bilateral market involves two distinct types of users, each of which obtains value by interacting with another through the common platform [17]. Mark Armstrong notes that bilateral prices are affected by three factors: the strength of cross externalities, pricing method and single home or multi-home [15]. Roson [18] believes that the distribution of bilateral price affects the market participation and overall demand scale. Therefore, the determination of price relies on the price transfer to some extent. Kaiser and Wright [19] advocates that advertisers pay much more attentions to the users than versa, the growth of users' demand will lead to higher advertising rates, while increased demand of advertising brings a decline price of the layout. Cheng [20] [21] divides social users into ad-averse users and no-difference users, suggests that the ad pricing performs differently periodically for a distinct "effects of relative value ratio", and then appears unilateral pricing, bilateral pricing and so on.

3 R-I Model Framework

The paper focuses on the analysis of ad pricing on a single monopolistic social platform (the choices of participants restrict to be "access" or "no access"). Based on the existing theoretical analysis, assumptions of R-I model is made firstly:

Hypothesis 1: The number of users and unit users' utility are relevant to the number of advertisers

For the issue of ad pricing belongs to the scope of the bilateral market, it mainly investigates the impact of the number of users to the ad pricing [15] [17]. Therefore, this paper mainly concerns the effects of social users' (fixed network structure) interaction on the SNAP (i.e. the cross-network externality). In this case, the bilateral market theory requires quantifying the impact of the cross-network externality [15].

Hypothesis 2: Social Advertising brings social users disutility

Cheng [20] [21] divides social users into ad-averse users and no-difference users. With the starting of the interactions between users and advertisers, the users limit to be ad-averse users effectively [21].

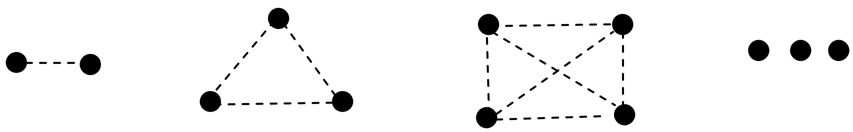
Hypothesis 3: Social networking platforms seek to maximize their own welfare

Given the failure of measuring the impact of users' behavior on the interests of social platform in the traditional environment, the paper cares more of the welfare of social network platform, when it comes to the social network environment.

3.1 Constructing R-I Model

Enterprises of monopolistic social network platform can change the bilateral price to maximize their behavior. Based on the assumptions above, we are able to quantify these effects.

With social network topology, the paper quantifies the social network externality. In this case, we pay attention to the network structure within fully connected diagram [22] (Figure 1), thus network externality can be measured by the permutation of nodes (A_n^2), each of which represents a social network user. As shown below:



$u_2 = 2 * 1 = 2$ $u_3 = 3 * 2 = 6$ $u_4 = 4 * 3 = 12$ $u_n = n * (n - 1)$

Fig. 1. The fully connected diagrams

In general, the social network externality can be linearized as $U = bN * (N - 1)$ (b is the strength of social relationships). Nitzan [23] uses joint strength, homogeneity, connection intensity to measure the social effects within social network. While Wu [22] divides the social relationship structure into two sides: the relationship between knowledge-acquired instrumental relations and friends-interacted expressive relations, and analyses these two relations. Here, in order to survey social network topology and the service level social platform comprehensively, the paper selects the clustering coefficient of all nodes [11] [23] [24] and users' online time length [10] to indicate the intensity of social relationships.

$b = f(C, T)$, b measures the monetary utility where unit user obtains from others within effective time; C represents network clustering coefficient, whose object is confined to be the inherent or spontaneous social circles; T measures users' average online length, which reflects the service level of social network platform. Centola [10] believes that spread behavior decays exponentially with time increases. Thus users' online time length can also expose users' preference for social platforms.

Clustering coefficient of a node represents the ratio of the total number between the most connections it may be connected to its neighboring nodes and all those close to the node [11] [23] [24], that is:

$$CC_i = \frac{n}{k_i(k_i - 1)/2} \qquad C = \sum_{i=1}^{N_1} C_i / N_1$$

Where ki represents the degree of node i, which involves the number of edges that connects to the node. Moreover, clustering coefficient of a network is the average of all nodes' clustering coefficient within the network. Where N1 is the number of nodes. b is the social relationship intensity. Clearly, strong ties impacts more influence to its relative users than weak ties, which indicates that on the relationship between joint users is higher than the weak joint, indicating that users are more susceptible to the impact of a friend instead of a friend of a friend, and this has been proven to be true [10].

