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Network closure among sellers and buyers in social commerce community

Bangming Xiao [a], Minxue Huang [a,*], Aaron J. Barnes [b]

[a] Economics and Management School of Wuhan University, Wuhan 430072, China
[b] College of Business, University of Illinois at Urbana-Champaign, USA

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ABSTRACT

Social commerce communities connect sellers and buyers and allow them to seek and share product information. Although the extant literature has realized its economic value, there has been little research on the antecedents of network closure in social commerce community with longitudinal network data. Based on the evolving network data from Taobao.com and network closure theory, this research analyzes network closure among sellers and buyers in social commerce community and we find that the drivers of network closure in social commerce communities vary across different types of relationships. Specifically, (1) from the buyers' perspective, they are more likely to follow other buyers and sellers through observational learning and contagion; (2) from the sellers' perspective, the homophily, reciprocity, and structural equivalence are the general mechanisms that drive them following both buyers and sellers; (3) the results from the robustness checks show that the findings would not be affected by the sample size or the duration of the observations.

This study contributes to the ongoing study of social networks analysis in social shopping and social commerce. Furthermore, the ties studied in this research connect both sellers and buyers, which are different from the ties of friendship in most social network literatures. Findings from this research will also help marketers better understand how social commerce community networks evolve and adjust their relationship management strategies.

1. Introduction

With the boom of social media, social network service (SNS) enables people to interact with each other and establish many kinds of communities online (e.g. Facebook, Twitter etc.). As the online communities grow in number and size, social networks among members evolve over time. Indeed, enterprises and marketers have derived economic value from these social networks (Stephen and Toubia 2010, Hinz et al. 2011, Libai et al. 2013). However, there is little knowledge regarding the antecedents of network evolution in many kinds of online communities. There are two typical kinds of online communities in the literature: (1) social community where members interact as friends, e.g. Facebook, MySpace (Ansari et al. 2011, Trusov et al. 2010) and (2) social commerce community where members, as strangers to each other, could seek or share product information for social shopping (Olbrich and Holsing 2011, Stephen and Toubia 2010), e.g. Epinions.com, Mogujie.com, and Taobao.com (consumers interact with each other in these platforms to seek and share product information) (Kumar et al. 2013). The purpose of this study is to understand the network evolution among consumers in social commerce communities and we choose this specific context for two reasons: (1) most members in a social commerce communities are strangers and their online interactions account for the entirety of the relationships among them, which helps us control the effect of their off-line interactions; (2) compared with the frequently studied social networks, e.g. Facebook, Twitter etc., whose economic value are questioned due to its indirect effect on business performance (Olbrich and Holsing 2011, Stephen and Toubia 2010), the social commerce community connects people where they intend to buy things (e.g. Epinions.com, Bangpai.taobao.com, etc.), which provide marketers with more efficient and direct commercial information (Curty and Zhang 2011, Kumar et al. 2013).

In the main body of this paper, network closure theory (Burt 1987, Allcott et al. 2007) is applied and several network closure mechanisms, including both external and internal effects, are operationalized to answer the following research questions: (1) what are the salient factors influencing users' intentions to initiate a

* Corresponding author. Tel.: +86 027 68753149.
E-mail addresses: bangmingshaw@163.com (B. Xiao), huangminxue@126.com (M. Huang), ajbarne2@illinois.edu (A.J. Barnes).

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tie with others in social commerce communities? (2) How do network closure mechanisms work differently for buyers and sellers in the community to build ties with others? In order to answer these questions, we reviewed the literatures regarding the network closure mechanisms and developed several hypotheses on the different mechanisms of network closure for sellers and buyers in social commerce communities. In addition, we built a hazard function (Cox 1992, Kleinbaum 1998) based on the network closure constructs in the modeling section and applied the Maximum likelihood approach for estimation. The remainder of the paper is organized as follows. In Section 2, the literature review and theoretical background are outlined and specific hypotheses are developed. Section 3 presents the data collection process and the hazard model upon which the hypotheses are examined. The operationalization of each construct (reciprocity, contagion, structural equivalence, and homophily) is also presented in this section. Section 4 shows the results from network visualization and hazard analysis, upon which we illustrate all of the results of model estimations and research findings. Section 5 is a discussion about the research findings including the theoretical and managerial contributions of this research. We conclude by offering limitations and directions for future research.

2. Literature review and hypotheses

2.1. Social commerce community

Social network sites (SNSs) are growing in number and size in the era of Web 2.0, and they are attracting more and more attention from both academics and managerial practitioners. These sites can be oriented towards work-related contexts (e.g., LinkedIn.com), romantic relationship initiation (e.g., the original goal of Friendster.com), connecting those with shared interests such as music or politics (e.g., MySpace.com), or the college student population (e.g., the original goal of Facebook.com) (Ellison et al. 2007). The network formation and evolution in these social network sites can vary significantly due to the nature of the relationship. Yet, they can all be demonstrated as complex systems with nodes and ties in social network analysis (Borgatti et al. 2009). In this paper, we focus on the social commerce community, which is comprised of both buyers and sellers, and we explore the network closure mechanisms among them over time. Social commerce communities (e.g. Ebay.com and its counterpart, Taobao.com in China) share some basic functions (e.g. social networking services, personal homepages, etc.) with other types of online communities, but they also have their own unique features. Both buyers and sellers—driven by different motivations—participate in the community and follow or be followed by others. In this way, the social networks in social commerce communities form and evolve over time. For example, members as buyers or sellers in Taobao.com can join in a certain community based on their own interests and once joined, they can interact with other buyers or sellers in the forum section; they can also follow or be followed by other buyers or sellers so that updated information such as product reviews, favorite items, and promotions or discounts (promotions and discounts are usually displayed in sellers' the electronic shops via hyperlinks on their personal homepages) can be shared through the hyperlinks in each member's personal homepage. Therefore, buyers' usually send out ties with both buyers and sellers to seek or share product information so that they can make better online shopping decisions; in contrast, sellers usually send out ties to generate awareness from buyers and cooperate or compete with other sellers (Stephen and Toubia 2010). Compared with other types of social network sites such as Facebook and Twitter, whose commercial value are questioned due to their indirect effects on business performance (Curty and Zhang 2011), the social commerce community connects people where they intend to buy or sell things, which can provide marketers with more efficient and direct commercial value (Marsden 2010).

2.2. Network closure in social networks

Investigating network closure in social networks is a complex undertaking due to the differentiated nature of ties among network members (Borgatti et al. 2009, Kossinets and Watts 2006). In general, the extant literature has proposed several major drivers of network closure that can be summarized into external and internal influences. The research stream focusing on the external influence (e.g. reciprocity, contagion, and observational learning) highlights the social influence from others within the same community and we generally argue that members in a certain community will learn, or merely imitate each other, and obey social norms so that they would increase similarity and build trust with each other. The literature focusing on the internal influence (e.g. structural equivalence and homophily (Kossinets and Watts 2006, Lewis et al. 2012)) highlights the selection effect on each community member and contributors generally argue that members befriend others who share similar features with them, such as common friends or joint participants (Kumar et al. 2013). We summarized the major variables of network closure from prior literature in Table 1, and included Fig. 1 to demonstrate the specific scenario of each variable in network closure. In the following section, we will illustrate the key variables one by one to understand the mechanisms of network closure in social networks.

2.2.1. Reciprocity and network closure

Reciprocity is a fundamental feature and generalized moral norm in interpersonal relationships that refers to the mutually contingent exchange of gratifications. It is usually analyzed in a dyadic view among community members (Gouldner 1960). For example, under the social norm of reciprocity, members would send back ties with those who originally sent ties to them. We summarize the variable of reciprocity as an external influence in Table 1 because it is usually a social norm from the community, and it is the response of a focal member to other users' actions (Falk and Fischbacher 2006).

