ABSTRACT

Three Essays on Firm-Hosted Online User Communities

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Firms have been increasingly relying on building online user communities (OUCs) to access external, distant knowledge and expertise. In OUCs, participants – i.e., external product users and internal employees of the host firm – can interact with each other to discuss questions and evaluate ideas for existing product support and new product development. In this dissertation, I try to comprehensively study OUCs with three separate yet related essays focusing on different community entities – i.e., external product users and/or internal employees – in different contexts – i.e., online support communities (OSCs) for existing product support or online user innovation communities (OUICs) for new product development. The first essay focuses on the role of internal employees and investigates the innovation outcomes of employees participating in OUICs. The second essay focuses on both product users and host firm employees and examines the antecedents and consequences of employee-generated content in OSCs. In contrast, the third essay focuses on product users and examines a self-reinforcing spiral relationship between users' social capital and knowledge contribution under a broader OUC context.

Three Essays on Firm-Hosted Online User Communities

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CHAPTER ONE

Introduction and Motivation

Firms have been increasingly relying on building online user communities (hereinafter OUCs) to access external, distant knowledge and expertise (Bayus et al., 2013; Di Gangi & Wasko, 2009; Huang et al., 2014). In OUCs, participants – i.e., external product users and internal employees of the host firm – can interact with each other to discuss questions and evaluate ideas for existing product support and new product development. Building OUCs allows companies to connect, engage and extend relationships with customers, employees and partners. Depending on a company's needs, owned OUCs present multiple opportunities for enhanced business value, including sales and marketing, customer service and product development and customer intelligence (Ogneva & Kuhl, 2014). For example, OUCs provision companies' potentials to conduct real-time market research and consumer intelligence, achieve higher customer retention and increased customer satisfaction, as well as derive customer-driven product innovation and insights (Ogneva & Kuhl, 2014). Much research therefore has been done to investigate the factors that impact the sustainability and long-term success of OUCs. (e.g., Franke et al., 2013; Porter & Donthu, 2008; Jeppesen & Frederiksen, 2006; Foss et al., 2011).

In this dissertation, I propose three essays to study the dynamics of firm-hosted OUCs. Each essay deals with one or both participating groups – i.e., external product users and/or internal employees – of OUCs in different contexts – i.e., online support communities (OSCs) for existing product support or online user innovation communities

(OUICs) for new product development. The first essay focuses on the role of internal employees and investigates the innovation outcomes of employees participating in OUICs. I first review extant literature on OUICs and employee innovativeness in organizations and develop my hypotheses drawing upon members' roles in OUICs and organizational knowledge creation theory (Nonaka, 1994). I then examine my hypotheses in the context of IdeaExchange, an OUIC hosted by Salesforce.com. I combine qualitative coding on 8,088 user ideas commented and/or voted on by 122 employees of Saleforce.com with quantitative participation data of these employees. In addition, I conducted qualitative coding on employee comments of 4,472 distinct user ideas created in a two-year period. Overall, my study shows that employees who are exposed to a higher degree of diverse and well-codified knowledge created by users are more stimulated to generate their own ideas. Employees' community participation and their resulting innovative behavior, in turn, positively influence the implementation of user ideas. With these findings, my goal is to offer specific suggestions for developing overall employee engagement in OUICs and point out directions for future research.

In the second essay, I focus on both product users and host firm employees and examine the antecedents and consequences of employee-generated content in the OSC context. I first review extant studies on OSCs and develop my hypotheses drawing upon the reviewed literature as well as the Hawthorne Effect (Adair, 1984). I then investigate the hypotheses in the OSC of BMC, a global leader in producing innovative software solutions. I collected a total of 815 community documents, including 3,257 versions, created by 231 employees of BMC in a two-year period. In addition, a total of 12,315 product users were identified as the readers of the 815 employee-contributed documents.

Overall, my study shows that employees (or the document authors) receiving a higher degree of readership are more motivated to contribute community content, although the marginal effect of readership decreases. On the other hand, product users who frequently access and read employee-generated content are more likely to contribute to product support using the knowledge they have learned from the content. With these findings, my study provides valuable implications for the research of OSC and the broader online Q&A community, as well as the sustainability and long-term success of OSCs.

Finally, in the third essay, I focus on product users and examine a self-reinforcing spiral relationship between users' social capital and knowledge contribution under a broader OUC context. I used a unique dataset to test the spiral relationship between knowledge contribution and social capital. The dataset consists of 3,512 active members of the OUC of BMC with their dynamic participating data collected over a 5-month period. I conducted a series of panel regressions to examine the interaction between social capital and knowledge contribution. My empirical results not only support a spiral relationship between knowledge contribution and social capital, but a moderating impact of community growth on the relationship. Accordingly, I discuss theoretical and practical implications of my study.

CHAPTER TWO

Participation in Online User Innovation Communities and Employee Innovativeness: An Empirical Investigation

Introduction

Firm-hosted online user innovation communities (hereinafter OUICs) refer to firm-sponsored initiatives designed to co-create value with firms' product users and customers. In OUICs, participants – i.e., external product users and internal employees of the host firm – can interact with each other to discuss and evaluate ideas for new product development. As the potential value of these communities has become more apparent, an increasing number of firms are leveraging such communities to gain access to user suggestions and to capture distant knowledge, thereby increasing their ability to innovate (Bayus, 2013; Di Gangi & Wasko, 2009; Huang et al., 2014). Despite the potential value of OUICs, recent evidence from both academic research and practice suggests that many OUICs suffer from the "Empty Bar Syndrome" because they lack active external and/or internal participation (Nambisan & Baron, 2010; Ogneva & Kuhl, 2014; Piezunka & Dahlander, 2014). Having sustainable participation from both external users and internal employees is imperative for the long-term success of any OUIC because it serves as the foundation upon which firms can further design, invest, build and grow their communities (Burt, 2004; Faraj et al., 2011; Grant, 2012).

While both internal employees and external users' participation is required to build a successful OUIC, the extant research has tended to focus only on external users. Many scholars have studied the participation of external product users in OUICs and the conditions under which their participation might lead to successful innovations (e.g., Foss et al., 2011; Franke et al., 2013; Porter & Donthu, 2008). Although these studies provide valuable insights into how external product users contribute to organizational innovation, they provide an incomplete account of *the role of internal employees* in OUICs. Acquiring knowledge related to internal employee participation is important because a thriving OUIC depends on participation and contribution from both sides of this external/internal duality, an issue that has received limited empirical research attention to date.

Scholars have thus called for empirical studies to better understand internal employees' participation in OUICs (e.g., Chesbrough & Brunswicker, 2014; Jeppesen & Frederiksen, 2006; Nambisan & Baron, 2010). Nambisan and Baron (2010), for example, highlighted that an important organizational decision relates to the choice of employees assigned to participate in an OUIC and the nature of their interactions with external product users. Other studies emphasize the importance of proactive and reactive attention from internal employees for eliciting more suggestions and ideas from external product users (Dahlander & Piezunka, 2014; Di Gangi et al., 2010). Overall, the few existing studies in this area confirm the key role of employee participation to build a successful OUIC and indicate a lack of understanding of outcomes related to such participation. This study therefore seeks to contribute to the OUIC literature by focusing on employee innovativeness and investigating the innovation outcomes from employee participation[1]. *I define employee innovativeness as the extent to which an employee actively promotes and generates new ideas* (Gray et al., 2011).

[1] Participation has been conceptualized to include both passive and active behavior of members in the online community literature (Malinen, 2015). In this study, we focus only on active innovative work behavior of employees in the OUIC contexts.

I believe that examining innovation outcomes of participating employees is important and valuable for the following reasons. First, internal employees are still considered by firms as the most important innovation partners followed by product users and other external entities (Chesbrough & Brunswicker, 2014). OUICs hold the potential to enhance participating employees' innovative performance because the communities offer participants a joint digital space to more effectively discuss new ideas and learn from each other (Schlagwein & Bjørn-Andersen, 2014; Wasko et al., 2004). As such, research that can produce evidence to help managers and researchers understand the innovation benefits employees might obtain from OUICs is likely to advance both research and practice. Second, and more importantly, many host firms still lack the requisite knowledge and motivation to mobilize their employees to engage in OUICs (Foss et al., 2011; Nambisan, 2002). Increasing numbers of firms hold only the community managers/moderators and some customer-facing positions responsible for participating in these communities. Because achieving long-term community success requires employee participation from various job levels and functions (Ogneva & Kuhl, 2014; Whelan et al., 2011), it is difficult for these firms to continue to build and grow their communities. Thus, by investigating and demonstrating the innovation outcomes of employee participation, my study underscores the importance of encouraging and enabling overall employee engagement in OUICs.

I review extant literature on OUICs and employee innovativeness in organizations and develop my hypotheses drawing upon members' roles in OUICs and organizational knowledge creation theory (Nonaka, 1994). I then examine my hypotheses in the context of IdeaExchange, an OUIC hosted by Salesforce.com. I combine qualitative coding on

8,088 user ideas commented and/or voted on by 122 employees of Saleforce.com with quantitative participation data of these employees. In addition, I conducted qualitative coding on employee comments of 4,472 distinct user ideas created in a two-year period. Overall, my study shows that employees who are exposed to a higher degree of diverse and well-codified knowledge created by users are more stimulated to generate their own ideas. Employees' community participation and their resulting innovative behavior, in turn, positively influence the implementation of user ideas. With these findings, my goal is to offer specific suggestions for developing overall employee engagement in OUICs and point out directions for future research.

Literature Review

To examine employee participation and innovativeness in OUICs and indicate gaps in prior studies, I review related research streams in two areas: *firm-hosted online user innovation communities and employee innovativeness in organizations*. For employee innovativeness in organizations, I focus particularly on the studies in the IS field.

As noted earlier, existing studies on OUICs have largely focused on product users and examined the dynamics related to their participation and contribution to the community. A large body of OUIC research explores the factors that motivate or demotivate product users to participate and share more ideas with the host firms. The motivations include, among others, product users' sense of responsibility and commitment to the community (Nambisan & Baron, 2009, 2007), the degree of community support from peers (Kosonen et al., 2013; Dholakia et al., 2009), trust in the host firms (Porter & Donthu, 2008; Kosonen et al., 2013), and individual attributes (e.g., online interaction propensity) (Wiertz & De Ruyter, 2007; Wasko et al., 2004). On the other hand, demotivation emerges when negative perceptions of fairness and dissatisfaction with the outcomes exist within members of the community (Franke et al., 2013; Gebauer et al., 2013).

Another major stream of research examines why some product users are more innovative than others (Dahlander & Frederiksen, 2012; Chen et al., 2012; Jeppesen & Laursen, 2009; Jeppesen & Frederiksen, 2006; Mahr & Lievens, 2012; Bayus, 2013). Studies in this research stream mainly focus on the social interactions and community network structures that influence individuals' innovativeness. For instance, Dahlander and Frederiksen (2012) found that product users' position in the core/periphery network structure of an OUIC is likely to explain why some participants are more innovative than others. Likewise, Chen et al. (2012)'s research showed that the duration of users' participation to help promote and share ideas is affected not only by users' level of network connectedness but also by the degree of interaction with peers in the community.

While these studies contribute to our in-depth understanding of user participation in OUICs, the role of host firm employees and their community participation has been neglected. In addition, although there are a handful of studies focusing on the activities and roles of product users in OUICs (such as leadership roles and roles that enable power, authority and status) (Lilien et al., 2002; Jeppesen & Laursen, 2009; Mahr & Lievens, 2012), these studies fall short in explaining and differentiating the roles between users and participating employees. Finally, recent research on OUICs suggests the necessity to increase employee involvement in the community to enhance host firms' absorption capacity and help grasp the benefits of external ideas (e.g., Di Gangi & Wasko, 2009; Di

Gangi et al., 2010). Benefits from employee participation may not only relate to the innovative performance of employees and host firms, but to the sustainability of OUICs (Nambisan, 2002; Hoyer et al., 2010). Hence, there is a need to understand employee participation in OUICs and the resulting innovation outcomes.

Although few studies specifically examine employee innovativeness in the OUIC context, the topic of employee innovativeness has received considerable attention in the organizational contexts. Organizational studies position employee innovativeness as a multi-dimensional concept, consisting of activities pertaining to idea generation as well as idea realization or implementation (Parzefall et al., 2008). Employee innovativeness is a function of both individual ability and organizational context (Amabile 1983; Anderson et al., 2014; Shalley et al., 2004). Different aspects of social context have been linked to employee innovativeness at work (see Anderson et al., 2014; Parzefall et al., 2008 for a recent review).

In the IS field, early research has focused on how the use of different techniques (facilitated by IT) during ideation affects the quantity and quality of ideas generated by employees. Numerous studies demonstrate how the use of different stimuli or cues during ideation results in more creative ideas with the use of computer support systems (Forgionne & Newman, 2007; Massetti, 1996), group support systems (GSS) (Knoll & Horton, 2011; Satzinger et al., 1999), and electronic brainstorming (Dennis et al., 1999; Thatcher & Brown, 2010). The techniques studied to enhance an employee's innovative performance range from cognitive priming (Dennis et al., 2013), external stimuli (Hender et al., 2002), cause and input cueing (Potter & Balthazard, 2004), and divergent and convergent thinking (Müller-Wienbergen et al., 2011). The vast majority of these studies have applied an experimental approach to evaluate the impact of a given technique on the innovative performance of individuals or groups. While these studies are highly valuable in providing insights into the facilitating role of IT in idea generation, it is nevertheless important to examine the phenomenon of employee innovativeness in its natural setting where the duration of idea generation is not limited to an experimental time slot and where the risks of innovation failure are palpable.

Recently, a growing body of research has made strides toward this end, examining how using digital technologies or innovation platforms – e.g., knowledge repositories (Durcikova et al., 2011; Kankanhalli et al., 2005), wikis (Arazy et al., 2015), enterprise social software (Kuegler et al., 2015), etc. – within an organizational setting can contribute to employee innovation and performance. Gray et al. (2011), for example, investigate the innovation impacts of employees using social bookmarking systems in a global professional services firm. The research of Leonardi (2014) offers a communication visibility theory and suggests that enterprise social software improves employee metaknowledge, leading to less knowledge duplication and more innovative products and services. A key premise under this stream of research is that digital technologies and innovation platforms enable employees to not only obtain the knowledge of who knows whom and who knows what, but to access diverse perspectives, ideas and approaches from multiple functions and sources (Oldham & Silva, 2013; Leonardi, 2015). And informational advantage derived from intra-organizational communications and interactions with diverse others is an important driver of individual innovative performance (Burt, 2004; Perry-Smith, 2006).

Building on these research streams, this study seeks to add a new perspective on facilitating employee innovativeness. In lieu of building social relations and connections among employees within an organization, I emphasize how participating in OUICs with product users outside the boundary of an organization may affect the innovativeness of internal employees. In particular, I focus on the user idea content accessed by employees and how the quality or attributes of the content may affect employee innovation. Moreover, I emphasize how organizations could harness the OUIC as a secondary, informal context to balance the primary contexts – e.g., GSS and organizational innovation platforms – that have been developed to facilitate employee innovativeness. By doing so, organizations will enable employees to engage in multiple but distinct contexts to access information and knowledge created by distinct groups (i.e., internal colleagues and external users/customers). Therefore, compared to existing studies mainly focusing on communications among employees within an organization, this study advances both theory and practice by investigating how digital interactions with an external entity in an online setting could benefit participating employees.

In short, my study is related to but significantly different from the research I draw upon. To the best of my knowledge, it is one of the first to focus on internal employees and empirically explore their participation and innovativeness in the context of OUIC. Table 1 summarizes my literature review.

