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Measuring social influence for firm-level financial performance

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ABSTRACT

Social influence is a universal concept that measures the interactions and links between entities. Existing social influence research primarily focuses on friendship networks among people. We propose a general approach to measure social influence in a type of objective entity, specifically in company networks. To construct the company influence network, we mine network links (company relationships) from the news and obtain node attributes (company influence) from search indices. Using the company influence network, two social influence measures are explored: the number of peers and weighted peer effects. To address time-series data, all variables are integrated into a vector autoregression model to forecast the company's financial performance in terms of stock return and risk. The results of our simulation and robust testing suggest that our social influence measures have the power to predict firm financial performance.

1. Introduction

Social influence is defined as the change in an individual's thoughts, feelings, attitudes, or behaviors that result from interactions with another individual or a group (Rashotte, 2007). Social influence is transmitted through social networks and has a strong impact on individual behavior (Amaldoss and Jain, 2015). For example, William Johnson, an editor at Big Eye Deers, reported that 81% of respondents indicated that posts from their friends and family directly influenced their purchase decisions (smallbiztrends.com/2014/10/influence-consumer-purchase-decisions.html). The social influence effect also occurs with social entities other than humans. For example, the performance of a firm is affected by its related companies. Michael Porter, a professor at Harvard Business School, and James Heppelmann, the president and CEO of the software company PTC, have said that connected products increasingly strengthen the relationships between companies, and, in such situations, the performance of one company can significantly affect other companies (hbr.org/2015/10/how-smart-connected-products-are-transforming-companies). Some supply chain studies have also demonstrated that a firm's performance is strongly affected by companies it cooperates with (Cao and Zhang, 2011; Huo, 2012; Tan et al., 1998).

In past research, social influence has been demonstrated to have enormous impact on individual behavior, such as purchasing (Sridhar and Srinivasan, 2012; Wang et al., 2012) and decision-making (Baddeley and Parkinson, 2012; Zhou, 2011). For example, Lee et al. (2011) found that positive social influence reinforces the relationship between beliefs and attitudes toward online shopping, as well as the relationship between attitude and intention to shop. Kwon et al. (2014) investigated the influence of peer behavior on group formation in social network sites. In these studies, there was a focus on friendship networks in which the participants are people.

As web-based applications have evolved, public information has provided a great number of resources to discover the nature of relationships between entities, especially between products and companies. As opposed to humans, who have social intelligence and emotions, the social relations between such objective entities are virtual and stable. Thus, methods of measuring social influence on objective entities should be different from previous studies on friendship networks. Zhang et al. (2013a,b) mined product networks based upon product reviews, and investigated the impact of network structures on product sales. To construct a company network, Ma et al. (Ma et al., 2011, 2009) focused on network links, and companies' competitive relationships (supporting or opposing). The social influence of company networks has also been investigated in network structures (Creamer et al., 2013; Jin et al., 2012).

We focus on the company influence network, which includes network links (company relationships) and node attributes (com-

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pany influence), and companies' financial performance to investigate how to objectively measure social influences. We ask:

(1) How is the company influence network constructed?
(2) How can the social influence effect be measured in an *objective entity network* (OEN)?
(3) Does social influence affect a company's financial performance?

We propose a novel method to construct the company influence network and measures of social influence. We use *vector autoregression* (VAR) in our simulation work. This method allows us to examine the immediate and lagged effects of social influence on a firm's performance, and it accounts for biases such as endogeneity, autocorrelation and reverse causality (Luo et al., 2013). This method also captures the carry-over effects over time through *generalized impulse response functions* and facilitates the assessment of the relative contribution of the different variables through *generalized forecast error variance decomposition* (Pesaran and Shin, 1998).

This study contributes to the literature in several ways. First, we propose a general approach to measure social influence in an OEN. It works well in company networks to measure social influence and demonstrates predictive power for financial performance, which can also be studied in other OENs, such as product networks and financial institution networks. Second, we use a VAR model to handle time-series data and estimate correlations. This study extends existing prior research on static models. Third, our approach combines multiple data sources, including news and search indice, to measure social influence.

