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Citation: Yun, Qiaoyun, and Peter A. Gloor. "The Web Mirrors Value in the Real World: Comparing a Firm's Valuation with Its Web Network Position." Computational and Mathematical Organization Theory 21, no. 4 (July 31, 2015): 356–379.

As Published: http://dx.doi.org/10.1007/s10588-015-9189-6

Publisher: Springer Science+Business Media

Persistent URL: http://hdl.handle.net/1721.1/103278

Version: Author's final manuscript: final author's manuscript post peer review, without publisher's formatting or copy editing

The Web Mirrors Value in the Real World: Comparing a Firm's Valuation with Its Web Network Position

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Abstract

This paper compares a firm's innovation and performance with its online Web presence measured through the Web network structure. 489 firms in five different industries listed on the United States and Chinese stock markets are investigated. Using Web link data collected from Bing, blogs, Twitter and Wikipedia, we find positive correlation between betweenness centrality of a firm in the Web network and its innovation capability; and between betweenness centrality and financial performance. In order to get more accurate forecasting results, regression analysis is done for each industry and the combined industries in the United States and China. We find that Twitter and Wikipedia only predict a firm's performance in the United States, which is not surprising as they are officially blocked in China. Blogs predict better in China than they do in the United States, as it might still be a major social media tool for Chinese firms; while for the US firms, blogs have been supplemented by Twitter and Wikipedia.

Keywords online social network analysis, Web link structure, betweenness centrality, degree centrality, innovation, performance, firm valuation

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1 Introduction

Throughout history financial experts have declared that "this time is different" – claiming that the old rules of valuation no longer apply. In their book of the same title, Reinhart and Rogoff (2009) proof these experts wrong, illustrating it with 800 years' worth of analysis of financial crises. As they show, one of the key reasons why financial experts fall into the same pitfalls over and over again is the lack of transparency from governments, banks, and corporations. In this paper we introduce a novel and transparent way for determining the valuation of a company based on its linking structure on the Web. Similar to Google PageRank for ranking the quality of documents based on the quality of documents linking back to them, we measure the financial and innovative quality of firms based on the myriad Web pages linking to their Web pages. Our paper is based on the assumption that a position in the link network of a firm is comparable to the position of the firm in a social network. This is reasonable because the link network reflects real-world relationships. It makes particular sense in the context of our study, comparing linking structure with valuation: The valuation of a company can be influenced on the Web in three ways (Luo et al. 2013): through social influence and contagion, through increased visibility and availability, and through customer engagement. The density and hub-spoke structure of a link network is related to all three criteria: the more pages about a company are back-linked from other central blogs or tweets, the more social influencers have been talking about the company. Obviously, a more richly linked company network is also more visible on the Web, and thus also gets more opportunities to get in front of consumer eyes.

The validity of this principle has been demonstrated measuring the importance of leading thinkers (Frick et al. 2013), where their social network has been approximated by a Web link network. (Luo et al. 2013) have investigated how social media presence predicts firm equity valuation. They find that frequency of Web searches and actual Web traffic is less good as a predictor of equity value than consumer sentiment on blog posts.

Therefore Web links can be taken as a proxy for relationships among firms in the real world. Relationships enable diversification and rapid technological development in changing economic environments and are thus recognized as an essential factor for a firm's adaptation to new market trends. For both theoretical and practical reasons, firms are motivated to generate, develop and maintain more relationships with other organizations to get market and technology advantage, and share risk with their partners (Gulati et al., 2000). Most of firms' social capital is embedded in relationships, networks, or societies (Nahapiet & Ghoshal, 1998). Networks are thus a key source of social capital (Adler & Kwon, 2002).

Although scholars in the field of innovation and performance have long emphasized the importance of social networks, researchers put most emphasis on offline or real-world social networks. With the development of Web 2.0 and social media, online social networks begin to play an important role in society and economy. Recent research started to consistently demonstrate the importance of online social networks and social capital of entrepreneurs and employees for enterprise innovation and performance improvements (Schilling & Phelps, 2007).

Until now, researchers have mainly analyzed online social networks of individuals, and their effect on innovation and performance within a firm or an organization. This approach assists in developing a better understanding of how individual online social networks influence a firm's innovative capabilities, and how they might be employed to optimize the firm's performance. However, few researchers have investigated firms' online social network position (such as e.g. Google PageRank of a firm's Website) on the global Internet level. Therefore, the main research objective of this paper is to investigate if a firm's online social network position is correlated to its financial performance and innovative capabilities, and which variables are the most important predictors for these relationships. We do this by comparing online social network centrality metrics with innovation and financial performance. First, we review the literature relevant to online social network metrics and its effect on a firm's innovation and financial performance. Second, we develop a conceptual model and hypotheses. Third, the research method is outlined and network data of the firms is collected; fourth, we discuss the results of the relationships between online social network structure and innovation and financial performance of firms, and finally draw some conclusions.

2 Related Work

Small world theory put forward by Milgram (1967) laid an early theoretical foundation for social network research. Social networks have been widely studied including network structure (Wellman, 1997), weak or strong network ties (Granovetter, 1973; Nohria & Eccles, 1992), embeddedness theory (Granovetter, 1973), social capital (Tsai & Ghoshal, 1998), network methods (Hanneman & Riddle, 2005), leadership and networks (Webber, 2003), innovation networks (Ahuja, 2000), interfirm alliances (BarNir & Smith, 2002), interfirm relations (Beckman et al., 2004), network governance (Provan & Kenis, 2007), and social influence (Sparrowe & Liden, 2005).

Several researchers studied the relationship between social networks, innovation and performance (Henard & Szymanski, 2001; Rindfleisch & Moorman, 2001). Capaldo (2007) empirically studied the network structure and innovation, and pointed out that the ability to integrate a large periphery of heterogeneous weak ties and a core of strong ties is a distinctive feature of a firm’s relational capability. It provides fertile ground for leading firms in knowledge-intensive alliance networks to gain competitive advantages. Its sustainability is primarily based on the dynamic innovation capability resulting from leveraging dual network architecture. Well-working social networks give better access to specialized knowledge and better R&D resources for firms (Podolny et al., 1996). We assess innovation capability through business success as well as through the Fastcompany innovation ranking (table 2).

The theoretical basis for linking network metrics and firm performance originates from models of networked firms (Podolny, 1993), where the prominence of an actor and its linkages determined the node and its relations to other firms. Social network methods suggested prominence in alliances results in better performance in many different industries, including getting preferential treatment from suppliers and higher returns from investment. Entrepreneurial networks also can provide a wide range of resources for start-up businesses (Anderson et al., 2007) and access to finance (Aldrich, 1989; Jenssen & Koenig, 2002). A study by Lavie (2007) argued that in software alliances with well-endowed partners, networks might provide an additional explanation for the market performance of firms.