2.2.2. Contagion and network closure

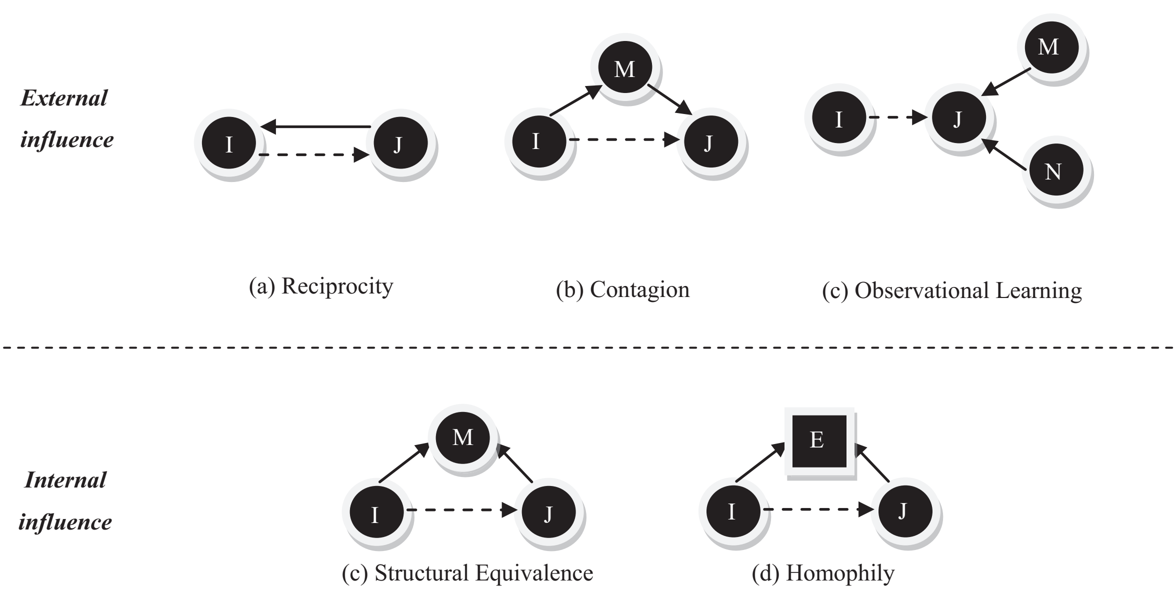
Contagion, another external influence, highlights the impact from neighbors. It generally means the nodes in a network would imitate the behaviors of others like an epidemic (Young 2009). Lewis et al. (2012) also argue that the members in a network may be similar due to peer influence or diffusion of their actions: the tendency for characteristics and behaviors to spread through social ties such that the members in a community increasingly resemble one another over time (Centola 2010, Rogers 2010). For example, members usually pay attention to their friends' personal homepages where their friends' followings are listed. If they find that certain members show up as followings on many of their friends' homepages, it will be more likely that they would also follow those members.

2.2.3. Observational learning and network closure

Bikhchandani et al. (1998) defined the term of observational learning, or social learning, as the influence resulting from rational processing of information gained by observing others. As another external influence, observational learning is different from contagion in that members would learn from all the members they can observe in the community rather than just their neighbors. In practice, the number of followers of each member in a community can usually be observed by anyone else. Thus, the hubs (members

Table 1
Literature on drivers of network closure in social networks.

	Variables	Definition	Mechanisms	Literatures
External influence	Social contagion	Cyclic closure, a tendency of clustering through the closure of triadic ties	Peer influence or diffusion: the tendency for behaviors to spread through ties such that friends increasingly resemble one another	Young (2009) and Lewis et al. (2012)
	Observational learning	The influence resulting from rational processing of information gained by observing others	Preferential attachment will make hubs more attractive	Bikhchandani et al. (1998) and Newman (2001)
	Reciprocity	Bi-directional confirmation, dyadic ties	A fundamental feature and generalized moral norm in interpersonal relationships	Gouldner (1960)
Internal influence	Structural equivalence	Mutual acquaintances, the number of common friends between two related users.	Structurally equivalent nodes have similar relations and they will be subject to similar behaviors	Burt (1987)
	Homophily	Homophily is the principle that a contact between similar people occurs at a higher rate than among dissimilar people	People's personal networks are homogeneous with regard to sociodemographic, behavioral, and intrapersonal characteristics and they usually interact with others similar to themselves	Kossinets and Watts (2006) and McPherson et al. (2001)



Note：Circles I,J,M,N refer to community member；
Square E refers to shared activity (post or reply to the same topic).

Fig. 1. Network closure drivers and scenarios.

who have relatively more followers than others in a community) are usually more attractive and more members would send out ties to them. This phenomenon is called "preferential attachment" and is also supported in the computer science literature. As Newman (Newman 2001) argues, the preferential attachment hypothesis has been shown to be quite successful to explain the existence of networks with power-law degree distributions. By studying the case of "CiteULike", Capocci and Caldarelli (2008) verified the significance of preferential attachment not only in social networks, but also in many other kinds of networks.

2.2.4. Structural equivalence and network closure

In contrast to the external influences we mentioned above, the internal influences from the literature highlight the similarities that already existed among community members. These similarities could be relational, structural, or behavioral (e.g. homophily). Prior literature generally suggests that members in a community would selectively follow others who are more similar to them (Burt 1997, Coleman 1990). Burt (1997) argues that "network closure" will happen between strangers when they have "common friends" and he labels this as structural equivalence. This is because structurally equivalent nodes in a network have similar relations with other nodes and they will be subject to similar thoughts and behaviors from their relations to others in the network no matter how they feel about each other (Friedkin 2006). Moreover, as the similarity of the relations with others increases between two nodes, their feelings of collaboration or competition also intensifies, increasing the likelihood of link between the two nodes (Burt 1997, Coleman 1990).

2.2.5. Homophily and network closure

The term homophily corresponds to the idea that "birds of a feather flock together" and is frequently used in the sociology literature (McPherson et al. 2001). As an internal influence, homophily generally suggests that links are more likely to form between members who share similar characteristics (demographical, cultural, etc.) or interests (activities, affiliations, etc.) (Crandall et al. 2008, Kossinets and Watts 2006). In a foundational study regarding the evolution of social networks among university students, Kossinets and Watts (2006) measured the homophily among university students by recording their demographical variables (age and gender) and affiliations to the same classes. Although it is difficult for us to get the real demographical information from the social commerce community users (for the concern of safety, demographical information is either hidden from others or intentionally falsified by community members), we can still infer the homophily among the community users from their activities within the community.

2.3. Buyers and sellers in social commerce community

As we mentioned above, the links among members in social commerce communities are different from the "friendship" in layman's terms and the reasons users connect are varied (Ellison 2007). Considering the different roles of members in a social commerce community, there are four types (2×2) of network closure: (1) links from buyers to buyers. Based on arguments from the social shopping literature, consumers are believed to rely on peers rather than marketers as their information sources (Trusov et al. 2010) and peer recommendations are desirable because they would trigger a sense of credibility and trust in consumers' minds; (2) links from buyers to sellers. Considering the commercial nature of social commerce communities, buyers would follow sellers so that they can receive updated information on items they were interested in. Furthermore, investing in relationships with sellers will help consumers express their specific needs and allow sellers to better meet those needs (Walter et al. 2001); (3) links from sellers to buyers. In order to generate awareness among buyers, sellers in a social commerce community would follow buyers, which can show the benevolence of sellers (Parvatiyar and Sheth 2001), involve the buyers in the early stages of product design, jointly provide supply and help increase demand, etc.; (4) links from sellers to sellers. Because the hyperlinks among sellers can increase the overall navigability and accessibility of the connected sellers' homepages, sellers in social commerce would follow other sellers so that the buyers can have more access to their online shops (Stephen and Toubia 2010). Additionally, the cooperative relationship among sellers (a kind of relationship that bears the features of both competition and cooperation) in a social commerce community would lead to enhanced performance for the partner sellers (Gnyawali and Madhavan 2001, Ross and Robertson 2007).

In social commerce communities, information seeking plays an important role when buyers and sellers build relationships with each other (Kirmani and Rao 2000) and there are two key issues confronted by both buyers and sellers in social commerce community: information asymmetry and information search cost. Buyers in a social commerce community must rely on information provided by sellers, without having the ability to judge quality before purchase, which creates information asymmetry. Information asymmetry leaves buyers vulnerable to potentially incomplete or distorted information transmissions (Lee et al. 1993), and poses a particularly serious threat in online transactions, because of the general lack of trust between buyers and sellers (Hughes et al. 2007). Furthermore, because of the many products/services offered by divergent sellers on the platform, buyers may incur high information search costs (e.g., time) as they seek well-matched sellers. Sellers in a social commerce community would also face high costs, such as those required to advertise to generate awareness and interest among potential buyers (Hendrix 1999). In sum, the external and internal influences on network closure in a social commerce community could be varied due to the different motivations of the community members of buyers and sellers. Next, we propose the hypotheses based on the different network closure drivers of community members as buyers and sellers.