2. Theory

2.1. Social influence

Social influence has been extensively researched in Social Science (Lewis et al., 2012), Marketing and Information Systems (Jin et al., 2012). These studies have indicated the strong effects of social influence on an *actor's behavior* (AB) (whether an actor will join a group, buy a product, behave in the same manner as their friends) and on an *actor's performance* (AP) (a product's sales, stock return, or risk). In Table 1, we summarize social influence research, which has mostly been related to human social networks. Zhang and Kline (2009) constructed a friendship network based on a questionnaire with 616 college student respondents. They examined the comparative influence of network neighbors on mate selection. Kwon et al. (2014) used social media communication data to build a *friendship network* (FN) and found social influence with respect to online behavioral choice. Social influence is measured by *network structure* (*NS*), *peer interaction* (*PI*), and *peer effects* (*PE*) in terms of peer behavior or peer attitude.

Structural holes theory (Burt, 2002, 2004, 2009) acknowledges that actors, including people and other objective entities (organizations, markets, stocks, products) are in a better position to profit from their relationships (interactions, transactions) with others if they are connected to others who are not themselves connected or well organized. The theory admits the existence of relationships among the objective entities, and these relationships are often studied in the form of networks, such as firm networks, and product networks. In firm networks, the relationship is often constructed by firm collaboration (Powell et al., 1996; Stuart, 1998) and has effects on firm innovation (Schilling and Phelps, 2007) and firm performance (Ang, 2008).

Furthermore, Barley (1990) investigated influence among organizations and studied the impact of organizations' social networks on the technologies they employ. Stuart et al. (Stuart et al., 1999) explored how company networks affect their ability to acquire the resources that are necessary for growth. As for previous research on product relationships, Raeder and Chawla (2009) used purchase data to construct a product network and researched how products might influence the sale of other products. Furthermore, a complex product network is composed of the different parts of a whole product, and a network structure has been used to assess change impacts on complex products (Cheng and Chu, 2012). The product relationship is also considered to present new product launch strategies (Lee and O'Connor, 2003).

As for social influence in OENs, most studies have focused on the basic influence of network structure on firm financial performance (see Table 1). For example, Creamer et al. (2013) constructed a company network by mining corporate news and analyzed the impact of network centrality on firm return and risk. Firm financial performance was investigated through company social network structure, such as degree and centrality in Ma et al. (2009). Zhang et al. (2013a,b) analyzed product sales ranking within a product network, constructed through online word-of-mouth. They tested the predictive power of network structure such as betweenness centrality, closeness centrality, PageRank centrality, and HITS centrality in forecasting product sales performance.

We extend social influence research on OENs and construct social influence measures for company influence networks. This

Table 1
A summary of social influence research.

Study	Network type		Social influence			Dependent variables		Research method				
	FN	*OEN*	*NS*	*PI*	*PE*	*AB*	*AP*	*CA, UMA*	LR	LOR	SEM	Others
Zhang and Kline (2009)	√				√	√			√			
Lewis et al. (2012)	√		√		√	√						SABM
Kwon et al. (2014)	√			√		√				√		
Singh et al. (2011)	√			√			√		√			
Lee et al. (2015)	√				√	√					√	
Iyengar et al. (2011)	√		√		√	√		√				HM
Sridhar and Srinivasan (2012)	√				√		√		√			
Nitzan and Libai (2011)	√		√	√		√						HM
Onnela and Reed-Tsochas (2010)	√				√	√		√				
Zhou (2011)	√			√		√					√	
Creamer et al. (2013)		√	√				√	√				
Ma et al. (2011)		√	√				√			√		Decision tree
Ma et al. (2011)		√	√			√						Classification
Jin et al. (2012)		√	√				√		√			
Zhang et al. (2013a,b)		√	√				√		√			

Note: LR: linear regression; LOR: logistic regression; SEM: structural equation model; CA: Correlation Analysis; UMA: univariate or multivariate analysis; SABM: stochastic actor-based modeling; HM: hazard model.