Social network structure and its influence on innovation and financial performance is an important part in the studies above. In individual and group level research, Shaw (1964) examined the relationship between group communication structure and performance. Sparrowe & Liden (1997) found that individuals enjoyed advantages or suffer disadvantages by virtue of their positions within social networks. Baldwin et al. (1997) advanced that team interaction patterns consistent with cohesive work groups were positively related to a team’s final grade. On the organization level, scholars highlighted the importance of external resources available to the firm through its networks (McEvily & Marcus, 2005). In seminal work, Burt (1992) identified social network structural holes rather than closure (Coleman, 1988) boosting firm performance. Gulati et al. (2000) found that embeddedness of firms in networks of external relationships with other organizations holds significant implications for firm performance. Wang (2009) studied the Liuyang fireworks companies and concluded that the network density and closeness centrality had positive effect on firms' export performance.

With the development of the Internet and Web 2.0, online social networks have become a key means of communications for individuals and organizations alike. Online social network analysis has been used to analyze relationships of users or organizations using web-links, e-mail, and direct interpersonal interaction on Webpages such as leaving a comment on a blog, online news article, or Facebook wall. Researchers studied how online social networks affected innovation performance in individuals or groups (Gloor, 2003; Kidane & Gloor, 2005; Tashiro, 2011; Bulkley & Alstyne, 2006). Gloor et al. (2011) studied online social network structure and found that the centrality in the network predicted entrepreneurial and academic success. (Iyer et al. 2006) looked at the evolution of the alliance network in the software industry over a 12-year period. They find that the connectivity, measured by a variety of network metrics, is increasing for all firms, and increases the most for industry leaders such as Google, Amazon, and Microsoft. In other research, it has been shown that Twitter activity and stock market valuation are correlated (Bollen et al. 2011, Zhang et al. 2011). Others have compared Google search behavior, and Wikipedia search and editor behavior to predict movement in the stock market (Preis et al. 2013, Moat et al. 2013).

Although previous research has demonstrated a relationship between social network structure and instrumental outcomes, few studies have explicitly examined the relationship between interfirm online social networks, innovation and performance. The current study breaks new ground by extending previous research on the correlation between a firm's online network and its innovation and financial performance to large scale automatically computed Web, blog, Twitter, and Wikipedia networks.

3 Conceptual Background and Research Hypotheses

Social network analysis (SNA) uses structural indicators including degree, closeness and betweenness centralities to analyze the network structure and measure the importance of each actor in the whole social network. Degree centrality takes the number of direct connections into account, closeness centrality considers the distance of one actor to all the other actors, and the measure of betweenness centrality rests upon the idea that the centrality of an actor depends upon the extent an actor is located "in between" two other actors (Hanneman, 2005), that is the node's likelihood to be on the shortest path between all other nodes. A study conducted by Freeman et al. (1979/80) emphasized the particular advantage of the degree and betweenness centrality measures (Wasserman & Faust, 1994). Betweenness centrality is considered especially suitable for revealing the kind of power situations in which brokering and control of the flow of information are vital. Betweeness centrality is also regarded as "finer grained" than the other two (Freeman, 1978/79; Freeman et al., 1979/80). Motivated through a wealth of earlier research on the relationships between betweenness centrality, degree centrality, innovation and performance, we employ betweenness centrality and degree centrality as the main indicators to empirically measure a firm's online social networks structure. Our research framework investigating the relationships between social network structure, innovation and firm performance is shown in figure 1.

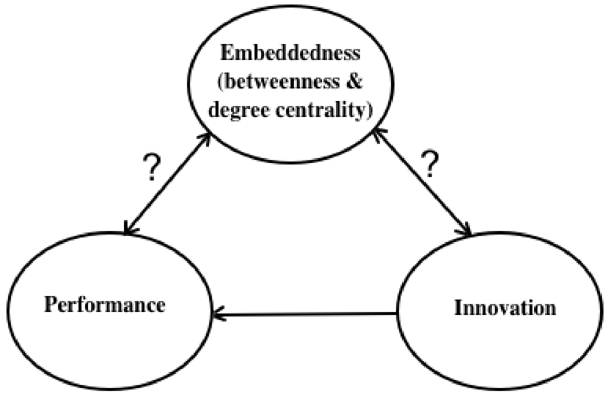

Figure 1 Research Framework

3.1 Betweenness Centrality, Firm Innovation and Financial Performance

Betweenness centrality represents the likelihood that a given node is included in the shortest path between any two nodes in the network (Wasserman & Faust, 1994). Betweenness centrality captures the broker activity bridging structural holes (Cross & Cummings, 2004). The importance of betweenness centrality has been documented in research on various communication networks and interlocking directorates (Mizruchi, 1982; Mintz & Schwartz, 1985). In particular, it was found that betweenness centrality was positively related to innovation and managerial performance (Brass, 1984; Mehra, 2001). The basic argument is that an actor who lies between two other nonadjacent actors occupies an important strategic position and maintains intermediary links between organizations that are not directly connected. This actor serves as a gatekeeper that has a central position in the network in terms of knowledge transfer to other intra-cluster firms and is strongly connected with external knowledge sources (Giuliani & Bella, 2005), and has greater control of the interaction information and resource flow (Freeman, 1979). Regarding technology innovation capability, technological gatekeepers contribute more actively to the acquisition, creation and diffusion of knowledge about extra-cluster technology trends on product and process innovation and thus achieve a competitive advantage in the market (Giuliani & Bella, 2005). Furthermore, betweenness centrality may also gain favorable terms in negotiations by playing the two unconnected firms against each other (Burt, 1992). The same argument as for companies and people can also be made for actors as Web sites (Gloor et al., 2009).

Based on these findings grounded in social network theory, we conjecture that high embeddedness demonstrated by betweenness centrality may allow firms to extract more value from its network through its powerful position in the network. This effect may also be shown in the online social network. Thus we conclude that:

H1a: Betweenness centrality of a firm in its online social network is positively related to its innovative capabilities.

H1b: Betweenness centrality of a firm in its online social network is positively related to its performance.