2.4. Hypotheses of network closure in social commerce community

2.4.1. Network closure from the perspective of buyers

Due to information asymmetry, buyers cannot easily differentiate between high- and low-quality sellers, and some sellers that lack the resources to provide high-quality products might fraudulently claim to possess them, creating an adverse selection problem (Mishra et al. 1998). The inability to differentiate between high and low product quality poses a serious risk for buyers. In order to reduce the information asymmetry, buyers in a social commerce community could connect to other buyers or sellers to look for references or other product related information. In contrast to sellers, the information asymmetry makes buyers more likely rely on or learn from others' behaviors rather than their own activities in the community. Therefore, social contagion and observational learning would be more relevant to buyers than the other aforementioned tie formation factors (e.g. reciprocity, structural equivalence, and homophily). Since the information search costs (e.g. time) could be high (due to the large number of users in most social commerce communities), they could apply the following strategies to make ties formation more efficient (e.g. connecting to the members who can provide as much useful information as possible): (1) Imitate the behaviors of their familiar neighbors, a process we defined as social contagion within the local clusters (Kossinets and Watts 2006, Young 2009). This is because the familiar neighbors within the local clusters are usually more trust-worthy and can serve as reference group for the decision making of the focal buyer (Arnold and Reynolds 2003). (2) Learn from the experience of the "opinion leaders" (Iyengar et al. 2011, Trusov et al. 2010). This is represented in a process we defined as observational learning within the whole community (Bikhchandani et al. 1998, Chen et al. 2011). Opinion leaders are usually considered to have valuable information (e.g. fashion, reputation, et al.) and hence, are more attractive to others (Iyengar et al. 2011). Because the buyers could get information or references from both buyers and sellers, they could apply the same strategy why they try to connect to either group. Based on the above arguments, we proposed the hypotheses as follows:

H1a. As compared with sellers, buyers are more likely to build ties with other buyers in the community through (1) observational learning and (2) social contagion.

H1b. As compared with sellers, buyers are more likely to build ties with sellers in the community through (1) observational learning and (2) social contagion.

2.4.2. Network closure from the perspective of sellers

The other type of user that coexists with buyers in social commerce community is the seller. In contrast with buyers, who are motivated to seek product or service information in the community, the sellers, who have hyperlinks to their electronic shops attached to their personal websites, have different motivations when connecting to buyers and other sellers. As compared with buyers, the motivation to generate awareness from the buyers and compete as well as cooperate with other sellers makes the sellers in the community more likely to rely on their own activities and the quality of their relationships with others in the community. Thus, among all the potential factors of tie formation we previously discussed, structural equivalence, homophily, and reciprocity would be more relevant to sellers than buyers. Specifically, they intend to generate awareness from the buyers and engage in a coopetition relationship with other sellers in the community (Ross and Robertson 2007). When sellers are motivated to generate awareness from the buyers, the high information search cost due to diversified customer needs and wants in the community would also make them frustrated. In order to make their connections to buyers more efficient, sellers could apply the strategies as follows: (1) connect to the buyers who have many common neighbors with them. This is because the high structural equivalence (similar relations with others) usually leads to similar thoughts and behaviors between sellers and buyers (McPherson et al. 2001). (2) Connect to the buyers who have many shared affiliations (e.g. homophily; joint participations such as posts and replies in the community forum) with them. Buyers with higher homophily with sellers could be more likely to be potential customers. (3) Sellers could be more actively responsive to buyers. That is, sellers should reconnect with buyers when they receive the links from them. This targeting would be more efficient because the buyers initially showed interest in the sellers.

Relationships among sellers bear the nature of coopetition (Gnyawali and Madhavan 2001, Ross and Robertson 2007). Gnyawali and Madhavan (2001) propose that both competition and cooperation can, and often do, coexist and that the combination of the two leads to enhanced performance for the partner sellers. In contrast to buyers, when sellers are motivated to engage in a coopetition relationship with other sellers in a social commerce community, their strategies would be affected by the concern of both cooperation and competition. Specifically, (1) sellers are more likely to connect to other sellers who have many common neighbors with them because the more that two sellers have similar relations with others in a community (e.g. the more that they could substitute for each other), the more intense that their feelings of collaboration (or competition) with each other are and the more likely that a tie will be established between them (Burt 1997). (2) Sellers are also more likely to connect to other sellers who have many joint participations with them because the common interests between them would trigger future cooperation such as information sharing, and alliances. (3) The reciprocal links between sellers would also be significant in that links from other sellers would be considered as intended surveillance (competition) or cooperation and the focal seller would connect back to watch for the updated information on their followers' shops. Based on the above arguments, we proposed the hypotheses as follows:

H2a. As compared with buyers, sellers are more likely to build ties with buyers in the community through (1) structural equivalence, (2) reciprocity, and (3) homophily.

H2b. As compared with buyers, sellers are more likely to build ties with other sellers in the community through (1) structural equivalence, (2) reciprocity, and (3) homophily.

3. Methodology

The network data from communities in Taobao.com comprise the sample for a social commerce community. Taobao is often thought of as China's version of eBay — without the bidding concept. It's primarily a C2C online hub that Chinese merchants and consumers flock to buy and sell goods. The marketplace is made up of many independent stores that list their products at fixed prices, much like eBay's ''Buy It Now'' feature (www.channeladvisor.com). Since 2010, Taobao.com provides a unique section (e.g. bangpai.taobao.com) to organize all the communities in the platform where all the communities are labeled and divided into different columns according to their subjects. For example, the communities focused on clothing would be classified into the column of ''clothing''; the communities focused on finance would be classified into the column of ''finance'', and so on. This would help the users identify the communities that suit their interests from the community homepage. The way we collect, store, and process data will be discussed in the following part of this section. In addition, in the later part of this section, we will illustrate the operationalization of the key constructs and build a hazard model to analyze the probability of network closure in a longitudinal way.

3.1. Data collection based on web crawler program

The social commerce community we studied is one of the most active communities in Taobao.com (bangpai.taobao.com). Until the date we collected the data, it had 7902 community members who are fans of digital gadgets (computers, digital cameras, etc.). Users in the community can seek or share product information through discussion with others and they can ''follow'' others so that the updated messages (postings or purchases of products) from their followed members will be sent to their personal webpages. The actual content of posts or replies is usually the advertisement from the sellers or shopping experiences from the buyers. For example, many sellers in our samples would like to post the news of promotions of their electronic shops, such as ''free shipping'', ''discount'', ''new product release'', and so on. In case of any unwanted messages, these posts from the sellers would only show up on the forum section of the community, and only their followers would see these messages directly from their own homepages. On the other hand, many buyers like to share their shopping experience on the same forum where sellers usually post advertisements. For example, whenever there is a topic discussing a particular product in the forum, some buyers would post or reply to this topic based on their own experience of buying or using the product. Many buyers are even experts on reviewing some products and they usually get more followers from both sellers and buyers in the community. This community was established on June 12th, 2012 and it had evolved for more than two years. In the empirical analysis, we would list the descriptive statistics of the community network as a whole, but as for the analysis of network closure among the community users, we would choose several samples from the community because we can only get the complete information of community activity (e.g. the exact time of tie formations between two community users) of the users by monitoring them through a period of time. In order to control for previous linkages among members whose community activities cannot be traced back, we chose new users who joined from April 1st to April 7th and had no previous ties in the sampled users. This procedure lead to a sample size of 482 community members (with 336 sellers and 146 buyers) that allowed us to monitor these users' community activities for a period of time. We applied a similar method to choose several additional samples from the same community that varied in size and duration of observation for the robustness check of our findings in a later section. In sum, we have an evolving network of approximately 20 weeks (134 days).

In order to get the longitudinal network data, we programed the ''web crawler'' based on the selenium browser automation tool. This instrument is open source and can be re-programed according to the requirements of our research. By doing this, we recorded all the posts, replies, tie formations and their time stamps from all the community members. Table 2 briefly summarized the data field we collected.

Table 2
Data collections from web crawler program.

