Network Exchange Patterns in Online Communities

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Abstract

Large-scale online communities rely on computer-mediated communication between participants, enabling them to sustain interactions and exchange on a scale hitherto unknown. Yet, little research has focused on how these online communities sustain themselves and how their interactions are structured. In this paper, we theorize and empirically measure the network exchange patterns of long-duration sustainable online communities. We propose that participation dynamics follow specific forms of social exchange: direct reciprocity, indirect reciprocity, and preferential attachment. We integrate diverse findings about individual participation motivations by identifying how individual behavior manifests in network-level structures of online communities. We studied five online communities over 27 months and analyzed 38,483 interactions using exponential random graph (*p**) models and mixed-effects ANCOVA analysis. In a test of competing models, we find that network exchange patterns in online community communication networks are characterized by direct reciprocity and indirect reciprocity patterns and, surprisingly, a tendency away from preferential attachment. Our findings undermine previous explanations that online exchange follows a power law distribution based on people wanting to connect to "popular" others in online communities. Our work contributes to theories of new organizational forms by identifying network exchange patterns that regulate participation and sustain online communities.

Keywords: Online communities, network exchange patterns, computer-mediated communication.

Network Exchange Patterns in Online Communities

Introduction

Online communities bring together individuals with mutual interests using electronic mediation to overcome the same-place same-time limitation inherent in face to face settings. As Sproull (2004, p.733) defines online communities, they are "a large, voluntary collectivity whose primary goal is member or social welfare, whose members share a common interest, experience, or conviction, and who interact with one another primarily over the Net." Large-scale online communities are usually self-organizing, sustain social and exchange activities on a scale hitherto unknown, and have an impact on a number of organizational activities. For example, online communities support distributed R&D efforts (Orlikowski, Yates, Okamura and Fujimoto 1995), enable open source software development (von Hippel and von Krogh 2003), support firm-hosted user interactions (Jeppesen and Frederiksen 2006), and sustain extra-organizational work practices (Wasko and Faraj 2005). The emergence of thousands of extra-organizational networks, which link millions of people, requires an extension and rethinking of traditional group theory-based perspectives on participation and knowledge exchange (DeSanctis and Monge 1999, Zammuto, Griffith, Majchrzak, Dougherty and Faraj 2007).

As participation in online communities continues to grow, so does researcher interest. Just as there is a diverse range of online community types, so is the range of research approaches diverse. One frequent research interest is individual motivation for participation (e.g., Kankanhalli, Tan and Kwok-Kee 2005, Wasko and Faraj 2000). Another research interest is the interpersonal processes that sustain online communities (e.g., Jarvenpaa and Leidner 1999, Kanawattanachai and Yoo 2007, Preece 2000, Ridings and Gefen 2004). Recognizing the primacy of communication in online communities, some studies examine individuals within the context of a communication network while others view the communication network structure itself as the subject of inquiry (e.g., Butler 2001, Jones, Ravid and Rafaeli 2004, Rice 1982). Recently researchers have started to include social network variables in research on online communities (e.g., Ahuja, Galletta and Carley 2003, Wasko and Faraj 2005). Despite the complementary insights offered by taking a network-level perspective, much existing research remains focused at the individual level.

In this paper, we apply theories of network research, social exchange, and network exchange to investigate how individual behavior manifests in exchange patterns in online community communication networks. We apply the core concepts of organizational network research (Kilduff, Tsai and Hanke 2006) to investigate participation dynamics of long duration online communities. Kilduff and colleagues (2006) define a core of key ideas, which we adopt in this research: the primacy of relationships, ubiquity of embeddedness, social utility of connections, and structural patterning of activity. We theorize and empirically measure the communication patterns of online communities – their network exchange patterns.[1] We extend the understanding of participation dynamics by analyzing these patterns. We use an exponential random graph ($p*$) model analysis to identify the likelihood of non-random appearances of network exchange patterns in communication networks formed by online community participants. Analysis of 38,483 interactions between 7,329 individuals in five online communities over 27 months provides evidence that participation dynamics in online communities are characterized by consistent network exchange patterns.

Our findings shed light on how diverse individual-level motivations aggregate into online community-specific network exchange patterns. We find that direct reciprocity and indirect reciprocity are common structural network tendencies, yet surprisingly that preferential attachment is not. These findings demonstrate how multiple motivations can coexist within an online community. First, we demonstrate the importance of both direct and indirect reciprocity as coexistent structural network patterns, despite their unique motivational foundations. Second, we not only find a lack of support for preferential attachment patterns in online communities, but also further find exchange patterns consistent with a tendency away from preferential attachment. This finding undermines previous explanations that

[1] Our focus in this paper is on long-duration sustainable online communities. For the balance of the paper, we use the term online community with that meaning in mind.

online exchange follows a power law distribution based on people wanting to connect to "popular" others in online communities. Finally, we find that all five online communities exhibit the same network exchange tendencies (direct and indirect reciprocity, tendency away from preferential attachment), but do so in a distinct constellation of magnitudes. This finding suggests the existence of community-specific social processes or norms that regulate participation dynamics. In summary, our work contributes to theories of new organizational forms by identifying network exchange patterns consistent with mass collaboration in sustainable online communities.

Theory

One stream of the early literature on online communities has emphasized the ability of the technology to sustain group sizes significantly larger than those possible when interactions take place under the same-place same-time constraint (e.g., Katz and Rice 2002, Wallace 1999). A more nuanced understanding of online communities suggests they are both enabled and limited by technology. On one hand, asynchronous, text-based electronic communication (the technology used to enable most online communities) is characterized by low media richness; that is, a low ability to provide immediate feedback, or the situational cues (e.g., gender, physical attributes, organizational rank) and interactional cues (e.g., facial expression, voice intonation) necessary for multiplexed communication. As a result, the exchange of electronic messages may be inadequate for tasks requiring complex negotiation of meaning and reciprocal feedback (Sproull and Kiesler 1991). On the other hand, a growing body of theory-building expands on early examples of electronic communication adaptation and transformation by users (e.g., Hiltz and Turoff 1993, Majchrzak, Rice, Malhotra, King and Ba 2000, Sudweeks, McLaughlin and Rafaeli 1998). Virtual users may appropriate or adapt the technology in unexpected ways to meet their needs by developing novel ways to structure their interactions (DeSanctis and Poole 1994, Yates, Orlikowski and Okamura 1999).

Thus, not only does technology change social interaction, but its impact is also significant enough to modify group processes (see Hinds and Kiesler 2002 for a recent review). Newcomers to online communities are more likely to continue participating if they receive a response to their initial post, irrespective of the quality and emotional tone of the response (Joyce and Kraut 2006). New participants are more likely to receive replies if they ask questions that are on-topic and if they provide some information about themselves (Arguello, et al. 2006). Further, the extent of anonymity in the online community appears to affect the kind of ties that people build online. Instead of attachment to specific individuals, anonymity fosters attachment to the online community (as a whole) and, in turn, supports norm sustenance (Ren, Kraut and Kiesler 2007). Thus, along with the content of interactions, the communication patterns supported by communication norms in online communities play an important role in motivating participants and determining the long-term sustainability of online communities.

