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 significant correlation between betweenness centrality and financial performance. We also find that Twitter, Wikipedia only predict a firm's performance in the US, which is not surprising as they are officially blocked in China. Blogs predict better in China than they do in the US, for they might still be the major social media tools for Chinese firms; while for U.S. firms, blogs have been supplemented by Twitter and Wikipedia.

Keywords online social network analysis, Web link structure, betweenness centrality, degree centrality, innovation, market capitalization, annual revenue, annual net income, performance, Bing, blog, Twitter, Wikipedia, China, United States

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.

These Web links can be taking as a proxy for cooperation among firms in the real world. Cooperation enables diversification and rapid technological development in changing economic environments and is 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, Nohria & Zaheer, 2000). Most of firms' social capital is embedded in relationships, communities, 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 Stanley Milgram (1967) laid an early theoretical foundation for social network research. Wellman (1997) points out that a major difference between

traditional sociology and social network theory consists of the social network combining actors' behavioral characteristics and social relations. 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, Haunschild & Phillips, 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).

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. In a study of investment banks, Podolny (1993) showed that syndicate relations between these banks not only led to resource transfers but that these relationships might provide some basis of status ordering to other market actors such as corporate issuers and investors. 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, Park, & Jack, 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. Guoshun 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 webpage interaction information semantics. Researchers studied how online social networks affected innovation performance in individuals or groups (Gloor 2003; Kidane & Gloor, 2005; Lau Tashiro, H., 2011; Bulkley & Van Alstyne 2006). Gloor, Dorsaz & Fuehres (2011) studied online social network structure and found that the centrality in the network predicted entrepreneurial and academic success. Cummings & Cross (2003) discovered that structural holes of leaders within groups as well as core-periphery and hierarchical group structures were negatively associated with performance.

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). 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.

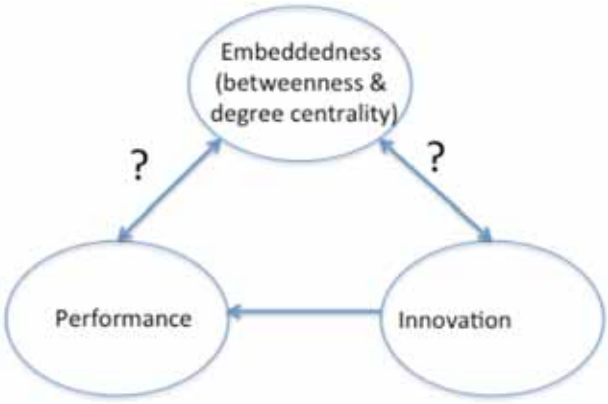

Figure 1 Research Framework

3.1 Betweenness Centrality, Firm Innovation and Financial Performance

Betweenness centrality represents the number of times 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 A., 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, Wu, & Luo, 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 approach described in Gloor et al. (2009), a Web mining approach tailored to social network analysis. Condor is based on a 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. The latter involves building a network map which displays the linking structure of a list of Web sites or blog posts returned in response to a search query, or the links among Twitterers retweeting an original Tweet (Gloor et al., 2009). Degree-of-separation searches are a practical way to find the most influential nodes in a given subset on the Web. By combining the nodes returned by different degree-of-separation searches, we can compare the betweenness or degree centrality of different individuals and identify those with the highest centrality values. Those individuals

represent bridging links on the Web or in the blogosphere.

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 and 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 has been

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.

Table 1. Detailed classification information of the firms investigated

United States Stock Market		China Stock Market	
Industry	Firm number	Industry	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

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. Market capitalization represents the public's consensus on the value of a company's equity. In a public corporation, ownership interest is freely bought and sold through purchases and sales of stock, providing a market mechanism, which determines the price of the company's shares. Market capitalization is defined as the share price multiplied by the number of shares issued, providing a total value for the company's outstanding shares[2]. Market capitalization, annual revenue, and annual net income are important indicators of a firm's financial performance. We therefore regard market capitalization as a direct reflection of the value of a firm's assets. As our innovation variable we use the innovation capability ranking data of 'The World's 50 Most Innovative Companies 2012' evaluated by American entrepreneurship journal "Fast Company".

4.2 Analysis and Results

4.2.1 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.