Table 1. Summary of literature review

Field of Study	Related IS Literature	Theoretical Focus of Previous Research Streams	Theoretical Focus of This Study
Firm-hosted online user innovation communities	Bayus, 2013; Chen et al., 2012; Dahlander & Frederiksen, 2012; Dholakia et al., 2009; Franke et al., 2013; Gebauer et al., 2013; Jeppesen & Frederiksen, 2006; Jeppesen & Laursen, 2009; Kosonen et al., 2013; Lilien et al., 2002; Mahr & Lievens, 2012; Nambisan & Baron, 2010, 2007, 2009; Wiertz & De Ruyter, 2007	• Motives for participation and idea contribution of product users • Innovativeness of product users • Activities and roles of product users	• The participation and different role of host firm employees in OUICs, compared to product users • The innovative work behavior of employees and the resulting innovation outcomes in OUICs
Employee innovativeness in organizations	Dennis et al., 1999, 2013; Gray et al., 2011; Hayne et al., 2003; Hender et al., 2002; Kankanhalli et al., 2005; Knoll & Horton, 2011; Kuegler et al., 2015; Leonardi, 2014; 2015; Massetti, 1996; Müller-Wienbergen et al., 2011; Potter & Balthazard, 2004; Satzinger et al., 1999	• The application of analytical and intuitive techniques to help generate ideas and solve business problems • The impact of different external stimuli or cues with the use of GSS in organizations • The capability to derive informational advantage enabled by digital technologies and intra-organizational innovation platforms	• Participation in OUICs and access to distinct information and knowledge created by external product users and customers • The use of OUIC as a secondary, informal context to complement existing organizational innovation contexts

Theoretical Development and Hypotheses

My study draws largely from the organizational knowledge creation theory complemented by the theorizing of different community roles played by product users and employees. The theory of organizational knowledge creation was first introduced by Nonaka (1994) and subsequently extended in his later works (see Nonaka et al., 2006; Nonaka & Toyama, 2003, 2005; Nonaka et al., 2000). Based on the theory, a core dimension of new knowledge creation in organizations is the level of social interaction between individuals (Nonaka, 1994). Specifically, because knowledge is created by individuals, organizations should provide a context, or "communities of interaction", wherein interactions between individuals can contribute to the sharing and development of new knowledge and ideas (Nonaka, 1994). Nonaka's later studies have highlighted that such a knowledge-creating place, or "ba", could be formal or informal, physical or virtual, and inside or outside organizational boundaries (Nonaka & Toyama, 2003; Nonaka et al., 2000; Nonaka & Konno, 1998). In this study, I treat firm-hosted OUICs as such communities of interaction that are virtual and span organizational boundaries. In OUICs, employees from various functions, levels and regions of the host firm can interact with external entities such as product users for knowledge sharing and creation. Exchanging knowledge and information between employees and product users in such communities of practice, versus the formal task-related procedures specified by the organization, may facilitate employee innovativeness by linking employees' routine work to active learning and innovation (Nonaka, 1994, Nonaka et al., 2006, Nonaka & Toyama, 2005).

Prior research has intensively examined the innovativeness of product users in OUICs, as reviewed earlier. Yet I suggest that the findings do not apply to employees because of *different roles* played by the two entities. Due to this role difference, as I will discuss in more detail below, different outcomes should result from the community participation between users and employees. In this study, I focus on one community behavior of *idea promotion*[2] and investigate its impact on *the implementation of user ideas*, a key construct examined in the existing OUIC literature (e.g., Li et al., 2016;

[2] In the OUIC contexts, idea promotion includes community behavior (e.g., voting) that reflects a member's intention to facilitate the implementation of user ideas.

Bayus, 2013). More specifically, I explain 1) how the innovative behavior of idea promotion of employees, versus users, influence the implementation of user ideas. On the other hand, despite a wide variety of antecedents of employee innovativeness identified in extant literature, in this study I propose a new viewpoint for augmenting employee innovativeness. Drawing upon organizational knowledge creation theory (Nonaka, 1994), I seek to connect OUIC research with the research of employee innovativeness in organizations by focusing on the impact of accessing community content created by product users. More specifically, I explain 2) how the diverse and well-codified knowledge contained in user idea content may stimulate the generation of new ideas by participating employees.

Members' Roles, Employee Innovativeness, and User Idea Implementation in OUICs

Employees and users play different roles in OUICs and this role difference entails multiple aspects. From a community activity perspective, product users post most ideas and initiate most discussion threads, forming the basis for further community interactions (Malinen, 2015). Besides sharing their own ideas, many users help develop and promote ideas of others via voting and commenting. In contrast, internal employees typically focus on screening and filtering user ideas in order to discover valuable ideas for further development (Ogneva & Kuhl, 2014; Di Gangi et al., 2010). They identify duplicate and redundant ideas, ask ideators to clarify incomplete and vague ideas, promote ideas of others and share their own ideas. From a motivation perspective, while voluntarily, employees view their community participation as an expected, in-role activity because of their relations with the host firms (Arazy et al., 2015; Wendelken et al., 2014). Some employees may possess a controlled motivation as they view their participation as expected/appreciated by the supervisors or by some work reward contingencies. On the other hand, product users overall perceive their participation as an optional, extra-role activity (e.g., Nambisan & Baron, 2010; Jeppesen & Frederiksen, 2006). They are largely driven by a state of autonomous motivation (e.g., intrinsic playful task, self-efficacy and information seeking) and their sense of self-determination should be high compared to employees. In addition, some nuanced difference may exist in some specific motivational factors between users and employees. For instance, users' community-specific commitment, when formed, primarily constitutes affective commitment, whereas employees usually start their commitment as normative community commitment (Bateman et al., 2011).

More importantly, employees and users possess different domain-specific knowledge in order to perform the respective community activities that carry out the corresponding participation motivations. In OUICs, this domain-specific knowledge can be further categorized into *technological knowledge, use knowledge and company-specific knowledge* (Kristensson & Magnusson, 2010; Boeddrich, 2004). I suggest that employees and users share similarity regarding technological and use knowledge. In other words, both groups can be familiar with the features and functionalities of a certain product or service and understand what will create value for the users based on the knowledge derived during the process of using the product or service (Kristensson & Magnusson, 2010). However, employees, in general, possess advantages over users in terms of company-specific knowledge because of the different relations with the host firm. This company-specific knowledge includes the use of idea management tools and processes, the K.O. criteria for projects, the needs of certain individuals or organizational units and the strategic goals of host firms (Floren & Frishammar, 2012). Finally, because most OUICs are open to users worldwide, differences also exist between employees and users with respect to culture, language, time and other demographic background and characteristics (e.g., Chua et al., 2015).

Because of these role differences between employees and users, I argue that employees' innovative behavior of idea promotion in OUICs will have different impact on the implementation of user ideas than product users. Many OUICs have been depending on product users to promote valuable ideas via counting and ranking the number of user votes and comments on ideas (Di Gangi et al., 2010). Existing studies, however, have demonstrated the limit of these approaches and conclude that in practice none of them has a significant impact on which ideas are being adopted and implemented by the organizations (Di Gangi & Wasko, 2009; Westerski et al., 2013). Some explanations include the lack of ability and tools for users to recognize and thereby work with massive redundancy and trivial ideas (Westerski et al., 2013; Di Gangi et al., 2010), minority group biases (Di Gangi et al., 2010), and most importantly, the lack of company-specific knowledge of product users (Füller, 2010). As a result, many highly promoted ideas lack novelty and/or usefulness, limiting their value to the host firms (Di Gangi & Wasko, 2009).

Contrary to product users, I suggest that employees' innovative community behavior may have significant impact on the implementation of user ideas. By commenting on the ideas that are vague and incomplete because of insufficient details (e.g., information related to personal experience), employees from various functions of the host firm can prompt the ideators to provide additional information to understand the ideas correctly. Consequently, participating employees might uncover novel ideas that were initially unnoticed because of a lack of details. More importantly, employees possess deeper company-specific knowledge than product users. This would lead an employee to consider whether the focal idea fits with the resource capacities of the project or firm, satisfies market needs, is technologically feasible, and/or aligns with existing product portfolio and strategy of the firm (Florén & Frishammar, 2012; Malhotra & Majchrzak, 2014). Accordingly, the employee is more likely to act on the idea (e.g., vote) based on how the idea will potentially add financial and/or technological value to the firm rather than "liking." Thus, I suggest that employees are more competent in filtering and identifying real valuable ideas than most product users.

More importantly, employees who frequently participate in the community may be more likely to promote and channel the valuable ideas they discover into the firm's internal innovation process. An employee of R&D may bring the ideas s/he discovered valuable to an employee of marketing for further assessment, and vice versa. Particularly, ideas supported and promoted by senior management will have a greater chance to be developed if executive champions become personally involved in the community (Ogneva & Kuhl, 2014). As argued by Nonaka (1994), individuals who pay attention or commit to discovering and interpreting information and knowledge are more likely to motivate themselves to facilitate the creation of new knowledge and innovation. Such passion and attention play a critical role in facilitating internal communication and thereby diffusing valuable user ideas to the appropriate or affected individuals, functions and departments for further assessment (Foss et al., 2011; Whelan et al., 2011; Florén & Frishammar, 2012). Overall, I suggest that while employees may exhibit varying levels of motivation in promoting and channeling user ideas, they are likely to devote these efforts to the ideas they evaluate positively and find particularly valuable for implementation.

Taken together, my arguments directly imply that employees' active engagement in communication with users can facilitate the understanding and thereby the filtering and implementation of user ideas. The more frequently employees participate in the community, the more ideas they are likely to discover. Furthermore, employees are likely to promote and channel valuable ideas for implementation. In other words, I can expect that as employees conduct more promotional behavior (e.g., via commenting and voting) in the community, more implementations will be facilitated for valuable user ideas. I therefore hypothesize that:

Hypothesis (H1): *Employee idea promotion in an OUIC facilitates user idea implementation.*

Knowledge Creation and Employee Innovativeness in OUICs

Drawing upon organizational knowledge creation theory (Nonaka, 1994), I suggest that employees' participation in OUICs will not only facilitate user idea implementation but will, in turn, impact employee innovativeness in terms of employee idea generation. Apart from the context of new knowledge creation and innovation (i.e., "communities of interaction"), organizational knowledge creation theory highlights *the relevance of information content in innovation processes* (Nonaka, 1994). Nonaka points out that in terms of innovation, the content of knowledge is more relevant than the form in which the knowledge content is embodied. Thus, he views the conversion and combination of different types of knowledge – i.e., tacit and explicit knowledge – as central for innovation. Applying this logic to my context, I suggest that the *interaction* *content*, rather than the interaction frequency, plays a relatively critical role in explaining individuals' ability to generate new ideas.

In the context of OUIC, product users generate knowledge content when they convert their tacit knowledge into explicit knowledge and post it as ideas. By accessing and reading user ideas, employees are able to acquire the explicit knowledge contained in the idea content and absorb it to create new tacit knowledge. As an employee continues to access and read user ideas, the accumulated tacit knowledge may inspire the employee to generate his/her own ideas. While accessing user ideas in OUICs is likely to facilitate employee idea generation, it is imperative to examine and analyze *the characteristics of knowledge* contained in the ideas. For example, an employee may frequently access and read user ideas, but s/he will be less likely to be inspired to generate new ideas if most of the user ideas s/he reads are vague and/or incomplete. Likewise, an employee may not be able to continue to generate new ideas if s/he tends to read user ideas about the same category of products/services (Bayus, 2013). Therefore, to examine the influence of user idea content on employee idea generation, I focus on two traits of knowledge that may affect individual idea generation via different cognitive mechanisms and processes: *diversity and codifiability*.

In OUICs, knowledge diversity represents the degree of distinct content exposed to an employee when s/he reads user ideas. Knowledge diversity can facilitate the innovative process by offering individuals the potential to create novel links and associations among different types of knowledge acquired (Cohen & Levinthal, 1990). A wide variety of studies have recognized the importance of knowledge diversity for individual idea generation (e.g., Burt, 2004; Faniel & Majchrzak, 2007; Jeppesen &

Laursen, 2009; Rodan & Galunic, 2004; Sosa, 2011). Faniel and Majchrzak (2007), for example, find that engineers who successfully access knowledge from other functional departments are more likely to become innovative than engineers who do not. Likewise, Sosa (2011) indicates that in new product development teams, employees who possess strong ties connected with diverse information generate more ideas than those who do not. I therefore expect that accessing diverse content in OUICs may enable employees to process the knowledge (via modifying and/or integrating) and thereby generate new ideas.

On the other hand, the positive effect of diverse content on idea generation should diminish after an employee has acquired numerous different types of content in the community. At this point, increasing content diversity may have only a minimal impact on idea generation because a wealth of information creates a substantial information-processing burden (Ocasio, 1997; Simon, 1971). Specifically, as an employee accesses increasing community content, there may be a great amount of content that remains unabsorbed (the absorptive capacity problem), few of the ideas may be taken seriously or given the required level of attention (the attention allocation problem), or many ideas may come at the wrong time and in the wrong place to be fully exploited (the timing problem) (Koput, 1997; Laursen & Salter 2006; Simon, 1971). Taken together, I posit:

Hypothesis (H2a): *The degree of diverse content an employee has accessed in an OUIC has an inverted U relationship with employee idea generation.*

In addition to diversity, knowledge has different levels of codifiability (Nonaka & Von Krogh, 2009). In OUICs, knowledge codifiability reflects how well the tacit knowledge of product users has been converted into explicit knowledge that is then posted as idea content. Compared to poorly codified ideas that are vague and/or incomplete, well-codified ideas are not only clear and complete, but usually contain figures/drawings, structured data and codes/reports to facilitate their mental representation. Accessing well-codified ideas is likely to facilitate individual idea generation because they are less ambiguous and hence more readily integrated into one's existing knowledge plans (Finke et al., 1992; Mahr & Lievens, 2012; Nonaka et al., 2000; Sosa, 2011). In addition, well-codified ideas present an opportunity to link one's ideas to those of others or to combine some of the shared ideas into more complete, novel or useful ideas (Kohn et al., 2011). I therefore expect that well-codified idea content, from the recipient's cognitive perspective, is easy to absorb, process and combine into new ideas. Meanwhile, because of the potential information overload problem discussed above, employees are unlikely to benefit from the idea content once they have reached a point of idea saturation. Consequently, I expect that the innovation effect of accessing well-codified content should become weaker when an employee is experiencing overabundant idea content, even though the content is all well-codified. In sum, I hypothesize that the effect of well-codified idea content on employee idea generation is nonlinear as follows:

Hypothesis (H2b): *The degree of well-codified content an employee has accessed in an OUIC has an inverted U relationship with employee idea generation.*

Methodology

Context: Salesforce.com's IdeaExchange Community

I selected IdeaExchange, the OUIC of Salesforce.com, as my empirical setting. Salesforce.com launched IdeaExchange around 2007 and has established a successful long-term relationship with its product users for value co-creation and product innovation (The Community Roundtable, 2015). According to my interview with the community manager, IdeaExchange was launched as a forum to gather users' suggestions and ideas for new product development. Ideas can either relate to an existing product or a new product for an incremental change or a radical change[3] . Not only are users encouraged to share their own ideas but to discuss and evaluate others' ideas via comments and votes. Employees of Salesforce.com are also encouraged to participate in the community. Participating employees will receive education from the community management team on how to communicate and interact with product users for better community results. Notably, while Salesforce employees from different levels/functions might possess different motives for participating in the community, their participation remains voluntary.

Data Collection

I applied a longitudinal data collection and collected 4,472 user ideas that were created from July 2012 to June 2014. To identify employees participating in the community, I analyzed all the ideas in the dataset. For each idea I accessed, I checked the ideator and any commenters/voters' community profiles to see if s/he is an internal employee or external product user. The entire process identified a total of 122 Salesforce.com employees in the community. Figure 1 below provides an example of community profile. In addition to some demographic information of the member, it records the contributions – e.g., number of comments, number of votes, and number of

[3] Upon joining the community, members agree to confer Salesforce.com a royalty-free, non-restriction license to use an idea if the idea is adopted.

ideas – that a member has made to the community. Table 2 summarizes the demographic characteristics of these employees as of June 2014.

