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RESEARCH NOTE

PARTICIPATION IN OPEN KNOWLEDGE COMMUNITIES AND JOB-HOPPING: EVIDENCE FROM ENTERPRISE SOFTWARE[1]

Peng Huang
Department of Decision, Operations, and Information Technologies, Robert H. Smith School of Business,
University of Maryland, College Park, MD 20742-1815 U.S.A. {huang@umd.edu}

Zhongju Zhang
Department of Information Systems, W. P. Carey School of Business, Arizona State University,
Tempe, AZ 85287-4606 U.S.A. {zhongju.zhang@asu.edu}

Using longitudinal data of IT professionals' activities in the SAP Community Network, and the career histories of these professionals obtained from LinkedIn, we investigate the relationship between an individual's participation in Internet-enabled open knowledge communities and a major event of his/her career development: job-hopping. We measure individual participation in open knowledge communities by two dimensions of related activities: contribution and learning. We provide empirical evidence that contribution to knowledge communities leads to a higher likelihood of job-hopping, yet a greater amount of learning is associated with a higher probability of retention. We argue that the effect of contribution can be attributed to job market signaling and the effect of learning is primarily driven by enhanced job performance and career advancement within the current organization. A series of robustness tests were conducted to address the self-selection bias and to rule out some possible alternative explanations to these mechanisms. Our work contributes to the existing body of literature on networks of practice and provides supporting evidence that participation in these networks indeed leads to career benefits and status advancements. Additionally, our study takes the first step to fill the gap in the current literature on voluntary employee turnover that has so far ignored the impacts of employee participation in external knowledge communities, thus providing both theoretical and practical insights in the area of organizational research.

Keywords: Knowledge community, network of practice, knowledge management, online forums, job-hopping, career development, enterprise software

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Introduction

Over the last decade, many firms have implemented knowledge management systems to promote the codification, sharing, and transferring of knowledge within the organization (Alavi and Leidner 2001). While traditional knowledge management systems are usually confined within the boundary of an organization, an emerging organizational form of managing knowledge—Internet-enabled open knowledge communities,[2] such as networks of practice[3]—has become increasingly popular and has drawn wide interest from practitioners and innovators (Ardichvili et al. 2003). These knowledge communities often utilize Web 2.0 tools such as wikis, blogs, and discussion forums to enable the creation and sharing of knowledge among community members. A vast body of literature has investigated this form of knowledge management practice. For example, recent research has theorized the community-based model of knowledge creation as an evolutionary process of learning driven by criticism (Lee and Cole 2003), which often expands beyond the boundary of firms (O'Mahony and Ferraro 2007). Some suggest that networks of practice help to solve problems quickly, facilitate the spreading of best practices by harnessing expertise dispersed among community members, and create high quality and variety of innovations (Füller et al. 2007; Wenger and Snyder 2000).

Although significant progress has been made, there remain at least two related issues that challenge the understanding of Internet-enabled open knowledge communities. First, to the extent that contribution to these communities is similar to the creation of public goods (Zhang and Zhu 2011), it is difficult to motivate members to actively participate and contribute to these communities. Some earlier research has offered excellent insights into the incentives to contribute to such communities (Ma and Agarwal 2007; Roberts et al. 2006; Wasko and Faraj 2005). In general, they found that participants are driven by both intrinsic motives, such as the sense of fulfillment and satisfaction, expression of creativity, or enjoyment, and extrinsic motives, such as economic incentives or self-interest (Lerner and Tirole 2002; Roberts et al. 2006). However, aside from anecdotal evidences or surveys, rigorous empirical studies on the *realized* career benefits of participation are lacking.[4] Additionally, it is not clear whether various types of participation activities in open knowledge communities might be associated with different forms of benefits.

Second, a particularly thorny issue of governing knowledge management practices emerges when the employees of an organization participate in an open knowledge community that spans outside the boundary of the organization. Although employee participation may bring in learning benefits (Brown and Duguid 1991) such as enhanced job performance and higher job satisfaction, such activities may also lead to dual allegiance (Chan and Husted 2010) that can cause tension and possible conflict between the external community and the employing organization, especially when the knowledge sharing behavior deviates from what the organization expects, such as unintended knowledge spillovers, or when knowledge communities help individuals build their personal brand and signal their expertise to alternative employers, leading to employee turnover. Empirical studies on this subject are lacking, and the existing literature offers few insights into how to manage an employee's participation activities in external knowledge communities.

In this study, we attempt to answer these questions by empirically investigating how participation in an open knowledge community related to enterprise software impacts the career development of IT professionals, particularly their job-hopping behavior. Job-hopping is one of the major events in an individual's career development that is often associated with financial gains and career advancements. For example, prior research shows that wage gains from job changes average about 10 percent and account for at least one-third of wage growth (Topel and Ward 1992). In addition, job-hopping often leads to knowledge spillover, which can impose significant costs on employers (Fallick et al. 2006; Tambe and Hitt 2013), and may result in loss of tacit knowledge (Hatch and Dyer 2004). We measure participation in open knowledge communities by two dimensions of related activities: contribution and learning. We argue that these two types of activities can influence an individual's access to career advancement opportunities both inside and outside the current employer, and the tradeoff between the two determines turnover intentions (Stahl et al. 2009). Consistent with our argument, we find empirical evidence that contributing

[2]In this paper we adopt the framework developed by Lee and Cole (2003) and use "knowledge communities" to describe the model of community-based knowledge creation in purposeful, loosely-coordinated, distributed systems, in contrast to a closed, within-firm knowledge management system. Open source software communities and networks of practice are special cases of such knowledge communities.

[3]According to Wasko and Faraj (2005), a network of practice is a large, loosely knit, geographically distributed group of individuals engaged in a shared practice, which often coordinate through third-parties such as professional associations and exchange knowledge through conferences and publications.

[4]An exception is Hann et al. (2013), who studied the relationship between OSS community participation and wage. Our study differs in the institutional setting, the form of economic benefit, and the different types of participation activities.

behavior leads to a higher likelihood of job-hopping, yet a greater amount of learning is associated with a higher likelihood of retention. Our explanation of the mechanisms behind these findings are as follows: the effect of contribution on turnover can be attributed to the signaling of superior expertise in the job market, and the effect of learning on retention is likely to be attributed to enhanced job performance and greater opportunity of career advancement with the current employer. We further conduct a series of robustness tests to address the self-selection bias and to rule out some possible alternative explanations to the above mechanisms.

Our study complements the existing literature on networks of practice by demonstrating that participation in these networks indeed leads to realization of career benefits for the participants. Therefore, we provide supporting empirical evidence to earlier theoretical developments that emphasize the role of extrinsic motives in participation and contribution (Lerner and Tirole 2002; Von Hippel and Von Krogh 2003). Additionally, this study takes the first step to bridge the gap in the existing literature that has so far ignored the implications of employee participation in open knowledge communities on organizations. For example, voluntary employee turnover is a topic of organizational research with significant managerial and practical implications because it leads to tacit knowledge loss, operation disruptions, human and social capital depletions (Dess and Jason 2001; Hausknecht and Holwerda 2013), and therefore may negatively affect firm performance. Our research advances this body of knowledge by showing that individuals' participation in these communities influences their turnover behaviors and, more importantly, that whether their participation benefits or hurts their employers ultimately depends on the type of activities with which the employees engage in the communities.

Open Knowledge Communities and Job-Hopping

We argue that participation in open knowledge communities may have implications for working professionals in terms of their career development. In general, individuals in the workforce aspire to career success, which is defined as "the real or perceived achievements individuals have accumulated as a result of their work experiences" (Judge et al. 1999, p. 622). Prior research has suggested that career success consists of extrinsic and intrinsic components. Extrinsic success is typically manifested in highly visible outcomes such as salary growth or upward mobility/promotion, while intrinsic success is relatively subjective and is commonly measured by career or job satisfaction (Cox and Harquail 1991; Judge et al. 1999; Seibert et al. 2001). It has also been noted that career advancement and growth opportunities present themselves both within and outside the current employer, and the tradeoff between the two is a critical determinant of turnover intentions (Stahl et al. 2009).