In face-to-face settings, researchers have identified a diverse set of motivations for both involvement in social groups and engagement in communities (Hesselbein 1998). Unsurprisingly, the set of motivations for participation in online communities shares this diversity, however; it differs in content. (Preece 2000). Existing studies offer conflicting explanations. Online community participants are sometimes motivated by self-interest, for example, seeking to enhance their reputation (Constant, Sproull and Kiesler 1996) or to gain other personal benefits (Fulk, Heino, Flanagin, Monge and Bar 2004, von Hippel and von Krogh 2003). At other times participants act selflessly and appear motivated by altruism (Peddibhotla and Subramani 2007). Sometimes participants identify closely with an online community, feeling an obligation to other community members (Wasko and Faraj 2000). Other times, despite long-term affiliation with an online community, participants feel no obligation to other members (Preece, Nonnecke and Andrews 2004).

We propose that large-scale sustainable online communities share similar network exchange patterns that transcend the diversity of individual motivations that bring participants to online communities. Whereas an individual-level perspective can answer the questions of why and when individuals are more or less likely to participate in online communities, our network-level approach can address how individual behaviors aggregate to form sustainable online communities. By taking a network perspective, we recognize that individuals are embedded in a web of relationships that are formed via repeated interaction over time in an online community. Studying the patterning of those interactions over time and across online communities provides a complementary perspective to previous studies that have prioritized individual motives and perspectives. Our use of network and social exchange theories are in line with calls to apply multilevel and network perspectives to new forms of organizing (Brass, Galaskiewicz, Greve and Tsai 2004, Contractor, Wasserman and Faust 2006). By focusing on how individual behavior aggregates to create the network-level structures of online communities (rather than how individuals behave within the structure of online community networks) we hope to reconcile conflicting findings about individual participation motivations.

Social exchange from a network perspective

Online communities provide forums for information exchange in open communication networks. Social exchange theory grew out of attempts to formalize the study of interpersonal relations and "social processes such as power and the exercise of influence…" (Cook and Rice 2001, p.699). A key development in social exchange theory was the incorporation of a network perspective with the view that exchange relations form network structures (Cook and Rice 2001). To develop a general "structural theory of power and dependence in networks" (Burke 1997, p. 134) network exchange theory complements social exchange theory through formal investigation of individual and group behaviors in resource networks.

Our perspective on online communities builds on the dual aspect of online interactions: they are social exchanges that take place between participants but they occur within a network context. Whether the resource exchanged be facts, know-how, answers to questions, or social niceties, the interactions are social in nature and thus, by definition, aim to influence others. Further, online community interactions take place within the context of a social network, which is both socially and historically constituted. The social aspect of the network is made even more salient by technological mediation of interaction: posts are visible to all other participants and are organized in discussion threads. Our view of online community interaction as social exchange embedded in communication networks draws on these complementary perspectives of network theories, social exchange and network exchange.

Social exchange theory both recognizes the importance of actions and interactions of individuals and provides a way of studying collective outcomes (Calhoun, Gerteis, Moody, Pfaff and VIrk 2002). Social exchange researchers have long recognized the utility of studying social exchange from a network perspective (e.g, Emerson 1972, Yamagishi and Cook 1988). Developing as a parallel yet complementary research stream, network exchange theory has focused primarily on power issues, including the effects of both positive and negative sanctions within social structures (Cook and Rice 2001). Network exchange theory has generated significant insight about how network positions allow access to more resources or positions of power. By focusing on exchange patterns among actors, one can develop a network representation of the evolving community structure. With a focus primarily on individual position in the network and availability of alternative ties among actors, network exchange theorists have used this approach to study the status and relative power of individuals in a network (Markovsky, Willer and Patton 1988, Walker, et al. 2000, Willer 1999). In the methods section, we describe how we similarly approach online community communication from a network perspective, and analyze the structural tendencies of those networks.

Exchange theorists have traditionally focused on lab experiments (Cook and Rice 2006). Our research context is consistent with recent efforts to apply exchange theories to naturalistic settings. The underlying assumption of exchange theory is that individuals possess different levels of resources and have opportunity and motivation to exchange them (Monge and Contractor 2003), a situation that accurately characterizes participants in online communities. Further, the analytical building blocks are social exchanges and resources, which correspond to electronic postings and to the information they provide, respectively. We draw on exchange theory to develop propositions regarding the collective outcomes embodied in network exchange patterns of online communities.

In applying exchange theory to online communities, where exchange is asynchronous, we expand the focus on power-oriented motivation favored in network exchange laboratory experiments. We view online community participants as motivated by a diversity of intrinsic and extrinsic motivations. The individual communication acts that come together to form an overall exchange may each be due to different motivations, and yet form consistent patterns. The power of our approach is its ability to rise above divergent findings regarding individual motivations. Although an individual may have different, potentially conflicting, propensities to act on selfless or selfish intrinsic motivations, exchange theory finds that when faced with similar structural constraints, individuals act—in aggregate, if not individually—in a consistent, predictable manner. For example, in an online community with a strong norm of direct reciprocity, responding to a participant increases the likelihood they will respond directly back. Thus, we argue that online communities comprised of individuals with conflicting motivations nonetheless manifest those motivations in consistent predictable network exchange patterns at an aggregate network level.

In this way, our research also shares the view of network theorists that consistent patterns are identifiable in networks. Importantly, though, our network exchange theoretical framework differs from the mechanistic empirically-oriented conceptualization in vogue among "new science of network" research dominated by physicists that posits human interaction networks as essentially similar to technical and physical networks in terms of distribution of ties (Barabasi 2002, 2005, Newman, Barabasi and Watts 2006). Our starting point is the recognition that a network is the result of continually enacted and reinforced patterns of action that are both defined by and define the behavior of their members. In a network, relational properties stand at the interstice between actors and should be studied at cross-level or multiple levels (Contractor, et al. 2006, Monge and Contractor 2003). Recent organizational research on how preferences for certain forms of social exchanges affect individual identity orientation (Flynn 2005) and on the network roles of leaders in open innovation communities (Fleming and Waguespack 2007) confirms the power of such socially-aware network analysis.

Exploration of network exchange patterns

In this study, our outcome of interest is the presence (or absence) of structural network exchange patterns as well as their relative magnitude and similarity when comparing online communities to each other. Due to our interest in such structures, we focus our theoretical arguments and empirical measures at the network level, not the individual level. Egocentric and individual–oriented measures such as centrality, closeness and structural holes are not consistent with our network-level focus. We seek to understand how the individual actions aggregate and manifest in network-level patterns, not how individual-level network position helps or hinders individual action.

One of the core concepts of network exchange theories (Kilduff, et al. 2006, Molm, Collett and Schaeffer 2007) is the primacy of reciprocation (be it direct reciprocity or indirect reciprocity). Indirect reciprocity (Flynn 2005), also known as generalized reciprocity (Putnam 2000), is a communication pattern characterized by indirect chains of communication that support generalized exchange (Mashima and Takahashi 2007). The preferential attachment pattern reflects a concentration of communication. Expressed positively, it is popularly referred to as a Matthew Effect where the rich get richer. Preferential attachment is an important network mechanism by which the choices of early entrants in a network may influence those of later entrants (Barabasi and Albert 1999, Shapiro and Varian 1999).