[1] Only 39 Finance & Insurance companies are listed in China stock market.
[2] http://en.wikipedia.org/wiki/Market_capitalization

Tabel 2 The betweenness centrality and degree centrality of 'The World's 50 Most Innovative Companies 2012' (Centrality data gathered everyday from Twitter during July, 2012)

RK	Company	BC	DC	RK	Company	BC	DC
1	Apple Inc.	0.09978581	23	26	LegalZoom	0.010740932	39
2	Facebook	0.11543908	43	27	Tapjoy	0.060798496	29
3	Google	0.07419833	61	28	Polyore	2.48203E-05	3
4	Amazon.com	0.055067394	16	29	Red Bull Media House	0	1
5	Square Inc.	0.005178027	18	30	LinkedIn	0.06067266	43
6	Twitter	0.040134616	45	31	Liquid Robotics	1.54511E-05	10
7	Occupy Movement	0.020421417	39	32	Gogo	0.000607299	37
8	Tecent	0.000109596	10	33	Bug Agentes Biologicos	0	1
9	Life Technologies	0.007127908	33	34	Chipotle	0.02985363	41
10	SolarCity	0.08891387	35	35	James Corner Field Operations	2.57854E-06	7
11	HBO	0.09712894	66	36	Narayana Hrudayalaya Hospital	1.17316E-05	21
12	New Hampshire College	0.08325199	16	37	Recyclebank	0.000130118	34
13	Tesla Motors	0.000126635	23	38	UPS	0.001036558	38
14	Patagonia	0.03130256	53	39	Networked Insights	0.007972238	11
15	National Football League	0.000131249	19	40	Chobani	0.042220958	57
16	National Marrow Donor Program	0.000176321	18	41	Kickstarter	0.032176487	60
17	Greenbox	0.000199528	30	42	SoundCloud	0.000788973	37
18	Jawbone	0.041014094	42	43	PayPal	0.05503279	55
19	Airbnb	0.04147076	55	44	Berg	0.000659262	29
20	72andSunny	0.011640396	43	45	Boo-box	0.017146481	38
21	Siemens	0.087966904	39	46	Amyris	0.00023132	36
22	Dropbox	0.024566114	53	47	Knewton	0.008479673	24
23	Kiva Systems	0.026415622	21	48	RedBus	8.53482E-06	2
24	Starbucks	0.07175948	46	49	OpenSky	0.02337713	43
25	Genentech	0.013765066	31	50	Y Combinator	0.064249806	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-side 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 *H1* 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 now significant correlation coefficient between degree centrality and innovation capability ranking (R=-0.046). Hypothesis *H3* is not supported.

4.2.2 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 US 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. *Figure 3* and *figure 4* below separately show the social network graphs 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 (Data collected using Google blog search in May-July, 2012)

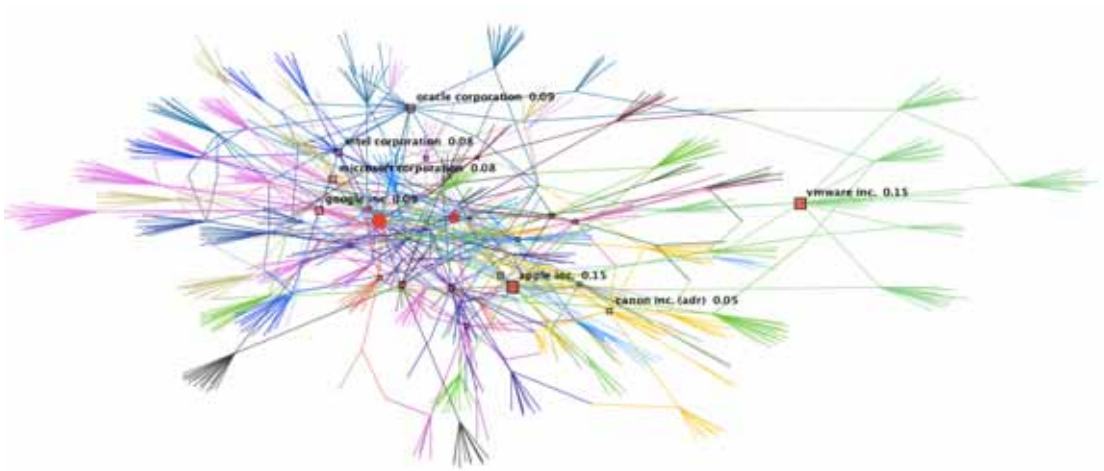

Figure 3 Social networks of 50 science and technology firms listed on the US stock market colored by actor betweenness centrality (Data collected from Google blog search during May-July, 2012)