Participation in open knowledge communities is likely to influence the tradeoff between accessing career advancement opportunities from inside and outside a company, which in turn results in varying likelihoods of job-hopping. Interestingly, the outcome may depend on the different types of participation activities. On the one hand, prior literature has highlighted that actively seeking knowledge in online communities may help individuals derive learning benefits and enhance their job performances (Bock et al. 2006). For example, by using open knowledge communities for peer support, and applying the knowledge learned to solve work-related problems (Lakhani and von Hippel 2003), individuals may enjoy enhanced job performance, and have a greater likelihood of advancing their career within the organization, leading to reduced turnover intentions. On the other hand, by contributing knowledge to these communities, individuals may signal their expertise that is otherwise difficult to observe, build their personal brand, and gain outside visibility, which can lead to greater access to career advancement opportunities from potential employers outside their current companies. Other things being equal, this should lead to increased likelihood of job-hopping. In the remainder of this section, we formalize these lines of logic in details and propose our hypotheses.

Contribution to Knowledge Communities and Job-Hopping

The informal structure and self-organizing model of operations of Internet-enabled open knowledge communities have defied the traditional model of knowledge management, which is usually governed by formal structures and hierarchies within a firm. To explain the voluntary knowledge contribution behavior in these communities, prior research has theorized a number of motivations (Roberts et al. 2006). For example, some researchers proposed that contributors are able to internalize extrinsic motivations, and therefore such contributions may generate tangible benefits in the long term (Hann et al. 2013; Roberts et al. 2006). Such extrinsic motivations may include career rewards, such as potential future job offers (Lerner and Tirole 2002), enhanced reputation (Lakhani and von Hippel 2003; Wasko and Faraj 2005), desire for peer recognition, and status seeking (Lampel and Bhalla 2007).

We believe the internalization of the economic returns of participation in open knowledge communities is likely to be attributed to signaling in the job market (Spence 1973; Weiss 1995). Because some desirable worker characteristics (for example, see Hann et al. 2013) cannot be directly observed, employers often seek observable quality signals such as educational credentials, job experiences, and professional certifications (Spence 1973). In the context of the enterprise software industry, such signaling or sorting models are particularly relevant. This is because the implementation, configuration, and effective use of enterprise software require a highly complex skill that often combines technological know-how with a deep understanding of business processes and complementary organizational practices (Aral et al. 2012), a skill that is extremely difficult to assess. Open knowledge communities provide users an avenue for signaling their expertise and can help professionals build their personal brand and market themselves. By making contributions to these communities, users have the opportunity to gain visibility and establish themselves as experts in the field of their profession (Ardichvili et al. 2003), sending a positive quality signal of their superior expertise and talent to potential employers, and therefore are bestowed better access to outside job opportunities. Anecdotal evidence also seems to support this line of argument (Lerner and Tirole 2002). As noted by the gamification consultant Mario Herger, earning points in the SAP online community has a potentially strong real-world effect: "If your CV list SDN [SAP Developer Network, which is part of SAP Community Network] points, you land on top of the list of candidates,"[5] an observation that is in line with Reeves and Read (2009). Julius Bussche, a SAP mentor (role model and subject-matter expert in the SAP Community Network) said,

> It [SAP Community Network] will help bring professionals and employers together by highlighting members' unique accomplishments and SAP credentials through contribution of content to the community network's forums, wikis, blogs and various collaboration areas.[6]

In summary, knowledge contributors are more likely to appear on the radar of recruiters from competing firms in the industry because contribution in knowledge communities sends a strong signal of an individual's expertise, increasing an individual's visibility, status, and reputation among peers in the same profession and beyond the boundary of his/her own organization. Therefore these individuals are provided with greater access to outside career opportunities and are more likely to jump ship.[7] So we hypothesize:

H1: A higher level of contribution to Internet-based open knowledge communities is associated with a greater likelihood of job-hopping.

Learning from Knowledge Communities and Job-Hopping

While knowledge contributors may gain greater visibility by sending quality signals to alternative employers, and thus are more likely to access outside employment opportunities, some community members choose to be primarily knowledge seekers in the community and become the recipients of the knowledge exchange. This type of participant may derive learning benefits from their involvement in the community. In comparison to knowledge contribution, we argue that learning has an opposite effect on job-hopping. Open knowledge communities, especially those related to information technologies, are increasingly used by practitioners as an avenue for peer support purposes (Jabr et al. 2014; Lakhani and von Hippel 2003). Preliminary studies show that questions posted on these communities usually receive a high response rate, great engagement intensity, and quick resolution time (Huang et al. 2012). Many of the questions posted on these open knowledge communities typically stem from issues that the members encounter in their daily work. For example, Paul Sammons, Senior SAP Business Analyst and Wireless Goods Movements Project Lead for Baylor, refers to SAP communities first before opening a support ticket.

> If you have a problem the SAP Community Network is a great place to visit to see what other people are doing about it...I have found a lot of great insight from some of the communities within the community that rally around a certain module or topic

[5]Sebastian Deterding, "Gamification Roundup, February 15: The New Application Edition," (https://storify.com/dingstweets/gamification-roundup-february-15-the-new-applicati2).

[6]"New Career Center Uses Social Media to Make Finding SAP Experts and Jobs Easier," PR Newswire (http://www.prnewswire.com/news-releases/new-career-center-uses-social-media-to-make-finding-sap-experts-and-jobs-easier-62027997.html).

[7]It should be noted that the expectation of extrinsic rewards may lead to a greater amount of knowledge contribution. As a result, if both knowledge contribution level and job-hopping frequency are driven by unobserved heterogeneities such as intention to change jobs, endogeneity issues might arise in the identification of the effect of knowledge contribution. However, prior research suggests that most individuals contribute to knowledge communities because it is intrinsically rewarding, with little expectation of its economic payoffs (Lakhani and von Hippel 2003). For example, Bock et al. (2005) show that individual attitudes toward knowledge contribution are primarily influenced by relational motivators rather than the expectation of extrinsic rewards.

> like mobile applications. It's also great for day-to-day tips setting up configurations.[8]

By bringing in the knowledge learned from open knowledge communities to solve work-related problems, an individual is likely to enjoy enhanced job performance, receive appreciation and recognition from his/her employer, and thus have a greater likelihood of advancing his/her career within the organization (Di Maggio and Van Alstyne 2012). Such improvement in job performance also likely leads to greater job satisfaction (Petty et al. 1984, p. 719). Prior research has shown that a higher level of job satisfaction negatively predicts withdraw cognitions (consisting of thoughts of quitting, search intentions, and intentions to quit), and therefore can lead to a higher likelihood of retention (Hom and Griffeth 1991). In other words, by proactively learning from open knowledge communities, individuals can improve their productivity and job performance within an organization, enjoy greater opportunities for career advancement and higher levels of job satisfaction, and as a result are less likely to leave their current employers.

It should be noted that learning may also contribute *positively* to job-hopping. For example, learning from knowledge communities may lead to enhanced human capital, which makes the learner more desirable and capable of moving. In addition, learning may send positive signals to potential employers: applying external knowledge to solve work-related problems shows the person possesses the ability to identify and articulate complex problems and knows how to source for valuable solutions. However, we expect this positive effect of learning on job-hopping to be negligible based on two reasons. First, enhancement in human capital through learning is often unobservable to potential alternative employers. Second, while most open knowledge communities have established formal structures to reward contributors and recognize their knowledge contributions, reputation mechanisms that highlight the amount of learning in these communities are usually lacking, leading to a much weaker signaling effect of learning. Therefore, we propose that the dominating effect of learning is to enhance job performance and reduce turnover intentions, and as a result we hypothesize:

H2: A higher level of learning from Internet-based open knowledge communities is associated with a lower likelihood of job-hopping.

[8]Tim Clark, "SAP Community Network Means Business," *Forbes/Business* (http://www.forbes.com/sites/sap/2011/01/27/sap-community-network-means-business/).