Data field		Details	Data format
(Members' ego-network information)	Members' IDs	Every member has her own ID	Text
	In-ward ties	In-degrees (followers' IDs)	Text
	Time stamp of in-ward ties	The time that receive ties from others	Date
	Out-ward ties	Out-degrees (followings' IDs)	Text
	Time stamp of out-ward ties	The time that send out ties to others	Date
(Profiles from personal webpage)	Joining Time	Date of joining in the community	Date
	Personal webpage	Linkage of personal webpage for members	Link
	Points	Measurement of members' experience	Number
	Views	The viewership of personal webpage	Number
(Post and reply activities in community)	Post ID	Linkage of each topic from the discussions	Link
	Poster ID	The ID of each poster	Text
	Replier ID	The ID of each replier	Text
	Posting time	The date of posting	Date
	Replying time	The date of replying	Date

3.2. Preprocessing of dynamic network data

After all the data were collected and stored, we applied a group of matrices to record the relationship structure among the sampled community members on a daily basis. Specifically, we used matrices A_t (unsymmetrical square matrices) to represent the relationship among the sampled community members at time t and B_t (non-square matrices) to represent the affiliations between the members and their community activities at time t. As the community evolves over time, these two matrixes can reflect the dynamic network structure at any time. Finally, based on the 134 days of network data we collected, we have 134 snapshots of relationships among members and their community activities stored in 134 matrices of A_t and 134 matrices of B_t respectively. The key variables of reciprocity, structural equivalence, social contagion, observational learning, and homophily can all be measured through these matrices and we will demonstrate how to use these matrices to measure those variables in the following part.

3.3. Measurement

As the dependent variable, relationship formation has a dummy value in a group of relationship matrices A_t where "1" stands for relationship formation at time t and "0" for otherwise. Since the matrices of A_t recorded the relationship structure among sampled community members on a daily basis, we can infer the exact date of each relationship formation by observing the changes of values in matrices of A_t. For the sampled community members in our research, we had 482 community members (with 336 sellers and 146 buyers) who joined in the community as strangers in the beginning, and as the time went by, they would build ties with each other, which will be shown as "followings" and "followers" on each member's personal webpage. With the help of the webcrawler program, we can browse the personal webpages of all the sampled community members and record the list of "followings" or "fans" of each community member daily. Within our sample, we could potentially observe 231,842 (482 * 481) tie formations if everyone in our sample built ties with everyone else. In the following section, we will explain the measurements of all the independent variables used in this study.

3.3.1. Reciprocity

According to the definition of reciprocity by Gouldner (1960), we operationalize the construct of reciprocity as the dyadic ties among community members. Specifically, we set the value of reciprocity between a focal member and a targeted member at time t as 1 if the focal member was followed by the targeted member before time t (we use "$t-1$" to represent the time before t in our equations), and if otherwise, the value of reciprocity is set as 0.

$$Rec_{i,j,t} = \begin{cases} 0, link_{j,i,t-1} = 0 \\ 1, link_{j,i,t-1} = 1 \end{cases} \tag{1}$$

where $Rec_{i,j,t}$ denotes the value of reciprocity between a focal member and a targeted member at time t; $link_{j,i,t-1}$ denotes whether member j had already sent out a tie with i before time t.

3.3.2. Contagion

The influences of contagion on a focal member come from his or her neighbors in the community. As the distance between the focal member and his or her neighbors increases, the effect would be diminished. In our operationalization of the effect of contagion, the influences are limited within 3° from a focal member. In other words, influence is limited to a maximum of 3 steps from a focal member to a targeted member. So, the contagion influence from the member i's neighbors is operationalized as follows.

$$Con_{i,j,t} = \sum_{p=2}^{m} Con_{i,j,A^p_{t-1}} \cdot p^{-1} \tag{2}$$

where m denotes the distance from i to his or her neighbors ($2 \leqslant m \leqslant 4$); A^p_{t-1} denotes the multiply algorithm of matrix A before time t; $Con_{i,j,A^p_{t-1}} * p^{-1}$ denotes the strength of contagion effects from member j to member i through i's neighbors who have the distance of p before time t.

3.3.3. Observational learning

Bikhchandani et al. (1998) illustrate the basic concept of observational learning (OL) using a model of consumer product adoption decision making, in which a consumer adopts a product if he believes that the quality of the product is high due to the amount of current adopters; Chen et al. (2011) operationalized OL as the ranking of sales in Amazon.com. Similarly, this paper operationalizes the variable of OL at time t as the number of followers (indegrees) before time t. Simply put, we take each member's indegree as the value of observational learning before the formation of relationship among the sampled community members.

$$OL_{i,j,t} = \text{Indegree}_{j,t-1} \tag{3}$$

where $OL_{i,j,t}$ refers to the member j's observational learning influence on the member i at time t, and it equals the indegree of j before time t.

3.3.4. Structural equivalence

Structural equivalence refers to the similarity of relations between two nodes in a network (Burt 1997, Coleman 1990). In our context, this is the extent to which two community members have connections with the same people. To operationalize this, we followed Kossinets and Watts (2006) and coded the structural equivalence as the number of "mutual friends" between two community members:

$$SE_{i,j,t} = NMF_{i,j,A_t \cdot A_{t-1}^T} \tag{4}$$

where $SE_{i,j,t}$ denotes the structural equivalence between i and j at time t; A_{t-1}^T denotes the transpose of matrix A before time t; $NMF_{i,j,A_t \cdot A_{t-1}^T}$ denotes the number of mutual friends between member i and j before time t.

3.3.5. Homophily

The operationalization of homophily is similar to the construct of structural equivalence. Since homophily refers to the similarity based on community activities rather than social relations, we measured homophily as the number of joint participations between two members. Instead of matrix A_t, we used B_t to measure the homophily among community members in that matrix B_t recorded the relationship between community members and their community activities until time t.

$$HO_{i,j,t} = NJP_{i,j,B_t \cdot B_{t-1}^T} \tag{5}$$

where $HO_{i,j,t}$ denotes the homophily between i and j at time t; B_{t-1}^T denotes the transpose of matrix B before time t; $NJP_{i,j,B_t \cdot B_{t-1}^T}$ denotes the number of joint participations between i and j in the community forum before time t.

3.3.6. Control variables

Since the users in social commerce communities can be scored based on their community activities in the whole platform (e.g. the number of posts, replies, and total duration in the current community and others), we apply those scores that showed on the community members' homepage to control the possible effect of community experience. Because the scores of members' experience are always changing due to the update of the members' community activities, the variable of community experience is time dependent and we label it as $Exp_{i,t}$ in our model, meaning the cumulative experience of member i until time t. Furthermore, we also control the effect of sociability because there could be many community members who are more social and prone to follow others while there also could be many community members who are less social and prone to follow others. We measure the time dependent variable of sociability as the out-degrees of the community members and label it as $Soc_{i,t}$, meaning the sociability of member i until time t.

3.4. Hazard modeling on tie formation

In the literature regarding tie formation (network closure) in social networks, the hazard analysis is frequently used (Kossinets and Watts 2006) and the hazard rate for each tie formation can be affected by a series of covariates. Cox proportional hazards regression model (introduced in a seminal paper by Cox (1992)) is an applicable, and the most widely used, method for survival analysis. We set the hazard rate $h(t)$ as the probability of the tie formation between two community members. So, $h(t)$ generally represents the instantaneous probability for the event (network closure) to occur, given that it has not happened until time t (Kleinbaum 1998). Based on previous hypothesis development, we assume that the probability for network closure would be affected by the covariates (e.g. reciprocity, contagion, observational learning, structural equivalence, and homophily) while the effects and significance of these covariates would vary due to the different roles of buyers and sellers. The full model can be written as follows:

$$\begin{aligned} h(t)_{i,j} = \exp(&\alpha + \beta_1 Rec_{i,j,t} + \beta_2 Con_{i,j,t} + \beta_3 OL_{i,j,t} + +\gamma_1 SE_{i,j,t} \\ &+ \gamma_2 HO_{i,j,t} + \delta_1 Exp_{i,t} + \delta_2 Soc_{i,t} + \varepsilon) \end{aligned} \tag{6}$$

where β is a group of parameters of the external effects, and β_1, β_2, and β_3 denote the effect of reciprocity, contagion, and observational learning respectively; γ is a group of parameters of the internal effects and γ_1 and γ_2 represent the effect of structural equivalence and homophily respectively; δ is a group of parameters of control variables and δ_1 and δ_2 represent the effect of community experience ($Exp_{i,t}$) and the community member's sociability respectively.