Adding the utility model of social network externality and fixed-proportion price transformation into Armstrong's two-sided market theoretical model [15], we can derive the Relationship Intensity model. Here, users' (represented by u) utility is impacted by the cross-network externality, social network effects and the price, while advertisers' (represented by a) utility is derived from the cross-network externality and advertising prices. Then the effects of unit bilateral participant can be expressed as:

$$u_u = \alpha_u n_a + b n_u^0 (n_u^0 - 1) - p_u ,\ (\alpha_u < 0) \quad u_a = \alpha_a n_u - p_a \tag{1}$$

p_u and p_a represents monopoly platform for users and advertisers initial asking price separately; α_u is the strength of the cross-network externality that advertisers acts to users, and α_a is the strength of the cross-network externality that users act to advertisers; While b still represents the social relationship intensity. n_u^0 is the number of social users within a certain social circle contained in the whole social web, and if the social network has one social circle, the number of social users and that of social circle will be equal. In this way, the paper will mainly pay attention to the number of effective social users, which connects the amount of social users and the topology structure of social network, and we are pleasure to make it simplified. According to the theoretical bilateral market model [15], The participants in the utility function is expressed as the number of participants, and assuming that the unit cost of the participants were bilateral image And image . The profits of social network platform is:

$$\pi = n_u(p_u - f_u) + n_a(p_a - f_a) \qquad V = \pi(u_u, u_a) + v_u(u_u) + v_a(u_a) \tag{2}$$

Where f is the cost of unit participants (user and advertiser). In this case, the benefits of the platform are added by the profits and bilateral participants' surplus (Vu and Va).

Take the equations above into consideration, we have:

$$p_u = f_u - \alpha_a n_a - b n_u (2n_u - 1) \qquad p_a = f_a - \alpha_u n_u$$

After calculating the initial asking price of social platforms, we need to draw into the fixed-proportion price transformation (ε is the proportion ratio).

$$P_a = p_a + \varepsilon p_u$$

Furthermore, the relationship intensity model (R-I model) is:

$$P_a = \varepsilon f_u + f_a - \varepsilon \alpha_a n_a - 2\varepsilon b n_u^2 + (\varepsilon b - \alpha_u) n_u \quad \alpha_u \le 0, \alpha_a >> 0, \varepsilon > 0$$

3.2 Analysis of R-I Model

The strength of social relationship affects the number of social users, thereby has an impact on the final SNAP. According to the proportion above, we care more about n_u

rather than b. Making $\partial P_a/\partial n_u = \varepsilon b - 4\varepsilon b n_u - a_u = 0$, we generate that when $n_u > \frac{1}{4}(1 - \frac{a_u}{\varepsilon b})$, $\partial P_a/\partial n_u < 0$, that is when the number of social users exceeds a certain 'threshold' value, the social network ad price declines as the number of users increases; and when $n_u < \frac{1}{4}(1 - \frac{a_u}{\varepsilon b})$, $\partial P_a/\partial n_u > 0$, the social network ad price increases with the number of users increases, which draws different conclusions with the analysis of traditional bilateral market.

3.3 Model Description

Without loss of generality, the paper gives an account of the R-I model with data. After analyzing the experiment conclusions with the Cox proportion hazards model, Centola [10] draws that triple stimulations of network signal can generate the most effective result of social users' spread behavior. (Z = 1, P <15%; Z = 2, P> 30%; Z = 3, P = 40%). thus we limit the studying scope within the cluster network and the strength of strong ties to be 3 (Z = 3). Thus, the topology of this kind of social network can be depicted as follows:

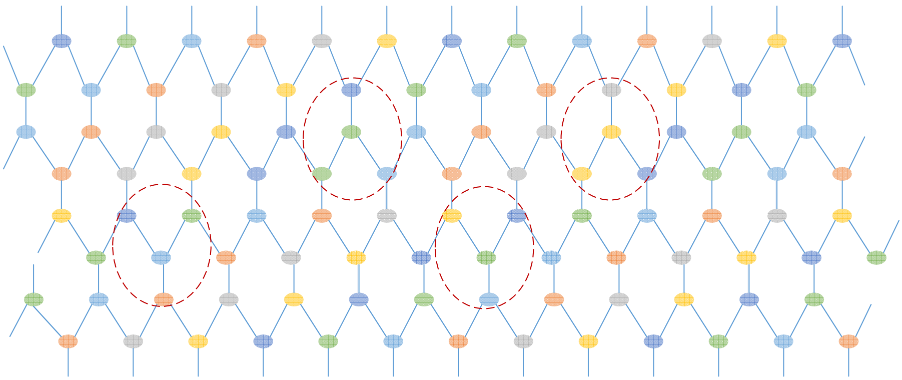


Fig. 2. Social network structure

Remarks: the number of social users ($n_u = 104$), within the structure, any user will be affected by his or her three friends effectively, which turn out to be the best impact degree of spread behavior by the study of Centola [10].

The clustering coefficient is: $C = CC_i = \frac{3}{(3 * 2)/2} = 1$. Then, the strength of the social relationship is mainly measured by social users' online time: $b = f(1, T) = f(T)$, and this is set as the linear relations: $b = T/40$. While the average length of the user's online time is two hours (T = 2).

Other information is in the table below:

Table 1. XX's community information

Name	Value	Unit	Remarks
Marginal cost	f_u=1200;f_a=800	Yuan	
The number of advertisers	n_a=5	/	n_a<<n_u
The proportion of pricing transformation	ε=0.2	/	
Users' cross-network intensity	a_u=-4	Yuan per advertiser	Ad-averse users
Advertisers' cross-network intensity	a_a=2	Yuan per user	User-depended

Putting these values into the R-I model we obtain:

If $b = 0.05$, $P_a = 1022 - 0.02n_u^2 + 4.01n_u$, and the threshold value is: $n_u^* = \frac{1}{4}(1 - \frac{\alpha_u}{\varepsilon * b}) = 100.25 \cong 100$.

With $n_u = 104$, $P_a^1 = 1222.72$, That is, the final ad asking price is 1222.72.

Otherwise, the number of social users is 104($n_u > n_u^*$). Thus, the final ad asking price drops, if the amount of social users increases further; and when the number of users is less than 100, , the final asking ad price increases along with the growth of the number of users.

4 R-I Empirical Evidence

To verify the robustness of the R-I model further, the thesis takes the example of China's typical social network – Renren to draw a brief demonstration. While the key evidence to verify the conclusion is whether the impact of social user on social network advertising pricing exists a threshold value. The paper adopt the monthly amount of Unique Visitor to reflect the number of social users and take cross-quarter online advertising revenue as the income of social network platform achieved from advertisers (fixed ad proportion). Thus, the paper extracted RenRen's relative data (the number of social user (2010 Q4-2014 Q1) and social ad revenues (2009 Q1-2014Q1)) from the 199IT Internet data centers, iResearch, DCCI and so on, which is shown in Figure .2. As we can see, the data especially Ad revenues represents a seasonal fluctuation. Thus it is necessary to adjust the data to remove the influence of season, and adjusting the statistics with MA (5) is reasonable.

As is seen from the chart, the change of advertising revenue shows an oscillatory growth trend, while the number of unique visitors draws a more substantial increase trend. Furthermore, with the scatterplot composed of advertising revenue (P) and the number of monthly unique users (U) (Figure .3), it is easy to judge that advertising revenue (advertising price) presents a first-increased-then-decreased trend by the impact of the number of social users, and when N = 4000 (March 2012), the threshold value appears, which verifies the conclusions. When we explore the statistical relationship between the ad price and the number of social users by SAS 9.3 further, we are able to draw the conclusion better (Figure .4)