Figure 1. An Example of Online Employee Profile[4]

Table 2. Demographic Characteristics of the Employees (N=122)

Gender	Male = 93 (76%); Female = 29 (24%)
Region	North America = 113 (93%); EMEA = 5 (4%); Asia-Pacific = 4 (3%)
Function	PPM = 59 (48%); R&D = 12 (10%); CS&UX = 33 (27%); IT = 1 (1%); S&M = 17 (14%)
Title	C-level/SVP = 4 (3%); VP/AVP = 16 (13%); SD = 9 (7%); D = 27 (22%); SM = 19 (16%); M = 16 (13%); E = 31 (25%)
Community Tenure (month)	0~11 = 4 (3%); 12~23 = 12 (10%); 24~35 = 10 (8%); 36~47 = 19 (16%); 48~59 = 12 (10%); 60 ~71 = 18 (15%); 72~83 = 14 (11%); 84~91 = 33 (27%)

Note: SVP (Senior Vice President); AVP (Assistant Vice President); SD (Senior Director); SM (Senior Manager); E (Employee); PPM (Platform & Product Management); CS&UX (Customer Success & User Experience); S&M (Sales & Marketing)

Measures

Independent Variables: To measure employee innovativeness in terms of idea promotion, I utilized employees' voting and commenting activities in the community. Not only do the voting activities objectively reflect employees' access and discovery of user ideas, but employees' intention to promote the ideas they discovered. Likewise, by analyzing the content of comments, I am able to identify whether an employee intends to promote an idea. To this end, I applied qualitative coding on all the employee comments identified under the 4,472 user ideas by supportive tone and assigned the comments into different categories. Table 3 categorizes, defines and examples the supportive tones

[4] Permission to use this individual profile and picture has been granted by the employee.

adapted from Connolly et al. (Connolly et al., 1990). I hired one graduate student as an independent rater to conduct the coding work. To assess the reliability of the coding procedure, another graduate student was hired to code a subsample of 718 user ideas[5] , resulting in a Cohen's Kappa score of 0.73 (Cohen, 1960). Further, one of the authors randomly selected and coded a sample of comments of 150 user ideas and compared the results to those from the first independent rater, resulting in a Cohen's Kappa score of 0.76.

Table 3. Coding Scheme for Employee Comments

Category	Description of Evaluative Tones[6]	Selected Employee Comments
Positive argument	Employee comments that support a user idea with argument and evidence.	1) "*Today it's unfortunately not possible to search for "New!" items in the Setup menu. However, I'm looking into ways to make this possible in the future, along with other enhancements like a "Pin to top" option.*" 2) "*The Setup menu is overdue for a facelift and overhaul, and we are working on it. I recognize how irrational the nodes under Customize are, and my team's made it a top priority to solve that.*"
Positive comment	Employee comments that support a user idea without additional argument.	1) *"This idea is near and dear to my heart!"* 2) "*I very much want to prioritize this during the coming year.*"
Neutral comment	Employee comments that are not supportive but related to idea clarification, general comment and idea/informational remark.	1) "*Not sure what delegated administration you're looking for with territories - Can you elaborate?*" 2) *"thanks for sharing this idea"* 3) *"here is a similar idea – [the idea link]"*

[5] In consistent with prior research (e.g., Hayne et al., 2003), employee comments of ~15% of the 4,472 user ideas (i.e., 718 ideas) were co-coded to assess the reliability of the coding procedure.

[6] When categorizing the tone of employee comments, I based the evaluation on the overall degree of support and promotion rather than the number, length, use of marks and/or response speed of the comments. For instance, ideas receiving both positive argument(s) and positive comment(s) were categorized as positive argument. Notably, no negative employee comments were identified.

To measure knowledge diversity and knowledge codifiability, I applied qualitative coding on all the user ideas that had been commented and/or voted on by the 122 employees (I assume that an employee had accessed and read the idea content before commenting and/or voting). Specifically, for each employee, via his/her online profile, I collected all the user ideas that s/he had commented and/or voted on within the two-year period. For all the 122 employees, a total of 8,088[7] user ideas were recorded (in a word document ordered by employee) to be qualitatively coded.

Knowledge codifiability reflects how well product users have converted their tacit knowledge into explicit knowledge posted as idea content. In other words, a higher degree of knowledge codifiability implies that the product users have codified their ideas to a fuller extent, which may hinge on many factors. For example, whether an idea was well thought out may affect the codifiability of the idea content. Or perhaps an idea was not well codified because the ideator proposing it lacked the knowledge necessary to articulate it properly. Or maybe the idea involved too much tacit knowledge to codify it well. Drawing upon the definition of knowledge codifiability and considering the above factors, I discussed and developed a coding scheme before coding the idea content. Table 4 details my coding scheme. During the process of content analysis of these 8,088 user ideas, an idea would receive a score of 0, 1, 2 or 3 based on its level of codifiability. Table 5 shows some user ideas representing different levels of codifiability according to my coding scheme.

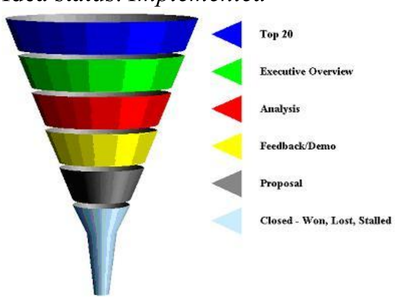
[7] Many user ideas were commented and/or voted on by multiple employees; the distinct ideas are less than 8,088.

Table 4. Coding Scheme for Codifiability of Idea Content

Score	Description
0	The idea is vague and/or incomplete; the ideator is asked to further elaborate the idea
1	The idea is complete but lacks the content (e.g., picture or figure) that could help illustrate and clarify the contextual elements related to the idea
2	The idea is not only complete but contains the picture, figure or external link to clarify the contextual elements related to the idea
3	The ideator not only presents his/her idea clearly but provides a draft (e.g., picture, figure, video or codes) to enhance the idea's mental representation

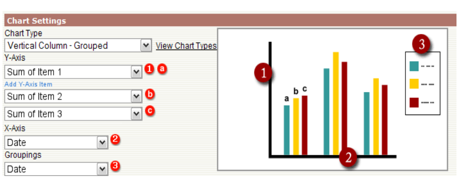
Table 5.Selected Ideas at Different Levels of Codifiability

Idea (Score 3): *"Campaign Inclusion Reports"* By – Steve Andersen
Idea tag: *Salesforce Platform, Marketing Automation, Reports & Dashboards, Sales Force Automation*
Idea status: *Implemented*



"Since Sales Reps are highly visual, if we could build a "funnel" of their opportunities, by stages, in a graphical format - they could tell at a glance where they need to focus more effort. Please add to both Reports & Dashboards. :)"

Idea (Score 2): *"Multiple Y-Axis items in Charts"* By – Mike Smith
Idea tag: *Salesforce Platform, Reports & Dashboards, Large Enterprise Ideas*
Idea status: *Implemented*



"It would be great if charts could display multiple Y-Axis items. For example, I have sums of three fields that I would like to display as vertical columns (grouped) over the span of a week (3 columns per day)."

Idea (Score 1): *"Display custom fields count on System Overview"* By – Modeste Ngom
Idea tag: *Salesforce Platform, Customization*
Idea status: *Under point threshold*

"The idea is to display the number of Custom fields created in an Org on the System Overview page, just as the number of Custom objects is displayed."

Idea (Score 0): *"Knowledge Article - Improve archiving "* By – Stratus Sysadmin
Idea tag: *Salesforce Platform, Salesforce Knowledge*
Idea status: *Not planned*

[Idea details request from one director of Salesforce.com]
"Hi, Can you be a little bit more precise?
Thanks."

Because the coding of knowledge codifiability is more subjective compared to the coding of supportive tone, two authors were involved in the coding process. I followed an iterative sample coding process suggested by Lombard et al. (2002) in order to evaluate the reliability of my coding scheme and results. Specifically, the authors independently coded a subset of 150 ideas. After categorizing the first 100 ideas, I achieved a Cohen's kappa of 0.71. I discussed sources of disagreement and how they could be overcome and reached an agreement on the guidelines to deal with the discrepancy. An achieved Cohen's kappa of 0.82 on the remaining 50 ideas ensured the level of reliability between the coders. Then one of the authors continued with the remainder of the ideas and assigned a final score for each of the 8,088 ideas[8] .

Knowledge diversity reflects how diverse the idea content is. To measure this variable, I utilized the idea tags assigned to each idea (Bayus, 2013; Di Gangi & Wasko, 2009). As shown in Table 5 above, idea tags are assigned to ideas about different product/service categories. Hence, idea tags objectively reflect the extent to which one idea is different from another. There are 41 idea categories listed by Salesfore.com (as of June 2014). To quantify this variable for each idea, I created an idea/category matrix – 8,088 rows (ordered by ideas accessed by each employee) x 41 columns. Each row represents an idea where I marked "1" under the corresponding column if the idea tag represented by that column was assigned. For example, an idea with three different idea tags would have three columns marked as "1".

[8] To further evaluate the reliability of the coding procedure, I also hired a graduate student as an independent rater to code a subsample of 1000 user ideas, resulting in a Cohen's Kappa score of 0.71.

Dependent Variables: I have two dependent variables in this study. The *number of new ideas* generated by an employee was collected from the records in his/her online profile[9] . The *idea implementation* variable was coded as "1" if the idea had a status tag of under pilot tests, partially implemented, or implemented[10] , and "0" if not.

Control Variables: Drawing upon previous research, I created several control variables. On the ideator level, I controlled for the *community tenure* because studies indicate that it may impact the likelihood of idea implementation (Bayus, 2013). For both users and employees, community tenure was measured in months by calculating the interval between the month of their first community activity and the end month of my data collection. Likewise, I controlled for the *readability* on the idea level (Li et al., 2016). Readability was measured by calculating the Flesch-Kincaid Reading Ease score[11] of each idea. I also included *idea tag* controlling for the number of readers an idea may attract. Ideas pertaining to several categories may relate to more products/services than those tagged with a single category. Idea tag was measured by calculating the total number of categories (including subcategories) assigned to an idea. Table 6 summarizes the major variables discussed.

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[9] In line with previous studies (e.g., Thatcher & Brown, 2010; Massetti, 1996), I use idea quantity (the number of new ideas) to measure employee idea generation.

[10] I treated both partially and completely implemented ideas as ideas adopted and implemented by Salesforce.com; I also ran an additional analysis without ideas having a status of "pilot/beta" or "partially implemented", the results are highly consistent.

[11] I used the "https://readability-score.com/text/" website to help calculate the readability score; embedded pictures/figures/links were not entered for calculation.

Table 6. Variable Definitions and Measures

Variable	Definition	Source of Measurement Data
Employee innovativeness – idea promotion (EmpVote & EmpComm)	The extent to which employees promote user ideas in the community	Employees' voting and commenting activities in the community
Employee innovativeness – idea generation (NewIdeas)	The extent to which an employee generates new ideas in the community	Employees' community profiles
Knowledge diversity (*KD*)	The degree of diverse content an employee has accessed in the community	Idea tags of user ideas
Knowledge codifiability (*KC*)	The degree of well-codified content an employee has accessed in the community	Qualitative coding on user ideas
User idea implementation (IdeaImp)	The likelihood of implementation of user ideas	Status tags of user ideas

Note: Variable abbreviation is in parentheses.

Modeling Strategy and Estimation Approach

In this study, I am interested in examining the innovation outcomes of employee participation in OUICs. To test hypothesis H1, I chose a logistic model to investigate whether employees' innovative behavior will positively impact the likelihood of implementation of user ideas. In other words, I seek to examine whether user ideas that are promoted by employees are more likely to be implemented than those that are not. To this end, I constructed a dataset where for each of the 4,472 user ideas, the dependent variable was entered as either 1 or 0 depending on the idea's implementation status. The independent variable of employee voting was entered by calculating the total number of employee votes of each idea. Employee commenting was treated as a categorical variable. Specifically, a user idea followed by employee comment(s) expressing supportive argument would be labeled as category "3", labeled as category "2" if only receiving supportive remark, and labeled as category "1" if the comment(s) are not supportive.

Ideas without employee comments were categorized into "0" and set as the reference category. The control variables (community tenure, idea tag and readability) were entered as measured. The resulting logistic model predicts the implementation probability of idea i and has the following framework:

$$\Pr(Implemented_{i} = 1|X_{i}) = \tau\{\alpha + \beta_1 * (employee\ voting_{i}) + \sum_{j=0}^{3} \Upsilon_{j} * (employee\ commenting_{ji}) + \beta_2 * (community\ tenure_{i}) + \beta_3 * (idea\ tag_{i}) + \beta_4 * (readability_{i}) + \varepsilon_{i}\} \quad (1)$$

where $\tau(x) = e^{x}/(1+e^{x})$, α is the constant term, ε_i is the error term. $\boldsymbol{\beta}$ and $\boldsymbol{\Upsilon}$ are coefficients.

To test hypotheses H2a&H2b, I constructed a panel dataset in order to take potential endogeneity into account. Endogeneity includes omitted-variable bias, measurement error and/or reverse causality (Greene, 2011). For example, one employee may generate more ideas than another not only because of accessing diverse and well-codified community content, but because of his/her personal characteristics and ability. Also, an employee may frequently access community content simply because his/her personal characteristics make him/her interested in reading user ideas or because his/her job function requires him/her to do so. Therefore, building a panel dataset allows us to include and control individual fixed-effects and avoid omitted variable bias (Greene, 2011). In addition, an employee may access and read more user ideas than others simply because s/he is interested in generating ideas. I therefore measure knowledge diversity and codifiability prior to measuring employees' behavior of idea generation. If accessing community content is to impact the idea generation of employees, the predetermined knowledge diversity and codifiability should demonstrate a significant effect. I also included employees' community tenure to help eliminate time effects.

Given the above, I constructed a panel dataset containing monthly observations for each employee from July 2012 to June 2014, a total of 24 months. Because there are 16 employees who joined the community after July 2012, their community behavior data are not complete in the present study. I therefore created two panel datasets: one trimmed, balanced panel dataset including 2,544 observations (106 x 24) and one unbalanced panel dataset including all the 122 employees (2,784 observations). For each unit of observation, knowledge codifiability is calculated by adding the idea codifiability score of all the ideas accessed by the employee in a particular month. For example, an employee would have a total knowledge codifiability score of 6 in a particular month if s/he commented and/or voted on a total of 3 user ideas with an idea codifiability score of 1, 2 and 3, respectively. Knowledge diversity is calculated by comparing and counting the number of distinct idea categories in the idea/category matrix. For example, an employee would have a total knowledge diversity score of 6 if all the user ideas s/he accessed in a particular month pertained to 6 different idea categories. Then I observed how many ideas the employee generated in the subsequent 30 (31 or 28) days and used this number as the dependent variable of number of new ideas for each unit of observation.

The dependent variable of ideas generated by an employee is a count variable, which fits with a Poisson panel model. The negative binomial (NB) panel model is a generalization of Poisson panel model in that the former allows the sample variance to be different from the sample mean; i.e., the data is over-dispersed. My subsequent model tests show that the over-dispersion parameter α is larger than 0, indicating a NB panel model fits better with my data (Greene, 2011). I chose a NB fixed-effects panel model over random effects to control individual fixed-effects and avoid potential omitted variable bias. The Hausman test statistic (shown in the results section) also indicates that a fixed-effects model is more appropriate than a random effects model. In addition, the dependent variable in my dataset suffers from excess zeros because some employees generated no or only a few ideas during the two-year time period. Thus in many observation months, there was no idea generated by the employees. To account for excess zeros, I added a zero inflation part to estimate a full zero-inflated negative binomial fixed-effects (ZINB) panel model (Greene, 2011)[12] .

The ZINB model assumes that excess zeros in the dependent variable are generated by two distinct processes. For example, in my study the excess zero outcomes might be attributed to two different processes – namely, participants vs. lurkers[13] . Put differently, of these excess zeros, some come from the employees who happen to yield zero ideas; and others come from the lurkers who might have new ideas but do not want to share them and therefore have "zero" ideas. The ZINB regression thereby entails two models: a count model – NB model – to model the count process, and a logit model to differentiate the two processes regarding the zero outcomes (UCLA, 2014).

I used a conditional estimator in Hausman et al. (1984) to estimate the NB fixed-effects panel model:

$$logL_c = \sum_{i=1}^{n} logP(y_{i1}, y_{i2}, \dots, y_{iT_i} \mid \sum_{t=1}^{T_i} y_{it}) \tag{2}$$

---

[12] To select between NB and ZINB, I conducted a Vuong (1989) statistic test; the results (shown in the results section) also favor the ZINB model.

[13] In the context of OUIC, lurkers refer to individuals who have no intent to share even if they may have new ideas (Wasko et al., 2004).