Data and Methods

Research Setting

Our research setting is the open knowledge community sponsored by SAP AG, the largest enterprise software vendor by revenue. As part of its platform strategy to engage its customers and partners, SAP established an Internet-based SAP Community Network (SCN) in 2004, which serves as a resource repository and a platform for SAP users, developers, architects, consultants, and integrators to collaborate and exchange knowledge on the adoption, implementation, and customization of SAP solutions. The SCN is one of the most successful open knowledge communities that draw wide participation from practitioners.[9]

We chose enterprise software knowledge communities as the research setting for several reasons. First, the adoption of enterprise software inspires wide-spread innovation in the use of corporate IT and is associated with significant improvement in firm financial and operational performance (Hitt et al. 2002). As such, knowledge about the effective implementation and use of enterprise software systems is valuable in deploying IT to meet strategic business objectives. Additionally, enterprise software products are highly business-process oriented and usually need to be tailored to fit business practices. In the process of software adaption, customization, and reengineering of business processes, IT professionals may accumulate in-depth business functional knowledge and technical skills. Participation in these knowledge communities is likely to influence the career development of IT professionals who work in the enterprise software field because their employers highly value these skills.

To encourage participation, SAP has developed a contributor recognition program (CRP), which awards points to community members for the contribution they make. For example, in the case of forum discussion participation, varying amounts of points may be awarded for forum posts in reply to existing threads marked as questions, depending on the *helpfulness* of the answer. Points are awarded at the discretion of the person who asks the question. In addition, anyone who registers as a member needs to provide basic personal information and build a user profile. The user profile includes information such as the country that a user comes from, company affiliation, relationship to SAP, email address, phone number, expertise, and a LinkedIn profile page, etc. Figure 1 presents a sample user profile.

[9]John Hagel and John Seely Brown, "How SAP Seeds Innovation," *Bloomberg Businessweek* (http://www.businessweek.com/stories/2008-07-23/how-sap-seeds-innovationbusinessweek-business-news-stock-market-and-financial-advice).

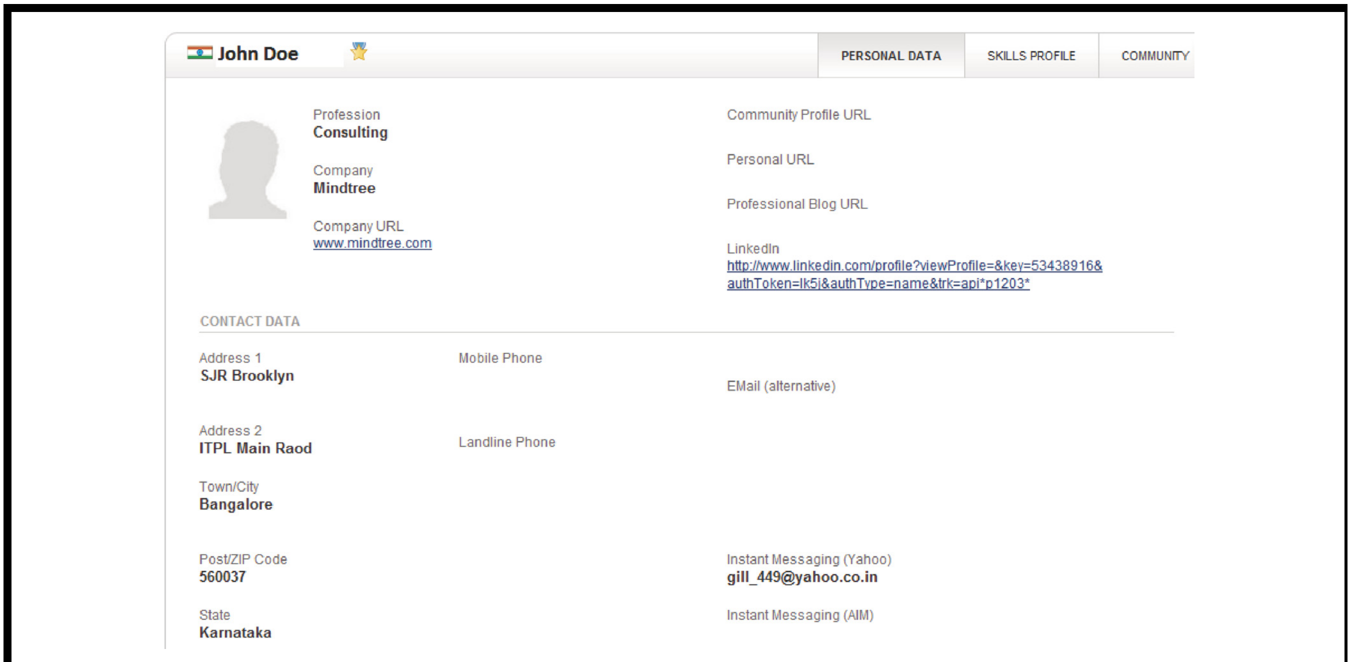

Figure 1. Sample User Profile

To track knowledge exchanges between the members of the SCN, we focus on user interactions through the most frequently used communication format: the discussion forums. The primary purpose of the discussion forums is to provide an avenue for conversations between the community members so that they help each other solve problems that they encounter during the implementation, deployment, and use of SAP software (Fahey et al. 2007). The *forums* are organized according to the domains of knowledge or expertise, each of which usually corresponds to a particular SAP software module or the application of the software solutions in a particular industry. Examples of the SCN forums include ERP manufacturing, product life cycle management, CRM-interaction center, and SAP for automotive solutions. A discussion *thread* is initiated by a knowledge seeker, who posts a specific question in a topic forum of his/her choice. Knowledge contributors, on the other hand, respond to the question and try to solve the problem by posting *messages* to the discussion thread. Once a correct solution (at the discretion of the knowledge seeker) is received, the discussion thread is closed.

Data

We assembled a dataset of IT professionals who participated in the SAP Community Network during the period of 2004–2011. Our data come from several sources. Specifically, we developed a web scripting tool and obtained the complete history of the SCN forum discussions as well as the user profiles of all registered members from 2004 to 2011. The dataset includes about 1.8 million discussion threads with over 8 million messages posted in 271 topic-specific forums. In addition, we used data on LinkedIn, the professional social network website, to obtain the complete career histories of the individuals in our sample. Career-related social network website data have been used by prior studies on IT labor mobility (Tambe and Hitt 2013) and job searching behavior (Garg and Telang 2011). We also supplemented our individual level data with information on the companies that employ these individuals, using sources such as the Compustat database, LinkedIn, and the Company Insight Center (CIC) database from *Businessweek* and Capital IQ.

Sample

The sample of our analyses is constructed in the following way: from the user profiles that we obtained from the SCN, we randomly retrieve a subset that represents 15 percent of registered users who are located in the United States and who disclose their company affiliations in their user profiles, resulting in 8,815 individuals. The next step involved matching the registered members to their professional profiles on LinkedIn to obtain their career histories. To ensure the quality of the matching, we performed a manual search on the LinkedIn website using the first name, last name, and company for each of the 8,815 registered members. We discarded records for those whom we could not find a matching profile on LinkedIn, or those with multiple matching profiles (meaning persons with the same first name, last name, and have worked for the same organization at some point of time) because we cannot uniquely identify the correct person. The matching resulted in 1,165 individuals for whom we have complete information on both their career histories and their SCN participation activities.[10] We compared observable individual characteristics (such as the amount of learning, contribution, and engagement intensity in forum discussions) between those for whom we found a matching profile on LinkedIn and those for whom we did not, and the differences are statistically insignificant. While this alone does not completely rule out the possibility of sample selection bias, it suggests the dissimilarities between individuals in the sample and those left out in the matching process are likely to be small. We further removed temporary, contract-based IT workers (details are provided in Appendix A), leaving us with 904 individuals in the final sample.[11]

Our data is organized in a longitudinal format. The SAP Community Network was established and made public in early 2004, so we use 2004 as the starting year of our analyses. We collected complete career histories for all the individuals in our sample from 2004 to 2011. Because of late entry (some individuals started their career in a year later than 2004) the sample is presented as an unbalanced panel. In total, we have 6,470 individual-year observations for 904 IT professionals over an 8-year sample period. By using a panel data set and adopting a within-individual approach, our estimate controls for all sources of between-individual heterogeneity and the results will not be confounded by a set of individual-level omitted variables such as reservation wage or personality traits (Obukhova and Lan 2013), which are typically available in survey research.