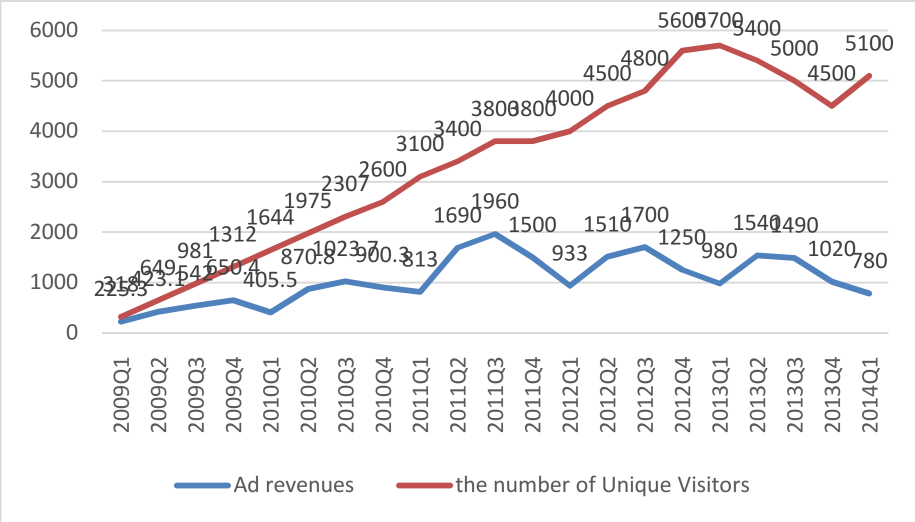


Fig. 3. The amount of the Unique Visitors and ad revenues

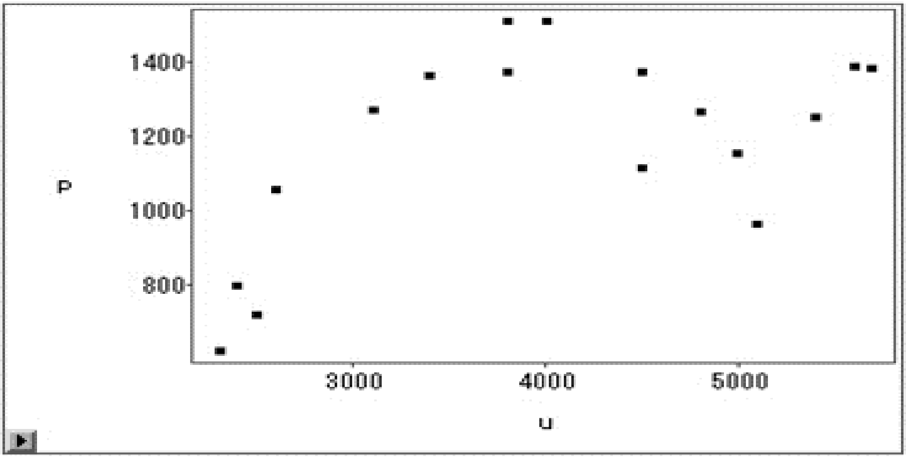


Fig. 4. Adjusted data of the number of the Unique Visitors and ad revenues

The regression fitting of parameter without intercept								
		Model		Error				
Curve	Times(ploynomial)	Free degree	Mean square	Free degree	Mean square	R square	F statistics	Pr > F
	2	2	12313894.3	15	41469.5208	0.9754	296.94	<.0001

Fig. 5. The regression fitting result of their relation between Ad revenue and the number of social users

5 Conclusions and Forecasts

5.1 Conclusions

The paper draws the following conclusions by using the analysis of R-I model, and we summarize two key points as follows:

(A) The intensity of social relationships indicates user's dependence level on social networking platforms, the more clustering social relations will leads to more frequent interactions among social users and higher dependence level of the platform, the more comprehensive social relationship network, and the higher user's utility level, which attracts more users to join the network. Meanwhile, the marginal effects of one's indirect relation users (weak ties) on the social users is degressive. In other words, a weaker degree of mutual trust and intimacy appears when the social network tends to be looser.

(B) Social relationships intensity affects the final price of social network platforms by two (direct and indirect) ways. The direct way is derived from the attention of social network platforms to social users, and the indirect way lies to social relation's effects on the number and utility of social users, and affect the final pricing further. What's more, when the indirect effects surpass the direct one and the amount of social users exceeds the threshold value, the final price will decline, which turns out to be perfect for both the platform enterprise and social network participants.

5.2 Forecasts

Further analysis will focus on two aspects: the empirical test by using the big data and modify the model; thinning the SNAP, making targeted analysis of pricing model of different advertising and extracting more rigorous theoretical model. Thus, there are much more tasks for us to launch.