Under this estimator, the model framework is:

$$E\left[y_{\mathrm{it}} \middle| \boldsymbol{x}_{\mathbf{i\,(t\text{-}1)}}\right] = exp\left(\delta_{\mathrm{i}} + \boldsymbol{\beta} * \boldsymbol{x}_{\mathbf{i\,(t\text{-}1)}}\right) = \lambda_{\mathrm{it}} \qquad (3)$$

where xi (t-1) is an m x 1 vector of explanatory variables (i.e., knowledge diversity and codifiability) and $\boldsymbol{\beta}$ is an m x 1 vector of corresponding coefficients (Hausman et al., 1984); δi is the error term. This NB fixed-effects part models the employees who behave as participants in the community. For those who may behave as lurkers, they are modeled by the logit part of the ZINB model. Specifically, I have yit = 0 with probability φit (behaving as lurkers), and have E (yit) = λit (negative binomial estimate from formula (2)) with probability 1 - φit:

$$\varphi\mathrm{it} = \frac{exp(\boldsymbol{\gamma\prime Z}\mathrm{i\ (t\text{-}1)})}{1+exp\ (\boldsymbol{\gamma\prime Z}\mathrm{i\ (t\text{-}1)})} \qquad (4)$$

where Zi (t-1) is a q x 1 vector of explanatory variables in the logit model and γ′ is a q x 1 vector of corresponding coefficients (Hausman et al., 1984).

To test the ZINB panel models, I used the NLOGIT 5 econometric software and followed a two-step procedure. I first fitted the ZINB model without fixed-effects to obtain a set of starting values for the panel model; I then fitted the panel model again with zero-inflated Poisson fixed-effects (Greene, 2011).

Results

Tables 7 and 8 present descriptive statistics and correlations of two datasets, respectively. Table 9 summarizes the results from the logistic model. The fit indices of Hosmer and Lemeshow test of model 3 ($\chi 2 = 9.748$; df=8; p=0.283) indicate a good fit of my logistic model with the dataset. The coefficient of employee voting is positive and significant ($\beta=0.205$, $p<0.001$), indicating that the degree of employee voting is positively associated with the likelihood of implementation of a user idea. Specifically, it indicates that, on average, with an additional employee vote, the odds ratio of user idea implementation is higher by 22.7% (exp(0.205)-1=0.227). The coefficients of employee commenting of supportive argument (category 3) and supportive remark (category 2) are significant and positive (β=0.681, p<0.001; β=0.920, p<0.001). This indicates that, on average, ideas receiving employee comments expressing support are more likely to be implemented than those that do not (category 0). For example, ideas followed by supportive employee argument are about 2 times (exp(0.681)=1.976) as likely to be implemented as those in category 0. In contrast, ideas with general remarks or clarification requests are not significantly different than those without employee comments. Combined, these results support H1.

Table 7. Descriptive Statistics and Correlations Matrix (N=4,472)

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6
1. IdeaImp	0.12	0.33	0.0	1.0	1.00					
2. EmpVote	3.50	3.30	0.0	27.0	0.31	1.00				
3. EmpComm	0.75	0.83	0.0	3.0	0.18	0.28	1.00			
4. Tenure	48.88	25.06	1.0	91.0	0.03	0.05	0.01	1.00		
5. Tag	3.55	2.06	1.0	10.0	0.02	0.09	0.01	-0.01	1.00	
6. Readability	59.06	10.34	29.4	103.2	0.19	0.49	0.15	0.03	0.04	1.00

Table 8. Descriptive Statistics and Correlations Matrix (Panel: by month)

Variable	Mean	S.D.	Min	Max	1	2	3	4
1. Tenure	51.92	24.97	1.0	91.0	1.00			
2. KC	7.23	12.73	0.0	137.0	0.24	1.00		
3. KD	5.59	6.52	0.0	39.0	0.21	0.67	1.00	
4. NewIdeas	0.15	0.42	0.0	4.0	0.03	0.46	0.57	1.00

Table 9. Logistic Model Results (N=4,472)

Variables	Model 1	Model 2	Model 3
Tag	0.024 (0.022)	-0.013 (0.023)	-0.008 (0.023)
Readability	0.048*** (0.004)	0.010* (0.005)	0.010* (0.005)
Tenure	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)
EmpVote		0.237*** (0.016)	0.205*** (0.017)
EmpComm - Category 1			-0.005 (0.113)
EmpComm - Category 2			0.920*** (0.163)
EmpComm - Category 3			0.681*** (0.168)
Constant	-5.130*** (0.275)	-3.684*** (0.285)	-3.669*** (0.295)
Nagelkerke R Squared	6.3%	15.8%	17.5%

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$

Table 10. Panel Data Results (Balanced: N=106, observations = 2,544; Unbalanced: N=122, observations = 2,784)

Variables	ZINB Fixed-effects Balanced Panel		ZINB Fixed-effects Unbalanced Panel	
	NB	Logit	NB	Logit
Constant		5.938*** (0.010)		4.778*** (0.010)
Tenure	-0.031*** (0.007)		-0.030*** (0.007)	
KC (lagged)	0.058*** (0.010)	-0.431*** (0.030)	0.060*** (0.010)	-0.497*** (0.028)
KD (lagged)	0.145*** (0.024)	-0.340*** (0.0001)	0.149*** (0.023)	-0.360*** (0.0001)
KC*KC	-0.0004*** (0.0001)		-0.0004*** (0.0001)	
KD*KD	-0.0018*** (0.0005)		-0.0019*** (0.0005)	
Vuong	6.78		7.00	
Hausman	107.38***		114.94***	
Alpha (α)	> 0		> 0	
Log-likelihood	-661.86		-708.24	

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$

Table 10 shows the results from the panel data. The α in both tables are larger than 0, indicating the over-dispersion in my dataset and thereby supporting the use of NB model. In addition, the Vuong statistics are all positive, supporting the use of ZINB over NB models. The large positive values ($p<0.001$) of Hausman tests in both ZINB models favor the fixed-effects. The positive and significant coefficients of knowledge diversity in the NB models in column 2 ($\beta=0.145$, $p<0.001$) and column 4 ($\beta=0.149$, $p<0.001$) indicate that accessing diverse content affects employee idea generation positively. Specifically, using the balanced model as an example, it indicates that with each one unit increase in content diversity, an employee will on average generate 15.6% ($\exp(0.145)-1=0.156$) more ideas in the subsequent month. Likewise, the positive and significant coefficients of knowledge codifiability in column 2 ($\beta=0.058$, $p<0.001$) and column 4 ($\beta=0.060$, $p<0.001$) indicate that accessing well-codified content positively affects employee idea generation. Using the balanced model as an example, it shows that on average, a one-unit increase in content codifiability is associated with an increase in employee idea generation by about 5.9%. In addition, the coefficients of quadratic terms are all negative and significant ($\beta=-0.0004$, $p<0.001$; $\beta=-0.0018$, $p<0.001$ in column 2, and $\beta=-0.0004$, $p<0.001$; $\beta=-0.0019$, $p<0.001$ in column 4). This indicates that the effects of content diversity and codifiability are weaker for those employees who have read a larger number of user ideas than those who only read a few. Taken together, Figure 2 shows that employees generate more ideas in the community when they access more diverse and well-codified content created by product users; however, the marginal effects of well-codified and diverse content decrease as employees access increasing community content. Hypotheses 2a and 2b are therefore supported.

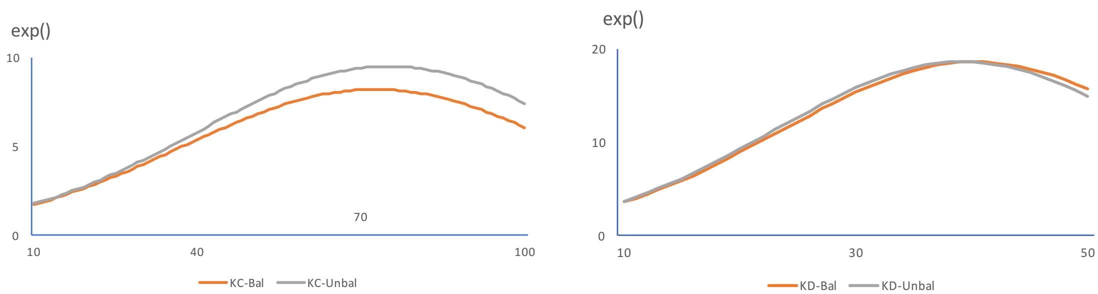

Figure 2. Effect of Knowledge Codifiability and Diversity on Employee Idea Generation

With respect to the logit section (columns 3 and 5), the coefficients of knowledge diversity and codifiability in all the logit models are negative and significant. This indicates that employees who access user ideas and leave comments or votes are unlikely to behave as lurkers. In other words, if they have new ideas, they will share their ideas with the community. In contrast, employees who seldom comment or vote on user ideas are less likely to contribute even if they may have new ideas.

Additional Analyses

I conducted several additional analyses. For the logistic dataset, I ran the model without the user ideas having a status of “pilot/beta” or “partially implemented” (this reduced the observations to 4,410 ideas) and compared the results with the original model. The results are highly consistent as shown in Table 11. I conducted this extra analysis because according to my interview with the community manger, ideas under pilot test by Salesforece.com are highly likely to be implemented, but this may not apply to all the cases.

For the panel dataset, I conducted several additional analyses. First, I used Shannon-Weiner Diversity Index (H)[14] as an alternative measure for knowledge diversity to avoid a range metric. Specifically, for each employee during each month, I first calculated a parameter p for each different idea category the employee encountered by dividing the total number of idea tags of that category by the total number of idea tags of all categories. I then used the following formula to calculate the Shannon-Weiner Diversity Index for each employee during each month (Magurran, 1988):

$$H = -\sum_{i=1}^{n}(pi * ln\,pi) \qquad (5)$$

where n is the number of distinct idea categories.

I reran the model using the absolute value of H and Table 12 summarizes the results of using the alternative measures. The results are consistent in terms of the sign and significance of the variables.

Furthermore, one criticism of panel model is that the choice of period cutoffs (calendar months in this study) may be arbitrary (Greene, 2011). As such, instead of building monthly observations for each employee, I broke down the panel and restructured my data into employee-bi-week pairs. This gave us a total of 5,512 observations (52 x 106) in the balanced panel model and 6,025 observations in the unbalanced panel model. I then ran the ZINB fixed-effects on both models; the results are highly consistent with those from the employee-month pairs. In addition, after breaking down the panel into biweekly observations, a majority of employees only generate one or no idea in most bi-weeks. I therefore modified my panel to fit a logit model estimated by

[14] The Shannon Wiener diversity index is largely used in the fields of ecology, evolution and environmental biology to measure species diversity in a community (Magurran, 1988).

unconditional fixed-effects[15]. Overall, the results indicate that for those employees who frequently access user ideas, they are more likely to generate an idea in the subsequent weeks than those who do not. This confirms the effects of community participation on employee innovativeness. Tables 13 and 14 present the results of my additional analyses of the panel data.

Table 11. Logistic Model Results (N=4,410)

Variables	Model 1	Model 2	Model 3
Tag	0.021 (0.022)	-0.016 (0.023)	-0.011 (0.023)
Readability	0.048*** (0.004)	0.010* (0.005)	0.010* (0.005)
Tenure	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)
EmpVote		0.238*** (0.016)	0.207*** (0.017)
EmpComm - Category 1			0.010 (0.113)
EmpComm - Category 2			0.919*** (0.163)
EmpComm - Category 3			0.681*** (0.168)
Constant	-5.112*** (0.276)	-3.665*** (0.286)	-3.656*** (0.296)
Nagelkerke R Squared	6.3%	16.0%	17.6%

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$

[15] To choose between fixed-effects and random effects for the logit model, I calculated the Hausman values by following the procedure suggested in Greene (2012).

Table 12. Panel Data Results – Shannon-Weiner Diversity Index (Balanced: N=106, observations = 2,544; Unbalanced: N=122, observations = 2,784)

Variables	ZINB Fixed-effects Balanced Panel		ZINB Fixed-effects Unbalanced Panel	
	NB	Logit	NB	Logit
Constant		3.857*** (0.001)		3.076*** (0.001)
Tenure	-0.032*** (0.007)		-0.032*** (0.007)	
KC (lagged)	0.060*** (0.011)	-0.520** (0.165)	0.066*** (0.011)	-0.514*** (0.153)
KD_SDI (lagged)	1.756** (0.556)	-0.023*** (0.0028)	1.835*** (0.503)	-0.025*** (0.0026)
KC*KC	-0.0004*** (0.0001)		-0.0004*** (0.0001)	
KD_SDI* KD_SDI	-0.223* (0.112)		-0.237* (0.102)	
Vuong	5.38		5.65	
Hausman	54.44***		58.64***	
Alpha (α)	> 0		> 0	
Log-likelihood	-692.93		-746.29	

Standard errors are in parentheses. *** Sig. at p < 0.001; ** Sig. at p < 0.01; * sig. at p < 0.05

Table 13. Balanced Panel Data Results (N=106; Observations = 5,512)

Variables	ZINB Fixed-effects Panel (Bi-week)		Logit Fixed-effects Panel
	NB	Logit	
Constant		16.40*** (0.040)	
Tenure	-0.013*** (0.003)		-0.024*** (0.005)
KC (lagged)	0.189*** (0.022)	-1.806*** (0.0003)	0.636*** (0.041)
KD (lagged)	0.367*** (0.044)	-1.779*** (0.0015)	0.994*** (0.070)
KC*KC	-0.002*** (0.0003)		
KD*KD	-0.009*** (0.0016)		
Vuong	10.43		
Hausman	138.99***		210.33***
Alpha	> 0		
Log-likelihood	-712.25		-571.84

Standard errors are in parentheses. *** Sig. at p < 0.001; ** Sig. at p < 0.01; * sig. at p < 0.05

Table 14. Unbalanced Panel Data Results (N=122; Observations = 6,025)

Variables	ZINB Fixed-effects Panel (Bi-week)		Logit Fixed-effects Panel
	NB	Logit	
Constant		14.44*** (0.040)	
Tenure	-0.013*** (0.003)		-0.025*** (0.005)
KC (lagged)	0.197*** (0.022)	-1.665*** (0.0003)	0.660*** (0.041)
KD (lagged)	0.366*** (0.044)	-1.675*** (0.0015)	1.011*** (0.070)
KC*KC	-0.002*** (0.0003)		
KD*KD	-0.009*** (0.0016)		
Vuong	10.22		
Hausman	151.56***		249.87***
Alpha	> 0		
Log-likelihood	-712.25		-590.47

Standard errors are in parentheses. *** Sig. at p < 0.001; ** Sig. at p < 0.01; * sig. at p < 0.05

Discussion

Despite an increasing number of studies in recent years on how firms can leverage users in OUICs to enhance their innovation capability, theoretical explanations on the role of internal employees in the community have been scant. This gap in the literature motivated us to focus on internal employees who voluntarily participate in OUICs and examine the resulting innovation outcomes. my study thereby extends the extant OUIC literature by revealing the role of participating employees and the benefits employee participation might yield. I find that employees' innovative work behavior such as voting and commenting positively impact user idea implementation. User ideas discovered and promoted by internal employees, versus those without receiving employee support (only promoted by other product users), are more likely to be implemented by the host firm. In addition, employees who frequently participate in the community and thereby access diverse and well-codified community content generate more ideas than those who do not, while the marginal effects of diverse and well-codified content decrease. Accordingly, my study 1) highlights the need to further examine the role and participation of employees in OUICs, 2) sheds light on a broader research stream of *open innovation community*[16], and 3) provides important implications for practice.