Dependent Variable

The primary dependent variable in our analyses is the job-hopping (or voluntary turnover) behavior of the individuals who participate in the SAP Community Network. To determine if a job-hopping occurs for individual i during year t, we first extract the individual's employer ($Company_{i,t}$) on January 1 in year t and on January 1 in year $t + 1$ based on the job histories we obtained from LinkedIn. An indicator variable, Job_Switch_{it}, is then created and is set to 0 if $Company_{i,t}$ and $Company_{i,t+1}$ are identical, and to 1 if $Company_{i,t+1}$ is different from $Company_{i,t}$.[12]

One challenge in defining our dependent variable is to differentiate voluntary turnover from job changes due to layoff or other types of organizational changes such as merger or acquisition. We took several measures to address this issue. First, we searched the Lexis-Nexis database for news releases that are related to mergers and acquisitions for all companies in our sample and removed job changes caused by such events. Second, we examined the D&B Who Owns Whom database to identify change of company affiliations of an individual as a result of transfers from one subsidiary of a company to its parent company, or from one subsidiary to another subsidiary of the same company. Finally, to ensure that our dependent variable truly reflects a voluntary job switch but not a layoff, we carefully examined the job histories and only retained job-hopping where there is no time a gap between two consecutive jobs. The assumption is that if the job switch is involuntary or the worker is laid off, it usually takes time to find the next job and there is likely to be a gap between consecutive jobs.

Independent Variables

We measure members' activities in Internet-based knowledge communities by two different dimensions: their contribution to the community and their learning from the community. We define each of the variables in turn in the following.

Contribution. We measure a user's contribution to the knowledge community using forum discussions that took place in the SAP Community Network. Specifically, the rules of the SAP reward program specify that, for each question that is posted in a topic forum, the knowledge seeker may use his/her discretion to judge the quality of answers posted by knowledge contributors. The knowledge seeker can distribute 10 reward points to a user whose answer is deemed correct (at most 1 answer can be evaluated as correct), 6 points if very helpful (at most 2 answers), and 2 points if helpful (no limit on the number of helpful answers). Therefore, a valuable knowledge contribution is made whenever the contributor receives reward points from the knowledge seeker who posted the question. For each individual i at year t, we retrieve the history of his/her posts in reply to knowledge seekers' questions. Based on the number of his/her posts evaluated by the

[10]A large fraction of unmatched records is caused by incomplete information in the user profiles, such as missing first name or last name, the use of nickname, or ambiguous employer information.

[11]We also ran separate tests using the sample including contract workers and all major results are robust to this alternative sample.

[12]To generate the dependent variable for year 2011, the last year of our sample, we also collect each individual's company affiliation on January 1, 2012.

knowledge seeker as correct, very helpful, or helpful, we compute the total reward points he/she earned. We use the number of total reward points that one earned by the end of year t, $Contribution_{i,t}$, as a proxy to measure his/her cumulative contribution to the community.

Learning. The amount of knowledge that an individual learned from his/her peers in the knowledge community is defined in a similar fashion. That is, learning occurs when the knowledge seeker receives valuable answers to the questions he/she posted. For each individual i at year t, we retrieve all of the questions that were asked by i prior to the end of year t, and examine the history of the answers posted by knowledge contributors. If i received any correct, very helpful, or helpful answers in year t, the number of reward points he/she gave to the knowledge contributors in recognition of their help is used as a proxy for inward knowledge flow (learning) to i. $Learning_{i,t}$ is thus defined as the sum of the reward points individual i gave to other knowledge contributors prior to the end of year t across all threads initiated by i.

Control Variables

We control for a number of variables at both the individual and the firm level. First, we obtain information on the educational background of the SCN participants from LinkedIn whenever such information is available, and created three dummy variables that capture different levels of educational attainment that are completed by an individual: *college degree*, *master's degree*, and *doctoral degree*. Using information from an individual's job history (i.e., the time when an individual started with a company and a job position), we created two control variables, *tenure in current company* and *tenure in current position*, to capture the number of years that the person has worked for the current company and has been employed for the current job position, respectively. In addition, because SAP is the sponsoring company of the knowledge network and has dedicated significant resources and personnel to support the community, we expect SAP's employees may display different patterns of participating behavior on the SCN than other users who are from its clients, partners, or system integrators. Therefore, we create a binary indicator variable, *SAP employee*, as a control.

We also control for the nature of the jobs by analyzing the job titles. Particularly, we differentiate between technical IT professionals and IT management professionals.[13] We created an indicator variable, *management*, and set its value to 1 if a job title contains manager, director, executive, supervisor, vice president, or other keywords that may indicate the job is mainly management related. Its value is set to 0 when a job title contains keywords such as analyst, programmer, architect, engineer, consultant, system administrator, or others that may indicate a technical nature of the job. In addition, although the vast majority of our sample works for the IT function within an organization, a very small fraction of our sample (less than 3 percent) works for non-IT business functions such as accounting, human resource, sales, and marketing, etc. We created an indicator variable, *non-IT function*, to capture the potential systematic difference in their behavior between IT professionals and non-IT professionals.

At the firm level, we control for the employer's industry, the type of organization, and the size of the firm which is measured by the number of employees. The data is collected from the company description on LinkedIn, supplemented by the Compustat database (for public companies) and Company Insight Center (CIC) database from *Businessweek* and Capital IQ (for private companies). While LinkedIn uses a variety of industry descriptors (over 160 in our sample), we created a mapping table to match these industry descriptors into the two-digit NAICS codes. The size of an organization is measured by the number of employees, which falls into one of the nine mutually exclusive and collectively exhaustive ranges (see Table 2 for details). Finally, depending on the type of the organization, each firm is classified into one of the following categories: educational institution, government agency, nonprofit, partnership, privately held, public company, self-employed, or sole proprietorship.

The summary statistics and correlations of some key variables are presented in Table 1. We find that the participants of the SAP Community Network are highly educated: about 85 percent earned a college degree and 28 percent earned a master's degree, consistent with the fact that they work in the high-tech industry. In addition, there is a high turnover rate for workers in the enterprise software field: on average, the unconditional hazard of a job switch during a year is about 21.5 percent, indicating an average person switches to another employer in a little less than 5 years. The Kaplan–Meier survivor curve, which describes the predicted unconditional probability of survival after a given time interval, is presented in Figure 2. On average, a member earned 24 points (equivalent to solving 2.4 questions, or contributing 4 very helpful answers), and gave 13 points (equivalent to receiving 1.3 correct solutions or 2 very helpful answers). In addition, about

[13]We define IT professionals as those who are concerned with issues related to advocating for users and meeting their needs within an organizational and societal context through the selection, creation, application, integration, and administration of computing technologies. IT management professionals refer to those who take a leadership role within the IT functional units in their organizations.

Table 1. Summary Statistics and Correlations

Variable	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. Job switch	0.215	0.411	0	1	1										
2. Tenure in current company	4.103	4.140	0	35	-0.0822	1									
3. Tenure in current position	3.753	3.854	0	35	-0.072	0.9125†	1								
4. SAP employee	0.078	0.268	0	1	-0.0707	-0.046	-0.0543	1							
5. College degree	0.851	0.357	0	1	0.0647	-0.0529	-0.0577	0.0262	1						
6. Master's degree	0.280	0.449	0	1	0.0228	-0.0239	-0.0414	0.0918	0.2612	1					
7. Doctoral degree	0.010	0.100	0	1	0.0216	-0.02	-0.0394	0.0509	0.0426	0.043	1				
8. Cumulative contribution	24.273	160.370	0	3,362	0.013	-0.0258	-0.0235	0.0549	0.0103	-0.0219	0.0774	1			
9. Cumulative learning	12.750	137.614	0	5,400	0.0018	-0.005	-0.0064	-0.0191	0.0256	0.0406	-0.006	0.1167	1		
10. Management	0.281	0.449	0	1	-0.0866	0.0721	0.0719	-0.0042	-0.0245	0.0084	0.0598	-0.0438	-0.0362	1	
11. Non-IT function	0.028	0.166	0	1	0.0008	-0.0427	-0.0399	-0.0045	-0.0222	0.0032	-0.0174	-0.0222	-0.0088	0.0545	1

Note: The sample includes 6,470 observations of 904 individuals over the period of 2004-2011.
†We note there is a high degree of correlation between tenure in current company and tenure in current position, which may lead to multicollinearity issues when both are included in the regressions. We have tested the models in which we excluded either one of them, and all the major results still hold.