4. Data analysis and results

In this section, we begin our analysis with the visualization of the network structure in the whole social commerce community (Fig. 2). This is the general map of relationships among 7902 community members. The descriptive statistics of the network are shown in Table 3. In order to analyze the network closure in a longitudinal way, that is, the evolution of network in the social commerce community, we empirically test the hazard model only on the sampled 482 users for whom we monitored their community activities for a time window of 134 days. In practice, the relationship among the 482 sampled users is sorted into four groups as buyer to seller, buyer to buyer, seller to buyer, and seller to seller. The same hazard model will be run within each group to see the different mechanisms of network closure in different type of relationships.

4.1. Global view of the network and descriptive statistics

After one week of sampling (from April 1st to April 7th, 2014), our observation of the sampled community members started from April 7th, 2014, and by the last day of our data collection (August 18th, 2014), only 2438 out of 7902 users in the social commerce community had established ties with each other. Based on the layout algorithm from Mashima et al. (2012), we provide a global view of the relatively sparse relationships among community members in Fig. 2. This is a global (and static) view on the general network structure by the date we collect the data. In this figure, the nodes (black) represent community members and the directed ties (gray) represent the established relationships (network closure) among them. The layout algorithm (Mashima et al. 2012) visualizes the network under the principle that nodes with higher degree will be placed in the central area while nodes with lower degree will be scattered around. So, in practice, during the whole process of network evolution, we can always find out the "hubs" (Iyengar et al. 2011) and monitor the dynamic change of the structure of the network at any time.

In Table 3, we represent the descriptive statistics regarding the main features of the network and compare the values of the network indexes between the start date and end date of our observation. By the end of our observation, August 18th, 2014, only 2438 out of 7902 community members had 4312 ties with each other in total, which yield a very sparse network with a density of approximately 0.001 $\left(\frac{4312}{2438*2437}\right)$, compared with the start date of our observation, April 7th, 2014, where 2128 out of 6726 community members had 3685 ties with each other in total, which also yield a very sparse network with a density of approximately 0.001 $\left(\frac{3685}{2128*2127}\right)$. This result generally reflects the difficulty in network closure among members in the context of social commerce

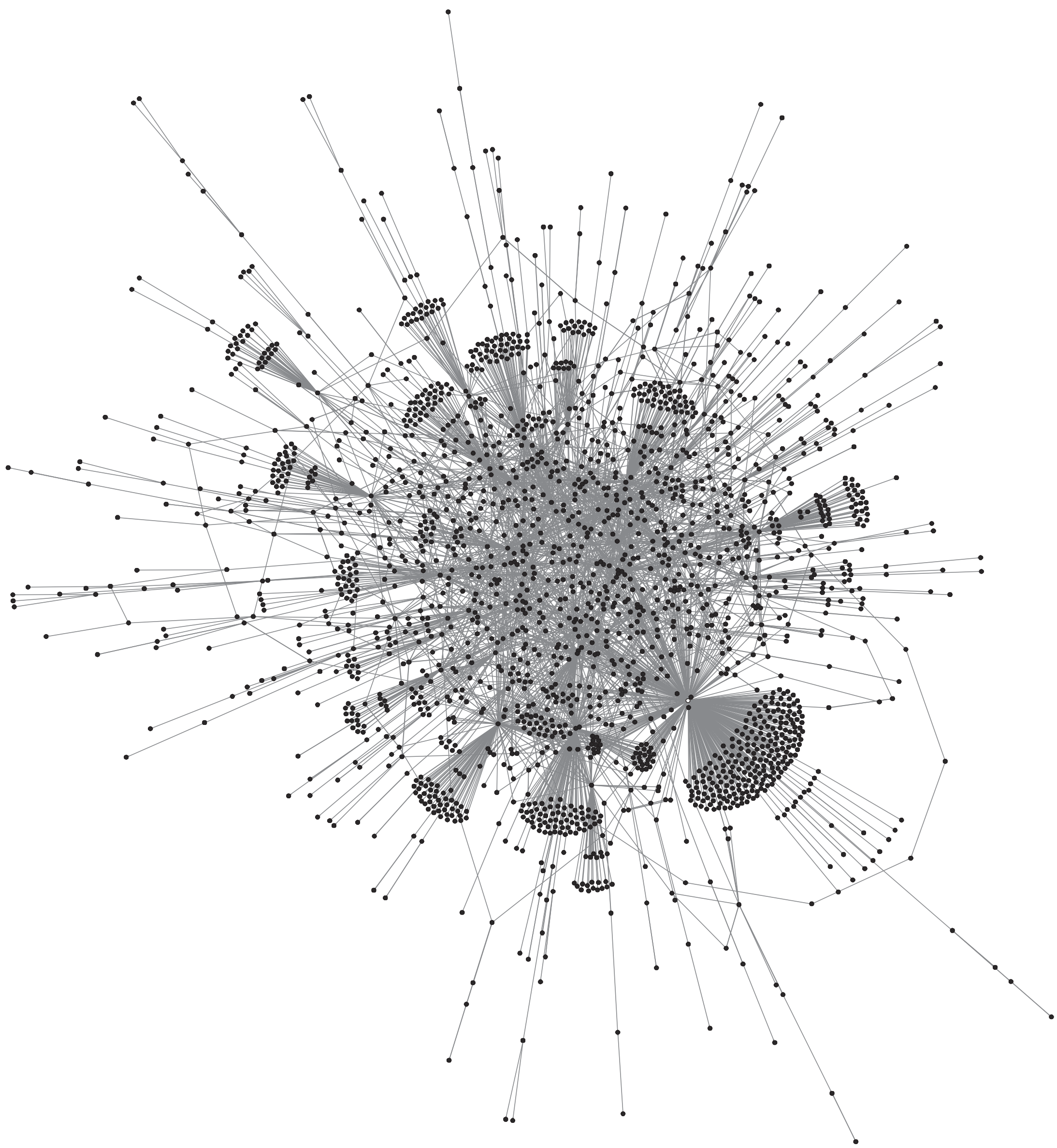


Fig. 2. Layout algorithm (Mashima et al. 2012) based network visualization.

Table 3
Descriptive statistics of the social commerce community.

Network Indexes	Start date (April 7th, 2014)	End date (August 18th, 2014)	Explanations
No. of users	6726	7902	Total number of community users
No. of nodes	2128	2438	Number of users who have connections to others
No. of edges (directed)	3685	4312	Number of directed links constructed in the community
No. of posts	1609	1876	Total number of posts in the forum section of the community
No. of replies	11,702	13,661	Total number of replies in the forum section of the community
Average degree	1.524	1.769	Average following and followers' number
Network diameter	18	16	The longest path between any two members in the community
Average distance	5.927	5.798	The average distance (length of path) between any two members
Network density	0.001	0.001	Existing links/all possible links
Average cluster coefficient	0.028	0.031	The degree to which nodes in a graph tend to cluster together

community. Therefore, the purpose of the rest of this paper will focus on the factors that affect the probabilities of network closure among community members.

Since we have the information about the time when each node was added to the network over a period of several years (from the establishing date of June 12th, 2012), we can construct a snapshot at any desired point in time. For the dataset, we find a version of densification power law (Leskovec, et al. 2005) (Fig. 3), in that the networks are becoming denser over time. According to Leskovec et al. (2005), the densification follows a power-law

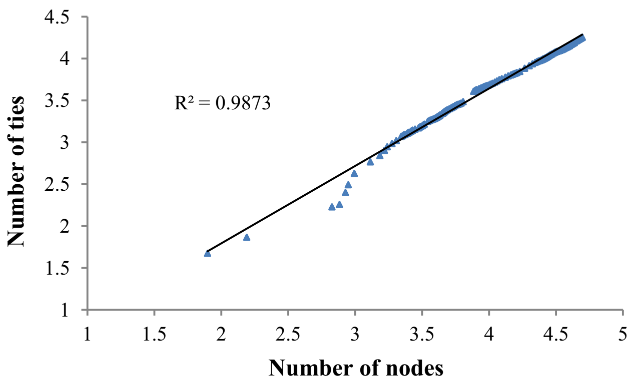


Fig. 3. Densification power law plot of the social commerce community.

pattern. In particular, the densification of the network is not arbitrary, we find that as the network evolves over time, it follows a version of the relation $e(t) \propto n(t)^a$ where "$e(t)$" and "$n(t)$" denote the number of edges and nodes of the network at time "t", and "a" is an exponent that generally lies strictly between 1 and 2.