For OUICs, I hope to catalyze research on the role of internal employees to help address the failure of many innovation communities and yield solutions that provide competitive advantage. As a first step toward this direction, my study differentiates internal employees from external product users. Doing so is important because the two entities play different but critical role for the long-term success of OUICs (Ogneva & Kuhl, 2014; Whelan et al., 2011). By comparing the roles between users and employees, I theorize and highlight the unique role of employees in terms of community activities, participation motivation and required innovation knowledge. Therefore, while prior research has extensively studied the factors and mechanisms that influence the sustainability and success of OUICs (Chen et al., 2012; Jeppesen & Frederiksen, 2006; Nambisan & Baron, 2010; Wasko et al., 2004), the findings may not apply to both users and employees. For example, whereas some users enjoy revealing their knowledge and ideas to other users (Jeppesen & Laursen, 2009; Mahr & Lievens, 2012), employees may share ideas in order to motivate more external users to post their opinions and knowledge. On the other hand, employees in OUICs may play similar roles as users such as voting and commenting on submitted ideas and championing elaborate ideas. Overall, the nature of employee participation and contribution in OUICs has been neglected in the extant literature. Further research is needed to illustrate how the behavior and individual actions

[16] I adopt Chesbrough's definition of open innovation: "Open Innovation means that valuable ideas can come from inside or outside the company and can go to market from inside or outside the company as well" (Chesbrough, 2003, p.43). OUICs is one form of open innovation community.

of participating employees shape innovative outcomes and contribute to the long-term success of OUICs.

From a broader perspective of open innovation community, my study confers implications for other forms of open innovation community that are related to but distinct from OUICs. One such open innovation form is *firm-sponsored open source software (OSS) communities*. Firm-sponsored OSS communities constitute collections of firms and individuals (external software users and developers) that contribute to the production and sharing of public and free software (Von Krogh & Von Hippel, 2006). Extant studies in this stream of research are largely conducted at organizational level and examine the dynamics of firm-community collaboration and innovation (e.g., Dahlander & Magnusson, 2005; Stam, 2009; West & O'Mahony, 2008; Germonprez et al., 2016; Spaeth et al., 2014). While some researchers start to focus on individuals who are employed by the firms but work on independent open-source projects (Mehra et al., 2011; Dahlander & Wallin, 2006), the role of such individuals and the outcomes of their community participation are under-investigated. For example, how do employees of sponsor firms, compared to external users/modifiers/developers, form relationships (or ties) with other community members? And what are the outcomes of the relationships in terms of sponsor firms' innovative performance or the design and evolution of OSS communities?

In addition, my study sheds light on the types of behaviors and knowledge-creation processes that contribute to open innovation communities to innovate and the role of information technologies in enabling such knowledge creation, an emerging and important topic in the open innovation community literature (Eservel, 2014; Agerfalk &

Fitzgerald, 2008; Von Krogh et al., 2003; West & O'Mahony, 2008). In the contexts of OUIC, my findings show that members are increasingly utilizing the IT affordances embedded in the community platforms to innovate. Through figures/pictures, video/web page links, personal drawings and other media, ideators are able to convert their tacit knowledge and details related to personal experience into well-codified idea content. Such well-codified content constitutes the knowledge base of the community and is subsequently accessed and processed by others to become part of their new ideas. The result is that individuals are able to achieve "externalization" (creating explicit knowledge from tacit knowledge) and "combination" (reconfiguring existing explicit information into new knowledge) of knowledge for innovation without face-to-face interactions (Nonaka & Toyama, 2003; Nonaka & Von Krogh, 2009). My study therefore indicates that, in the IT-enabled open innovation contexts, intellectual engagement with tacit-knowledge embedded IT artifacts (e.g., software codes and ideas) resides at the core of socialization aiming at new knowledge creation and innovation.

From the practical perspective, my study highlights the necessity of continued participation from both internal and external participants to build a thriving community. OUICs have been increasingly adopted and implemented across industries. Nevertheless, many empirical studies point out some hard challenges (e.g., moving ideas forward and picking the winners (Erat et al., 2006; Piezunka & Dahlander, 2014; Westerski et al., 2013) faced by the host firms in managing ideas with the aim of producing innovations (Chesbrough & Brunswicker, 2014; Di Gangi et al., 2010; Westerski et al., 2013). My study suggests that continued participation and contribution from internal employees is as essential as finding and retaining external product users for the sustainability of OUICs.

On the one hand, by facilitating the implementation of user ideas, participating employees can elicit more user ideas and attract more users to join the community for new product development. On the other hand, the resulting new ideas contributed by participating employees will augment host firms' innovative performance. I therefore suggest that host firms should develop a strategic vision and action plan to increase the scope and level of employee participation.

My investigation of Salesforce.com's OUIC allows us to obtain valuable insights and knowledge to provide advice on when and how host firms should develop employee participation. Specifically, I suggest that host firms or the community management teams take multiple steps in order to build levels and scopes of employee engagement. The first step is to target and enable internal champions, including executive sponsors and senior management. My study shows that a large number of employees of senior management of Salesforce.com are engaged in the community. Not only does their initial participation help galvanize and legitimize the rest of the firm to join, but their subsequent community behavior will form community culture and impact incoming employees (Dahl et al., 2011; Ogneva & Kuhl, 2014). Communicating the importance and value of building a thriving OUIC will help enable these internal champions. For example, community managers may use my results and the positive effects associated with employee innovativeness to encourage the kind of participation and activities they wish to promote. Once the participation of internal champions is achieved, engaging key middle managers and team leaders is the next step given that peer-to-peer evangelism is more effective than top-down (Dahl et al., 2011). To this end, host firms may need to emphasize different benefits to different participants. Over time, this extended team should include different functions and levels from the host firm to act as influencers and connectors within the community.

Limitations and Conclusion

There are several limitations to this research that might affect its broad application. First, by focusing on community content, I am unable to capture and investigate other important community properties such as social relationships, ties and structures that may affect individual innovativeness. Hence, future studies taking a social network perspective may be able to uncover other outcomes and factors in explaining knowledge creation and employee innovativeness in OUICs. An example is that employees who are actively engaged in the community might develop tight bonds with product users (Ma & Agarwal, 2007; Ren et al., 2012). If so, what are the related benefits for individual employees as well as the host firm?

Second, while employees are exposed to idea content when they comment and/or vote on user ideas, they may not leave a comment or vote every time they read an idea. Identifying and coding the idea content based on employee comments/votes thus may not include all the idea content an employee has accessed. In addition, by only coding those user ideas accessed by an employee, I do not take into account all user comments an employee may have accessed. Some comments from product users may be diverse and well-codified as well. Adding complementary, subjective measures via employee self-report or survey could help provide an alternative measure of content diversity and codifiability.

Third, there are room for improvement regarding the variable measures. For example, future research could measure idea generation in terms of both quantity and quality. By adding the quality dimension, I may reveal whether ideas of employees, versus those of users, are more likely to be adopted and implemented by the host firms. Additionally, I could further compare the novelty and usefulness (Dean et al., 2006) between user and employee ideas to reach other conclusions. Similarly, future studies could add other dimensions, such as positivity, optimism and encouragement, into account when evaluating the "tone" of employee comments to confirm and complement my findings.

Fourth, as in any other empirical study based on a single setting, the generalizability of my findings is limited. This is especially true considering the extent and purpose of adopting and implementing OUIC as a value co-creation initiative is different across industries. According to Chesbrough and Brunswicker (2014), high-tech industries are likely to leverage users/customers for new product development and innovation more frequently and intensively than other industries. Therefore, future studies applying multi-community analysis in other contexts will be valuable to deepen and extend my understanding on employee participation and contributions in OUICs.

Notwithstanding these limitations, my study extends prior research on firm-hosted OUICs by focusing on internal employees and examining their participation and related outcomes. My study offers preliminary evidence that interacting with product users in OUICs has significant impacts on employee innovativeness. I thus suggest that host firms develop and leverage the OUIC as a secondary context or structure wherein employees are engaged with non-routine tasks and innovations. While developing strategies and taking actions to increase employee engagement levels, host firms should recognize that it takes time to change how their employees participate in and contribute to the communities. Accordingly, host firms should take sustainable management efforts with employees' interests in mind.

CHAPTER THREE

Employee-Generated Content in Online Support Communities: Antecedents and Effects

Introduction

Firm-hosted online support communities (hereinafter OSCs) refer to web-based gathering places developed for providing customers product support (Nambisan, 2002). In OSCs, participants from *external product users and internal employees* of the host firms interact to discuss questions/problems/issues resulting from the use of host firms' products/services. Due to their potential to become a real-time, constantly updated product knowledge repository to serve customers, OSCs are widely adopted and implemented across industries (Grohol, 2016). Not only do companies treat OSCs as a useful supplement of their customer service departments but cultivate OSCs as places where experienced product users help other users for user self-support (Shiao, 2014).

To help provide product support and thereby augment customer satisfaction, employees of the host firms are increasingly being encouraged by their firms to join the community on a voluntary or mandatory basis (Nuse, 2015). They start their participation by replying to users' questions and problems and then undertake to further contribute their knowledge and expertise by writing product-related reviews, blogs and technical articles. Marketing employees, for example, write blogs to broadcast the launch of new product features and services whereas engineers post technical articles showcasing a particular product design or use process. Over time, this employee-generated content forms the collective content shared across the community for product support.

As companies increase their user base with expanding product lines, this employee-generated content plays a critical role in facilitating product support, especially user self-support. Writing community blogs helps marketing teams collect initial user questions regarding the new products/features introduced and provides corresponding feedback that may be helpful for prospective users sharing the same questions. Likewise, elaborating technical articles involving detailed use cases, methods or applications helps answer existing user questions as well as provisions solutions to potential user problems in advance. Some technical articles and product reviews serve the answers to most complicated or common issues arising from the use of the products (e.g., in the event that customers use the products for their own product design and application). Such community content is therefore often pinned at the top of all discussion threads to reduce the repetition in community posts asking the same questions. More importantly, experienced members are able to absorb the knowledge in this employee-generated content and assist novices and new members who now possess the same questions as they had before. Such interactions facilitate deep social connections among community members and thereby the building of a strong, thriving community (Dholakia et al., 2009; Sivertstøl, 2015).

Despite the importance of employee participation and resulting contribution, extant research on OSCs has largely focused on product users and examined the various dynamics resulting from their community interactions, as I will discuss in more detail below. Hence, to deepen my understanding of the nature of employee participation, this study attempts to explore the outcomes and impacts of employee-generated content in OSCs. Specifically, I seek to answer the following research questions: 1) *what drives* *employees to generate community content?* And 2) *how does employee-generated content influence user contribution in OSCs?*

I review extant studies on OSCs and develop my hypotheses drawing upon the reviewed literature as well as the Hawthorne Effect (Adair, 1984). I then investigate the hypotheses in the OSC of BMC, a global leader in producing innovative software solutions. I collected a total of 815 community documents, including 3,257 versions, created by 231 employees of BMC in a two-year period. In addition, a total of 12,315 product users were identified as the readers of the 815 employee-contributed documents. Overall, my study shows that employees (or the document authors) receiving a higher degree of readership are more motivated to contribute community content, although the marginal effect of readership decreases. On the other hand, product users who frequently access and read employee-generated content are more likely to contribute to product support using the knowledge they acquired from the content. With these findings, my study provides valuable implications for the research of OSC and the broader online Q&A community, as well as the sustainability and long-term success of OSCs.

Related Literature and Theoretical Development

Related Studies

In this section, I identify and briefly review extant research on OSCs. My objective is not to exhaustively include all the studies but to highlight gaps that motivate this study to fill.

As noted earlier, existing literature on OSCs has tended to explore the varying community dynamics by focusing on product users. A large body of studies have investigated a variety of intrinsic and extrinsic motivations driving users' participation and contribution in OSCs. Nambisan and Baron's research, for example, finds that users' sense of responsibility to the community, expectations of private rewards (e.g., expertise and self-image enhancement), anticipated cognitive, social and hedonic benefits, as well as attitudes and perceptions regarding the host firm itself are significantly related to users' actual participation (Nambisan & Baron, 2010, 2009, 2007). Gu & Jarvenpaa (2003) add another dimension of users' social identities to explain why users are inclined to contribute in terms of product support to peers. Likewise, Dholakia et al. (2009)'s study reveals that functionality offered by the design features of OSCs (e.g., profiles and badges) plays a key role in strengthening users' identification with the community which, in turn, enhance users' intention to interact with others for product support. In addition, there are a handful of studies examining the impact of individual characteristics as motivations on community participation and contribution. For instance, Wiertz & De Ruyter (2007)'s study illuminates that online interaction propensity is an important individual trait that should be considered in explaining product users' knowledge sharing behavior. Similarly, Jeppesen & Laursen (2009) focus on product users with a high degree of lead user characteristics, and find that they are more likely to enjoy revealing their knowledge and help others in product support, compared to peer users.

More recently, OSC research has focused on distinct aspects and dynamics to explain nuanced difference in members' discussion behavior. Bateman et al. (2011), for example, develop a theory focusing on three forms of community commitment (continuance, affective, and normative) and claim that they have unique power to predict members' specific discussion behaviors (e.g., reading, posting, and moderating). In contrast, Haas et al. (2015) are interested in individuals' attention allocation and show that the features of a particular provider–problem match (i.e., expertise fit, problem characteristics, and problem crowding) decide repliers' choice of specific problems to answer. Similarly, Beck et al. (2014) focus on the quality of answers and demonstrate that it is largely decided by replier/asker characteristics at the individual level and relationship characteristics at the dyadic interaction level.

While extant literature provides valuable insights into how external product users contribute to product support, it falls short in explaining the role of *internal employees* in OSCs, specifically the outcomes related to employee participation. Acquiring knowledge related to internal employee participation is important because a thriving OSC depends on participation and contribution from both sides of this external/internal duality. Indeed, recent evidence from both academic research and practice suggests that many OSCs suffer from the "Empty Bar Syndrome" because they lack active external and/or internal participation (Ogneva & Kuhl, 2014; Nambisan & Baron, 2010). As such, by focusing on employee-generated content, this study contributes to understanding the participation of internal employees, an issue that has received limited attention to date.

Hypotheses Development

Below I develop three hypotheses dealing with the antecedents and consequences of employee-generated content in the OSC context. Specifically, I explain how the level of readership may influence an employee's incentives to generate more content, and how product users accessing employee-generated content may impact their subsequent contribution in product support. In addition, I consider content age as a potential moderator that may moderate the relationship between access to employee-generated content and contribution in product support of users.

Readership and Content Generation in OSCs: It is natural to expect that readership should impact an author's writing behavior. The Hawthorne Effect (Adair, 1984) finds that individuals improve or change their behavior in response to their awareness of being observed. In OSCs, employees write blogs, reviews and technical articles in the hope that their contributions will be useful for users looking for product support. The change of readership is one indication showing how popular the content is. For those employees who notice a high degree of readership of their content, they may perceive a greater usefulness or attribute greater value toward their content. As a result, they are more likely to change their writing behavior to contribute more content. More importantly, the readership in most OSCs is reflected not merely by the number of views but by the number of incoming ties or bookmarks[1]. Employees who receive a surge of followings and/or bookmarks after posting an article may attribute this to the high popularity of their content, motivating them to write more (Phang et al., 2009; Madupo et al., 2010). Indeed, Goes et al. (2014) find that online reviewers who receive more incoming ties or followers tend to write more review articles. Likewise, Zhang and Zhu (2011)'s study shows that individuals' incentives to contribute to the Chinese Wikipedia are positively related to the size of content audience. Moreover, a high degree of

[1] In the OSC of BMC, for example, members can choose to bookmark the content they like and/or follow the content authors (i.e., incoming ties) such that members will be notified if there are updates on the existing content or new content posted by the authors.

readership and the resulting higher connections enhance one's recognition and reputation[2] in the community, which may, in turn, serve as an extrinsic motivation to contribute (Madupo et al. 2010). Combined, I expect that observing a higher readership should encourage an employee to contribute more content in OSCs.

Meanwhile, I expect that the effect of change of readership on content generation should become weaker once the content has already received many views. In other words, an employee who has already owned a great deal of popular content may not be motivated to write more after seeing his/her readership increases, compared to one who only owns a little. Taken together, I hypothesize the following:

Hypothesis (H1): *The degree of readership of an employee's content in an OSC has an inverted U relationship with the generation of content of the employee.*

Employee-Generated Content and User Contributions in OSCs: It is rational to expect that product users accessing employee content will, in turn, facilitate their subsequent contributions in OSCs for several reasons. Cognitively, employees convert their tacit knowledge into explicit knowledge when they write community content (Nonaka, 1994). By reading employee content, users are able to absorb the explicit knowledge contained in the content, increasing their cognitive capital in the community (Wasko & Faraj, 2005). This benefit of expertise and knowledge enhancement resulting from interactions with employees will, in turn, promote helpful behavior in the community (Nambisan & Baron, 2010; Wasko et al., 2004). It is consistent with social capital theory (Nahapiet & Ghoshal, 1998) that members' relationships or relational capital in the community impact their obligation and sense of responsibility to help others.