3.2 Degree centrality and Firm Performance

Degree centrality measures the extent to which an actor occupies a central position in a network by having many ties to other actors. Most of the studies in the context of network structure and performance report a positive relationship between degree centrality and performance at an individual (Bulkley et al., 2006) and a group level (Tsai, 2001). Gloor et al. (2007) found that the success of an alliance was directly correlated with the degree centrality of its members. On the firm level, degree centrality measures a firm's capacity to develop communication within a network of suppliers, customers, and alliance partners. If the firm is more central in the industry network, it will have more opportunities to communicate with peers, thus leading to preferred access to information and opportunities to grow social capital. This collective social capital can enhance the likelihood of returns (Lin, 2008), increase efficiency (Burt, 1992) and effectiveness (Gabbay & Leenders, 1999), reduce innovation time and costs (Marinova & Phillimore, 2003), thus positively impact long-term firm performance and outweigh the immediate cooperation costs (DeBresson & Amesse, 1991; Zhou et al., 2007). In such a network, more central positioning (locally or globally) generates visibility and reputation and, thus facilitates timely access to information and resources. Firms more centrally located should have more timely access to promising new opportunities and ventures. Their experience should also result in more opportunities to benefit from further relationships (Malerba & Vonortas, 2009). Therefore, degree centrality of social networks should be directly and positively associated with firm performance. We expect the same behavior for a firm's position in its online Web link network. We therefore postulate that:

H2a: Degree centrality of a firm in its online social network is positively related to its innovative capabilities.

H2b: Degree centrality of a firm in its online social network is positively related to its performance.

4 Research Method

4.1 Measurement

In order to measure the betweenness and degree centrality of the firms in our sample (US and Chinese firms), we used the software tool Condor (Gloor & Zhao, 2004) that enabled us to compute these variables for a company name in an online social network automatically. One advantage of such an automated approach is that it is straightforward to apply and replicate. It is based on the algorithm described by Gloor et al. (2009), a Web mining approach tailored to social network analysis, applying the simple idea: “You are who links to you”. The application analyzes different types of communication archives automatically, such as e-mail, mailing lists, forums, phone logs, chat, web structures (through the Google, Bing, and Yahoo search API), blogs, Twitter, and Wikipedia.

Condor measures centrality by looking at the linking structure of Web sites or blogs to determine how Web pages displaying a search term (for example “Tesla Motors”) are connected. It uses high-centrality Web sites returned in a search engine query for a company name as a proxy for the significance of this company (Gloor et al., 2009). Condor’s data mining approach combines measuring the centrality of Web sites with a degree-of-separation search. Condor constructs a bipartite graph, using high-betweenness Web sites returned in a search engine query for a company name as a proxy for the significance of this company (Gloor et al., 2009, Frick et al., 2013). Condor collects the most important Web sites mentioning say “Tesla”, and then inputs these URLs into a Web search engine to see which other Web sites link back to them. This process leads to a network map (Figure 2) which displays the search term, e.g. “Tesla”, in its core, surrounded by the Web sites or blog posts returned in response to the search query, or the links among Wikipedia pages linking back to the original Wikipedia page about “Tesla” (Gloor et al., 2009). In Figure 2 the Web pages containing the search results originating from the search terms “Tesla”, “Microsoft”, etc. are denoted by the black squares.

Degree-of-separation searches are a practical way to find the most influential nodes in a given subset on the Web. By combining the bipartite graphs – the search term surrounded by the Web linking structure – returned by different degree-of-separation searches, we can compare the betweenness centrality of different companies and identify those with the highest betweenness values. Those companies represent bridging links on the Web or in the blogosphere (Gloor et al., 2009). Condor thus builds a network map which displays the linking structure of a list of Web sites or blog posts returned in response to a search query on the Web or in Wikipedia, or the links among Twitterers retweeting an original Tweet (Gloor et al., 2009).

The difference between this approach and the Google search strategy is that top Google search results do not necessarily have the highest centrality (Gloor et al., 2009). Google sorts search results using the PageRank algorithm, which looks at the Web pages linking back to a particular page (Brin & Page, 1998). In terms of social network analysis, Google measures the in-degree of a page, that is, the number of incoming links from its nearest neighbors. The more pages link to a particular page, the higher is its page rank. This algorithm also accounts for the page ranks of neighboring pages, assigning more weight to incoming links from sites that themselves have a high page rank. In contrast to this static linking structure, the Condor approach based on betweenness or degree centrality is a dynamic concept as it looks at all the shortest paths within the local network that go through a particular node. Therefore, a node that has a high page rank does not necessarily also exhibit high betweenness or degree centrality (Gloor et al., 2009).

The same approach can also be applied to Twitter, where the network is constructed through retweets, i.e the search terms are the central nodes, and the degree-of-separation network is constructed by users retweeting tweets containing the search term. For Wikipedia, the network is computed through Wikipedia pages originating from, and linking back to the companies Wikipedia pages.

4.2 Data collection

In order to rule out the effect of national and regional differences, the 489 firms investigated in this paper are firms in different industries listed on the American and Chinese stock markets. By focusing on subcategories of each industry, we obtained comparable industry categories of the China and U.S. stock markets, and paired them for the following comparative analysis. In order to get scientific results for correlation analysis, most of the industries we selected have more than 50 listed firms. In each industry, we sorted firms by Market Capitalization (Market Cap.) from highest to low. We took the 50 firms with the highest market capitalization as our research sample in each industry to avoid the impact of scale and market capitalization differences. To better understand the characteristics of different Web 2.0 media, we collected the firms' online social network data from Google Blog Search, Bing Search, Twitter, and Wikipedia. For each firm, we collected its top 20 results by betweenness and set Degree of Separation as defined in the previous section to "2" (Gloor & Zhao, 2004). Data from Google Blog and Twitter was collected periodically from May 1, 2012 to July 31, 2012 to even out short-term fluctuations. Table 1 shows the general information of the firms we investigated.

U.S. Industry	U.S. Firm number	Chinese Industry	Chinese Firm number
Technology	50	Information Technology	50
Transportation	50	Transportation & Storage	50
Financial	50	Finance & Insurance	39[1]
Utilities	50	Electricity, gas and water production and supply	50
Chemical manufacturing	50	Chemical manufacturing	50
Sum	250	Sum	239

Table 1. Detailed classification information of the public companies (listed companies) investigated

In addition to online social network data, a firm's financial performance is measured by its real-time market capitalization, annual revenue, and annual net income. While there are many ways to identify the fair market value of a company such as Discounted Cash Flow (DCF), Return on Equity (RoE) and factoring Intangible Assets (Hooke 2010), market capitalization represents the public's consensus on the value of a company's equity. Market capitalization, annual revenue, and annual net income are important indicators of a firm's financial performance (Hooke 2010). While market capitalization indicators poorly reflect the underlying decision-making processes at the firm

[1] Only 39 Finance & Insurance companies are listed in China.

level, the overall aim of our study is to approximate firm value from the stock market perception of it as a benchmark, and not to assess the underlying firm valuation as such.

As second criteria for future performance we take capability of a firm to innovate. The link between a firm's capability to innovate, and its future performance has been shown many times (Drucker 1984, Christensen 1997, Gloor 2005). To measure innovation, we use the innovation capability ranking data of 'The World's 50 Most Innovative Companies 2012' evaluated by American entrepreneurship journal "Fast Company" and gathered these companies' social network data everyday from Twitter during July 2012.

