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Network Prominence in Social Network Services and Seller Performance in Social Marketplaces: An Exploratory Study

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Abstract: Social network services (SNS) have been used to support sellers in e-commerce marketplaces for years. It offers multiple affordances to sellers to promote their products, maintain relationships with customers and learn from other sellers. However, the open nature of online SNS also fosters competition as sellers can closely follow each other. How SNS impacts the sales performance of online sellers has not been studied in the literature. This research presents a preliminary study to explore the role of SNS on the performance of online sellers, with a focus on seller's network prominence in SNS. Four types of network prominences are proposed in the research and data from 83,462 stores were collected over two years to empirically verify our hypotheses.

Keywords: social network service (SNS), network prominence, social marketplace, sales performance

1. INTRODUCTION

Social network services (SNS) are a web-based service that allows individuals to construct a public or semi-public profile within a bounded system, articulate a list of other users with whom they share a connection, and view and traverse their list of connections and those made by others within the system [1]. SNS, also called open social graph, is one of the major enablers of social marketplaces such as EBay and Etsy. It has multiple and conflicting affordances. On one hand, it bonds buyers with common product interests together and facilitates product discovery. It also supports seller's reputation building and social learning from peers. On the other hand, the open social structure of SNS intensifies competition among sellers and causes knowledge and customer spillover. However, to date there is limited understanding of the role of SNS as an open social graph in the field of e-commerce, particularly on its implication to sellers [2].

Based on the social network theory, this study makes preliminary efforts to understand the impact of structural embeddedness of online stores in SNS on their sales performance. We focus on the role of network prominence, an important aspect of structural embeddedness. Network prominence represents a store's network position and has been studied under the concept of centrality in the literature.

2. THEORETICAL BACKGROUND

Social network analysis (SNA) is the process of investigating social structures through the use of networks and graph theory [3]. Centrality is a key measure of network prominence in SNA [3,4]. It is the extent to which a focal actor is linked to others and occupies the central position in a network. High centrality is normally considered a strategic position in which an organization achieves high status within the network. There are a wide variety of centrality measurements, and in this research, we focus on studying the impact of degree centrality. Degree centrality is the number of direct ties a node owns in the network. It reflects the relative dominance of a single node and its popularity, active participation and involvement in the network [4].

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3. HYPOTHESES

In social marketplaces, there are two prominent groups of SNS users, buyers and sellers. The two groups, although mixed together in SNS, join and use the SNS functionalities with different purposes and should be studied as separate networks in order to tease out the differential impacts of network position on store performance. In both networks, we distinguish between outdegree and indegree centrality [4] as online SNS are directed networks. One can follow others and be followed by others. We propose four hypotheses:

H1: A seller's indegree centrality among buyers in online social marketplaces is positively related to the store sales, and such positive relationship is strengthened when a seller's indegree centrality increases. This is mainly due to the social capital, preferential attachment, directed social learning effects that a seller enjoys.

H2: A seller's outdegree centrality among buyers in online social marketplaces is positively related to the store performance, and such positive relationship diminishes with the increase of a seller's outdegree centrality. In other words, there is an inverted-U shape relationship between outdegree centrality among buyers and store performance. The U-shaped relationship is mainly due to the positive social learning effect and the negative information overload effect.

H3: A seller's indegree centrality among sellers in online social marketplaces is positively related to the store performance, and such a positive effect quickly diminishes with the increase of a seller's indegree centrality. In other words, there is an inverted U shape between indegree centrality among sellers and store performance. This is mainly because the signaling, social learning and bridging effects that a seller enjoy, but such benefits can be eroded by the negative effect of competitive ties.

H4: A seller's outdegree centrality among sellers in online social marketplaces is negatively related to the store performance, and such a negative relationship is weakened with the increase of a seller's outdegree centrality. In other words, there is a U shape relationship between indegree centrality among sellers and store performance. This is mainly because the negative social imitation effect can be offset by the positive customer bridging effect that a seller enjoys.