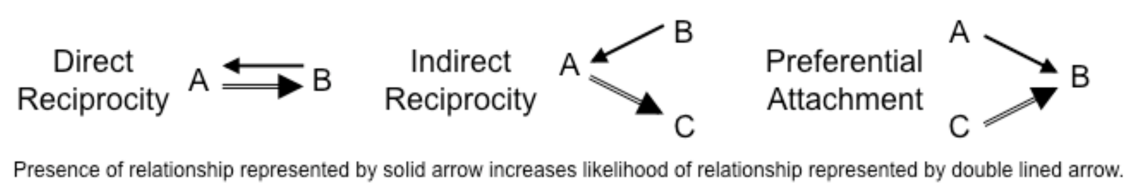

Figure 1: Network exchange patterns

Direct and indirect reciprocity are key elements of social exchange theory and a focus of recent interest in management literature (Flynn 2005). Preferential attachment has been a focus of recent network research (c.f., Newman 2003) and represents a complementary logic to reciprocity (Kadushin 2005). These three exchange patterns that can be used to characterize any communication network (Monge and Contractor 2003). Despite related research regarding communication networks (e.g., Rice and Aydin 1991, Rice 1982), these theoretically important exchange patterns remain understudied in online communities. Figure 1 provides a graphical depiction of these network exchange patterns. We discuss these in further detail below.

A network exchange framework of online community structure

Online community participation is a social phenomenon, and as in any endeavor governed by human behavioral patterns, we expect participants in online communities to exhibit non-random, intentional communication choices. We make no assumptions as to why a participant chooses to engage in a direct communication with another participant. It may be for self-interest or selfless (altruistic) reasons. Previous research has found that individuals provide knowledge in online communities because they want to interact with like others and to exchange knowledge (Kankanhalli, et al. 2005, Wasko and Faraj 2000). Their actions are influenced by both utilitarian and social influence explanations (c.f., Heinz and Rice 2009). A number of individual factors leading to increased participation have been identified: functional role (Ahuja, et al. 2003), self-interest (von Hippel and von Krogh 2003), boundary spanning roles (Fleming and Waguespack 2007), trust (Jarvenpaa and Leidner 1999), and reputation (Constant, et al. 1996). An initial non-random communication is a starting point for more complex and interesting structural network tendencies. Of greater theoretical interest are the exchange patterns conditioned upon this simple interaction. We move next to the discussion of direct reciprocity, indirect reciprocity and preferential attachment.

Social exchange theories stress the importance of reciprocity. Reciprocity is crucial for all exchanges because humans keep score, assign meaning to exchanges, and change their subsequent interactions based on a reciprocity balance (Ekeh 1974). In organizations, individuals that provide knowledge help can count on their own help requests to be answered by those who have been helped (Cross and Sproull 2004). Because knowledge work relies on joint problem solving and sensemaking, providing help to others may be a valuable investment in meeting one's own future help needs (c.f. Brown and Duguid 2001). In a careful empirical study of knowledge exchange in two online groups, Fulk et al. (2004) found that those individuals providing help strongly expected that their help would be returned. Indeed, Rice (1982) also found support for direct reciprocity in a study of 24 months of computer conference system use among 10 groups involving over 87,000 total network links.

If resources (for example, in the form of knowledge) are distributed among community participants, then the process of exchanging those resources will give rise to differentiated obligations as well as create a gradation of status and power (Emerson 1972). As Coleman (1990) notes, performing favors for friends creates an obligation that is callable at an unstipulated time. The process of exchange begins without any assurance that a provision of resources will be reciprocated. But any help provision (or other social exchange) reinforces the invisible gift exchange scorecard that is the basis for solidarity and social support (Coleman 1990, Putnam 2000). Thus, we suggest the following proposition:

P1: online communities demonstrate a structural network tendency toward direct reciprocity.

Indirect reciprocity offers an alternative logic for the sustenance of online communities. Indirect reciprocity occurs when one's giving is not reciprocated directly by the recipient, but indirectly by a third party (Ekeh 1974, Takahashi 2000). For example, individual **A** posts a message that is responded to by individual **B**. Rather than responding directly back to individual **B, A** in turn responds to a message posted by individual **C**. Compared to directly reciprocated exchanges that are characterized by self-interest or role-oriented behavior (Flynn 2005), indirectly reciprocated exchanges "are characterized by reduced emotional tension, a credit mentality, actors with a more collective orientation, and high levels of trust and solidarity" (Molm, et al. 2007: 208). Indirect reciprocity has consistently been linked to social solidarity, trust, and norms of sharing and helping. (Coleman 1990, Ekeh 1974). Thus, indirect reciprocity is about returning an exchange (e.g., a gift, kindness, or communication), but not to the original provider. Each contribution to an individual stimulates greater general contribution to the whole.

Flynn (2005) theorized that people with collective identity orientation express a preference for indirectly reciprocated exchange over direct exchange. One reason for the development of generalized, indirectly reciprocated exchange is that complex knowledge is distributed and emergent, the individual that was previously helped may not be the one able to formulate an effective answer. The operation of a system of indirect reciprocity requires a collective orientation, norms of unilateral giving, and concern toward the well-being of others (Bearman 1997, Yamagishi and Cook 1993).

Indirect reciprocity is likely to develop in online communities for a number of reasons. First, knowledge is distributed and expertise uneven. For example, if **A** (an expert) helps **B** (a novice), then it is not clear that **B** can return the favor when **A** posts a question no matter how willing they may be to oblige. Second, because the virtual interaction or help provision is visible to all, everyone has a chance to note the contribution and thus may be more willing to help in turn (Rheingold 1993, Wasko and Faraj 2000). Third, many online communities develop social solidarity and strong norms of helping others (Katz and Rice 2002). For example, advice giving and receiving on a corporate technical online community were found to be unaffected either by previous ties or by similarity between participants (Constant, et al. 1996). Finally, the presence of indirect reciprocity patterns may be a key reason for online community sustenance. In one of the first empirical studies of a large number of virtual posters, Joyce and Kraut (2006), found that new participants who received replies to their original posts were more likely to continue participating in the online community. In summary, indirect reciprocity is likely to be an important characteristic of online community exchanges. Thus, we propose:

P2: online communities demonstrate a structural network tendency toward indirect reciprocity.

In contrast to reciprocity, where interactions are based on returning exchange (either directly or indirectly), preferential attachment occurs in a network when new actors choose to interact with already well connected others over more typical others. Preferential attachment has increasingly been recognized as an important explanation for why the distribution of inter-organizational and organizational ties follows a power law distribution (Baum and McKelvey 2006). The preferential attachment framework has been refined and used to explain network development in a variety of economic, engineering, and social settings (see Watts 2004 for a review). In the video game industry, developers strategically align themselves with popular gaming platforms (Venkatraman and Lee 2004). Economists use the language of network externalities and positive feedback to explain how a few economic actors become dominant in network product industries (e.g., Shapiro and Varian 1999).

The preferential attachment mechanism is consistent with characteristics of online communities. First, one motivation identified for online community participation is to improve reputation (Constant, et al. 1996, Wasko and Faraj 2000). Second, in many online communities participants can readily assess the relative characteristics of existing participants. For example, in the online communities in this study, a summary participant profile appears (next to each posted message) showing the number of previous messages posted. Third, preferential attachment assumes a shared sense of who the most desirable partners for interaction are. This sense of shared preferences is consistent with collective identity and shared interests in online communities (Postmes, Spears and Lea 2000, Preece 2000) and reinforced by the ability to read previous communication between online community members.

Network newcomers often choose to attach to other people (or network nodes) that offer the most resources. Merton (1968) referred to the Matthew effect to explain how material and symbolic rewards tend to accrue to already famous scientists. In open source software development, an individual goal may be to interact with influential others (Kuk 2006). In a longitudinal study of an online innovation network, those who occupy brokerage and boundary-spanning positions were shown to benefit from their network position (Fleming and Waguespack 2007). Recent investigations of international scientific collaboration (Wagner and Leydesdorff 2005) and the makeup of creative teams (Barabasi 2005) are based on a preferential attachment argument. In summary, for a social setting such as online interaction, the implication is that individuals prefer to initiate communication with those members that are highly active and visibly well connected. Thus we propose,

P3: online communities demonstrate a structural network tendency toward preferential attachment.