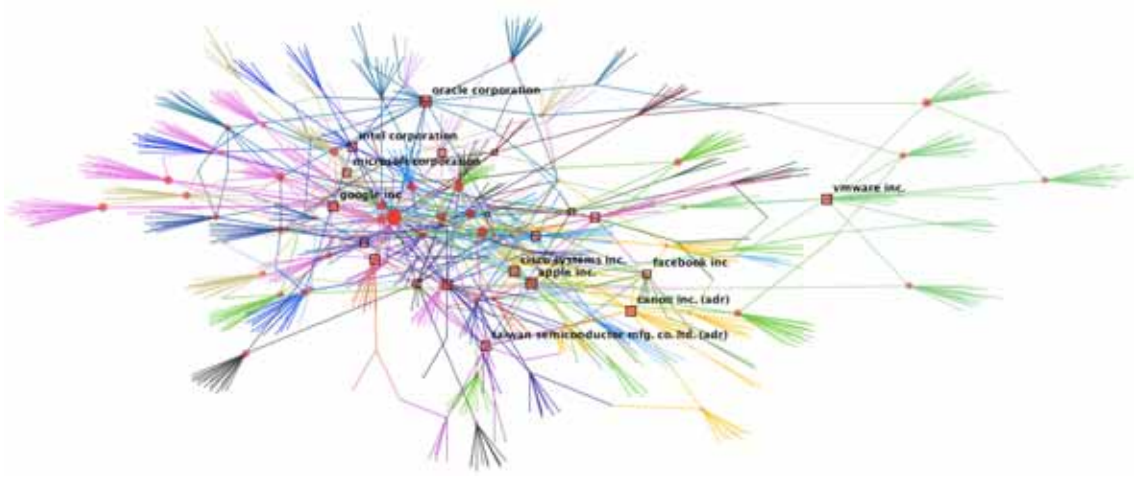

Figure 4 Social networks of 50 Science and Technology firms in the US stock market colored by actor degree centrality (Data collected from Google blog search during May-July, 2012)

The results of the correlation analysis are shown in *table 3* and *table 4*.

As evident from *table 3* and *table 4*, positive correlations are recorded for betweenness centrality and financial performance indicators for most Chinese firms (data collected from Google blog search) and for U.S. firms (data collected from Twitter and Wikipedia). Therefore *H2* is confirmed 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, we found no significant correlation for most of the firms.

Table 3 Correlation of betweenness centrality and a firm's financial performance in the U.S. and China stock markets in different industries (Data collected during May-July, 2012)

Correlation coefficient of betweenness centrality and financial performance variables													
United States Stock Market							China Stock Market						
Industry	Market Cap.		Ann. Revenue		Ann. Net Income		Industry	Market Cap.		Ann. Revenue		Ann. Net Income	
	Google Blog	Bing	Google Blog	Bing	Google Blog	Bing		Google Blog	Bing	Google Blog	Bing	Google Blog	Bing
Technology	0.111	-0.189	-0.108	-0.204	0.035	-0.188	Information Technology	.599**	0.08	.562**	0.094	.412**	0.057
(*P-Value*)	(0.445)	(0.249)	(0.457)	(0.214)	(0.812)	(0.251)	(*P-Value*)	(0)	(0.58)	(0)	(0.518)	(0.003)	(0.694)
Transportation	.524**	-0.06	.562**	0.041	.569**	-0.059	Transportation & Storage	.291*	0.222	.356*	.492**	0.233	0.157
(*P-Value*)	(0)	(0.677)	(0)	(0.779)	(0)	(0.686)	(*P-Value*)	(0.04)	(0.121)	(0.011)	(0)	(0.103)	(0.277)
Financial	.407**	-0.09	.488**	-0.092	.360*	-0.107	Finance & Insurance	.369*	.414**	.385*	.408*	.368*	.351*
(*P-Value*)	(0.004)	(0.534)	(0)	(0.525)	(0.011)	(0.46)	(*P-Value*)	(0.021)	(0.009)	(0.015)	(0.01)	(0.021)	(0.028)
Utilities	0.044	0.149	0.015	0.07	0.197	0.271	Electricity, gas and water production and supply	.448**	0.173	.280*	.287*	.313*	0.035
(*P-Value*)	(0.764)	(0.313)	(0.919)	(0.639)	(0.176)	(0.063)	(*P-Value*)	(0.001)	(0.23)	(0.049)	(0.043)	(0.027)	(0.808)
Chemical Manufacturing	-0.004	0.249	-0.107	.284*	-0.129	0.071	Chemical Manufacturing	.338*	-0.121	0.131	-0.132	0.169	-0.129
(*P-Value*)	(0.98)	(0.081)	(0.46)	(0.046)	(0.373)	(0.624)	(*P-Value*)	(0.017)	(0.403)	(0.364)	(0.361)	(0.24)	(0.372)