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References

1. The 33th Statistical Report on Internet Development in China, `http://www.cnnic.net.cn/hlwf-zyj/hlwxzbg/hlwtjbg/201401/t20140116_43820.htm/` (read April 16, 2014)
2. iRresearch. China's Online Ad Key Data (2013), `http://a.iresearch.cn/others/20-140109/224661.shtml` (read January 9, 2014)
3. Zeng, S.: Commodity Recommended System Based on the Social Network Trust Model. University of Technology of South, Guangzhou (2012)
4. Social Network Analysis Report in 2010-2011, `http://report.iresearch.cn/1658.html` (read February 20, 2012)

5. The Blue Paper of China's ad network, `http://www.dcci.com.cn/hotreport/view/id/51116-6.html` (read December 15, 2011)
6. Social Network Service, `http://zh.wikipedia.org/zhcn/%E7%A4%BE%E4%BA%A4%E7-%B6%B2%E8%B7%AF%E-6%9C%8D%E5%8B%99,2013` (read October 8, 2012)
7. Wen, C.: The Impact of Advertisement appeal, sources and type on Social Network Performance. Department of Industrial Engineering in Tsinghua University, Beijing (2011)
8. Lu, M.: The Analysis of WEB Data Mining And its Application in Social Network. University of Electronic Science and Technology, Chengdu (2012)
9. Watts, D.J., Strogatz, S.H.: Collective dynamics of 'small-world' networks. Nature 393, 440–442 (1998)
10. Centola, D.: The Spread of Behavior in an Online Social Network Experiment. Science 329, 1194–1197 (2010)
11. Borgatti, S.P., Mehra, A., Brass, D.J., et al.: Network Analysis in the Social Sciences. Science 323, 892–895 (2009)
12. Vaughn, R.: How Advertising Works: A Planning Model. Journal of Advertising Research 20, 773–779 (1980)
13. Lee, D., Kim, H.S., Kim, J.K.: The Impact of Online Brand Community Type on Consumer's Community Engagement Behaviors Consumer-Created vs. Marketer-Created Online Brand Community in Online Social-Networking Web Sites. Cyber-Psychology, Behavior and Social Networking 14(1-2), 59–63 (2011)
14. Meng Lingsheng, D.: The Analysis of online adverting strategy and pricing model. Jilin University, Changchun (2008)
15. Armstrong, M.: Competition in two-sided markets. RAND Journal of Economics (10), 668–691 (2006)
16. Rochet, J.-C., Tirole, J.: Platform competition in Two-sided Markets. Journal of the European Economic Association 1(4), 990–1029 (2003)
17. Wrigh, J.: One-sided Logic in Two-sided Markets. Review of Network Economics 3(1), 1–21 (2004)
18. Roson, R.: Two-Sided Markets: A Tentative Survey. Review of Network Economics 4(2), 142–160 (2005)
19. Kaiser, U., Wright, J.: Price structure in two-sided markets: Evidence from the magazine industry. ZEW Discussion Papers 24(1), 1–28 (2004)
20. Cheng, G., Li, Y.: The Bilateral Pricing Strategy of Media Platform with Negative Network Externalities. Journal of Shanxi University of Finance and Economics 31(4), 7–13 (2009)
21. Cheng Guisun, D.: The Analysis of Operating Mechanisms and Competition regulations in Media Industry Based of Bilateral Marker Theory. Shanghai Jiao Tong University, Shanghai (2007)
22. Wu, L.: Social Network Effects on Productivity and Job Security: Evidence from the Adoption of a Social Networking Tool. Information Systems Research 24(1), 30–51 (2013)
23. Nitzan, I., Libai, B.: Social Effects on Customer Retention. Journal of Marketing 75, 24–38 (2011)
24. Luo Jiade, M.: Social Network Analysis, 2nd edn. Social Science Document Press (2010)
25. Kleinberg, J.: The Small-World Phenomenon: An Algorithmic Prospect, pp. 12–24. ACM Press, New York (2000)
26. Boulos, M.N.K., Wheeler, S., et al.: The emerging Web 2.0 social software: an enabling suite of sociable technologies in health and health care education. Health Information and Libraries Journal (2007)

27. Richin, M.L.: Social Comparison and the Idealized Images of Advertising. Journal of Consumer Research (1991)
28. Fritsch, M., Kauffeld-Monz, M.: The impact of network structure on knowledge transfer: An application of social network analysis in the context of regional innovation networks. Jena Economic Research Papers (2008)
29. Katz, M.L., Shapiro, C.: Network externalities, competition and compatibility. The American Economic Review, 424–440 (1985)
30. Huijboom, N., van den Broek, T., Frissen, V., et al.: Key areas in the public-sector impact of social computing. European Communities (2009)