[2] In the OSC of BMC, for example, receiving new bookmarks and followings increases a member's community points which reflect the member's community reputation and recognition.

Much of the research on OSCs has indicated that users' expectations of private rewards such as topic-related expertise act as powerful incentives to assist peer users (Shih et al., 2010; Nambisan & Baron, 2009).

From a trust perspective, employees' efforts to write reviews and articles and thereby to provide users access to quality content have significant trust-building effects with product users (Porter & Donthu, 2008; Kosonen et al., 2013). Such trust motivates deeper forms of relational behaviors among product users and host firms, augmenting users' loyalty toward the community and their willingness to cooperate in product support initiatives (Woisetschläger et al., 2008). Kosonen et al. (2013), for example, demonstrate that the extent of knowledge support provided by the host firm as well as users' trust in the host firm are positively associated with their intention to share knowledge. Moreover, in many cases, users not only read employee articles but interact with the authors by leaving comments, questions and opinions. The positive feelings arising from such interactions shape users' perceptions and attitudes (e.g., trust and identification) towards the host firm, which, in turn, increase their willingness to participate in future product support (Nambisan & Baron, 2007; Wasko et al., 2004).

Finally, from a community design perspective, the feature of allowing employees to contribute their knowledge via writing blogs and technical notes, over time, facilitates the creation of repository-based knowledge. The greater host firms incorporate design features that relate to collective knowledge acquisition and distribution, the greater likelihood users participate in product support activities (Benlian & Hess, 2011; Nambisan, 2002). In addition, with community search tools, this collective knowledge from employees will be especially instrumental in benefiting newcomers and thereby boosting their attachment to the community (Ren et al., 2007; Tsai & Bagozzi, 2014). Taken together, I expect that the more product users access employee content and benefit from doing so (e.g., acquiring product-related expertise and knowledge), the more likely they contribute to product support, leading to the following hypothesis:

Hypothesis (H2): *Accessing employee-generated content in an OSC will positively impact a product user's contribution to product support.*

The Moderating Role of Content Age in OSCs: Considering the context of OSC, I include content age when examining user contribution outcomes related to employee-generated content. As host firms upgrade the existing product lines or release new products, the topics ongoing in OSCs start shifting toward the new products. Over time, topics involving old and legacy products receive decreasing attention as the base of users shrinks. In the OSC of BMC, for example, over 70% of user questions discussed between March 2016 to August 2016 relate to the products that are released after 2014, based on my community observation. And host firms often open sub-forums dedicated to the support of new added product lines. Accordingly, I suggest that product users who access relatively older employee content may not be able to acquire the cognitive benefits they intend to derive because the content is likely irrelevant to the products they are using. As a result, they may be less likely to actively participate in future product support (Chiu et al., 2006; Tsai & Pai, 2014). Even for some users who do obtain cognitive benefits from older content, they may not be able to contribute the expertise and knowledge back to ongoing community discussions because of the irrelevance of the content. Therefore, I expect that content age should play a moderating role in the relationship between access to employee-generated content and contribution in product support. Specifically, I posit:

Hypothesis (H3): *The impact of accessing employee-generated content on a product user's contribution to product support in an OSC decreases as content age increases.*

Methodology

Context and Data Collection

I selected the OSC of BMC as my empirical setting. Headquartered in Houston, Texas, BMC is a global leader in innovative software solutions that enable businesses to transform into digital enterprises for competitive advantage (BMC, 2016). In 2002, BMC established its OSC through which it has developed a successful, long-term relationship with its customers or product users. Based on my interview with the community manager, almost all BMC employees from regular employees to senior management are encouraged to participate in the community for product support. While employees from different functions possess different motivations, their participation in the community remains voluntary.

Apart from directly answering questions from users, employees of BMC contribute content to the community via writing documents. Based on my community observation and interviews with the community management team, employee documents largely focus on the description, explanation, use and application of existing and new product functions and features. Notably, when contributing community documents, an employee may choose to either write new documents or update his/her existing documents given which approach is more appropriate. For example, an employee may only conduct an update if the new information and knowledge s/he wants to contribute is largely related to an existing document content.

My data collection process relates to three entities examined in this study: employee-generated content (*documents*), employees (*authors*) and product users (*readers*). I started my data collection with identifying employee-contributed documents through which I further accessed and collected the data of authors and readers. To this end, I collected all the documents contributed by employees in a two-year period, from January 2014 to January 2016[3]. For each document, I recorded 1) the link of the author's community profile where I can further access his/her community data[4], 2) the version history of the document[5], and 3) the interaction data of the document including views, viewers (i.e., readers), comments, likes and bookmarks. The entire process generated a total of 815 documents (3,257 versions) contributed by 231 employees, and a total of 12,315 readers. Figure 3 provides an example of online member profile. Figure 4 shows one document's interaction data. Table 15 summarizes the demographic data of the 231 employees.

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[3] When I identified and collected documents, I excluded those that only relate to new product announcement and general product information.

[4] The community profile includes employees' demographic data (e.g., title and function), network data (following/followers), participation data (e.g., discussion and document contributions), reputation data (e.g., points and levels), etc. Notably, through the menus such as "Content", "Connections" and "Reputation" in the online profile, members can access more detailed information such as the discussions and threads they have participated, the profiles of people following them, and the entire ranking list of the community.

[5] Each document has a version history link where all old versions can be accessed.

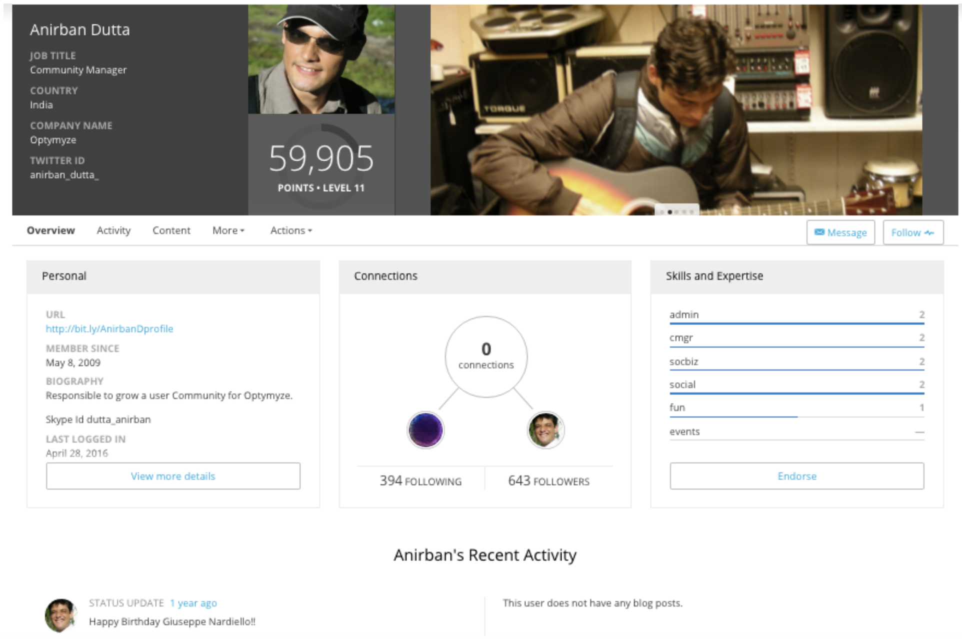

Figure 3. An Example of Online Member Profile

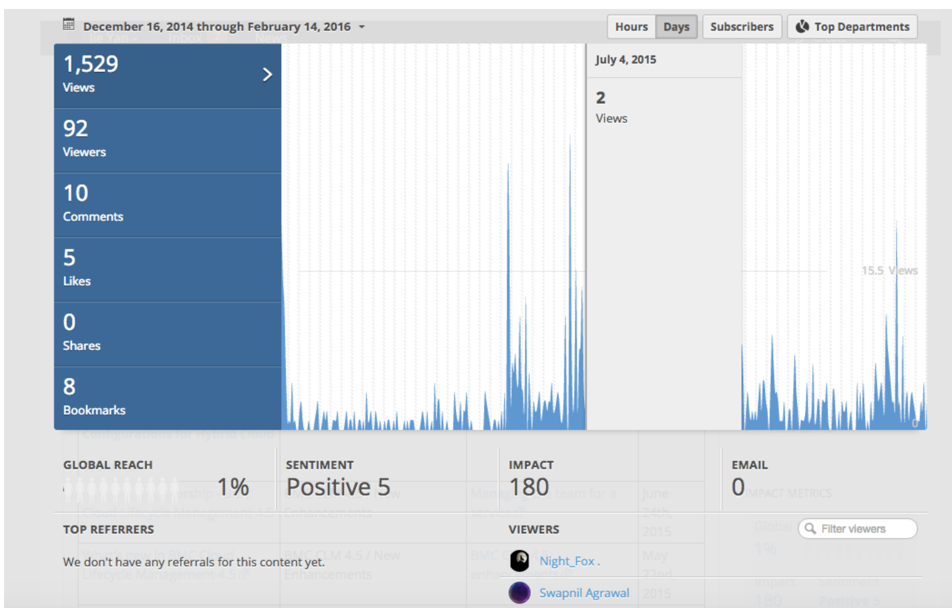

Figure 4. An Example of Document Impact Metrics

Table 15. Demographic Characteristics of the Employees (N=231)

Gender	Male = 167 (72%); Female = 64 (28%)
Region	North America = 173 (75%); EMEA = 14 (6%); Asia-Pacific = 44 (19%)
Function	S&M = 6 (2%); ES = 18 (8%); CS&CE = 12 (5%); P&A = 89 (39%); DEMT = 73 (32%); DPSM = 33 (14%)
Community Tenure (month; as of Jan 2014)	0~12 = 2 (1%); 13~60 = 110 (48%); 61~120 = 115 (49%); 121~140 = 4 (2%)

Note: S&M (Sales & Marketing); ES (Enterprise Solutions); CS&CE (Customer Success & Customer Experience); P&A (Performance & Analytics); DEMT (Digital Enterprise Management Technology); DPSM (Digital Product and Service Management)

Variables and Measures

There are five major variables investigated in this study: *readership of employee content, age of employee content, employees' writing behavior, product users' reading behavior and contribution in product support*. To measure readership, I utilized each document's interaction data because the number of views, likes, comments and bookmarks objectively reflects the degree of readership of a document. Nevertheless, several behavioral factors were considered when I measured the variable using the interaction data. For example, using the number of views alone may not truly represent a document's readership because many viewers or readers may only take a rapid glance or skim through the document. Likewise, a record of like, bookmark and comment may come from the same reader rather than three different individuals; and many readers may not take an action (e.g., like, bookmark and comment) after reading a document. Further, a document receiving 100 comments should be more popular versus the one only receiving 100 likes. Taking the above factors into account, I measured the variable of readership by calculating a *readership factor score* based on the number of "likes", "bookmarks" and "replies" that each document received. Specifically, I created a factor score matrix including three factors of likes, bookmarks and replies, and calculated the corresponding readership factor scores in SPSS using the regression method.

Content age was measured as the number of days since the document was first posted in the community. Employees' writing behavior was measured from the community profile data as the number of documents and the number of corresponding revisions they contributed during the two-year period. Product users' reading behavior was also measured from the community profile data as the number of documents they participated during the two-year period. I operationalize user participating in a document as a user takes actions, including commenting (replies), liking and/or bookmarking, after accessing and reading the document.

One challenge in measuring the variable of product users' contribution in product support is that the relationship between product users' reading behavior and their corresponding contribution behavior is unobservable. For example, when a user contributes to a discussion, it is difficult to distinguish whether his/her motivation to contribute results from access to employee content. Furthermore, the source of contributed expertise and knowledge is unclear; it could either come from the users themselves or the employee content they have accessed. To overcome this obstacle, I utilized the record of incoming links of each document. The incoming links contain the citation history[6] of each document. Through these links, I was able to find out when, where and by whom the document was cited from the time it was first posted in the community. The citation itself not only reflects a user's reading behavior but well proves the motivation and knowledge source behind the contribution. Then for each user, the contribution in product support was measured by the number of citations s/he made in the

[6] A link to the document will appear in the discussion threads when a user cites it.

discussion threads. One limitation of this measure is that it does not take account of user contributions that were based on employee content but did not cite it. I therefore included *discussion quantity* as a control variable. Discussion quantity was measured by counting the total discussion replies of each user.

In addition to discussion quantity, I included several other control variables. At the document level, I controlled for the number of documents posted in the same place and the number of documents posted outside a place. The OSC of BMC creates different *places* for the support of different product categories; and there are a total of 21 places (i.e., product categories) in the OSC of BMC as of March 2016. Some products have larger customer bases than others and accordingly the number of participating users across different places varies. Also, some product categories are somewhat related because they are derived from the same product line whereas others are not. Hence, adding these two variables allows us to take into account the "competition" among documents that may influence their readership.

At the individual level for both employees and users, I controlled for the community tenure. Community tenure was calculated in months based on each member's profile data. For the employees, I also controlled for their writing experience suggested by prior research (Boudreau, 2012). Experience equals the total number of documents an employee has contributed prior to the post of his/her latest document. For product users, I also controlled for *place scope*. Place scope counts for the number of distinct places a user has participated in product support. Some users focus their participation on only one or two places whereas others span multiple places; prior research indicates that the degree of boundary spanning impacts product users' contribution (Dahlander & Frederiksen, 2012).

Finally, I included *new product release* as an important control variable at both document and author levels to account for potential omitted-variable bias regarding the impact of readership on content generation. More specifically, I expect that an employee is likely to contribute new content not only because of the increase of readership but largely because of the release of new products/versions from the host firm. In other words, participating employees may be more motivated to write and discuss about new products/versions than existing ones. To measure this variable, I accessed to the product history database of BMC and downloaded the product release history data from January 2014 to January 2016; I then, by month, counted the number of total releases pertaining to each product category.

Modeling Strategy

I constructed panel data to take account of potential endogeneity issues. Endogeneity mainly arises from omitted variables, measurement error and/or reverse causality (Greene, 2011). Although using public, objective data minimizes the measurement error issue, my data may suffer from omitted variables bias and reverse causality. For example, while the participation is voluntary, employees from different functions may possess different types and levels of motivation to write community documents. Also, some employees contribute more content than others simply because their personal characteristics or levels of expertise and knowledge enable them to do so. As such, constructing a panel data allows us to control for these individual fixed-effects and mitigate omitted variable bias (Greene, 2011). On the other hand, my unique context features and data sources help us mitigate some reverse causality bias. For example, product users' reading behavior should be logically followed by their citation behavior. Also, employees' decision to revise and update documents should come after interactions, such as comments and replies, with users. Yet employees may still choose to write more with the intent to benefit from increasing readership. To account for this potential reverse causality, I measured readership prior to measuring employees' writing behavior. If readership does influence document writing, the predetermined change of readership should have a significant impact.

I therefore constructed panel data at three different levels including *document*, *author*, and *reader* to test my hypotheses. At the document level, I constructed document-month pairs from January 2014 to January 2016. A document entered into my panel when it first appeared in the community. I then calculated monthly readership for the document till the end month of my data collection. The dependent variable of document update was calculated one month after the readership and the variable recorded the number of times a document was updated in the next month. Document age was entered as the number of days since a document first appeared to the last day of current month. For the control variables, I calculated the number of documents posted in the same place and documents outside the place for each document during each observation month. In addition, I entered the number of new product/version releases belonging to the place where the focal document was.

To account for the writing of new documents, I constructed an author-month panel. In this panel, the readership was calculated for each author by summing up the readership of all the documents (including revisions) the author received in the current month. Then I calculated the dependent variable for each author-month pair by observing the number of new documents the author posted in the next month. Experience was calculated as the cumulated documents an author had contributed up to the current month. I also controlled for new product/version releases by counting the total number of releases occurred in the current month.