Fig. 3 shows the DPL (densification power law) plot; the slope is $a = 1.02$ and corresponds to the exponent in the densification law. Note that "a" is higher than 1, indicating a deviation from linear growth. When a graph has $a > 1$, it's average degree increases over time. This means that the average connection among users increases over time. Another global view of a complex network is a plot of degree distribution across the community.

Fig. 4 shows the degree distribution in log–log scale (with a slope of 1.66) where some nodes (hubs) are highly connected while the majority of nodes have few connections. So the social commerce community has the scale-free structure that is similar to the traditional social networks that studied in the literatures.

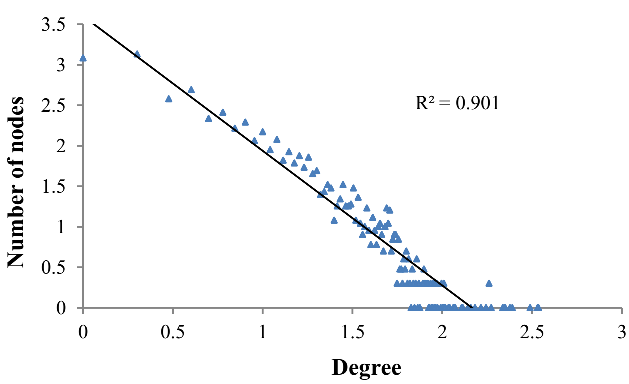


Fig. 4. Degree distribution in log–log scale.

4.2. Maximum likelihood estimation and hypotheses testing

We used the Cox proportional hazards model (1992) to estimate the effect of the covariates on the hazard rate. Since all the variables in this study are time dependent, we extracted the variables' values on the last day of our time window and calculated the correlation among these variables in Table 4. We classified all the ties among the sampled users in the social commerce community into four categories: model 1 only includes the ties between buyers (B–B), model 2 only includes the ties between buyers and sellers (B–S), model 3 only includes the ties between sellers and buyers (S–B), and model 4 only includes the ties between sellers (S–S). Above all, the covariates and the control variables we mentioned previously are the same for each model and the purpose of this study is to explore the different effects of all the variables on the network closure among users as sellers and buyers in social commerce community. The results of the models estimation were showed in Table 5.

4.3. Results and findings

As the social commerce community includes both sellers and buyers, different mechanisms are at work when different types of relationships are formed. Results from Table 5 shed light on how network closure in social commerce community varied across different types of relationships. Specifically, buyers are more likely to follow other buyers and sellers through observational learning and contagion (model 1, $\beta_2 = 0.115$, $\beta_3 = 0.045$; model 2, $\beta_2 = 0.688$, $\beta_3 = 0.033$); from the sellers' perspective, the homophily, reciprocity, and structural equivalence are the general mechanisms that drive them following both buyers (model 3, $\beta_1 = 1.715$ $\gamma_1 = 0.018$, $\gamma_2 = 0.214$) and sellers (model 4, $\beta_1 = 1.857$ $\gamma_1 = 0.711$, $\gamma_2 = 0.631$). These results are consistent with our previous hypotheses that suggest that the drivers of network closure varied according to the nature of the relationship. Specifically, buyers in social commerce community would like to seek information, reduce information asymmetry and information search cost, which makes them more subject to the external influence from both their neighbors (the significant effect of contagion) and the whole community (the significant effect of observational learning); in contrast, sellers in social commerce communities would like to generate awareness from the buyers, which makes them more responsive to the incoming connections from buyers (the significant effect of reciprocity) and pay more attention to the buyers who have similar relations or interests with them (the significant effect of structural equivalence and homophily). Moreover, the ties between sellers would be built on the principle of coopetition where the sellers would like to consider the potential cooperation with other sellers who have similar relations with them (the significant effect of structural equivalence) and the potential competition with other sellers who have followed them in the first place to check the updated information from their personal homepages (the significant effect of reciprocity).

Table 4
Descriptive statistics and correlation of variables.

Variable name	Min	Max	Median	Average	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Reciprocity	0	1	0	0.001	0.112	1						
(2) Contagion_1	0	6	2	3.070	0.281	0.006	1					
(3) Contagion_2	0	4	1	2.163	0.193	0.003	0.032	1				
(4) Contagion_3	0	3	0	1.311	0.131	0.012	0.004	0.012	1			
(5) Observational learning	0	187	7	3.981	15.871	0.351	0.214	0.002	0.091	1		
(6) Structural equivalence	0	14	4	2.842	3.440	0.159	0.188	0.016	0.013	0.241	1	
(7) Homophily	0	23	8	6.263	5.201	0.029	0.014	0.031	0.004	0.199	0.164	1

Note: contagion_1, contagion_2, and contagion_3 refer to the contagion path with a distance of 2, 3, and 4 respectively.

Table 5
Proportional hazards regression (Cox regression) results.

Dependent variable: hazard rate of ties formation (sample size: 482; duration: 134 days)	Model 1 (B–B) No. of ties = 68	Model 2 (B–S) No. of ties = 96	Model 3 (S–B) No. of ties = 152	Model 4 (S–S) No. of ties = 136
External influence				
β_1: Reciprocity (RE)	0.138 (0.266)	0.096 (0.185)	1.715 (8.436)***	1.857 (9.150)***
β_2: Contagion (CO)	0.115 (7.407)***	0.688 (8.729)***	0.010 (0.111)	0.356 (0.074)
β_3: Observational learning (OL)	0.045 (9.362)***	0.033 (9.976)***	0.013 (0.795)*	0.016 (0.170)
Internal influence				
γ_1: Structural equivalence (SE)	0.026 (0.122)	0.215 (0.348)	0.018 (7.112)***	0.711 (7.021)***
γ_2: Homophily (HO)	0.012 (0.462)	0.013 (0.531)	0.214 (6.612)***	0.631 (5.045)***
Controls				
δ_1: Experience (EXP)	0.550 (5.528)***	0.454 (5.537)***	0.274 (0.578)	0.287 (6.260)***
δ_2: Sociability (SOC)	0.021 (0.071)	0.324 (8.334)***	0.219 (1.112)**	0.001 (0.128)
R-square = 0.54				
Likelihood ratio test = 1570				
Wald test = 423.71				

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; No. of sellers = 336; No. of buyers = 146.

4.4. Additional analyses and robustness checks

The sample size in our main study is 482 social commerce community users, with 336 sellers and 146 buyers over a period of 134 days. However, it is possible that the size of the sample and the length of the observation would also affect the final results. In order to confirm the robustness of the findings, we complement the analysis with several additional samples that were chosen in the same manner as the previous study. The additional samples come from different sub communities on the same platform of Bangpai.taobao.com, such as "clothes" (community C1 and C2) and "finance and investment" (community C3 and C4), and all the additional samples are different in sample size and length of observation. In practice, we applied the same data collection tool introduced in the Section 3.1, ran the same hazard model on all of these complemented samples in the same social commerce community, and distinguished the roles of the community members as buyers and sellers. Table 6 lists the statistics and major differences of these samples, and the results of model estimation over these samples are listed through Tables 7–10.

According to the results from Tables 7–10, neither the sample size nor the duration of observation would have major impact on the final results of the main study. Specifically, as a first robustness check, we estimated the model on two different samples with the sample size of 238 users and 1072 users respectively. As we expected, they yield similar results on all the variables (see the results in Tables 7 and 8); as a second robustness check, we estimated the model on two different samples with the duration of

Table 6
Descriptive statistics of the complemented samples.

Community Code	Sample size	Duration	Total number of ties	Purpose of robustness check
C1	238 (110 sellers and 128 buyers)	May 1st to August 1st, 92 days	387	To check the effect of sample size
C2	1072 (560 sellers and 512 buyers)	May 1st to August 1st, 92 days	791	
C3	1072 (560 sellers and 512 buyers)	May 1st to November 1st, 184 days	1141	To check the effect of duration
C4	1072 (560 sellers and 512 buyers)	May 1st to June 15th, 45 days	431	

Table 7
Proportional hazards regression on community C1.