5 Results

5.1 Online social network centrality and a firm's innovation

The resulting betweenness and degree centralities of 'The World's 50 Most Innovative Companies 2012' calculated from the Twitter retweet network are shown in table 2 below (Variables: *RK* is innovation capability ranking; *BC* is betweenness centrality; *DC* is degree centrality; innovation capability ranking data is from "Fast Company"). The value of *RK* is from 1 to 50, which means the smaller the *RK* value is, the more innovative the company is.

Table 2. The betweenness centrality and degree centrality of 'The World's 50 Most Innovative Companies 2012' [2]

[2] http://www.fastcompany.com/section/most-innovative-companies-2012

RK	Company	*BC*	*DC*
1	Apple Inc.	0.0998	23
2	Facebook	0.1154	43
3	Google	0.0742	61
4	Amazon.com	0.0551	16
5	Square Inc.	0.0052	18
6	Twitter	0.0401	45
7	Occupy Movement	0.0204	39
8	Tecent	0.0001	10
9	Life Technologies	0.0071	33
10	SolarCity	0.0889	35
11	HBO	0.0971	66
12	New Hampshire College	0.0833	16
13	Tesla Motors	0.0001	23
14	Patagonia	0.0313	53
15	National Football League	0.0001	19
16	National Marrow Donor Program	0.0002	18
17	Greenbox	0.0002	30
18	Jawbone	0.0410	42
19	Airbnb	0.0415	55
20	72andSunny	0.0116	43

21	Siemens	0.0880	39
22	Dropbox	0.0246	53
23	Kiva Systems	0.0264	21
24	Starbucks	0.0718	46
25	Genentech	0.0138	31
26	LegalZoom	0.0107	39
27	Tapjoy	0.0608	29
28	Polyore	2.5E-05	3
29	Red Bull Media House	0	1
30	LinkedIn	0.0607	43
31	Liquid Robotics	1.6E-05	10
32	Gogo	0.0006	37
33	Bug Agentes Biologicos	0	1
34	Chipotle	0.0299	41
35	James Corner Field Operations	2.6E-06	7
36	Narayana Hrudayalaya Hospital	1.2E-05	21
37	Recyclebank	0.0001	34
38	UPS	0.0010	38
39	Networked Insights	0.0080	11
40	Chobani	0.0422	57

41	Kickstarter	0.0321	60
42	SoundCloud	0.0008	37
43	PayPal	0.0550	55
44	Berg	0.0006	29
45	Boo-box	0.0171	38
46	Amyris	0.0002	36
47	Knewton	0.0085	24
48	RedBus	8.5E-06	2
49	OpenSky	0.0234	43
50	Y Combinator	0.0642	38

We studied the relationships of betweenness centrality *(BC)*, degree centrality *(DC)* and innovation capability ranking (*RK*). The hypotheses were tested using Pearson and Spearman correlation with two-sided test analysis for linear or nonlinear correlation analysis. The correlation coefficient for betweenness centrality and innovation capability ranking is *-0.399*, showing significant negative correlations for these 50 firms ($p<0.01$). This result shows that the bigger a company's betweenness centrality in the bipartite Twitter graph is, the more innovative it is. Hypothesis *H1a* is thus confirmed through the correlation analysis: the more innovative a company is, the more do the most influential Twitterers tweet about it.

Unlike betweenness centrality, there is no significant correlation coefficient between degree centrality and innovation capability ranking ($R=-0.046$). Hypothesis *H2a* is not supported.

5.2 Analyzing correlation between online social network centrality and financial performance

Considering that Twitter and Wikipedia are not widely used in China, the online social network data of the two countries' listed firms in different industries is collected through Google Blog Search and Bing Search. For the U.S. firms we additionally collected social network data from Twitter and Wikipedia for further analysis. Then we calculated betweenness centrality and degree centrality of these firms with Condor. The two countries' listed firms in different industries were separately studied. *Figure 2* shows the online social network of the 50 Science and Technology firms in United States stock market (data collected using Google blog search in May-July, 2012), and *figures 3* and *4* below separately show this social network graph colored by actor betweenness centrality and degree centrality. The greater an actor's betweenness centrality or degree centrality is, the redder and bigger it's representing square.

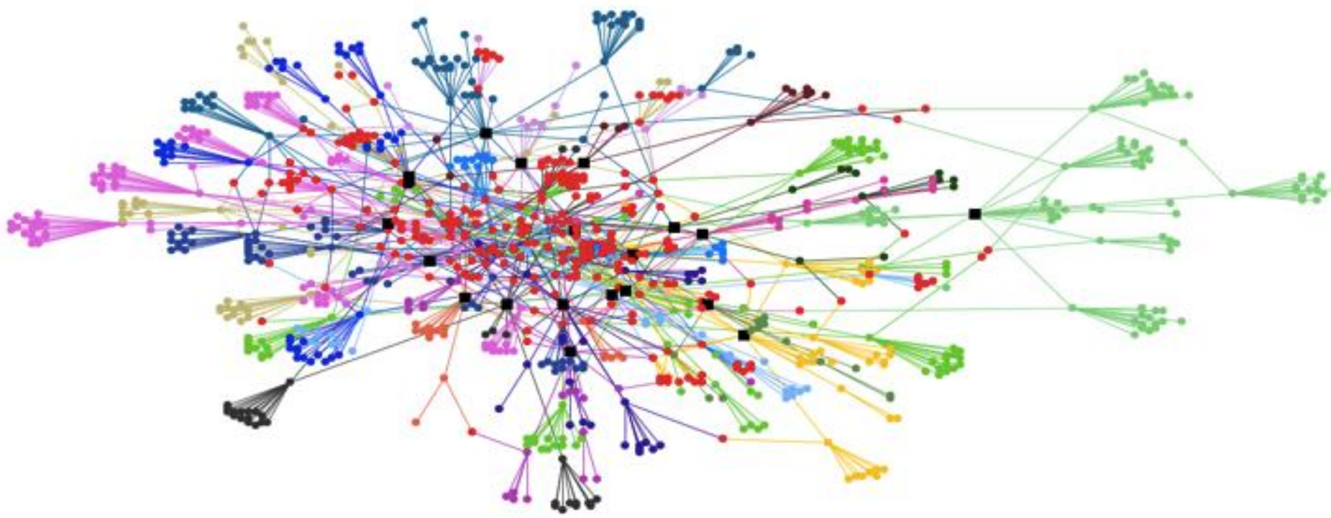

Figure 2 The online social network of 50 science and technology firms listed in the US stock market