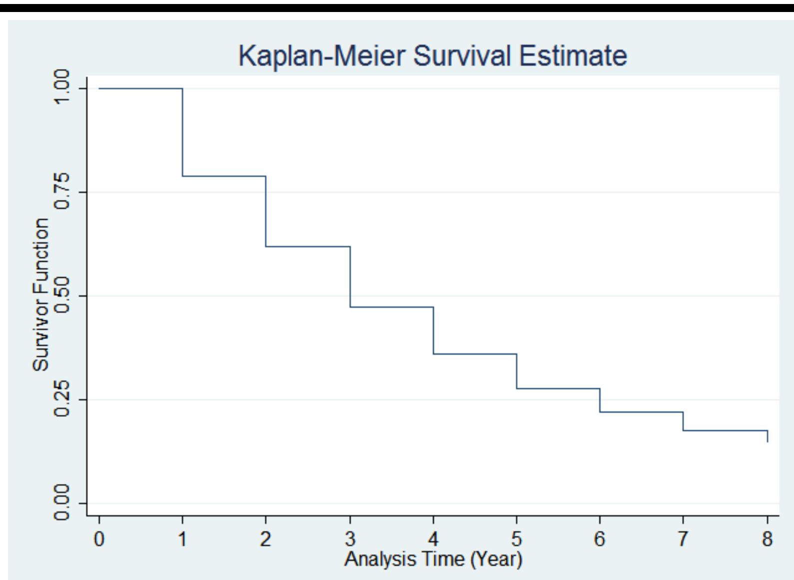

Figure 2. Kaplan–Meier Graph of Survival Function

28 percent of our sample works in a management position, and very few workers who participate in the SCN are from a business function other than IT (2.8 percent).

In Table 2 we present a breakdown of our sample by industry, firm size, and firm type. We find the participants are highly concentrated in a few industry sectors such as *professional, scientific, and technical services*, *manufacturing*, and *information*. This is consistent with the fact that these industries are either suppliers or the major clients of SAP enterprise software. We also find that majority of the IT workers in this field are employed by large public firms.

Table 2. Sample Breakdown

(a) By Industry Sector

2-digit NAICS	Description	Freq.	Percent
—	Unknown	411	6.35
11	Agriculture, Forestry, Fishing, and Hunting	18	0.28
21	Mining, Quarrying, and Oil and Gas Extraction	171	2.64
22	Utilities	121	1.87
23	Construction	32	0.49
31–33	Manufacturing	1,586	24.51
42	Wholesale Trade	23	0.36
44–45	Retail Trade	112	1.73
48–49	Transportation and Warehousing	94	1.45
51	Information	1,123	17.36
52	Finance and Insurance	223	3.45
53	Real Estate and Rental and Leasing	19	0.29
54	Professional, Scientific, and Technical Services	2,011	31.08
56	Administrative and Support and Waste Management and Remediation Services	85	1.31
61	Educational Services	107	1.65
62	Health Care and Social Assistance	123	1.90
71	Arts, Entertainment, and Recreation	68	1.05
72	Accommodation and Food Services	10	0.15
81	Other Services (except Public Administration)	58	0.90
92	Public Administration	75	1.16
Total		6,470	100.00

(b) By Size

Size	Freq.	Percent
Missing	512	7.91
Myself Only	51	0.79
1–10 Employees	197	3.04
11–50 Employees	297	4.59
51–200 Employees	443	6.85
201–500 Employees	286	4.44
501–1000 Employees	225	3.48
1001–5000 Employees	900	13.91
5001–10,000 Employees	530	8.19
10,001+ Employees	3,028	46.80
Total	6,470	100.00

(c) By Type

Type	Freq.	Percent
Missing	471	7.28
Educational Institution	96	1.48
Government Agency	114	1.76
Nonprofit	157	2.43
Partnership	124	1.92
Privately Held	1,900	29.37
Public Company	3,536	54.65
Self-Employed	35	0.54
Sole Proprietorship	37	0.57
Total	6,370	100.00

Empirical Models

We use hazard models as a starting point to analyze how individual participation in Internet-based knowledge communities influences the time to a voluntary job-hopping event. Hazard models (also referred to as survival, duration, or event history model) are useful in our setting because they directly model time to event and do not depend on the normality assumption imposed in linear regressions (Allison 2010; Huang et al. 2013). For example, modeling binary dependent variable (under our context, job-hopping) in a linear model will result in heteroskedasticity that needs to be corrected. Hazard models also allow for the occurrence of multiple hazard events (e.g., under our context, an individual may switch jobs multiple times during the sample period), and provide an approach to address the incomplete observation of survival times when censoring occurs (Hosmer and Lemeshow 1999). Specifically, we chose the Cox proportional hazard model as our model specification. This model is a semi-parametric specification that makes no parameterization of the baseline hazard and assumes that covariates multiplicatively shift the baseline hazard function. The hazard rate for the i^{th} subject at time t is specified as $h_i(t|\mathbf{x}_{i,t}) = h_0(t)\exp(\mathbf{x}_{i,t}\,\boldsymbol{\beta})$, where

$$\boldsymbol{x}_{i,t}\beta = \beta_0 Contribution_{i,t} + \beta_1 Learning_{i,t} + \boldsymbol{\theta C}_i + \boldsymbol{\gamma}\mathbf{Z}_{i,t}$$

$\mathbf{C}_i$ represents a set of time-invariant control variables (such as educational attainment), and $\mathbf{Z}_{i,t}$ represents a vector of time-varying individual- and firm-level control variables (such as tenure, job position characteristics, and firm characteristics, etc.).

To control for the possibility of unobserved individual heterogeneity, we run alternative model specifications using fixed effects (FE) panel data models. Estimating nonlinear models such as hazard models using individual fixed effects is likely to lead to biased and inconsistent estimates because of the well-known incidental parameters problem (Greene 2003). We address this problem by using a linear probability model (LPM) that directly models the probability of job-hopping, rather than modeling the hazard rate. In particular,

$$Prob(\text{Job\_Switch}_{i,t}) = F(\beta_0 Contribution_{i,t} + \beta_1 Learning_{i,t} + \boldsymbol{\gamma}\mathbf{Z}_{i,t} + \mu_i + \varepsilon_t)$$

Where we assume $F(.)$ is the identity function, and μ_i and ε_t represent a set of individual and time period fixed effects. The LPM can be viewed as a linear approximation to the nonlinear model counterpart of $F(.)$ such as binary logistic models (Heckman and Snyder 1997).[14] It is well known that LPM has its limitations—in particular, the predicted probabilities of such models are not bounded by a zero–one interval, and its error term is inherently heteroskedastic. However, with the appropriate robust standard error corrections, this model can provide useful approximations to the underlying relationship of interest (Angrist and Pischke 2009). Furthermore, prior work has shown that the LPM generates reasonable estimates within the region of support of the data (e.g., Miller and Tucker 2009).

[14]As a robustness test, we also run alternative models where the link function $F(.)$ is specified as a logistic function using a population-averaged generalized estimating equations (GEE) approach. All of the findings are consistent and the results are presented in Appendix C.

Analyses and Results

Main Results

The results of the Cox proportional hazard models are presented in Table 3. Because the distributions of contribution to and learning from the SAP community network are highly skewed, we took the log form of the variables *contribution* and *learning* and used them as independent variables. In Column 1 of Table 3 we present a baseline model specification where we include only the key variables of interest, *contribution* and *learning*, together with the indicator variable of *SAP employee*. To control for the systematic differences between SAP employees and non-SAP employees,[15] we also add the interactions of *SAP employee* and *contribution/learning* variables. We add a series of individual level control variables, including those related to educational background, tenure, and the job title in Column 2. In Column 3 we present a model that incorporates firm level controls such as industry sector, firm size, and firm type, in addition to individual level controls. For comparison purposes, in Column 4 we present a benchmark model in which our contribution/learning constructs are excluded.