Dependent variable: hazard rate of ties formation (sample size: 238; duration: 92 days)	Model 1 (B–B) No. of ties = 76	Model 2 (B–S) No. of ties = 89	Model 3 (S–B) No. of ties = 101	Model 4 (S–S) No. of ties = 121
External influence				
β_1: Reciprocity (RE)	0.212 (0.246)	0.112 (0.341)	0.775 (5.436)***	0.827 (4.150)***
β_2: Contagion (CO)	0.123 (0.301)	0.231 (4.231)***	0.012 (0.782)	0.126 (0.002)
β_3: Observational learning (OL)	0.231 (6.362)***	0.211 (0.976)**	0.014 (0.901)*	0.021 (0.170)
Internal influence				
γ_1: Structural equivalence (SE)	0.082 (0.451)	0.031 (0.241)	0.411 (8.121)***	0.711 (4.052)***
γ_2: Homophily (HO)	0.034 (0.082)	0.001 (0. 092)	0.257 (7.152)***	0.262 (6.182)***
Controls				
δ_1: Experience (EXP)	0.152 (0.528)	0.154 (0.132)	0.014 (0.578)	0.278 (4.260)***
δ_2: Sociability (SOC)	0.412 (0.071)	0.421 (8.334)***	0.568 (1.112)**	0.721 (0.128)
R-square = 0.43				
Likelihood ratio test = 1115				
Wald test = 421.52				

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; No. of sellers = 110; No. of buyers = 128.

Table 8
Proportional hazards regression on community C2.

Dependent variable: hazard rate of ties formation (sample size:1072; duration: 92 days)				
	Model 1 (B–B) No. of ties = 211	Model 2 (B–S) No. of ties = 198	Model 3 (S–B) No. of ties = 236	Model 4 (S–S) No. of ties = 146
External influence				
β_1: Reciprocity (RE)	0.781 (0.266)	0.016 (0.125)	0.215 (8.436)***	0.251 (9.150)***
β_2: Contagion (CO)	0.215 (4.407)***	0.451 (8.719)***	0.010 (0.111)	0.312 (0.021)
β_3: Observational learning (OL)	0.345 (6.312)***	0.871 (9.971)***	0.012 (0.795)*	0.016 (0.123)
Internal influence				
γ_1: Structural equivalence (SE)	0.023 (0.641)	0.042 (0.521)	0.248 (8.132)***	0.721 (7.021)***
γ_2: Homophily (HO)	0.041 (0.051)	0.231 (0. 521)	0.517 (9.718)***	0.462 (8.930)***
Controls				
δ_1: Experience (EXP)	0.220 (4.511)***	0.414 (4.517)***	0.245 (7.523)***	0.487 (6.411)***
δ_2: Sociability (SOC)	0.021 (0.042)	0.124 (7.344)***	0.119 (0.122)**	0.001 (0.161)
R-square = 0.56				
Likelihood ratio test = 1611				
Wald test = 511.32				

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; No. of sellers = 560; No. of buyers = 512.

Table 9
Proportional hazards regression on community C3.

Dependent variable: hazard rate of ties formation (sample size: 1072; duration: 184 days)				
	Model 1 (B–B) No. of ties = 261	Model 2 (B–S) No. of ties = 321	Model 3 (S–B) No. of ties = 298	Model 4 (S–S) No. of ties = 261
External influence				
β_1: Reciprocity (RE)	0.532 (0.266)	0.036 (0.185)	0.615 (8.436)***	0.451 (6.150)***
β_2: Contagion (CO)	0.342 (4.307)***	0.658 (7.719)***	0.011 (0.211)	0.152 (0.031)
β_3: Observational learning (OL)	0.546 (9.362)***	0.423 (9.976)***	0.243 (0.195)	0.026 (0.470)
Internal influence				
γ_1: Structural equivalence (SE)	0.016 (0.662)*	0.015 (0.648)	0.018 (14.112)***	0.711 (11.000)***
γ_2: Homophily (HO)	0.001 (0.053)	0.002 (0. 099)	0.257 (10.758)***	0.262 (8.930)***
Controls				
δ_1: Experience (EXP)	0.230 (4.512)***	0.578 (8.517)***	0.174 (5.512)***	0.481 (0.260)
δ_2: Sociability (SOC)	0.041 (0.172)	0.124 (5.321)***	0.168 (1.112)**	0.011 (0.124)
R-square = 0.61				
Likelihood ratio test = 1513				
Wald test = 481.32				

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; No. of sellers = 560; No. of buyers = 512.

Table 10
Proportional hazards regression on community C4.

Dependent variable: hazard rate of ties formation (sample size: 1072; duration: 45 days)				
	Model 1 (B–B) No. of ties = 91	Model 2 (B–S) No. of ties = 106	Model 3 (S–B) No. of ties = 104	Model 4 (S–S) No. of ties = 130
External influence				
β_1: Reciprocity (Rec)	0.142 (0.266)	0.096 (0.185)	0.415 (8.436)***	0.257 (9.250)***
β_2: Contagion (Con)	0.214 (4.407)***	0.688 (8.729)***	0.210 (0.511)	0.446 (4.024)***
β_3: Observational learning (OL)	0.145 (5.312)***	0.033 (10.976)***	0.113 (0.195)	0.246 (7.120)
Internal influence				
γ_1: Structural equivalence (SE)	0.112 (0.465)	0.215 (0.341)	0.518 (6.432)***	0.312 (5.024)***
γ_2: Homophily (HO)	0.211 (0.225)	0.012 (0.049)	0.121 (5.158)***	0.578 (8.930)***
Controls				
δ_1: Experience (Exp)	0.550 (0.518)*	0.254 (5.231)***	0.173 (6.528)***	0.781 (6.260)***
δ_2: Sociability (Soc)	0.021 (0.071)	0.781 (4.134)***	0.219 (1.142)**	0.091 (0.128)
R-square = 0.31				
Likelihood ratio test = 1211				
Wald test = 371.61				

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; No. of sellers = 560; No. of buyers = 512.

184 days and 45 days respectively. As we expected, there is no significant change on the findings of the previous analyses according the results from Tables 9 and 10.

5. Discussion

Our objective was to study the network closure between sellers and buyers in the context of a social commerce community. Considering the transactional nature in social commerce community, it would be very important for both marketers and academic researchers to get an insight into the relationship formation among the users in a social commerce community. This analysis of the network closure in a social commerce community shows that the buyers and sellers would like to follow each other through different mechanisms, such as reciprocity, contagion, observational learning, structural equivalence, and homophily. The findings enrich our understanding of tie formation among buyers and sellers in social commerce communities and also provide new insights into social network analysis in general.

This study contributes to the studies of social networks analysis in social shopping and social commerce communities. The ties studied in the current research connect both buyers and sellers. These ties are different from the ties of friendship in most social communities and the reasons why users connect are varied. We distinguished the varied motivations for buyers and sellers to connect to others in the social commerce community and examined the different patterns for network closure among community users. Specifically, we extracted two major approaches (e.g. external effects and internal effects) from prior literature regarding network closure and explore their impact on different types of tie formation among the users in social commerce communities. The results showed that it is necessary to distinguish the motivations of network closure among the users in social commerce community and our findings will help both the marketers and academic researchers to better understand the different patterns of network closure when the users participated as buyers and sellers in the social commerce community.

The results can provide particularly significant managerial implications for social commerce communities. This study offers a novel way to understand and predict the tie formation among buyers and sellers in the context of social shopping and social commerce. This is important when both buyers and sellers want to identify the potential hubs from an evolving community. For example, since the social commerce communities are classified based on the subjects such as ‘‘clothing’’, ‘‘digital products’’, ‘‘entertainment’’, and so on, both buyers and sellers can have a clear map on the fashion trend within each subject. Buyers can build ties with others to reduce information asymmetry and information search cost while sellers can build ties with buyers to generate awareness and engage in coopetition relationships with sellers to enhance their sales performance. This analysis of the drivers of network closure in social commerce communities provides specific guidance on how to build ties to make the information seeking more efficient for the buyers or to bring more business values to the sellers.