Variation in online community exchange patterns

Thus far, we have proposed that online communities share common network exchange patterns – that is, direct and indirect reciprocity, and preferential attachment. If, as proposed, there exists a consistent set of network exchange patterns across online communities, it raises a related question: do online community interactions differ markedly from one online community to another? There are two major reasons to expect a large-scale sustainable online community to converge around an online-community specific norm of interaction. First, online communities differentiate themselves based on topic and the kind of members they attract. The individual participants in an online community represent a unique combination of participation motivations and online community identification that will be expressed in a distinctive combination of direct reciprocity, indirect reciprocity, and preferential attachment. Second, in online communities, just like other groups, repeated interactions are likely to give rise to norms and consistent patterns of interaction over time (Flynn 2005). Depending on the extent to which members identify with the online community or bond with specific other members, the norms of interaction will be unique for each online community (Ren, et al. 2007). Indeed, based on observations of participants in 27 different online communities, Ridings and Gefen (2004) found that individuals provided different reasons for joining different communities and had an awareness of each community's norms. Likewise, in a study of a work-related online community, Vaast (2007) found that group interactions reflected existing organizational arrangements and role positions.

Given the importance of group norms in dictating the expectations of member behaviors in any social system (Coleman 1990) —and, in light of differences between online communities' topic, membership, and history—we expect to see unique interaction dynamics. With the voluntary nature of participation and the ease with which members can move to other online communities, norm maintenance is a crucial aspect of online community management (Preece 2000). Just like in face to face settings, norms are most likely to be enforced when (a) the norm facilitates group survival, (b) the norm makes behavior more predictable (it simplifies behavioral expectations), (c) the norm helps avoid group member embarrassment, or (d) the norm is central to the group's identity (Feldman 1984). As the principal activity of online communities, communication meets these conditions. Several empirical studies covering a variety of settings offer evidence of the existence of norms in online communities (Shah 2006, Wasko and Faraj 2000, Wellman and Gulia 1999). Recent research on the importance of identity and bonds in virtual settings indicates that members are likely to develop a growing sense of togetherness that may translate into consistent patterns of interaction (Postmes, et al. 2000, Ren, et al. 2007). In summary, we expect online communities to be characterized by network exchange patterns that are consistent *within* online communities yet differ *across* online communities. Thus we propose:

P4: The network exchange patterns (direct reciprocity, indirect reciprocity, and preferential attachment) are consistent over multiple time periods and distinct across online communities.

Methods

To test the propositions introduced above, we collected data from multiple asynchronous web-based threaded discussion groups. Specifically, we collected all publicly available communication between online community members in three month time periods from five non-overlapping time periods (covering a total of 27 months). To test the first three propositions, we used exponential random graph (*p**) model analysis of communication networks. Due to space limitations, we present detailed results for P1, P2 and P3 for only a single three-month period.[2] To test the final proposition, we supplemented the exponential random graph model results with additional social network analysis measures (number of nodes and number of links) and ran an ANCOVA analysis to further identify similarities in exchange patterns among online communities.

Sample

We collected data from five online communities covering similar topics and using similar technology. We used several selection criteria in order to select domain-relevant online communities and

[2] The results for each of the observed time periods are substantially equivalent to the single time period presented. Results for the remaining four time periods are available upon request from the authors.

meet empirical requirements. First, we selected online communities driven by a common technology engine in order to minimize the complicating impact of technology or user interface issues. We chose online communities hosted on vBulletin (from JelSoft), an electronic bulletin board engine that powers approximately 60% of all large message boards (BigBoards.com, 2004). Second, we limited our domain to online communities related to technology and focused on software. Software knowledge networks have been shown to be rich in knowledge exchange (Fleming and Waguespack 2007, Kuk 2006, Shah 2006). Finally, we focused on online communities that have demonstrated viability by showing sustained message traffic over a period of at least 3 years. In addition, all five online communities provide standard vBulletin functionality and provide a full archive of messages posted since website inception.

We used a multi-stage process to identify these five vBulletin message boards. In the first stage, we identified a list of thousands of web sites that might be vBulletin message boards. This list came from three sources: the 383 largest vBulletin message boards (as compiled by bigboards.com), web sites returned by a Yahoo! search for "Powered by vBulletin," and URLs harvested via an automated agent from user profiles at the vBulletin customer support message board.

In the second stage, using a second automated agent we identified which URLs were indeed vBulletin websites and, further, supported open data access. In the third stage, through a visit to each of the resulting 1,643 unique URLs, we identified the primary content type of each web message board. Ultimately, there were 14 sites that were technology-related, had been in active sustained existence for more than 27 months, retained full message history, had at least 1,200 registered users, and had a standard configuration including major vBulletin features (namely, the ability to view single messages and to view member profiles). Of those, we randomly chose the five included in this study. Table 1 provides descriptive statistics for these five online communities.

Table 1: Online community statistics					
Network	**PRES**	**CNEW**	**WINX**	**DBPW**	**PFLW**
Inception Date	6/21/2003	6/6/2002	8/2/2001	4/8/2002	3/2/2002
Inception to 9/30/2005					
Registered Users	3,189	2,428	7,651	8,765	6,224
Message Threads	2,838	3,283	14,722	8,646	6,723
Messages	8,628	17,776	34,502	43,780	35,681
Averages Messages per Thread	3.0	5.4	2.3	5.1	5.3
Average Messages per Day	10.4	14.7	22.7	34.4	27.3
Primary Analysis Period for P1-P3 (7/1/2005 - 9/30/2005)					
Number of Messages	626	853	352	2950	339
Number of Unique Authors (Network Nodes)	166	125	123	597	107
Number of Unique Author Combinations (Network Relationships)	349	398	246	1447	199

The first website, programmersresource.com (PRES) covers web-based programming languages. The second website, codenewbie.com (CNEW) is about web-based programming with a focus on C, C++ and PHP languages in open source environments. The third website, winxpcentral.com (WINX), is about Windows operating systems with a focus on Windows XP. The fourth website, forum.dbpoweramp.com (DBPW), is a support website for a sophisticated PC audio program that includes programmable plug-in and skin support. The fifth website, pictureflow.com/forum (PFLW), is a support website for digital photography support tools.

Communication network formation

We collected data from five non-overlapping, non-contiguous three-month time periods for each community. The five observation periods were: 7/1/03 to 9/30/03, 1/1/04 to 3/31/04, 7/1/04 to 9/30/04, 1/1/05 to 3/31/05, and 7/1/05 to 9/30/05. The five periods cover a total elapsed time of 27 months (July 2003 to October 2005).

Like many online communities, vBulletin uses message threads to keep originating and reply messages together. In accordance with our theoretical frame of communication choices, we created a network representation based on inbound links where the presence of a reply represents a directed relationship *from* its author *to* the author of the immediately prior message in the message thread. We choose inbound links as a visible, representative expression of relationship formation in online communities. This criteria, where messages that receive no responses from others are excluded from the communication network, is consistent with previous empirical analysis of relationships in online community communication networks (Ravid and Rafaeli 2004, Wasko and Faraj 2005). This is in contrast to studies of continued participation, message responses, and message content in online communities where message threads with no responses are also of theoretical interest (Joyce and Kraut 2006, Rafaeli and Sudweeks 1998). Finally, we chose a three-month study period to balance the need for a large enough data set to identify persistent patterns with a short enough period to minimize exogenous factors.