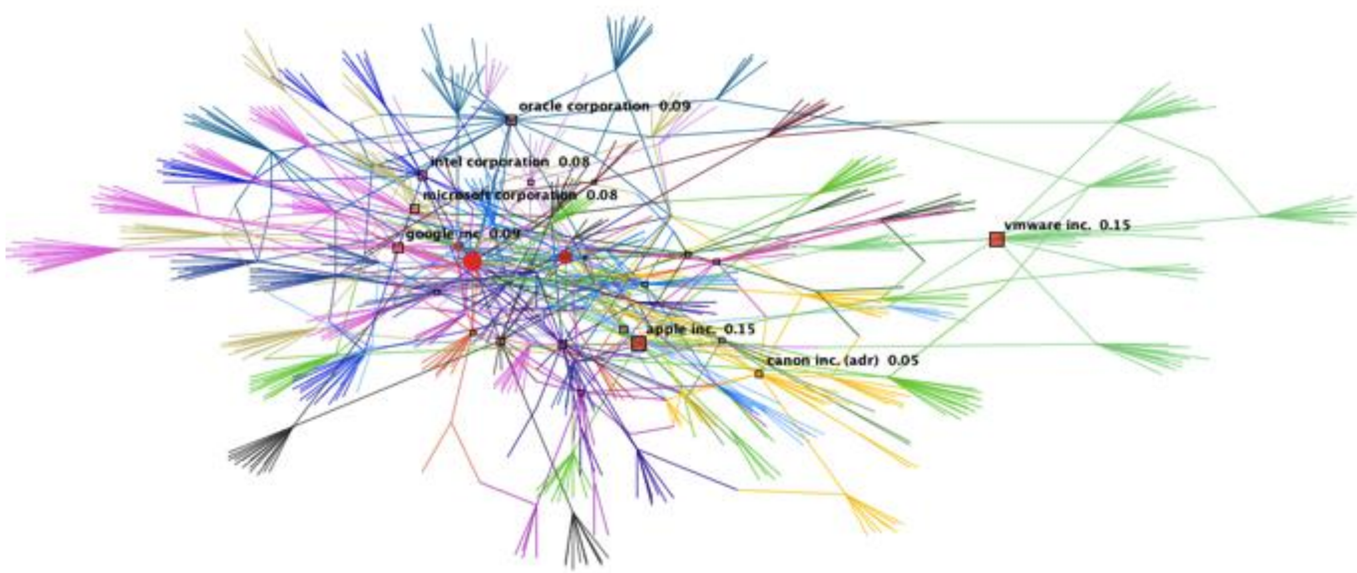

Figure 3 The online social network of 50 science and technology firms listed on the US stock market (node size is actor betweenness centrality)

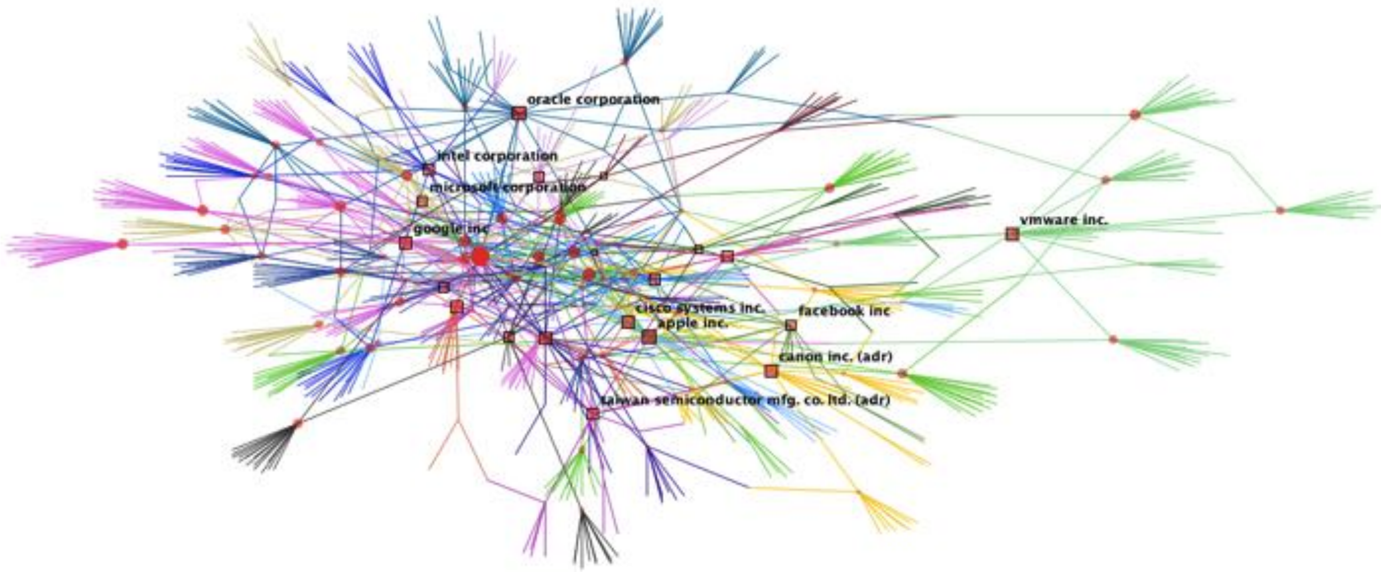

Figure 4 The online social network of 50 Science and Technology firms in the US stock market (node size is actor degree centrality_

The results of the correlation analysis are shown in *tables 3* to *8* (data collected during May-July, 2012). We are not using QAP and p* models (Borgatti & Feld, 1994), as we are not comparing network metrics between the different networks, but doing an "egocentric analysis" comparing structural actor-level network metrics with endogeneous variables. As evident from *table 4* and *table 7*, positive correlations are recorded for betweenness centrality and financial performance indicators for most Chinese firms (data collected from Google blog search) and U.S. firms (data collected from Twitter and Wikipedia). Therefore *H1b* is confirmed to some extent in the correlation analysis for most firms in the different industries, suggesting that network's betweenness centrality indicates a firm's financial performance, especially its market capitalization. However when we analyzed data collected from Bing search (*tables 3*, *4*), we found no significant correlation for most of the firms.