At the reader level, I constructed reader-month pairs for the two-year period. For each reader I identified, the variable of user reading behavior was calculated by counting the total number of documents s/he participated in the current month. I averaged the age of all the documents a user participated in the current month to calculate content age. Then the dependent variable of user contribution was entered by counting the citations a user made in the same month. I also entered and controlled for the total number of discussion replies a user contributed in the current month, as discussed earlier. Finally, the place scope was calculated as the number of distinct places a user had participated in the current month. For both authors and readers, I calculated community tenure in the panels to account for time effects. Table 16 summarizes all the variables investigated in the models of this study.

Table 16. Variable Definitions and Measures

Variable	Definition	Source of Measurement Data
Employee content readership (*ReadershipDoc & ReadershipAuthor*)	The degree to which employee-contributed documents are accessed and read by product users in the community	The interaction data of each document
Employee content age (*Age*)	The number of days since the document was first posted in the community	The interaction data of each document
Employee content contribution (*WritingUpdate & WritingNew*)	The extent to which an employee contributes documents to the community	Online profile data of each employee
User content access (*Access*)	The degree to which a product user accesses employee documents in the community	Online profile data of each user
Contribution in product support (*Support*)	The degree to which a user contributes to product support using information and knowledge derived from employee-contributed documents	The citation history contained in the record of incoming links of each document
User discussion quantity (*Quantity*)	The total discussion replies of each user	Online profile data of each user
Documents in place (*PlaceIn*)	The number of documents posted in the same community place	The interaction data of each document
Documents out of place (*PlaceOut*)	The number of documents posted outside a community place	The interaction data of each document
Community Tenure (*Tenure*)	The number of months since the registration of a product user or an employee	Online profile data of each user and employee
Employee writing experience (*Experience*)	The total number of documents an employee has contributed prior to the post of his/her latest document	Online profile data of each employee
User place scope (*Scope*)	The number of distinct places a user has participated in product support	Online profile data of each user
New product release (*ReleasePlace & ReleaseTotal*)	The number of releases pertaining to each product category	The product history database of BMC

Note: Variable abbreviation is in parentheses.

Estimation Approach

I chose to estimate a negative binomial (NB) fixed-effects panel model considering my three dependent variables (i.e., # document updates, # new documents and # contributions in product support) are all count variables and my data's sample variances are different from sample means (i.e., over-dispersed). In addition, for the author and reader panels I added a zero-inflation part because of excess zeros in the dependent variables (Greene, 2011). More importantly, the existence of excess zeros has theoretical implications. Specifically, the online community literature has introduced the concept of *lurkers* and investigated their community behaviors[7]. Drawing upon this concept, I suggest that the excess zeros should result from two different groups of individuals. One group is participating users who happened to yield zero contributions because they might lack access to employee content in a particular time period. The other group behaves like lurkers who may have accessed the content and acquired the required knowledge but did not participate in the discussions and therefore had "zero" contributions. Likewise, some employees may contribute zero documents simply because they were no longer interested in writing community content or had left the community. I therefore chose to estimate a full zero-inflated negative binomial fixed-effects (ZINB) model for the author and reader panels.

The ZINB model assumes that two distinct processes (e.g., participants and lurkers in this study) generate excess zeros. Accordingly, the ZINB regression entails two models: a count model – NB model – to model the count process, and a logit model to differentiate the two processes regarding the zero outcomes (UCLA, 2014). I used a conditional estimator in Hausman et al. (1984) to estimate the NB fixed-effects panel model:

$$log\mathrm{Lc} = \sum_{\mathrm{i}=1}^{\mathrm{n}} log\mathrm{P}(\mathrm{yi1}\ , \mathrm{yi2}, \ldots, \mathrm{yiTi} \mid \sum_{\mathrm{t}=1}^{\mathrm{Ti}} \mathrm{yit}) \qquad (6)$$

Under this estimator, the model framework for the document and author panels is:

$$\mathrm{E}\left[\mathrm{yit}\middle|\mathrm{xi\ (t\text{-}1)}\right] = exp\left(\delta\mathrm{i} + \beta * \mathrm{xi\ (t\text{-}1)}\right) = \lambda\mathrm{it} \qquad (7)$$

[7] Lurkers refer to community members who only read others' posts with no contribution to the community (Wasko et al., 2004).

The model framework for the reader panel is:

$$E[yit|xit] = exp(\delta i + \beta * xit) = \lambda it \quad (8)$$

where xi is an m x 1 vector of explanatory variables and β is an m x 1 vector of corresponding coefficients (Hausman et al., 1984); δi is the error term. This NB fixed-effects part models the individuals who behave as participants in the community. For those who may behave as lurkers, they are modeled by the logit part of the ZINB model. Specifically, I have yit = 0 with probability φit (behaving as lurkers), and have E (yit) = λit (negative binomial estimate from formula (2) or (3)) with probability 1 - φit:

$$\varphi it = \frac{exp(\gamma' Zi\ (t\text{-}1))}{1+exp\ (\gamma' Zi\ (t\text{-}1))} \qquad \text{(Author)} \qquad (9)$$

$$\varphi it = \frac{exp(\gamma' Zit)}{1+exp\ (\gamma' Zit)} \qquad \text{(Reader)} \qquad (10)$$

where Zi is a q x 1 vector of explanatory variables in the logit model and γ' is a q x 1 vector of corresponding coefficients (Hausman et al., 1984).

I used the NLOGIT 5 econometric software to test my datasets. To test the ZINB panel models, I followed a two-step procedure in NLOGIT 5. I first fitted the ZINB model without fixed-effects to obtain a set of starting values for the panel model; I then fitted the panel model again with zero-inflated Poisson fixed-effects (Greene, 2012).

Results

Tables 17, 18 and 19 show the correlations and descriptive statistics of three panel datasets. Table 20 presents the results from the document panel. The positive α value indicates the over-dispersion of the dataset and supports the use of NB model over a Poisson model. The results of Hausman test ($p<0.001$) favor the fixed-effects over the random effect. The coefficient of readership index is positive and significant (Model 3, β=1.098, p<0.001), indicating a positive relationship between readership and document updates. More specifically, my results show that with one unit increase in readership index (documents), a document will on average receive 1.1 more updates in the subsequent month. Nevertheless, the negative and significant coefficient of the quadratic term of readership index (documents) (Model 3, β=-0.066, p<0.001) indicates that the marginal effect of readership on document updates diminishes. Notably, the coefficients of two control variables (PlaceIn and PlaceOut) are positive and significant. This indicates that a document is more likely to be updated as more new documents or updates are contributed to the community, regardless of the place of the document. In other words, there is no readership "competition" among employee-contributed documents.

Table 17. Descriptive Statistics and Correlations Matrix (Document Panel)

Variable	Mean	S.D.	Min	Max	1	2	3	4	5
WritingUpdate	0.26	0.70	0	8	1.00				
ReadershipDoc	0.38	1.25	0	17.17	0.83	1.00			
PlaceIn	6.18	3.58	0	21	0.20	0.17	1.00		
PlaceOut	124.78	9.22	85	154	-0.02	-0.01	-0.27	1.00	
ReleasePlace	0.90	1.10	0	5	0.01	0.01	-0.04	0.04	1.00

Note: Correlations less than 0.01 are rounded to 0.01.

Table 18. Descriptive Statistics and Correlations Matrix (Author Panel)

Variable	Mean	S.D.	Min	Max	1	2	3	4	5
WritingNew	0.141	0.41	0	7	1.00				
ReadershipAuthor	0.38	1.00	0	16.8	0.62	1.00			
Tenure	74.59	26.00	11	134	0.08	0.14	1.00		
Experience	1.94	3.38	0	61	0.39	0.53	0.23	1.00	
ReleaseTotal	20.16	10.29	2	33	0.06	0.01	-0.04	-0.05	1.00

Note: Correlations less than 0.01 are rounded to 0.01.

Table 19. Descriptive Statistics and Correlations Matrix (Reader Panel)

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6
Support	0.01	0.14	0	2	1.00					
Access	2.04	1.25	0	12	0.18	1.00				
Age	331.71	185.48	0	729	0.01	0.29	1.00			
Quantity	3.85	4.04	0	87	0.24	0.39	0.06	1.00		
Tenure	78.98	32.66	1	137	-0.01	-0.01	-0.01	-0.01	1.00	
Scope	2.23	1.29	0	14	0.19	0.59	0.30	0.43	-0.01	1.00

Note: Correlations less than 0.01 are rounded to 0.01.

Table 20. Document Panel Results (N=815; Observations=11,976)

Variables	NB Fixed-effects (DV: WritingUpdate)		
	Model 1	Model 2	Model 3
Constant	-4.442*** (0.361)	-0.098 (0.562)	-0.258 (0.535)
ReleasePlace	0.038 (0.025)	-0.029 (0.027)	-0.016 (0.027)
PlaceIn (lagged)	0.126*** (0.006)	0.057*** (0.006)	0.056*** (0.006)
PlaceOut (lagged)	0.019*** (0.002)	0.006* (0.002)	0.005* (0.002)
ReadershipDoc (lagged)		0.661*** (0.011)	1.098*** (0.024)
ReadershipDoc*ReadershipDoc			-0.066*** (0.003)
Hausman	428***		
Alpha	> 0		
Log-likelihood	-5350.58	-3587.15	-3270.19

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$
Values less than 0.001 are rounded to 0.001

Table 21 presents the results from the author panel. The positive α value indicates the over-dispersion of the dataset and supports the use of NB model over a Poisson model. The results of Hausman test ($p<0.001$) support the use of fixed-effects. The positive and significant coefficient of readership index (NB Part Model 3, $\beta=0.778$, $p<0.001$) supports the positive effect of readership on new document generation. Specifically, the results show that with one unit increase in readership index (authors), an author will on average generate 0.8 more new documents in the subsequent month. The negative and significant coefficient of the quadratic term of readership index (authors) (NB Part Model 3, $\beta=-0.057$, $p<0.001$) indicates that the effect of readership on new document generation is weaker for those authors who have already received numerous readership than those only receiving a few. Combined, the results related to readership in Tables 20 and 21 support H1. In addition, the estimates of the control variable (ReleasePlace) in all Table 6 models are nonsignificant whereas those of ReleaseTotal in Table 7 are all positive and significant, indicating that as new products/versions are released, employees are more likely to write new documents rather than updates.

Table 22 presents the results from the reader panel. The positive and significant coefficient of access (NB Part Model 3, $\beta=0.464$, $p<0.001$) indicates that access to employee-generated documents affects users' contribution of product support positively. Specifically, the results show that with one unit increase in access, a user will on average contribute 0.5 more product supports. H2 is therefore supported. However, the coefficient of the interaction term between access and document age is nonsignificant (NB Part Model 3, $p>0.1$). This indicates that the positive impact of accessing employee-generated documents on product support contribution is not moderated by document age. As such, H3 is not supported.

Table 21. Author Panel Results (N=231; Observations=5,544)

Variables	ZINB Fixed-effects (DV: WritingNew)			
	NB Part - Model 1	NB Part - Model 2	NB Part - Model 3	Logit Part - Model 3
Constant				-32.617*** (0.004)
Tenure	-0.055*** (0.006)	-0.065*** (0.006)	-0.059*** (0.007)	
Experience (lagged)	0.023** (0.007)	0.053*** (0.007)	0.020* (0.008)	-0.921*** (0.001)
ReleaseTotal	0.014*** (0.003)	0.012** (0.004)	0.016*** (0.004)	
Readership Author (lagged)		0.297*** (0.024)	0.778*** (0.076)	
ReadershipAuthor* ReadershipAuthor			-0.057*** (0.011)	
Hausman	217***			
Alpha	> 0			
Log-likelihood	-1523.90	-1447.31	-1393.90	

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$
Values less than 0.001 are rounded to 0.001

Table 22. Reader Panel Results (N=12,315; Observations=152,983)

Variables	ZINB Fixed-effects (DV: Support)			
	NB Part - Model 1	NB Part - Model 2	NB Part - Model 3	Logit Part - Model 3
Constant				12.236*** (0.029)
Tenure	-0.003 (0.002)	-0.001 (0.002)	-0.001 (0.002)	
Quantity	0.048*** (0.003)	0.036*** (0.003)	0.036*** (0.003)	
Scope	0.928*** (0.026)	0.646*** (0.031)	0.646*** (0.031)	-1.941*** (0.003)
Access		0.474*** (0.028)	0.464*** (0.039)	
Age*Access			0.001 (0.001)	
Hausman	8117***			
Alpha	> 0			
Log-likelihood	-2277.82	-2136.43	-2136.37	

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$
Values less than 0.001 are rounded to 0.001

Regarding the logit models, the negative and significant coefficient of Experience in Table 21 (Logit Part Model 3, β=-0.921, p<0.001) shows that authors who are active in terms of community content contribution are less likely to behavior as lurkers. Put differently, they will update or write new documents if they have new ideas and motivations. Similarly, the coefficient of place scope in Table 22 is negative and significant (Logit Part Model 3, β=-1.941, p<0.001). This indicates that product users who are active in terms of community participation (i.e., participating in different community places) are less likely to behavior as lurkers. In other words, they will contribute what they have learned from the community to product support if there is a need.

Additional Analyses

To evaluate the robustness of my models and corresponding results, I conducted two additional analyses. First, to avoid potential bias from outliers, I removed 42 documents with extremely high readership over the observation periods. This process reduced the sample size to 10,968 observations. Table 23 reports the results from the modified document panel and they are highly consistent with those in Table 20. Likewise, I removed the 7 most popular authors. Table 24 presents the results and the signs and significance of coefficient estimates remain unchanged as those in Table 21.

Table 23. Document Panel Results (N=773; Observations=10,968)

Variables	NB Fixed-effects (DV: WritingUpdate)		
	Model 1	Model 2	Model 3
Constant	-3.212*** (0.311)	-0.043 (0.312)	-0.104 (0.317)
ReleasePlace	0.043 (0.019)	-0.035 (0.023)	-0.019 (0.025)
PlaceIn (lagged)	0.193*** (0.004)	0.073*** (0.005)	0.071*** (0.005)
PlaceOut (lagged)	0.027*** (0.002)	0.009** (0.003)	0.008* (0.003)
ReadershipDoc (lagged)		0.731*** (0.013)	1.285*** (0.029)
ReadershipDoc* ReadershipDoc			-0.071*** (0.003)
Hausman	442***		
Alpha	> 0		
Log-likelihood	-5523.32	-3294.34	-3012.46

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$
Values less than 0.001 are rounded to 0.001

Table 24. Author Panel Results (N=224; Observations=5,376)

Variables	ZINB Fixed-effects (DV: WritingNew)			
	NB Part - Model 1	NB Part - Model 2	NB Part - Model 3	Logit Part - Model 3
Constant				-28.129*** (0.003)
Tenure	-0.083*** (0.006)	-0.071*** (0.005)	-0.064*** (0.007)	
Experience (lagged)	0.029** (0.007)	0.058*** (0.007)	0.027* (0.008)	-0.864*** (0.002)
ReleaseTotal	0.016*** (0.003)	0.013** (0.004)	0.017*** (0.004)	
Readership Author (lagged)		0.332*** (0.028)	0.813*** (0.077)	
ReadershipAuthor*R eadershipAuthor			-0.063*** (0.012)	
Hausman	283***			
Alpha	> 0			
Log-likelihood	-1643.35	-1509.17	-1462.64	

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$
Values less than 0.001 are rounded to 0.001

Discussion and Conclusion

Companies across industries have increasingly implemented OSCs for product support. Apart from having product users participate in the communities, more and more host-firms start encouraging their employees from different levels and functions to interact with users for better community results. Existing research on OSCs, however, has tended to focus on external product users while the role and participation of internal employees has received limited attention. This study therefore extends the OSC literature by focusing on participating employees and examining how their contributions impact the product support dynamics within the communities. More specifically, I find that community content such as documents contributed by participating employees facilitates user self-support. Users are likely to help peers with the information and knowledge they have acquired from employee-contributed content. In addition, receiving increasing user access and readership will, in turn, motivate employees to generate more community content. My findings, accordingly, confer implications for both research and practice.