We find supporting empirical evidence for both Hypothesis 1 ($p < 0.1$) and Hypothesis 2 ($p < 0.05$). Particularly, the estimated coefficient in Column 3 suggests that a 1 percent increase in knowledge contribution is associated with a 3.8 percent increase in the hazard ratio of a voluntary job-hopping. In comparison, learning from the knowledge community has an opposite effect: a one percent increase in learning is associated with a 5.1 percent decrease in the hazard ratio of a voluntary job change. This reinforces our earlier argument that signaling effect is not salient for learners, possibly due to the way the contribution recognition program was designed on the SCN: unlike contribution, the amount of learning is not prominently displayed in the user profiles. Additionally, a likelihood ratio test comparing Column 3 and Column 4 indicates that the increase in the model fit by adding contribution/learning constructs is significant ($\chi^2(4) = 9.05$, $p = 0.0598$). Aside from the hypothesized relationships, we also find empirical evidence that more educated workers tend to change their jobs more frequently (especially for those with a college degree and those with a doctoral degree), consistent with the theory that

[15]For example, some SAP employees are dedicated to support the community and are assigned a job role of moderating the discussion forums. Even for those SAP employees who are not assigned such job roles, they may still have different contribution patterns since they are more likely to be affected by peer influences, or promotional efforts (sometimes even financial rewards) from SAP as their employer.

Table 3. Results of Hazard Models

Variables	(1)	(2)	(3)	(4)
Contribution	0.052**	0.049**	0.038*	
	(0.022)	(0.022)	(0.023)	
Learning	-0.046*	-0.062***	-0.051**	
	(0.024)	(0.024)	(0.024)	
SAP employee	-0.721***	-0.787***	-0.697***	-0.745***
	(0.167)	(0.165)	(0.188)	(0.162)
SAP employee * Contribution	-0.150*	-0.161**	-0.155**	
	(0.077)	(0.076)	(0.076)	
SAP employee * Learning	0.180	0.217*	0.210*	
	(0.115)	(0.114)	(0.115)	
College degree		0.446***	0.453***	0.443***
		(0.090)	(0.091)	(0.091)
Master's degree		0.070	0.083	0.085
		(0.060)	(0.062)	(0.062)
Doctoral degree		0.557**	0.530**	0.518**
		(0.227)	(0.232)	(0.232)
Tenure in current company		-0.210***	-0.200***	-0.196***
		(0.047)	(0.047)	(0.047)
(Tenure in current company)^2		0.007***	0.007***	0.007***
		(0.002)	(0.002)	(0.002)
Tenure in current position		0.173***	0.168***	0.164***
		(0.050)	(0.050)	(0.050)
(Tenure in current position)^2		-0.008***	-0.008***	-0.008***
		(0.002)	(0.002)	(0.002)
Management		-0.451***	-0.505***	-0.509***
		(0.067)	(0.069)	(0.068)
Non-IT function		0.058	-0.041	-0.044
		(0.161)	(0.167)	(0.167)
Industry dummies	No	No	Yes	Yes
Firm size dummies	No	No	Yes	Yes
Firm type dummies	No	No	Yes	Yes
No. of subjects	904	904	904	904
Observations	6,470	6,470	6,470	6,470
No. of failures	1,394	1,394	1,394	1,394

Notes: Cox proportional hazard models in all columns. Standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

better-educated individuals are more effective in pursuing their aspirations than poorly educated people (Vila and García-Mora 2005). Interestingly, our results in Column 2, 3, and 4 of Table 3 also suggest that management personnel are less likely to change their jobs; however, there is no systematic difference between IT and non-IT professionals in terms of the probability of a job-hopping.

In Table 4 we present the results of the fixed effects linear probability models. Columns 1–4 correspond to the same parametric specifications as those in Table 3 but are estimated with FE panel data models instead. The results of these models are consistent with those presented in the hazard models, although they have a more intuitive interpretation based on the standard marginal effects on probabilities, rather

Table 4. Results of Fixed Effects Linear Probability Models

Variables	(1)	(2)	(3)	(4)
Contribution	0.015**	0.016**	0.012*	
	(0.007)	(0.007)	(0.007)	
Learning	-0.018**	-0.021***	-0.020***	
	(0.007)	(0.008)	(0.008)	
SAP employee	-0.189***	-0.184***	-0.106*	-0.096*
	(0.046)	(0.050)	(0.059)	(0.058)
SAP employee * Contribution	-0.021	-0.015	-0.012	
	(0.017)	(0.018)	(0.019)	
SAP employee * Learning	0.038	0.034	0.035	
	(0.026)	(0.028)	(0.028)	
Tenure in current company		0.024**	0.028***	0.029***
		(0.010)	(0.010)	(0.010)
(Tenure in current company)^2		-0.001	-0.001	-0.001
		(0.000)	(0.000)	(0.001)
Tenure in current position		0.026***	0.024**	0.023**
		(0.010)	(0.010)	(0.010)
(Tenure in current position)^2		-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)
Management		-0.087***	-0.081***	-0.083***
		(0.024)	(0.025)	(0.024)
Non-IT function		0.010	0.001	-0.004
		(0.060)	(0.063)	(0.063)
Constant	0.220***	0.077***	0.123	0.099
	(0.015)	(0.023)	(0.246)	(0.251)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes
Firm size dummies	No	No	Yes	Yes
Firm type dummies	No	No	Yes	Yes
Observations	6,470	6,470	6,470	6,470
Number of subjects	904	904	904	904
R-squared (without FE)	0.008	0.043	0.054	0.052
R-squared (with FE)	0.2303	0.2574	0.2658	0.2646

Notes: Fixed effect panel data models in all columns. Robust standard errors in parentheses.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

than the marginal effect on hazard ratios as in the previous analyses. For example, based on the estimates of Column 3, we find that a 1 percent increase in knowledge contribution to the community is associated with a 1.2 percentage point increase in the probability of job-hopping ($p < 0.1$), while a 1 percent increase in learning lowers the job-hopping probability by a 2.0 percentage point ($p < 0.01$). Similar to the hazard models, we find supporting evidence for Hypotheses H1 and H2. In addition, a likelihood ratio test comparing Column 3 and Column 4 indicates that the increase in R-squared by adding contribution/learning constructs is statistically significant ($\chi^2(4) = 10.13$, $p = 0.038$).

Addressing Alternative Explanations

One alternative explanation for the effect of contribution behavior on job-hopping is that instead of signaling desirable traits that are associated with higher productivity, greater contribution is associated with unobserved changes in human capital (Weiss 1995). For example, as an IT professional turns from a novice to an expert in enterprise software, she may contribute increasingly more to open knowledge communities. Although our use of fixed effects methods controls for between-individual heterogeneities, there might still be longitudinal, within-individual changes in human capital that are correlated with knowledge contribution. To the extent that such heterogeneities are omitted, they could cause potential bias in our estimates.

We took advantage of a gamification[16] feature of the SCN introduced by SAP during our sample period to investigate whether our results are driven by this alternative explanation. Specifically, around year 2009, SAP introduced a new feature to the existing reputation system that awards platinum, gold, silver, and bronze medals to active contributors according to their various levels of lifetime contribution.[17] SAP made the medal winners highly visible: the medal badges are displayed in the business card of the contributors, in the discussion forums and blogs whenever the individuals make a post, and next to the individuals' names in the list of top contributors. As a result, the introduction of the medal system by SAP represents a "natural experiment" that exogenously increases the visibility of the active contributors on the SCN and amplifies the job market signaling effects for the medal winners. In fact, we find that the medal winners highly value this honor, and many of them even put the medal acquisitions as part of their resumes on LinkedIn.

To test the human capital acquisition versus job market signaling hypotheses, we adopted a "difference-in-difference" approach that takes advantage of this exogenous shock to the signaling effect. In particular, we created an indicator variable *medal winner*, which is set to 1 if the individual was awarded any of the platinum, gold, silver, or bronze medals. In addition, we divided the sample period into 2004–2008 and 2009–2011, which correspond to the time periods before and after the introduction of the medals system, and created another binary variable *period 2*, which is set to 1 for observations during and after year 2009. We run both the fixed effect linear probability model and the Cox hazard model by adding *medal winner*, *period 2*, and their interaction into the regressions. We expect a positive and significant interaction between these two variables, if our signaling hypothesis is the main driver of the relationship between contribution behavior and job-hopping. This is because only the medal winners experience an increase in the signaling effect after the experiment, while such effect is absent for non-medal winners. The identification approach we adopted is similar to Meyer et al. (1995, pp. 335-336).