Table 3 Correlation coefficient of betweenness centrality and a firm's financial performance variables in the U.S. (Data collected from Google Blog and Bing during May-July, 2012)

Industry	Market Cap.		Ann. Revenue		Ann. Net Income	
	Google Blog	Bing	Google Blog	Bing	Google Blog	Bing
Technology	0.111	-0.189	-0.108	-0.204	0.035	-0.188
(*P-Value*)	(*0.445*)	(*0.249*)	(*0.457*)	(*0.214*)	(*0.812*)	(*0.251*)
Transportation	.524**	-0.06	.562**	0.041	.569**	-0.059
(*P-Value*)	(*0*)	(*0.677*)	(*0*)	(*0.779*)	(*0*)	(*0.686*)
Financial	.407**	-0.09	.488**	-0.092	.360*	-0.107
(*P-Value*)	(*0.004*)	(*0.534*)	(*0*)	(*0.525*)	(*0.011*)	(*0.46*)
Utilities	0.044	0.149	0.015	0.07	0.197	0.271
(P-Value)	(*0.764*)	(*0.313*)	(*0.919*)	(*0.639*)	(*0.176*)	(*0.063*)
Chemical Manufacturing	-0.004	0.249	-0.107	.284*	-0.129	0.071
(P-Value)	(*0.98*)	(*0.081*)	(*0.46*)	(*0.046*)	(*0.373*)	(*0.624*)

** Significantly associated on .01 level (two-side); * Significant associated on 0.05 level (two-side)

Table 4 Correlation coefficient of betweenness centrality and a firm's financial performance variables in China (Data collected from Google Blog and Bing during May-July, 2012)

Industry	Market Cap.		Ann. Revenue		Ann. Net Income	
	Google Blog	Bing	Google Blog	Bing	Google Blog	Bing

Information Technology (*P-Value*)	.599** (*0*)	0.08 (*0.58*)	.562** (*0*)	0.094 (*0.518*)	.412** (*0.003*)	0.057 (*0.694*)
Transportation & Storage (*P-Value*)	.291* (*0.04*)	0.222 (*0.121*)	.356* (*0.011*)	.492** (*0*)	0.233 (*0.103*)	0.157 (*0.277*)
Finance & Insurance (*P-Value*)	.369* (*0.021*)	.414** (*0.009*)	.385* (*0.015*)	.408* (*0.01*)	.368* (*0.021*)	.351* (*0.028*)
Electricity, gas and water production and supply (*P-Value*)	.448** (*0.001*)	0.173 (*0.23*)	.280* (*0.049*)	.287* (*0.043*)	.313* (*0.027*)	0.035 (*0.808*)
Chemical Manufacturing (*P-Value*)	.338* (*0.017*)	-0.121 (*0.403*)	0.131 (*0.364*)	-0.132 (*0.361*)	0.169 (*0.24*)	-0.129 (*0.372*)

** Significantly associated on .01 level (two-side); * Significant associated on 0.05 level (two-sided)

As evident from *tables 5, 6,7, and 8*, when we analyze the data collected from Google blog search, Bing and Twitter, the correlation analysis shows that *H2b* is supported only for a few of the investigated firms because degree centrality and financial indicators exhibit weak or no correlation for most of the industries. Ranked by data from Wikipedia (*table 8*), *H2b* is supported for all investigated US firms.

Table 5 Correlation coefficient of degree centrality and a firm's financial performance variables in the U.S. (Data collected from Google Blog and Bing during May-July, 2012)

Industry	Market Cap.		Ann. Revenue		Ann. Net Income	
	Google Blog	Bing	Google Blog	Bing	Google Blog	Bing
Technology	0.12	.329*	-0.198	.307*	-0.012	.400**
(*P-Value*)	(*0.428*)	(*0.026*)	(*0.188*)	(*0.038*)	(*0.937*)	(*0.006*)
Transportation	0.038	0.178	0.24	0.182	0.053	0.125
(*P-Value*)	(*0.806*)	(*0.222*)	(*0.117*)	(*0.211*)	(*0.731*)	(*0.392*)
Financial	0.099	-0.004	0.233	0.014	0.085	-0.054
(*P-Value*)	(*0.503*)	(*0.978*)	(*0.11*)	(*0.926*)	(*0.568*)	(*0.718*)
Utilities	0.044	0.063	0.015	0.168	0.197	-0.107
(P-Value)	(*0.764*)	(*0.67*)	(*0.919*)	(*0.249*)	(*0.176*)	(*0.463*)
Chemical Manufacturing (P-Value)	-0.191 (*0.183*)	-0.168 (*0.422*)	-0.232 (*0.105*)	-0.392 (*0.053*)	-0.257 (*0.072*)	-0.25 (*0.228*)

** Significantly associated on .01 level (two-side); * Significant associated on 0.05 level (two-sided)

Table 6 Correlation coefficient of degree centrality and a firm's financial performance variables in China

(Data collected from Google Blog and Bing during May-July, 2012)

Industry	Market Cap.		Ann. Revenue		Ann. Net Income	
	Google Blog	Bing	Google Blog	Bing	Google Blog	Bing

Information Technology	0.01	0.117	0.189	0.164	-0.117	0.108
(*P-Value*)	(*0.945*)	(*0.461*)	(*0.204*)	(*0.298*)	(*0.432*)	(*0.496*)
Transportation & Storage	.355*	-0.078	.383**	-0.059	0.112	-0.015
(*P-Value*)	(*0.014*)	(*0.597*)	(*0.008*)	(*0.691*)	(*0.453*)	(*0.921*)
Finance & Insurance	0.071	0.004	0.06	0.003	0.041	0.027
(*P-Value*)	(*0.686*)	(*0.982*)	(*0.731*)	(*0.985*)	(*0.816*)	(*0.884*)
Electricity, gas and water production and supply	.400**	-0.172	.402**	-.358*	0.228	0.019
(*P-Value*)	(*0.004*)	(*0.253*)	(*0.004*)	(*0.015*)	(*0.112*)	(*0.898*)
Chemical Manufacturing	0.201	0.266	0.095	0.032	0.022	0.246
(*P-Value*)	(*0.161*)	(*0.089*)	(*0.514*)	(*0.842*)	(*0.879*)	(*0.116*)

** Significantly associated on .01 level (two-side); * Significant associated on 0.05 level (two-sided)

Table 7 Correlation coefficient of betweenness centrality and a firm's financial performance variables in the U.S. (Data collected from Twitter and Wikipedia during May-July, 2012)

Industry	Market Cap.		Ann. Revenue		Ann. Net Income	
	Twitter	Wikipedia	Twitter	Wikipedia	Twitter	Wikipedia
Technology	.480**	.611**	.392**	.509**	.521**	.536**
(*P-Value*)	(*0.001*)	(*0*)	(*0.007*)	(*0*)	(*0*)	(*0*)

Transportation	.537**	.673**	.516**	.534**	.525**	.473**
(*P-Value*)	(*0*)	(*0*)	(*0*)	(*0*)	(*0*)	(*0*)
Financial	.362*	.732**	0.162	.487**	.300*	.498**
(*P-Value*)	(*0.011*)	(*0*)	(*0.265*)	(*0*)	(*0.037*)	(*0*)
Utilities	.475**	.536**	0.067	.561**	0.227	.325*
(P-Value)	(*0.001*)	(*0*)	(*0.645*)	(*0*)	(*0.117*)	(*0.008*)
Chemical Manufacturing (P-Value)	.457** (*0.001*)	.498** (*0.001*)	.509** (*0*)	.671** (*0*)	.366** (*0.009*)	.439** (*0.008*)

** Significantly associated on .01 level (two-side); * Significant associated on 0.05 level (two-sided)

Table 8 Correlation coefficient of degree centrality and a firm's financial performance variables in the U.S.