Analysis approach

We used exponential random graph (p*) model analysis to test P1-P3 regarding structural network tendencies. Exponential random graph (p*) models provide a statistical test of the likelihood that an observed network, as compared to random networks of a similar size, exhibits specific characteristics (Robins, Pattison, Kalish and Lusher 2006, Wasserman and Pattison 1996). It is based on a census of dyadic and triadic patterns in a directed network. For example, a dyad census provides a count of each of the three possible types of dyadic relationships in a directed network: null relationships, unreciprocated relationships, and reciprocated relationships. Consider two networks (P and Q) with the same number of nodes. If network P has ten times more relationships than network Q (that is, network P is much denser), it is likely to have a higher percentage of directly reciprocated relationships. Exponential random graph models provide a statistical test of the likelihood that a network is characterized by a non-random tendency towards direct reciprocity (or other network properties) compared to their natural occurrence in a network of the same size (see Crouch and Wasserman 1998, Monge and Contractor 2003).

Furthermore, p^* analysis is multi-level. It tests the presence of related relationship patterns in the presence of one-another. For example, in our full model, we test the tendency for the presence of non-random interaction, direct reciprocity, indirect reciprocity, and preferential attachment each controlling for the presence of each other. [3] This is a critical assumption because non-random interaction (**A→B**) is a necessary first step for the formation of the "higher level" patterns of direct reciprocity (**A→B→A**), indirect reciprocity (**A→B→C**), and preferential attachment (**A→B←C**). In p^* analysis network tendencies are identified from a comparison of a series of models and through evaluating their relative "badness of fit" statistic. A single model is comprised of multiple predictor variables where each variable corresponds to a specific exchange pattern. Thus, like other logistic regression procedures, models with a smaller -2 Log Likelihood (-2LL) statistic are considered better models. For each predictor variable, the p^* method estimates a coefficient and a measure of fit for the predictor variable.

Because p^* analysis is relatively novel, a description of the analysis steps is in order. We start with a p^* model that includes all of the parameters (non-random, direct reciprocity, indirect reciprocity, preferential attachment). We then remove one parameter in turn to develop comparison models. A statistically significant decrease in the -2LL badness of fit measure (as measured by the χ^2 distribution) provides evidence that the network exhibits those tendencies.[4] For models that show a significant drop in the -2LL, an additional step is required to interpret the nature of the relationship. Interpretation of the values of B and Exp(B) provides further information about the direction and magnitude of the effect. Much as the drop in -2LL is analogous to an increase in R^2 for a linear regression model, the value of B is analogous to the predictor variable coefficient. The sign (positive or negative) of the B variable is a measure of the direction of the observed effect. The value of Exp(B) can be interpreted as the increased

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[3] All of our p^* models included a non-random parameter which establishes that network interaction is not random. For the sake of brevity we do not report this parameter in our results.

[4] A χ^2 change of 3.84 between models is significant at $p < .05$; a change of 6.63 is significant at $p < .01$ and a change of 10.83 is significant at $p < .001$.

likelihood that a tie of that type exists. For example, for a direct reciprocity model, if Exp(B) equals 2, the interpretation is that reciprocal ties are twice as likely to be formed as random formation would suggest. A value of exactly 1.0 for Exp(B) is consistent with a parameter that has no effect on the overall likelihood of tie creation.

Mixed effect ANCOVA analysis to test online community differences

To test if network exchange patterns differ markedly from one online community to another (P4) we relied on mixed effect ANCOVA analysis. For each of the five online communities we used the three measures of network structure calculated for the tests of P1-P3. We used the calculated B parameters for direct reciprocity, indirect reciprocity, and preferential attachment for all five networks for all five study periods (a total of 25 communication networks). We used a mixed-effect ANCOVA model to analyze the impact of online community source for these three network measures, controlling for effects of data collection time period and differences in network sizes. The analysis of covariance class (ANCOVA) partitions overall variance observed in a sample into the effects of multiple unique factors while also accounting for co-variates. ANCOVA is a powerful tool for testing for statistically significant differences among nonequivalent groups (Pedhazur and Schmelkin 1991).

In this case, a mixed-effect model is appropriate, as there are both random and fixed factors. The online community the data was collected from is considered a random effect as the range of effects of online community membership is unknown and these online communities were randomly selected from a larger population. The first control variable is the data collection time period. Time period is a fixed effect, as the time periods are of fixed duration and spacing. Finally, to account for the effect of network size, which could affect variance allocation, we included two measures of network size (number of nodes and number of links) in the model. For each of these dependent variables we performed a mixed-effects ANCOVA with four parameters: the online community (1 to 5), the data collection time period (1 to 5), the number of nodes, and the number of links. Finally, as a diagnostic in addition to the mixed-effects ANCOVA analysis, we also tested an auto-correlation function (Box and Jenkins 1976) to test for serial correlation across the data collection time periods. The auto-correlation and partial auto-correlation functions provided no evidence of time-lagged values being serially correlated.

Results

To test our first three propositions, we used a nested series of p^* analyses to test for the proclivity of members to engage in direct reciprocity, indirect reciprocity, and preferential attachment network exchange patterns. Because our analysis compares nested models, the order of parameter entry may matter in p^* analyses. Just like in regression, the variable that is entered in the model first changes the apportioning of the variance. For example, should the model include preferential attachment first before entering indirect reciprocity or vice versa? Rather than attempting to justify a certain order of entry based on tentative theoretical grounds, we chose to run all various permutations of entered variables and selected the "best" partial model to compare with the full model. Thus, the analysis ensures against any order of entry effects and provides a higher degree of evidence.

Table 2: Fit Statistics for *p Models for Five Networks (-2LL)**						
Network		**PRES**	**CNEW**	**WINX**	**DBPW**	**PFLW**
Parameters	***d.f.***	**-2LL Values per Model**				
***Model 1* - Indirect Reciprocity, Preferential Attachment** *(All parameters but Direct Reciprocity)*	3	2697	2423	1879	10302	1007
***Model 2* - Direct Reciprocity, Preferential Attachment** *(All parameters but Indirect Reciprocity)*	3	2394	1623	1735	9559	1028
***Model 3* - Direct Reciprocity, Indirect Reciprocity** *(All parameters but Preferential Attachment)*	3	2572	1817	1729	11180	1087
***Model 4* – Direct Reciprocity, Indirect Reciprocity, Preferential Attachment** *(Full Model)*	4	2118***	1488***	1659***	8168***	679***

*** Improvement over next best fitting model at p<.001

Table 2 shows the goodness of fit (-2LL) for three permutations of three-parameter models (models 1-3) and compares them against a full model (Model 4, containing four exchange patterns as parameters). We also provide more specific parameter-level results in Table 3 which lists the *B* and Exp(*B*) values for each network mechanism. The results were generated using MultiNet 4.55 (Richards and Seary 2004, Seary and Richards 2000), a network analysis tool that includes a *p** model designed for large sparse matrices such as ours.