We present the results of the Cox hazard model in Column 1 of Table 5, and the fixed effect linear probability model in Column 2. Our empirical results show that, as we have expected, the interaction term is positive and significant in both the hazard model ($p < .05$) and the fixed effect model ($p < .10$). Interestingly, we note that once the treatment effect is added to the regressions, the marginal effect of contribution is significantly reduced, and loses its significance in both models. Also consistent with our theory, we find that medal winners are not more likely to switch jobs prior to the introduction of the medal system, as suggested by the negative (and insignificant) coefficient in the hazard model,[18] which indicates that unobserved heterogeneity in human capital is not driving our results. Combined, our results provide empirical support for the job market signaling theory interpretation.

A second concern over alternative explanations is related to the effect of learning. While our results indicate that a greater amount of learning from open knowledge communities is associated with a lower likelihood of job-hopping, it is possible that this observation is caused by a selection effect rather than by the improvement in job performance. In other words, learning is likely to be associated with some unobserved personal traits that make the individual less mobile. For example, a greater amount of learning may indicate that a person is a novice in the enterprise software field and is less productive, and therefore is less mobile due to the difficulty of finding better, alternative employment. This would offer a different interpretation of the results in contrast to our arguments that learning improves an individual's job performance and enhances job satisfaction. To test this alternative hypothesis, we conducted two additional exercises. First, we constructed a variable, the *number of questions* that one asked in a particular year, and include this variable in the model in addition to our *learning* measures (which is a quality weighted number of helpful answers received). If one suspects that our observed "loyalty" was indeed driven by the lack of skill, we would observe the variable, *number of questions*, to be negatively associated with job-hopping, regardless of the amount of actual learning. This is because the number

[16]Gamification refers to the use of game mechanics in non-game contexts to encourage community engagement.

[17]For details about this feature, see "SCN Contributor Reputation Program FAQ" (http://scn.sap.com/docs/DOC-18475).

[18]Note in the fixed effects model this variable is absorbed into the individual-level fixed effects.

Table 5. Test of Human Capital Versus Job Market Signaling Explanations

Variables	(1) Hazard model	(2) FE model
Medal winner	-0.039	–
	(0.226)	
Period 2	-0.321**	-0.067***
	(0.125)	(0.019)
Medal winner * period 2	0.714**	0.117*
	(0.325)	(0.064)
Contribution	0.026	0.010
	(0.023)	(0.007)
Learning	-0.048**	-0.020***
	(0.024)	(0.008)
SAP employee	-0.677***	-0.105*
	(0.190)	(0.059)
SAP employee * Contribution	-0.171**	-0.019
	(0.076)	(0.019)
SAP employee * Learning	0.211*	0.037
	(0.116)	(0.028)
College degree	0.419***	–
	(0.091)	
Master's degree	0.082	–
	(0.062)	
Doctoral degree	0.459**	–
	(0.231)	
Tenure in current company	-0.180***	0.028***
	(0.046)	(0.010)
(Tenure in current company)^2	0.006***	-0.001
	(0.002)	(0.000)
Tenure in current position	0.150***	0.024**
	(0.049)	(0.010)
(Tenure in current position)^2	-0.007***	-0.001
	(0.002)	(0.001)
Management	-0.468***	-0.080***
	(0.068)	(0.025)
Non-IT function	-0.025	-0.000
	(0.166)	(0.063)
Constant	–	0.190
		(0.247)
Year dummies	n/a	Yes
Industry dummies	Yes	Yes
Firm size dummies	Yes	Yes
Firm type dummies	Yes	Yes
Observations	6,470	6,470
Number of subjects	904	904
R-squared (without FE)	–	0.054

Notes: Cox proportional hazard model in Column 1. Fixed effect linear probability model in Column 2. Variable *medal winner* is set to 1 if the individual obtained either a platinum, gold, silver or bronze medal. Also included in all models are industry, firm size, and firm type dummies.
***p < 0.01; **p < 0.05; *p < 0.1.

of questions raised is more likely to be correlated with low capability/skill, while the amount of helpful answers received (our measure of learning) is a result of other members' contribution behavior—therefore more or less beyond the knowledge seeker's control. In fact, what we found in our analysis is the opposite: the variable *number of questions* is not significant but the variable *learning* is still negative and significant (the results are presented in Table 6), therefore contradicting this alternative explanation. Second, although we could not observe job performance or job satisfaction directly, we created another dependent variable that is likely to be highly correlated with job performance and job satisfaction: an indicator of an internal *promotion* for each individual-year observation in our sample. Prior research shows that organizational advancement and promotion are strongly associated with job performance, and are more reliable performance indicators than salary increase (Wise 1975). We define an internal promotion as a job title change (without switching companies) from a junior position to a senior position (such as a transition from a system analyst to a senior system analyst, or from a functional manager to a director/senior vice president), or from a technical position to a managerial position (such as from a software engineer to a software development manager).[19] We run the same set of model specifications using this dependent variable and the results are presented in Table 7. We note that a higher level of learning is significantly associated with a greater likelihood of an internal promotion in the fixed effect linear probability model (Column 1 of Table 7). In the Cox hazard model specification (Column 2 of Table 7), although the coefficient of learning is less precisely estimated, the direction of the marginal effect of learning on internal promotion is still positive. Overall, our empirical results do not support the selection hypothesis that learners are underperformers, but are consistent with our theory that learning leads to better job performance and greater job satisfaction, and therefore reduces turnover intention.

Conclusion and Discussion

Internet-based open knowledge communities are rapidly growing and are becoming an effective avenue where professionals can turn to for knowledge exchange, learning, and collaborative innovation beyond the boundary of their organizations. They are double-edged swords for organizations that embrace them. On the one hand, the open channels of communication and interactions in these communities can generate tremendous value and opportunities for organizations (Huang et al. 2012). On the other hand, such knowledge sharing practices could have serious organizational implications including potential talent loss and knowledge spillover to competitors. In this paper, we study if and how participation in Internet-enabled open knowledge communities can influence the job-hopping behavior of IT professionals. With the assumptions that employees in general desire status advancement and financial reward, and that career advancement opportunities can arise from both within and outside the current employer, we develop the theoretical basis for our two main hypotheses: (1) knowledge contribution sends a strong signal of the contributor's superior expertise and talent to potential employers, thus leading to better access to outside career advancement opportunities, and more frequent job-hopping, and (2) learning (seeking knowledge) from open knowledge communities, on the other hand, helps an individual with improved job performance, thus leads to higher job satisfaction and potential career advancement within the current employer, which in turn reduces turnover intentions and job-hopping. We found supporting empirical evidence for both hypotheses. Additionally, our extensive robustness tests (see Appendix C) provide further evidence in support of the underling mechanisms that drive our main results.

Limitations

There are several limitations of the study. The sample was selected by including only people who have a presence in the SAP Community Network and for whom we find a matching profile on the professional networking site LinkedIn. Even though we took a number of measures, including the use of a matching sample (see Appendix B), to try to address the sample selection bias, there are likely remaining systematic differences in different populations. For example, it is possible that people who participate actively in these communities might be somewhat different than people who don't. Another concern involves the choice of our research setting in a single enterprise software knowledge community. Labor mobility and subsequent knowledge spillover may be economically more attractive in these fairly recent and emerging technologies than that for mature technologies. Hence caution must be exercised when interpreting and generalizing our findings beyond the bounded set of our data sample, and we call for further research to examine the economic benefits of participation in other types of knowledge communities and collaborative platforms.

This study did not explicitly examine the many kinds of social interactions and social capital that people derive from these interactions in open knowledge communities. Interactions other than giving and receiving reward points through forum

[19]The coding of this variable was done independently by an author and a research assistant, and inconsistencies were resolved by consulting a third-party industry expert with IT human resource management background.