(Data collected from Twitter and Wikipedia during May-July, 2012)

Industry	Market Cap.		Ann. Revenue		Ann. Net Income	
	Twitter	Wikipedia	Twitter	Wikipedia	Twitter	Wikipedia
Technology	0.008	.533**	0.057	.453**	0.027	.454**
(*P-Value*)	(*0.957*)	(*0*)	(*0.705*)	(*0.001*)	(*0.858*)	(*0.001*)

Transportation (*P-Value*)	.458** (*0.001*)	.675** (*0*)	.675** (*0*)	.675** (*0*)	.471** (*0.001*)	.492** (*0.001*)
Financial (*P-Value*)	0.144 (*0.325*)	.438** (*0*)	0.178 (*0.22*)	.594** (*0*)	0.094 (*0.522*)	.353* (*0.02*)
Utilities (P-Value)	0.119 (*0.416*)	.398* (*0.04*)	0.277 (*0.054*)	.353* (*0.04*)	0.112 (*0.443*)	.386* (*0.01*)
Chemical Manufacturing (P-Value)	.337* (*0.017*)	.449* (*0.01*)	0.228 (*0.112*)	.342* (*0.01*)	0.215 (*0.133*)	.494* (*0.001*)

** Significantly associated on .01 level (two-side); * Significant associated on 0.05 level (two-sided)

Tables 9 and 10 list the correlations between blog betweenness and degree centrality with market cap and total assets of all firms across the five industries for both the Chinese and US firms. The correlation between total assets and market cap for Chinese firms is much stronger than for US firms, illustrating that the Chinese stock market still seems to pursue a fundamental valuation strategy. On the other hand, the correlation between Web betweenness and market cap is much stronger for the US firms, illustrating that the Web is a much better mirror of the real world for the Western world than for China.

Table 9 Correlations between Chinese firms' blog betweenness and degree and market cap and total assets

		logtotalassets	betweenness	degree
marketcapital	Pearson Correlation	.647**	.169**	.069
	Sig. (2-tailed)	.000	.009	.291
	N	239	239	239
logtotalassets	Pearson Correlation		.402**	.209**
	Sig. (2-tailed)		.000	.001
	N		239	239
betweenness	Pearson Correlation			.536**
	Sig. (2-tailed)			.000

	N	239

Table 10 Correlations between US firms' blog betweenness and degree and market cap and total assets

		logtotalassets	betweenness	degree
marketcapital	Pearson Correlation	.413**	.260**	-.103
	Sig. (2-tailed)	.000	.000	.111
	N	241	241	241
logtotalassets	Pearson Correlation		.119	-.239**
	Sig. (2-tailed)		.066	.000
	N		241	241
betweenness	Pearson Correlation			.336**
	Sig. (2-tailed)			.000
	N			241

For the significant correlation between degree centrality and total assets of a firm, the picture is the opposite: for Chinese firms, degree centrality is positively correlated with the value of the assets of a firm, while for US firm total assets are significantly negatively correlated with degree centrality. This means that a US company with large assets on average has fewer blogs talking about it than a company with fewer assets. This result does not make sense. According to the results shown above, for every Chinese and US industry we analyzed, there is no correlation or week correlation between degree centrality and total assets. So, to some extent, the five industries' combined regression analysis results of degree centrality and market capitalization may not make any sense.

Regressing Chinese firms' blog betweenness against market capital as the dependent variable with total assets as control variable shows that the adjusted R squared increases from 0.416 to 0.423 when betweenness is added to total assets as additional explanatory variable (table 11). This means that both blog betweenness and total assets explain the market capitalization. Total assets explain a significant part of the market capitalization for the Chinese firm. However, the less central by betweenness the Chinese firm is, the higher is its market capitalization. Maybe, among the firms analyzed together here, there are some large-scale Chinese firms with low public perception; especially the state-owned firms care little about social network and public buzz. In China, state-owned firms play a dominant role in the national economy. Although the number of state-owned firms is comparatively small, their average size is among the largest in terms of assets or revenue. Among the top 500 enterprises in China and the Chinese firms among the Global 500 enterprises in "Fortune", most are state-owned. Chinese state-owned firms focus on basic and strategic industries that are closely related to people's livelihood and security. 80% of the state-owned firms focus on petroleum, petrochemical, power, telecommunications, defense and other pillar industries of transport, mining, and machinery. The state-owned firms can get active support and protection from the government. High assets, stability, social acceptance, relationship with the government etc. are more important for their growth and profitability than online social networking (Li 2006). In contrast, some private Chinese high-tech companies depend more on blogs or other social media sites.

This is very different for the US firms, where both total assets and Web betweenness are significant positive predictors of the market capitalization (table 12).

Table 11 Chinese firms' blog betweenness regressed against market capital (N=240) with total assets as control variable

	Model 1		Model 2	
	Standardized coefficient	sig	Standardized coefficient	sig
betweenness			-0.109	.044
Log total assets	0.647	.000	0.690	.000
R square adj	0.416		0.423	

Table 12 US firms' blog betweenness regressed against market capital (N=239) with total assets as control variable

	Model 1		Model 2	
	Standardized coefficient	sig	Standardized coefficient	sig
betweenness			0.214	.000
Log total assets	0.413	.000	0.387	.000
R square adj	0.167		0.209	

From these regression results, we notice that for Chinese firms, a firm's size measured as total assets plays a major role for its market capitalization. For US firms, their position on the Web – measured by betweenness centrality of their brand in the Blogosphere – significantly influences their market capitalization in addition to their total assets. The conclusion is that, at least until now, social networks and blogs are not yet major indicators of a company's valuation in China. This is very different for US firms, whose position on the Web is a significant predictor for their individual market capitalization.

6 Discussion

6.1 Difference between Online Social networks of U.S. and Chinese firms

Focusing on the data collected from Blog and Bing search networks, we find that most of the U.S. firms have more extensive and higher-density networks than Chinese firms. U.S. firm networks have more nodes and edges that are directly or indirectly linked. It therefore seems that these networks are more widely commercially used in the U.S. than in China. Even so, the blog networks show a significant correlation with firm valuation both for U.S. and Chinese firms.