Table 3: Parameter Estimates for *p Analysis for Five Networks**

Network	Statistic	Direct Reciprocity	Indirect Reciprocity	Preferential Attachment
PRES	*B*	4.33**	0.14**	-0.20**
	Exp(*B*)	75.61	1.15	0.82
CNEW	*B*	5.02**	0.11**	-0.10**
	Exp(*B*)	151.40	1.11	0.91
WINX	*B*	3.09**	0.05**	0.05**
	Exp(*B*)	22.03	1.06	1.05
DBPW	*B*	4.26**	0.04**	-0.04**
	Exp(*B*)	70.97	1.04	0.96
PFLW	*B*	5.95**	0.14**	-0.25**
	Exp(*B*)	382.81	1.15	0.78

** p < 0.01

To test our first proposition (direct reciprocity) we compared the results of Model 1 to Model 4 in Table 2. Model 4 is a test with four network exchange patterns; Model 1 contains all but direct reciprocity. The statistically significant improvement between Model 4 and Model 1 in the -2LL fit measure ($p < 0.001$) for all five networks (Δ-2LL d.f. = 1 = 579 for PRES; Δ-2LL d.f. = 1 = 935 for CNEW; Δ-2LL d.f. = 1 = 220 for WINX; Δ-2LL d.f. = 1 = 2134 for DBPW; Δ-2LL d.f. = 1 = 328 for PFLW) supports the proposition that network structures exhibit a tendency regarding direct reciprocity. The direction and statistical significance of the direct reciprocity parameters in Table 3 further support the proposition: all five networks demonstrate a statistically significant ($p < 0.01$) tendency towards direct reciprocity. Additionally, the significance levels for the parameter estimates are consistent ($p < 0.01$) in all five observed time periods for all five networks.

To test the second proposition (indirect reciprocity) we compared the results of Model 2 to Model 4 in Table 2. Model 4 contains four network exchange patterns; Model 2 contains all but indirect reciprocity. The statistically significant improvement between Model 4 and Model 2 in the -2LL fit measure (p<0.001) for all five networks (Δ-2LL $_{d.f. = 1}$ = 276 for PRES; Δ-2LL $_{d.f. = 1}$ = 134 for CNEW; Δ-2LL $_{d.f. = 1}$ = 77 for WINX; Δ-2LL $_{d.f. = 1}$ = 1391 for DBPW; Δ-2LL $_{d.f. = 1}$ = 348 for PFLW) supports the proposition that network structures exhibit a tendency regarding indirect reciprocity. The direction and statistical significance of the indirect reciprocity parameters in Table 3 further support the proposition: all five networks demonstrate a statistically significant (p<0.001) tendency towards indirect reciprocity. Additionally, the significance levels for the parameter estimates are consistent ($p < 0.01$) in all five observed time periods for all five networks.

To test the third proposition (preferential attachment) we compared the results of Model 3 to Model 4 in Table 2. Model 4 contains four network exchange patterns; Model 3 contains all but preferential attachment. The statistically significant improvement between Model 4 and Model 3 in the -2LL fit measure ($p < 0.001$) for all five networks (Δ-2LL $_{d.f. = 1}$ = 455 for PRES; Δ-2LL $_{d.f. = 1}$ = 328 for CNEW; Δ-2LL $_{d.f. = 1}$ = 70 for WINX; Δ-2LL $_{d.f. = 1}$ = 3012 for DBPW; Δ-2LL $_{d.f. = 1}$ = 408 for PFLW), supports the conclusion that these networks demonstrate a tendency regarding preferential attachment. As shown in Table 3, however, the negative sign of the preferential attachment coefficient provides evidence that this tendency exists in these networks in the *opposite* direction as proposed.[5] Additionally, for three of the five networks the parameter estimates for preferential attachment are significant at p<0.001 for all five time periods. For the two remaining networks they are significant at p<0.05 for four of the five time periods.

Results for online community differences

Table 4 provides the ANCOVA analysis used to formally test proposition P4 regarding similarity of exchange patterns across online communities. The analysis offers a stronger omnibus test of how much variance is explained by online community differences after accounting for time period and network size.

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[5] For four of the five networks the estimated parameter for preferential attachment was negative in all five time periods; for the fifth network it was negative for three of the five observed time periods.

Each table column provides results for one of the five different mixed-effects ANCOVA models (each with a different network structural measure as DV). Table 4 notes statistically significant F-values in the test of between-subject effects. To facilitate comparison of effect sizes within and across the five ANCOVA analyses, the table also reports partial eta-squared (η_p^2), a relative indicator of effect size (Cohen 1973).

Table 4: Partial eta-squared Values from Three Mixed-effect ANCOVA Models (n = 25)

Model	Partial Eta-Squared for ANCOVA 1: Direct Reciprocity	Partial Eta-Squared for ANCOVA 2: Indirect Reciprocity	Partial Eta-Squared for ANCOVA 3: Preferential Attachment
Intercept	0.85 ***	0.42 **	0.13
P4: Online Community (1-5)	0.61 **	0.58 *	0.53 *
Control variables:			
Observation Period (1-5)	0.01	0.09	0.16
Number of Nodes	0.00	0.03	0.02
Number of Links	0.00	0.04	0.04

* p<.05, ** p<0.01, *** p<0.001

We interpret the results as follows: the table shows that controlling for observation time period and changes in network size (measured as both the number of nodes and the number of links), Online Community is a statistically significant predicator of the magnitude of the parameter estimates in all three ANCOVA analyses. The effect size η_p^2 is also consistently larger for Online Community than any other variable. Thus, as proposed in P4 the online community effect is strong and significant. In total, the results from this 27 month analysis provide empirical support that these five online communities have distinctive community-specific levels for all three measures of network exchange patterns. (We also tested for and found no patterns of convergence or evolution over time within each online community.)

We can further view the relationships between *p** parameter estimates for each of the online communities in a multivariate manner. Figure 2 is a three-dimensional scatter plot with the parameter estimate for indirect reciprocity as the X-axis, preferential attachment as the Y-axis, and direct reciprocity as the Z-axis. Of the twenty-five data points, there are five per each online community (one for each online community for each time period). Data points for the same online community are represented with the same shading and symbol. In the scatter plot it can be seen that there is a strong tendency for data points from the same online community to appear in close proximity in the three-dimensional space. For all online communities at least four of the five data points (if not all five) are grouped closely together.

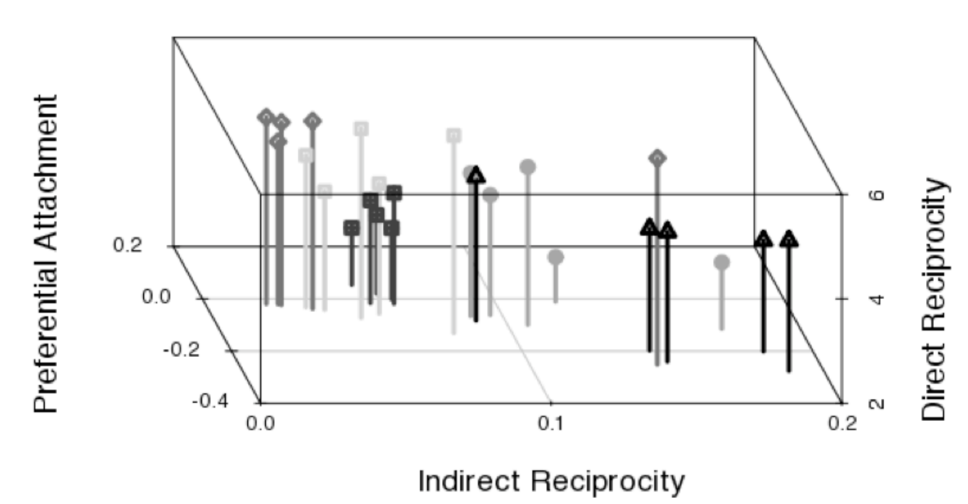

Figure 2: Parameter Estimates by Online Community

As an additional method for exploring the differences between online communities, we also present visual network representations. Figure 3 shows representations of all five online communities (PRES, CNEW, WINX, DBPW, and PFLW) for three time periods (July to Sept. of 2003, Jan. to March of 2004, and July to Sept. of 2004). Using the NetDraw program (Borgatti 2002), the network representations are created with the same algorithm and the same settings. Dark lines connect two nodes (online community participants) that sent messages to each other during the same time period. Light lines represent a dyadic relationship where only one of the two responded to a message posted by the other. The networks are ordered from smallest average size (PRES, at top) to largest average size (PFLW, at bottom). The network diagrams show a consistent pattern: diagrams of networks from the same online community (those in the same row) are more similar to one another than they are to networks from other online communities (networks shown in other rows). This is consistent with proposition P4 that online communities demonstrate unique network exchange patterns.