The conclusions that we draw from our analyses are limited in at least the following ways. First, despite the variables of both external and internal effects in our studies, our set of drivers of network closure among users in the social commerce community is not exhaustive. Second, although we considered the number of user participation in the social commerce community, the actual content is not analyzed. The valence or variance of each post or reply from the users in the social commerce community could have an impact on the network closure among community users. Third, we chose samples rather than the full relationships among all community members to simplify the computation of several evolving networks. Given the capacity of more advanced computation, it will be more practical for future research to calculate the variables on full network data. Fourth, given by the data we have in this research, all of the major variables (e.g. observational learning, reciprocity, social contagion, structural equivalence, and homophily) are measured based on the community members' actions. We do not know much about their actual mental processes when they are subject to these tie formation patterns. With the help of more designed experiments, future research can explore the mechanisms of these tie formation patterns under the context of social commerce. Finally, as previously noted, we cannot trace back each user's actual time of following others and therefore, we could only start with a certain timestamp and monitor the newly joined users as samples for a period of time. We cannot analyze the whole process of evolution of the social commerce community from the very beginning. An important direction for further research is to more deeply examine the effect of the content of the discussion on network closure among community users with complete network evolution data. Indeed, there has been an increasing amount of empirical investigation that focuses on the technique of text mining on online forums. Future research can combine the techniques of text mining and social network analysis together to get deeper understanding of how and why the users build ties with others in the social commerce community.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.elerap.2015.10.001.

References

Allcott, B.H., Karlan, D., Möbius, M.M., Rosenblat, T.S., Szeidl, A., 2007. Community size and network closure. Am. Econ. Rev., 80–85
Ansari, A., Koenigsberg, O., Stahl, F., 2011. Modeling multiple relationships in social networks. J. Mark. Res. 48 (4), 713–728.
Arnold, M.J., Reynolds, K.E., 2003. Hedonic shopping motivations. J. Retail. 79 (2), 77–95.
Bikhchandani, S., Hirshleifer, D., Welch, I., 1998. Learning from the behavior of others: conformity, fads, and informational cascades. J. Econ. Perspect., 151–170
Borgatti, S.P., Mehra, A., Brass, D.J., et al., 2009. Network analysis in the social sciences. Science 323 (5916), 892–895.
Burt, R.S., 1987. Social contagion and innovation: cohesion versus structural equivalence. Am. J. Sociol., 1287–1335
Burt, Ronald S., 1997. The contingent value of social capital. Adm. Sci. Q. 42 (2), 339–365.
Capocci, A., Caldarelli, G., 2008. Folksonomies and clustering in the collaborative system CiteULike. J. Phys. A: Math. Theor. 41 (22), 224016.
Centola, D., 2010. The spread of behavior in an online social network experiment. Science 329 (5996), 1194–1197.
Chen, Y., Wang, Q., Xie, J., 2011. Online social interactions: a natural experiment on word of mouth versus observational learning. J. Mark. Res. 48 (2), 238–254.
Coleman, Lames S., 1990. Foundations of Social Theory. Harvard University Press, Cambridge, MA.
Cox, D.R., 1992. Regression Models and Life-Tables. In Breakthroughs in Statistics. Springer, New York, pp. 527–541.
Crandall, D., Cosley, D., Huttenlocher, D., Kleinberg, J., Suri, S., 2008. Feedback effects between similarity and social influence in online communities. In: Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, pp. 160–168.
Curty, R.G., Zhang, P., 2011. Social commerce: looking back and forward. Proc. Am. Soc. Inf. Sci. Technol. 48 (1), 1–10.
Ellison, N.B., 2007. Social network sites: definition, history, and scholarship. J. Comput. Mediat. Commun. 13 (1), 210–230.
Ellison, N.B., Steinfield, C., Lampe, C., 2007. The benefits of Facebook ‘‘friends:’’ Social capital and college students' use of online social network sites. J. Comput. Mediat. Commun. 12 (4), 1143–1168.

Falk, A., Fischbacher, U., 2006. A theory of reciprocity. Games Econ. Behav. 54 (2), 293–315.
Friedkin, N.E., 2006. A Structural Theory of Social Influence, vol. 13. Cambridge University Press.
Gnyawali, D.R., Madhavan, R., 2001. Cooperative networks and competitive dynamics: a structural embeddedness perspective. Acad. Manag. Rev. 26 (3), 431–445.
Gouldner, A.W., 1960. The norm of reciprocity: a preliminary statement. Am. Sociol. Rev., 161–178
Hendrix, P.E., 1999. Build it, and they will come. Mark. Manag. 8 (4), 31.
Hinz, O., Skiera, B., Barrot, C., Becker, J.U., 2011. Seeding strategies for viral marketing: an empirical comparison. J. Mark. 75 (6), 55–71.
Hughes, J.S., Liu, J., Liu, J., 2007. Information asymmetry, diversification, and cost of capital. Account. Rev. 82 (3), 705–729.
Iyengar, R., Van den Bulte, C., Valente, T.W., 2011. Opinion leadership and social contagion in new product diffusion. Mark. Sci. 30 (2), 195–212.
Kirmani, A., Rao, A.R., 2000. No pain, no gain: a critical review of the literature on signaling unobservable product quality. J. Market. 64 (2), 66–79.
Kleinbaum, D.G., 1998. Survival analysis: a self-learning text. Biometrical J. 40 (1), 107–108.
Kossinets, G., Watts, D.J., 2006. Empirical analysis of an evolving social network. Science 311 (5757), 88–90.
Kumar, V., Bhaskaran, V., Mirchandani, R., Shah, M., 2013. Practice prize winner-creating a measurable social media marketing strategy: increasing the value and ROI of intangibles and tangibles for hokey pokey. Mark. Sci. 32 (2), 194–212.
Lee, C.M., Mucklow, B., Ready, M.J., 1993. Spreads, depths, and the impact of earnings information: an intraday analysis. Rev. Financ. Stud. 6 (2), 345–374.
Leskovec, J., Kleinberg, J., Faloutsos, C., 2005. Graphs over time: densification laws, shrinking diameters and possible explanations. In: Proceedings of the Eleventh ACM SIGKDD International Conference on Knowledge Discovery in Data Mining. ACM, pp. 177–187.
Lewis, K., Gonzalez, M., Kaufman, J., 2012. Social selection and peer influence in an online social network. Proc. Natl. Acad. Sci. U.S.A. 109 (1), 68–72.
Libai, B., Muller, E., Peres, R., 2013. Decomposing the value of word-of-mouth seeding programs: acceleration versus expansion. J. Mark. Res. 50 (2), 161–176.
Marsden, P., 2010. Social Commerce: Monetizing Social Media. Grin Verlag.
Mashima, D., Kobourov, S.G., Hu, Y., 2012. Visualizing dynamic data with maps. IEEE Trans. Vis. Comput. Graph. 18 (9), 1424–1437.
McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in social networks. Annu. Rev. Sociol., 415–444
Mishra, D.P., Heide, J.B., Cort, S.G., 1998. Information asymmetry and levels of agency relationships. J. Mark. Res., 277–295
Newman, M.E., 2001. Clustering and preferential attachment in growing networks. Phys. Rev. E 64 (2), 025102.
Olbrich, R., Holsing, C., 2011. Modeling consumer purchasing behavior in social shopping communities with click stream data. Int. J. Electron. Commer. 16 (2), 15–40.
Parvatiyar, A., Sheth, J.N., 2001. Customer relationship management: emerging practice, process, and discipline. J. Econ. Soc. Res. 3 (2), 1–34.
Rogers, E.M., 2010. Diffusion of Innovations. Simon and Schuster.
Ross Jr., W.T., Robertson, D.C., 2007. Compound relationships between firms. J. Mark. 71 (3), 108–123.
Stephen, A.T., Toubia, O., 2010. Deriving value from social commerce networks. J. Mark. Res. 47 (2), 215–228.
Trusov, M., Bodapati, A.V., Bucklin, R.E., 2010. Determining influential users in internet social networks. J. Mark. Res. 47 (4), 643–658.
Walter, A., Ritter, T., Gemünden, H.G., 2001. Value creation in buyer–seller relationships: theoretical considerations and empirical results from a supplier's perspective. Ind. Mark. Manage. 30 (4), 365–377.
Young, H.P., 2009. Innovation diffusion in heterogeneous populations: peer influence, social influence, and social learning. Am. Econ. Rev., 1899–1924