4. DATA COLLECTION, ANALYSIS AND RESULTS

We collect social network data from Etsy, a social marketplace that support the sales of crafts and vintage or creative products. We crawled its SNS data for 104,674 sellers in June 2017 and 2018, respectively. Our final sample includes 83,462 stores and a two period, balanced panel data of 166,924 observations.

Because the dependent variable is a count of number of products sold or favorited, and the variance of our dependent variable exceeds its mean, we adopt the negative binomial model. Since we have a two period panel data, we use fixed effect negative binomial model in this research [5]. The fixed effect model can allow us to control non-observable stable store variables.

Table 1 regression results

	Dependent variable: *Sales*		
	(1)	(2)	(3)
lg_*NumProd*	0.348***	0.277***	0.276***
	(0.00226)	(0.00211)	(0.00211)
lg_PriceMed	-0.125***	-0.244***	-0.247***
	(0.00254)	(0.00234)	(0.00233)
NumChannels	-0.0353***	-0.0589***	-0.0524***
	(0.00936)	(0.00912)	(0.00901)
Instagram	0.0451***	0.0942***	0.0735***
	(0.0115)	(0.0109)	(0.0108)
Blog	0.0938***	0.00519	0.00158
	(0.0140)	(0.0128)	(0.0126)
Facebook	0.116***	0.0881***	0.0691***
	(0.0118)	(0.0112)	(0.0111)
Pinterest	-0.0299**	0.0640***	0.0694***
	(0.0126)	(0.0118)	(0.0117)
Twitter	0.0644***	0.0368***	0.0489***
	(0.0127)	(0.0118)	(0.0117)
website	0.149***	0.133***	0.118***
	(0.0121)	(0.0114)	(0.0113)
Rating	0.0510***	0.0525***	0.0551***
	(0.00260)	(0.00248)	(0.00248)
lg_IndegBN		0.563***	0.356***
		(0.00283)	(0.00539)
lg_IndegBN^2			0.0365***
			(0.000804)
lg_OutdegBN		-0.0260***	0.0216***
		(0.00268)	(0.00537)
lg_OutdegBN^2			-0.0099***
			(0.000777)
lg_IndegSN		-0.151***	0.0596***
		(0.00294)	(0.00532)
lg_IndegSN^2			-0.0365***
			(0.000777)
lg_OutdegSN		-0.0748***	-0.0756***
		(0.00297)	(0.00535)
lg_OutdegSN^2			0.00581***
			(0.000800)
Constant	-1.690***	-1.173***	-1.189***
	(0.0168)	(0.0156)	(0.0158)
Observations	166914	166914	166914

$$\Pr(Y_{it} = y_{it}|x_{it}, \delta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)}\left(\frac{1}{1+\delta_i}\right)^{\lambda_{it}} \left(\frac{\delta_i}{1+\delta_i}\right)^{y_{it}}$$

Where: $y_{it} = Sales_{it}$

$\lambda_{it} = \exp(\alpha + \beta X_{it} + \gamma X_{it}^2 + \lambda Z_{it} + \varepsilon_{it})$ where

$X_{it} = [lg\_IndegBN_{it}\ lg\_OutdegBN_{it}\ lg\_IndegSN_{it}\ lg\_OutdegSN_{it}]$

$Z_{it} = [\lg\_PriceMed_{it}\ \lg\_NumProd_{it}\ Rating_{it}\ NumChannels_{it}$ $Instagram_{it}\ Blog_{it}\ Facebook_{it}\ Pinterest_{it}\ Twitter_{it}\ website_{it}]$

In the equation, δ_i is the dispersion parameter, X is a vector of dependent variables and Z is a vector of control variables. *SN* represents seller network and *BN* represents buyer network. We log-transform variables such as degrees, median prices and number of products since these variables are highly skewed.

Table 1 summarizes the regression results. We run three regressions: the regression with control variables only, with independent variables added, and with the quadratic terms of independent variables added. All the hypotheses are confirmed. We run several tests to test the validity of the results. For example, the model also may suffer from the problem of heteroskedasticity, we run the models with robust errors. The results of model are very robust, remain the same as the original model.

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