Among the four online social media sources including Google Blog search, Wikipedia, Bing search and Twitter we find that blogs are still a major social media tool for Chinese firms. Blogs contain the latest information and combine the "wisdom of the crowd" with expert knowledge (Gloor et al., 2009). Web data mining gives valuable clues about firms as an aggregated indicator of a collective opinion. The firms investigated might be discussed on sites of varying popularity and actuality such as online news sites, company Websites, information Websites, etc..

Different from Chinese firms we find that for US firms its social network centrality does not always show significant relationship with financial performance when using data collected from blogs. We suspect two reasons: first, key opinion makers such as Reuters or Bloomberg have their own private blog platforms that are not directly linked into Google blog search; another reason is that more recent social media channels, such as twitter are more widely used now. Wikipedia, which is spontaneously created and edited by unpaid volunteers, thus truly reflects people's collective intelligence; also thanks to prominent placement among Google's search results, it has become a key Web 2.0 platform for a firm's network.

Furthermore, we find that data collected from Bing search shows no correlation between a firm's social network structure and performance. Bing search returns comprehensive and exhaustive search results, which however are not updated frequently enough to reflect latest developments. We speculate that this is one of the key reasons why we do not obtain correlation between a firm's social network position and its real-world standing reflected through market capitalization.

6.2 Managerial implications for the firms

The purpose of this paper is to study the relationship between online social network position, a firm's innovation and financial performance. The impact of online social networks on individuals' and groups' performance, as well as of offline social networks to a firm's performance has been well established in many studies. The relationship between a firm's online social networks structure and performance has been much less discussed. The mechanisms by which online social networks are reflected in a firm's performance are still not clear.

This study contributes to this emergent line of research by investigating the correlation between a firm's online social network centrality, innovation and its financial performance. Although causality is still unclear, our results suggest the importance of building well-connected online social networks for increasing a firm's performance. Our findings support earlier research results about social networks providing a firm with more access to resources, complementary skills, capabilities, and knowledge not internally available (Doving & Gooderham, 2008; Pittaway et al., 2004), extending them to the Internet. In this study we found that betweenness centrality of online social networks exhibits more significant correlation with a firm's performance than degree centrality. Degree centrality indicates the number of edges directly linked of an actor and to some extent reflects its level of activity and direct influence in the online social network. Most of the firms investigated in this paper have top market capitalization and are well known in their own right, so there is a small differentiation in their degree centrality except for the data collected from Wikipedia. In addition, even for a firm that has high degree centrality online, the nodes it links to may be not important in the social network. Therefore we can't determine the importance of a firm in its online social network by only measuring its degree centrality. Instead, betweenness centrality reflects the firm's intermediary effect and the capability of controlling resources of the online social network. The higher betweenness centrality is, the more important the firm is for the whole network, and the higher the reliance on it by the other nodes for communication. Firms with high betweenness centrality connect structural holes between other firms.

Therefore, in order to improve innovation and financial performance, firms should advance their online social network betweenness centrality by connecting to less "obvious" or prominent sources. Li (2009) details the level of social media engagement of companies in the top 100 global brands list from the 2008 BusinessWeek/Interbrand Best Global Brands ranking, describing how major companies are engaging with their customers and communities using social media. She found that the companies with the greatest social media depth and breadth into a group on average grew 18% in revenues over the last 12 months, compared to the least engaged companies who on average saw a decline of 6% in revenue during the same period. The same holds true for two other financial metrics, gross margin and net profit.

In fact, most of the firms with high market capitalization and online social network embeddedness are deeply engaged in social media. Apple, for instance, operates its own social networks including "Snaf.me[3]" and "Ping" which allows users to interact with Ping directly from iTunes and follow their favorite artists and friends to discover the music they are talking about, listening to and downloading[4]. Apple combines online shops and community networks to provide customers with an active online shopping environment. Apple uses e-mail marketing to optimize populations, delivery time, and interface elements, to get a good conversion rate. Microsoft also heavily invests in online social networking. For example it formally launched a new generation blog service named Windows Live Spaces in 2006, which includes blog, Web albums, and reminder updating. Windows Live Spaces also added new social networking features to help users search, discover, make new friends and expand their circle of friends. More recently Microsoft acquired Yammer, a provider of enterprise social networking services to increase the social networking capabilities of its SharePoint business collaboration platform[5]. SAP, which is ranked number 10 in a rating of the world's top 100 brands', is cooperating with different online social media channels (Li, 2009). SAP serves as an intermediary to promote the cooperation among its customs, partners and consultants through a series of social media tools in its online innovations community. Users can use SAP Tech Tour and SAP TechEd[6] to cooperate online. SAP's board

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[3] https://Snaf.me

[4] http://www.apple.com/itunes/ping/ (in the meantime discontinued)

[5] http://www.microsoft.com/en-us/news/Press/2012/Jun12/06-25MSYammerPR.aspx

[6] http://www.sdn.sap.com/irj/scn/sapteched

moderators, with members from inside and outside the firm post articles and invite others to discuss them.

All the steps described above increase the centrality of these companies in their online social network by connecting to different sources of varying prominence, thus bridging the structural holes in their online social networks.

7 Concluding Remarks

Calculating the online social network position and impact provides a novel way to measure the valuation and innovative capability of a company. Prominence in the online social network affords access for worldwide firms to communicate with each other. Firms therefore should try to act as network bridges for structural holes to get specific information and link different partners so as to boost their performance via their agility and network structure (Burt, 1992).

Some limitations of this paper must be noted. First, the data collected in this study is only from firms in specific industries of the United States and China. Therefore we make no claim to reflect the full breadth of the phenomena investigated. Furthermore, the databases we queried (with the exception of Wikipedia and Twitter.) do not contain longitudinal data that would be valuable to inform the debate on causality of social networks and the factors that facilitate performance. Future studies will have a wealth of information captured in all industries and countries, and may compare the data at different times. Also, although Twitter and Wikipedia are not widely used in China, some similar Web 2.0 tools, such as micro-blogging and Baidu Encyclopedia are popular in China. Data from these sources should be collected for future in-depth analysis.

In addition, mining these databases over extended periods of time will be useful to investigate whether intermediate variables mediate the online social network structure and performance relationship. It may also be interesting to explore if the social network position differentiates properties such as propensity to innovate, through which firms affect performance. This could be the subject of future research.

In this paper we have shown a new way to measure the valuation of a company by tapping the collective intelligence on the Web. By aggregating the back links from Wikipedia, Twitter, blogs, and the Web, we propose a transparent mechanism to give indications about the financial success of a company.

Acknowledgements

This research has been supported by National Natural Science Foundation of China Project No.71272144, Social Science and Humanity on Young Foundation of the Ministry of Education of China Project No.10YJC870044, and Soft science research project of Guangdong province No. 2013B070206046.

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