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

Table 4 Correlation of degree centrality and a firm's financial performance in the U.S. and China stock markets in different industries (Data collected during May-July, 2012)

United States Stock Market							China Stock Market						
Industry	Market Cap.		Ann. Revenue		Ann. Net Income		Industry	Market Cap.		Ann. Revenue		Ann. Net Income	
	Google Blog	Bing	Google Blog	Bing	Google Blog	Bing		Google Blog	Bing	Google Blog	Bing	Google Blog	Bing
Technology	0.12	.329*	-0.198	.307*	-0.012	.400**	Information Technology	0.01	0.117	0.189	0.164	-0.117	0.108
(*P-Value*)	(0.428)	(0.026)	(0.188)	(0.038)	(0.937)	(0.006)	(*P-Value*)	(0.945)	(0.461)	(0.204)	(0.298)	(0.432)	(0.496)
Transportation	0.038	0.178	0.24	0.182	0.053	0.125	Transportation & Storage	.355*	-0.078	.383**	-0.059	0.112	-0.015
(*P-Value*)	(0.806)	(0.222)	(0.117)	(0.211)	(0.731)	(0.392)	(*P-Value*)	(0.014)	(0.597)	(0.008)	(0.691)	(0.453)	(0.921)
Financial	0.099	-0.004	0.233	0.014	0.085	-0.054	Finance & Insurance	0.071	0.004	0.06	0.003	0.041	0.027
(*P-Value*)	(0.503)	(0.978)	(0.11)	(0.926)	(0.568)	(0.718)	(*P-Value*)	(0.686)	(0.982)	(0.731)	(0.985)	(0.816)	(0.884)
Utilities	0.044	0.063	0.015	0.168	0.197	-0.107	Electricity, gas and water production and supply	.400**	-0.172	.402**	-.358*	0.228	0.019
(*P-Value*)	(0.764)	(0.67)	(0.919)	(0.249)	(0.176)	(0.463)	(*P-Value*)	(0.004)	(0.253)	(0.004)	(0.015)	(0.112)	(0.898)
Chemical Manufacturing	-0.191	-0.168	-0.232	-0.392	-0.257	-0.25	Chemical Manufacturing	0.201	0.266	0.095	0.032	0.022	0.246
(*P-Value*)	(0.183)	(0.422)	(0.105)	(0.053)	(0.072)	(0.228)	(*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-side)

As evident from *table 4* and *table 6*, degree centrality and financial indicators exhibit weak or no correlation for most of the investigated firms in the different industries when we analyze the data collected from Google blog, Bing and Twitter. The correlation analysis shows that *H4* is supported only for few of the investigated firms.

4.2.3 Analyze centrality and financial performance using other social medias

Because Twitter and Wikipedia are not widely used in China, we only collect U.S. firms' data from two media sources. The results are shown in *table 5* and *table 6* below.

Table 5 Correlation coefficient of betweenness centrality and financial performance of U.S. firms (Data collected 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	.457**	.498**	.509**	.671**	.366**	.439**
(*P-Value*)	(0.001)	(0.001)	(0)	(0)	(0.009)	(0.008)

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

Table 6 Correlation coefficient of degree centrality and financial performance of U.S. firms (Data collected 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	.458**	.675**	.675**	.675**	.471**	.492**
(*P-Value*)	(0.001)	(0)	(0)	(0)	(0.001)	(0.001)
Financial	0.144	.438**	0.178	.594**	0.094	.353*
(*P-Value*)	(0.325)	(0)	(0.22)	(0)	(0.522)	(0.02)
Utilities	0.119	.398*	0.277	.353*	0.112	.386*
(*P-Value*)	(0.416)	(0.04)	(0.054)	(0.04)	(0.443)	(0.01)
Chemical Manufacturing	.337*	.449*	0.228	.342*	0.215	.494*
(*P-Value*)	(0.017)	(0.01)	(0.112)	(0.01)	(0.133)	(0.001)

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

5 Discussion

5.1 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 it's real-world standing reflected through market capitalization.

5.2 Management and financial revelation 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 of 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. Charlene 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 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.

6 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

[3] http:// Snaf.me
[4] http://www.apple.com/itunes/ping/
[5] http://www.microsoft.com/en-us/news/Press/2012/Jun12/06-25MSYammerPR.aspx
[6] http://www.sdn.sap.com/irj/scn/sapteched

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.

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