Table 6. Controlling for the Number of Questions		
Variables	**(1) Hazard model**	**(2) FE model**
Contribution	0.043*	0.012*
	(0.027)	(0.007)
Learning	-0.056*	-0.022***
	(0.032)	(0.008)
Questions	-0.025	0.006
	(0.076)	(0.014)
SAP employee	-0.735***	-0.107*
	(0.206)	(0.059)
SAP employee * Contribution	-0.157*	-0.012
	(0.081)	(0.019)
SAP employee * Learning	0.221*	0.036
	(0.126)	(0.028)
College degree	0.465***	–
	(0.101)	
Master's degree	0.098	–
	(0.071)	
Doctoral degree	0.608**	–
	(0.287)	
Tenure in current company	-0.200***	0.028***
	(0.051)	(0.010)
$(\text{Tenure in current company})^2$	0.007***	-0.001
	(0.002)	(0.000)
Tenure in current position	0.162***	0.024**
	(0.054)	(0.010)
$(\text{Tenure in current position})^2$	-0.008***	-0.001
	(0.002)	(0.001)
Management	-0.533***	-0.081***
	(0.077)	(0.025)
Non-IT function	-0.040	0.002
	(0.191)	(0.063)
Constant	–	0.125
		(0.246)
Year dummies	–	Yes
Industry dummies	Yes	Yes
Firm size dummies	Yes	Yes
Firm type dummies	Yes	Yes
Observations	6,470	6,470
Number of subjects	904	904
R-squared (without FE)	–	0.054

Notes: Robust standard errors in parentheses.
***p < 0.01; **p < 0.05; *p < 0.1.

Table 7. Results of Using Internal Promotion as Dependent Variable

Variables	(1) FE Linear Prob Model	(2) Hazard Model
Contribution	-0.005*	-0.030
	(0.002)	(0.058)
Learning	0.007***	0.041
	(0.003)	(0.063)
SAP employee	0.000	-0.171
	(0.017)	(0.342)
SAP employee * Contribution	0.008	0.266**
	(0.005)	(0.119)
SAP employee * Learning	-0.016	-0.338*
	(0.011)	(0.185)
College degree	–	0.098
		(0.272)
Master degree	–	0.260
		(0.160)
Doctor degree	–	-0.644
		(0.570)
Tenure in current company	0.164***	1.385***
	(0.013)	(0.081)
(Tenure in current company)^2	-0.006***	-0.074***
	(0.001)	(0.007)
Tenure in current position	-0.176***	15.554
	(0.014)	(0.000)
(Tenure in current position)^2	0.006***	-14.781***
	(0.001)	(1.018)
Management	0.017*	0.202
	(0.009)	(0.153)
Non-IT function	-0.001	-0.273
	(0.017)	(0.516)
Constant	0.027***	–
	(0.009)	
Year dummies	Yes	–
No. of subjects	904	904
Observations	6,470	6,470
R-squared (without FE)	0.324	–

Notes: Internal promotion is used as the binary dependent variable. Fixed effects linear probability model in Column 1; Cox proportional hazard model in Column 2.
***p < 0.01; **p < 0.05; *p < 0.1.

discussions are not accounted for here. It is well known in the literature that network properties and structures formulated through interactions with other members in online communities are important and can yield additional useful insights in analysis. Additionally, there are potentially different clusters of community participants (e.g., those that both learn and contribute, in contrast to those that merely free ride by learning but not contributing). In our study context, a consensus has not been reached as to what is the appropriate metric to capture such social interactions and, more importantly, how the social network structure of an individual participant influences his/her career development such as job-hopping. Theoretical development linking social capital with career outcomes has provided several plausible underpinning mechanisms and explanations (see Burt 2000; Granovetter 1973). However, empirical evidence of a consistent relationship between social capital and career development is missing; the findings often depend on the context of the social network and the measurement of social capital (see McPherson et al. 1992; Mossholder et al. 2005). Future studies investigating the main effect of network structure as well as its potential moderating effect on job-hopping is recommended to fully understand the role of participation in open knowledge communities.

Implications for Research

From a theoretical perspective, this research makes an incremental contribution to the broad literature on communities of practice (Wasko and Faraj 2005), open source communities (Singh et al. 2011), and mass collaboration networks (Zhang and Wang 2012) where a collective of individuals work together to achieve certain objectives (e.g., innovation, new ideas, or problem solving). Earlier studies have focused on identifying factors that motivate individuals to contribute to these communities (Kankanhalli et al. 2005; Roberts et al. 2006), and argued for the tangible benefits that members can derive by participating in these communities (Lakhani and von Hippel 2003; Lerner and Tirole 2002). Our study, to the best of our knowledge, is among the first to empirically establish the link between participation in open knowledge communities and the realization of career benefits. In addition, while prior literature focuses primarily on the contribution behavior (Wasko and Faraj 2005; Zhang and Wang 2012), our study provides empirical evidence that different types of participation activities are associated with different career benefits, such as switching to a more rewarding job or getting better recognition from the current employer. These results highlight the importance of using a rich dataset to gain a holistic understanding of an individual's participation in open knowledge communities.

This study also adds value to organizational research on voluntary employee turnover, particularly for IT professionals (Joseph et al. 2007). While most of these studies examine factors related to the internal work environment or external market conditions as predictors for employee turnover, they have so far ignored the employees' activities outside the boundary of the employer organization, such as their participation in Internet-enabled knowledge networks. We provide supporting empirical evidence that such activities may indeed influence employee retention and the access to outside job opportunities. Therefore it may impose significant cost on employers, such as unintended knowledge spillovers or the loss of human capital and social capital (Jason et al. 2005), stressing the challenges of retaining talents in today's hyperconnected business environment enabled by information and communication technologies.

Implications for Practice

From a managerial perspective, employees are the greatest asset of an organization. The identification, attraction, and retention of high-caliber employees are among the top priorities in organizations. Recent trends in globalization and advancements in information technology have changed the dynamics of work and intensified competition for key employees. For example, workforces are becoming increasingly mobile, and the collaboration of work often extends beyond a single physical location to a more virtual and community-based environment. This calls for organizations to be flexible in human resource policies and practices, and to develop more sophisticated strategies to acquire and retain top talents for organizational success. For example, managers should make efforts to identify the top contributors to external knowledge communities among their employees who have established themselves as experts in the field, and design retention programs accordingly in recognition of their high status and visibility in the field.

Our research supports earlier literature and acknowledges that Internet-based knowledge communities are great avenues for employees to learn and expand their skill sets as long as they do not deviate from organizational goals. Learning from beyond the boundary of the firm is critical when knowledge is broadly distributed and the locus of innovation is embedded in interorganizational networks (Powell et al. 1996). Interestingly, our results show that learning from open knowledge communities enhances retention, possibly due to better job performance and greater job satisfaction. Too much contribution in these knowledge communities, however, can lead to greater visibility of the contributor to outside employers, resulting in loss of both top talent and knowledge for organizations. Hence, managers need to be conscious and prudent when they develop employee retention programs and contingency plans to fill potential gaps in skills. While it is not possible to completely control employee access to external knowledge networks, efforts should be made to create incentives that try to influence what employees should do in these communities; for example, encourage active learning and absorption of collective knowledge from these sources, or leverage such communities for free peer-to-peer support to solve work-related problems (Lakhani and von Hippel 2003).

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About the Authors

Peng Huang is an assistant professor of Information Systems at the Robert H. Smith School of Business, University of Maryland, College Park. He has a Ph.D. from the College of Management, Georgia Institute of Technology. His research interests include

platform technologies and innovation ecosystems, knowledge-sharing virtual communities, as well as consumer decision-making in e-commerce. His recent work has appeared in journals such as *Management Science*, *MIS Quarterly*, *Journal of Marketing*, and *Communications of the ACM*. His research has received the Kauffman Dissertation Fellowship from the Ewing Marion Kauffman Foundation, and the best conference paper (runner-up) award at the 2009 International Conference on Information Systems.

Zhongju Zhang is an associate professor of Information Systems at the W. P. Carey School of Business, Arizona State University. Prior to that, Zhang was on the faculty of the School of Business at the University of Connecticut, and was the founding director of the MS degree program in business analytics and project management. He has extensive knowledge with experiential and executive learning. His research focuses on how information technology and data analytics impact consumer behavior and decision making, create business value, and transform business models. Zhongju's work has appeared in academic journals including *Information Systems Research*, *MIS Quarterly*, *Production and Operations Management*, *INFORMS Journal on Computing*, *Journal of Management Information Systems*, *Decision Support Systems*, *European Journal of Operational Research*, and *Decision Sciences*. Zhongju has consulted extensively for General Electric on various data-centric analytics projects, and has experience teaching data analytics in the Leadership Development Program for Travelers.