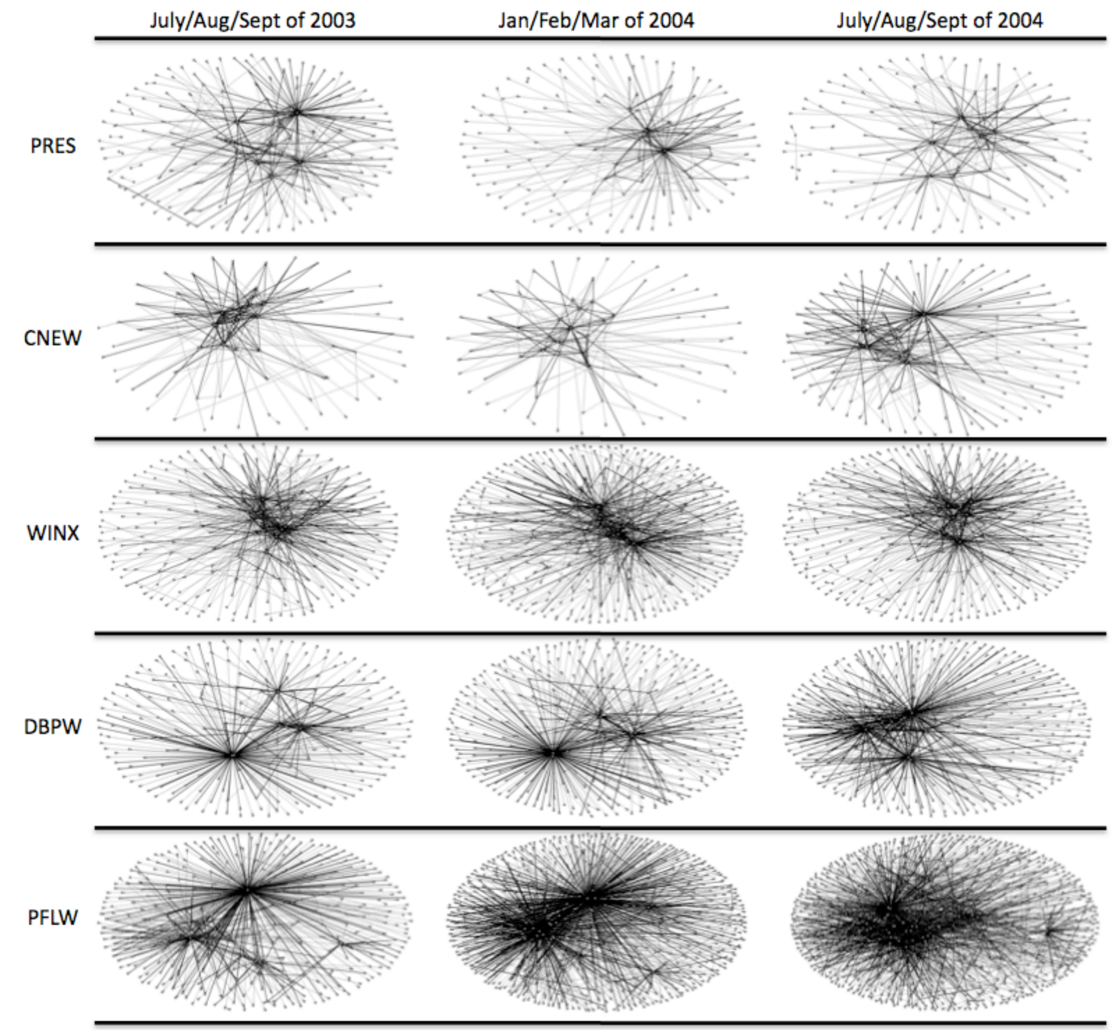

Figure 3: Graphical Representation of Five Communication Networks at Three Time Periods

In this paper we study how individual behaviors within communication networks aggregate to create network-level structures. We speculate that a range of viable alternative configurations of network exchange patterns may exist in sustainable online communities. For example, Figure 2 suggests a relationship between observed levels of preferential attachment and indirect reciprocity. Figure 3 provides preliminary evidence of how community-specific norms may emerge and sustain. Consistent with skewed distribution of participation, these network diagrams suggest a core and periphery structure with a small proportion of highly connected participants (primarily via dark-lined reciprocated relationships) and the majority of participants have few connections (mostly via light-lined unreciprocated relationships). Both

Figure 2 and Figure 3 support our assertion that community-specific social processes or norms regulate participation dynamics in sustainable online communities. Additional study is required to identify whether the same highly connected individuals sustain norms over time as well as how inter-relationships among exchange patterns are established and maintained.

Sensitivity analysis

We performed additional analyses to test the sensitivity of the results of P1-P3 to the length of the data collection period. This kind of analysis may be useful for novel network techniques such as $p*$ to improve confidence in the results. We found that our results remained substantially unchanged for data collection periods covering one, two, three, and four months. We found that the same models—those with tendencies regarding direct reciprocity, indirect reciprocity and preferential attachment—remained the best fitting models. Likewise, we found that the sign of the parameters estimates for each exchange pattern remained consistent with presented results. Predictably, as shorter time periods result in smaller networks (and, therefore, less statistical power), some of the parameter estimates and some of the model improvements were not found to be significant to the same statistical level for shorter periods. By demonstrating the robustness of network exchange patterns within online communities, the results of the sensitivity analysis also provide greater confidence in the test of P4 regarding differences between online communities.[6]

Discussion

By studying network exchange patterns on five technology-focused online communities, this study explored the nature of interaction in large-scale online communities. Until recently, little was known about such network-level interaction dynamics. We applied theories and methods of network analysis, social exchange, and network exchange to investigate how individual behavior manifests in exchange patterns in online community communication networks. We theorized and empirically measured the network exchange patterns characterizing sustainable online communities. We proposed and

[6] We thank an anonymous review for pointing this out.

tested for the existence of tendencies for direct reciprocity, indirect reciprocity, and preferential attachment. We found consistent results across five independent online communities during 27 months of data observation encompassing 38,483 interactions between 7,329 individuals. Our principal results indicate that the pattern of ties is consistent with norms of direct reciprocity and indirect reciprocity, and a tendency away from preferential attachment. The absence of a positive preferential attachment tendency in these online communities undermines previous assertions that power law distributions in online communities are due to preferential attachment motivations.[7] Finally, we find that all five online communities exhibit the same network exchange tendencies (direct and indirect reciprocity, a tendency away from preferential attachment), but do so in a distinct constellation of magnitudes.

Our study's primary contribution is to theorize and investigate multiple models of online community interactions. Surprisingly, contrary to widely cited models of large scale social networks (Barabasi 2002, Newman 2003), we found not only a lack of evidence for preferential attachment, but rather a disinclination towards preferential attachment after accounting for direct reciprocity and indirect reciprocity. The disinclination towards preferential attachment suggests a preference for novelty in choice of communication partners that is consistent with a norm of welcoming behavior towards new participants. One possible explanation is that online communities as *social communication* networks differ from physical and technological networks (e.g., the electric grid and the Internet) studied by many network researchers. It is also possible that our purposeful selection of sustained technology-oriented online communities represents a unique sample, and that either less successful online communities or ones with other topic orientations would differ. Nonetheless, our findings are consistent with a simulated model of online community formation that found the presence of preferential attachment is not required to generate power law distributions (Johnson and Faraj 2005). Overall, the results of our study do indeed

[7] For each of the 25 communication networks measured in this study, the distribution of in-degree follows a power law distribution (average k = 1.57, R-squared = 0.94).

bring into question the applicability of simplistic preferential attachment models of network evolution (Barabasi and Albert 1999) to this setting.

Also, whereas direct reciprocity and indirect reciprocity have been previously theorized to be alternative logics for network exchange, we demonstrate their coexistence. By testing and extending network models of social exchange, we are able to generate a keener insight regarding online community dynamics and to augment social relational explanations underlying online communities. While we could not directly measure the attitudes of participants toward the community, the link between reciprocity in social interactions and theories of social capital and social solidarity is well established in the literature (see Coleman 1990, Molm, et al. 2007). Thus our findings bolster the findings of previous studies that developed collective action (Fulk, et al. 2004) and social capital (Wasko and Faraj 2000) explanations of virtual social interactions (see Heinz and Rice 2009). Indeed, several studies that focus on understanding why actors contribute knowledge and help unknown others online have consistently shown the importance of social explanations such as: organizational citizenship (Constant, et al. 1996), expectations of future help (Lakhani and von Hippel 2003), and expectations of reciprocity (Shah 2006).

More recently, our understanding of online community interactions has deepened with the recognition that participation is unevenly distributed and that a core subset of actors plays a key role in sustaining the group (Jones, et al. 2004, Kuk 2006). In a study of online communication networks formed by online auction participants, Flanagin (2007) found that diversity of motivations (utilitarian and status-oriented) were associated with uneven distribution of contributions. Our findings of strong support for reciprocity in open membership, technically oriented communities may not hold in other types of forums. For example, innovative users on a firm-hosted and product-focused forum were more interested in firm recognition compared to peer recognition and reciprocity by peers (Jeppesen and Frederiksen 2006). Similarly, a study of high contributors of reviews on Amazon found them to be less driven by other-orientation (Peddibhotla and Subramani 2007). On a legal forum, the expert posters had little expectation of their actions being reciprocated (Wasko and Faraj 2005). Such emergent findings seem to indicate that online communities where reputational factors are key or where a firm plays a focal role are likely to be characterized by a more utilitarian interaction dynamic. The conditions under which the norms of direct and indirect reciprocity stop holding in online communities is an open research question.

Another major finding was that although these online communities exhibit the same network exchange tendencies (direct and indirect reciprocity, a tendency away from preferential attachment), they each do so in a distinct constellation of magnitudes. These results indirectly support the contention that community-structuring processes may be at play or that norms are present. More importantly, the clear differences across online communities bring to the fore the importance of social context in studying interactions. This finding points to the need to stop viewing online communities as an archetype and to pay more attention to online community characteristics (see Porter 2004). Recent research has noted that individual motivations (Ridings and Gefen 2004) and communication network structures (Fisher, Smith and Welser 2006) differ based on online community topic. Future research may benefit from ceasing to conflate similarities among online communities and more carefully evaluating the specific context of each online community. Indeed, even though our online communities share the same topic (technology) and technology platform (vBulletin) they still demonstrate measurable community-specific differences.

This finding raises a further puzzle: how do online communities maintain consistent interaction patterns over time when many online communities have high turnover rates? Because our study is focused at a network level of analysis, we cannot offer a specific theoretical explanation as to how these online communities sustain their consistent patterns of interaction. However, our results are consistent with social explanations from identity and bond theories (Ren, et al. 2007) and other suggestions that norms and obligations (Shah 2006, Wasko and Faraj 2000) are reasons for online community sustainability. While it was outside the scope of this study to explore how and when online communities develop group-specific communication patterns, researchers may want to focus on how these interaction patterns or norms emerge or evolve over a community's lifecycle.

Finally, by looking at online communities at a group rather than individual level, this study confirms the benefit of investigating the connections in addition to the attributes of interacting people. We have established that online communities develop specific patterns of interaction (e.g., direct and indirect reciprocity) that seem to be consistently present over time and across communities. These patterns are present in spite of the variety of motivations driving individual actors—a diversity of motivations that much of the extant literature has remained focused on identifying. Further, by investigating interactions at the network level rather than at an egocentric level, we go beyond previous network studies that focused on the relative advantages of networks with closure versus networks with structural holes (Brass, et al. 2004). Watts (1999) has noted that any actual network study is a compromise between different possible ways to study the network. Future research is likely to augment our findings by exploring online community structure in different ways than offered here.

The research reported here has clear limitations that need to be addressed in future work. First, the theoretical insight about the nature of information exchanges in online communities is based on an investigation of only five technology-focused, relatively large, sustained online communities, and thus may be limited. Because our primary goal was to analyze interactions in online-communities focused on knowledge-rich practices, we consciously chose to restrict our sample to well-established technology-oriented communities. Therefore, there is an inevitable tradeoff between sample breadth and analysis depth. Future work is needed to ascertain how these findings generalize to a more diverse set of online communities in terms of topics, size, and stage in online community life cycle. While our results should extend to similar technology-oriented online communities, such as open source and technology support, the large variation in types of online communities (Porter 2004) generates the need to clarify boundary conditions for online community research.

Second, our study simultaneously gained focus and was limited by the primacy of network ties. While we gained clarity about the nature of the network-level interactions, we could not address interesting questions about the kind of individuals that are more highly connected and whether certain of their attributes (e.g. role or motivation) drive their online activity. For example, interaction patterns may differ systematically between core and peripheral community members. Applying additional research methods, such as participant surveys and content analysis, would provide greater understanding into variations among network exchange patterns and participant experiences in an online community. Finally, our cross-sectional comparison of networks is relatively static and allows little theorizing as to how these networks came to be and what factors affect their evolution. Yet, the similarity of our findings across five different networks and the duration of observation (over 27 months) partially mitigates this concern by demonstrating consistency in our findings.

In conclusion, this study applies theories of network research, social exchange, and network exchange to investigate how individual behavior manifests in exchange patterns in online community communication networks. We find that network exchange patterns in online communities are characterized by direct reciprocity, indirect reciprocity, and an inclination away from preferential attachment patterns. This calls into question previous assumptions that skewed distributions of online participation are due to a desire to connect with the most popular participants in online settings. Our findings shed light on how diverse individual-level motivations may manifest in similar network exchange patterns across online communities, yet demonstrate online community-specific magnitudes within online communities. As new organizational forms evolve, both individuals and organizations are adapting to new ways of organizing and working that are highly dependent on electronic knowledge exchange. Studies are needed that investigate how online communities are structured and how large-scale interaction patterns can inform theories of mass collaboration and knowledge exchange. By combining network analysis techniques with theories of online communities, this study is an important step in that direction.

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