For OSCs, this study highlights the need to explore the role of host firms' employees and the nature of their participation in the communities. Apart from contributing community content via writing articles and blogs, participating employees often directly engage in community discussions to provide product support. Such engagement may involve multiple forms including replying to askers' questions, identifying correct/best/helpful answers and encouraging more discussions for an unsolved issue (Grohol, 2016). Differentiating the roles between employees and product users and examining the outcomes of employee participation will therefore confer a holistic picture of community interactions and resulting outcomes. For example, while prior research has identified various factors that shape users' contributions in OSCs, it is still unclear the conditions under which employees are likely to be motivated to participate. In contrary to product users, employees may possess different motivations to participate because of their relations with the host firms. While voluntarily, employees may overall perceive their participation as an in-role activity appreciated or expected by their supervisors or firms, whereas product users are largely driven by autonomous motivations (e.g., information seeking) (Arazy et al., 2015; Wendelken et al., 2014). Also, employees, versus product users, may anticipate different types of benefits (e.g., cognitive, social and personal) from participating in the communities.

Moreover, my findings indicate that examining the employee-user interaction is an integral part to understand the dynamics and thereby the success of OSCs. On the one hand, employees interact with users in various forms (e.g., community content, ongoing discussions) in the community aiming to meet users' needs and expectations toward product support. Employee participation thereby contributes to users' satisfaction toward the community as well as the host firm (Nambisan, 2002). This may further help build the community name among product users and attract more users to participate in and contribute to the community. On the other hand, as employees observe positive outcomes resulting from their participation, they are more motivated to engage in the community and interact with users. Such a positive, spiral interaction pattern between employees and users is essential for the long-term success of any product support community (Butler, 2001; Faraj et al., 2011). Overall, the nature of employee participation and contribution in OSCs has received limited attention. Much research is needed to illustrate how the behavior of participating employees shape product support outcomes and contribute to the long-term success of OSCs.

Apart from OSCs, my study holds implications for research under a broader context of online Q&A communities. Unlike OSCs, which are hosted by firms for the good of their own products and services, online Q&A communities are usually autonomous and established for a wide variety of purposes by individuals or groups (e.g., education, healthcare, sports and entertainment). Online Q&A communities resemble OSCs in that the former also provides a place where members or askers can post questions and problems and have them discussed by their peers (Shah et al., 2009). Furthermore, as employees in OSCs, community moderators, editors and some experienced members of Q&A communities regularly contribute articles and post summaries in the hope of facilitating knowledge sharing and community support (Lou et al., 2013). While extant studies have examined various psychological motives for knowledge contribution in Q&A communities (e.g., Jin et al., 2015; Phang et al., 2014; Khansa et al., 2015), little is known about how these articles and post summaries may change the dynamics of members' knowledge seeking and sharing behavior. Given the difference between OSCs and Q&A communities, community content such as articles and post summaries in Q&A communities may relate to different antecedents and effects than those examined in this study. For example, compared to those in OSCs, readership and the resulting response rate and volume are usually higher in many Q&A communities because of their large member bases (Wise et al., 2006). Such difference in content consumption may induce different patterns (e.g., frequency and variance) of reacting behavior of the content contributors (Liu & Jansen, 2013). In addition, many Q&A communities use programming algorithms to promote and demote community content (Ghosh & Hummel, 2014), changing the accessibility and resulting impacts of the content accordingly.

From a practical perspective, my study highlights the necessity of having employee participation from different levels and functions to build a vibrant and thriving

OSC. I suggest that overall engagement of employees is essential for several reasons. First, although users can usually derive answers from peers, they still prefer employee joining the discussion, helping identify incorrect answers, and elaborating or answering the most complicated questions (Nuse, 2015). Therefore, not only could participating employees act as discussants and repliers but connectors and influencers to help members develop social connectedness and thereby a sense of community. More importantly, my study shows that the degree of employee-user interactions influences employees' contribution in terms of community blogs, articles and documents. Such contributed-knowledge, in turn, plays a critical role in facilitating user learning, self-support and peer exchange. Notably, I suggest that host firms and participating employees develop schedules and approaches to spot community trends and ensure the relevance and freshness of community content. Although not supported in my study, I suggest that as the content contributed by employees becomes obsolete, it may engender decreasing impact on product support in the community. One path to keep up user support trends is to build and maintain a rich profile of product usage of users and challenges they faced as employees interact with users in the community (Grohol, 2016; Shiao, 2014). Doing so helps provide a comprehensive "view of the users" to inform future product support.

To conclude, the present study extends the existing research of firm-hosted online support communities by focusing on community content contributed by participating employees. My findings indicate that employee-generated content such as technical articles plays a critical role in facilitating user self-support in the communities. On the other hand, the continuance of employee content contribution hinges on the popularity as well as the usefulness of existing content. To better utilize these findings, I suggest that host firms develop a strategic vision to increase the level and scope of employee participation. Not only can participating employees help moderate the community dynamics but contribute to the long-term success and sustainability of the communities by interacting with users for product support.

CHAPTER FOUR

Examining Social Capital and Knowledge Contribution in Firm-Hosted Online User Communities: A Spiral Perspective

Introduction and Motivation

Firms have been increasingly relying on building online user communities (hereinafter OUCs) to access external, distant knowledge and expertise (Bayus et al., 2013; Di Gangi & Wasko, 2009; Huang et al., 2014). Participants in OUCs are mainly the customers or users of the products/services of the host firm. They voluntarily engage in the community and contribute their knowledge and expertise for existing product support and new product development. Much research therefore has been done to investigate why these users are willing to cooperate with host firms and contribute their knowledge on a daily basis (e.g., Franke et al., 2013; Porter & Donthu, 2008; Jeppesen & Frederiksen, 2006; Foss et al., 2011).

One stream of research focuses on examining the relationship between social capital and knowledge contribution in OUCs. Social capital is typically defined as "resources embedded in a social structure that are accessed and/or mobilized in purposive action" (Lin, 2001, p.29). Drawing upon the seminal work of Nahapiet and Ghoshal (1998), research on OUCs often approaches the social capital concept as consisting of three dimensions: *structural capital, cognitive capital, and relational capital*.

Structural capital refers to the connections and structural links among individuals (Nahapiet & Ghoshal, 1998). Research on the structural aspect of social capital has tended to focus on the structural position of individuals and how it will impact knowledge exchange in OUCs (Huysman & Wulf, 2005; Wasko & Teigland, 2004; Wasko et al., 2009). Whelan (2007), for example, developed several propositions suggesting the relationships between community members' core/periphery structure and connectivity and members' knowledge contribution. Dahlander and Frederiksen (2012) found empirical evidence that an individual's position in the core/periphery structure of a user community is consequential for knowledge contribution. Likewise, Chen et al. (2012) empirically showed that users' level of contribution varies with the change of his/her network connectedness (i.e., the extent to which a user is connected with others in the community).

Cognitive capital refers to the capability of individuals to understand and apply the knowledge when connecting with each other (Nahapiet & Ghoshal, 1998). Research on the cognitive aspect of social capital has largely focused on the cognitive benefits users anticipate deriving from engaging in OUCs (Dholakia et al., 2009; Chiu et al., 2006; Tsai & Bagozzi, 2014; Huysman & Wulf, 2005). For instance, Nambisan and Baron's research revealed that users' expectations of expertise enhancement and actual experiences in community learning are significantly related to users' participation in value creation and innovation (Nambisan & Baron, 2010, 2009, 2007). Similarly, Brabham (2010) pointed out that the opportunity to improve one's expertise and skills is an important motivator for users to contribute in the community.

Finally, relational capital refers to the characteristics of the relationship such as mutual respect, trust and generalized reciprocity (Nahapiet & Ghoshal, 1998). Several studies on OUCs have found that community trust (or the norm of collaboration) affects users' knowledge-sharing intentions with both other users and the host firm (e.g., Porter & Donthu, 2008; Wasko et al., 2004; Kosonen et al., 2013). Also, building a norm of reciprocity has significant effects on the quality and quantity of knowledge contribution (e.g., Wiertz & De Ruyter, 2007; Dholakia et al., 2004; Bergquist & Ljungberg, 2001).

The above literature review illuminates significant effects of social capital on knowledge contribution in OUCs. Yet I know little about how contributing knowledge will impact members' social capital. It is intuitive to expect that an individual's knowledge contribution should, in turn, influence his/her social capital in the community. For example, for users who extensively participate in product support and contribute their knowledge, they receive more connections or ties and thereby gain their reputations and community statuses (Phang et al., 2009; Madupo et al., 2010). This will change their structural capital in the community. Also, when users participate in the discussions and reply to others' questions, they will learn the correct and/or helpful answers from other knowledge providers, augmenting their cognitive capital. Likewise, the norm of collaboration and trust is cultivated between members who reactively and proactively contribute their knowledge in the community (Dholakia et al., 2004; Zhao et al., 2012). In addition, experienced members usually follow the new members back when they receive ties from the new members (Jin et al., 2010). These combined will impact relational capital between individuals. Therefore, I suggest that, in lieu of one-way impact, there should be a spiral relationship between social capital and knowledge contribution. In other words, I expect that *a self-reinforcing spiral exists between an individual's social capital and his/her knowledge contribution in an OUC such that an increase in one leads to an increase in the other*.

Investigating such a spiral relationship has both theoretical and practical implications. Theoretically, it will not merely consolidate prior research but more importantly, extend the literature by demonstrating the reciprocity between social capital and knowledge contribution. The inclusion of effects of knowledge contribution on social capital will also add a layer of explanation to the participation and contribution dynamics under a broader context of online community (Faraj et al., 2011; Zwass, 2010). For example, it is still unclear how social capital initially emerges from knowledge contribution in some online marketplaces (e.g., Amazon reviews) and how social capital translates into other capital forms (e.g., game credits) as a result of participation in online games (Zwass, 2010). Drawing upon this study, future research could explore more outcomes arising from the interaction between social capital and knowledge contribution, an issue that has received limited attention to date.

Practically, my findings will provision empirical evidence on the design of OUCs for those host firms that still suffer from the "Empty Bar Syndrome" (Ogneva & Kuhl, 2014). For example, host firms could create a panel on the homepages of their communities updating the top contributors. Doing so will, on the one hand, encourage knowledge contribution by building a reputation system (Füller, 2006; Nov et al., 2010). On the other hand, it will facilitate the connections or structural capital between members, particularly for novices who want to seek experts or experienced product users. Likewise, Firms could add community features that help members build cognitive and relational capital after knowledge exchange. Allowing members to recognize and confirm correct and/or helpful answers will, for example, facilitate community learning (cognitive capital) whereas adding the following/followers and mutual friends features (like those applied in social media) will boost relational capital between members.

I used a unique dataset to test the spiral relationship between knowledge contribution and social capital. The dataset consists of 3,512 active members of the OUC of BMC with their dynamic participating data collected over a 5-month period. I conducted a series of panel regressions to examine the interaction between social capital and knowledge contribution. My empirical results not only support a spiral relationship between knowledge contribution and social capital, but a moderating impact of community growth on the relationship. Accordingly, I discuss theoretical and practical implications of my study.

Methodology

Empirical Model

Figure 5 shows the empirical model I used to test the relationship between social capital and knowledge contribution in the OUC context. I based the model on the work of Wasko and Faraj (2005). In their study, the effects of structural capital, cognitive capital and relational capital on knowledge contribution were examined respectively. To test a spiral relationship, I complement their model by adding a recursive path accounting for the impact that knowledge contribution has on an individual's social capital, including structural, cognitive and relational. Then the new-formed social capital should, in turn, impact one's knowledge contribution. Building such a model thereby allows us to examine the two-way interactions between social capital of community members and their knowledge contributions.

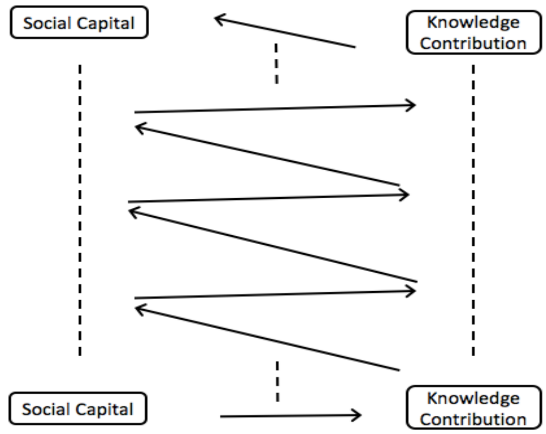

Figure 5. Empirical Model

In addition to these focal relationships in Figure 5, I consider the moderating role of *community growth*. Community growth and the resulting community size determine the sustainability of an online community (Butler, 2001; Panzarasa et al., 2009; Koh, et al. 2007; Otto & Simon, 2008). Different levels of community growth and size often lead to different levels and forms of community participation (Ren et al., 2007; Hsiao & Chiou, 2012). For example, as communities grow, they can attract more members but meanwhile will induce more negative outcomes such as free riding and social loafing (Wasko et al., 2004; Bock et al., 2015). Also, a large community provides more diverse interaction opportunities but individual interactions are more likely to remain unnoticed by other members (Wang et al., 2013; Wasko et al., 2004). These may impact the emergence, form and loss of social capital within a community (Wasko & Faraj, 2005; Lin, 2001). On the other hand, it will be difficult for members to continue to grow their social capital in a community that grows slowly, regardless of their knowledge contribution. Yet a relatively small community tends to facilitate the form of strong structural ties and sharing of information resources which may, in turn, impact community learning (Bock et al., 2015; Tsai & Pai, 2014; Zheng et al., 2013). Taken together, I expect that *a strong community growth should either strengthen or weaken the impact of knowledge contribution on social capital, although I am slightly in favor of the former.*

Data Collection and Variables

I collected my data from the OUC of BMC, a global leader in innovative software solutions that enable businesses to transform into digital enterprises for competitive advantage (BMC, 2016). BMC established its OUC in 2002 and through which has developed a successful, long-term relationship with its product users for existing product support and new product development.

As of January 2016, the community has 26,597 registered members. To create a sample of the study[1], I utilized the community's people list that ranks all the members based on their community levels[2] and selected a stratified random sample of 6,836 members. Doing so allows us to ensure that the dataset represents various member populations. I then checked the record of recent community activities of each member in my dataset and removed those individuals who did not have any community activities during the last 3 months[3]. I suggest that these individuals are largely community lurkers or inactive members that do not participate in the community. The entire process results

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[1] I did not include all the members in order to make the study manageable and feasible in terms of sample size and empirical design.

[2] Community members achieve different levels based on their cumulative community contributions (i.e., community points earned). And each level corresponds to a different range of community points from level 1 (lowest points) to level 13 (highest points).

[3] Community members without any login records during the past 3 months will be assigned with a status of "inactive" by the systems.

in a total of 3,512 active members included in my dataset. Table 25 summarizes the demographic characteristics of the sample.

Table 25. Demographic Characteristics of the Members (N=3,512)

Gender	Male = 2,575 (73%); Female = 937 (27%)
Region	North America = 2,318 (66%); EMEA = 245 (7%); Asia-Pacific = 949 (27%)
Community Level	Level 1 = 1,292 (36.8%); Level 2 = 630 (17.9%); Level 3 = 479 (13.6%); Level 4 = 436 (12.4%); Level 5 = 162 (4.6%); Level 6 = 136 (3.9%); Level 7 = 105 (3.0%); Level 8 = 90 (2.6%); Level 9 = 73 (2.1%); Level 10 = 47 (1.3%); Level 11 = 37 (1.1%); Level 12 = 17 (0.5%); Level 13 = 8 (0.2%)
Community Tenure (month; as of Mar 2016)	0~12 = 597 (17%); 13~60 = 1,897 (54%); 61~120 = 983 (28%); 121~140 = 35 (1%)

To examine the dynamics between social capital and knowledge contribution, I conducted a 5-month empirical study based on these 3,512 members from March 1st 2016 to August 1st 2016. At the beginning of March, I measured and recorded the initial social capital of each member via his/her online community profile. BMC developed a rich online profile template for its members demonstrating their community activities and contributions[4]. Figure 6 provides an example of online community profile.

[4] The community profile includes members' demographic data (e.g., title and function), network data (following/followers), participation data (e.g., discussion and document contributions), reputation data (e.g., points and levels), etc. Notably, through the menus such as "Content", "Connections" and "Reputation" in the online profile, members can access more detailed information such as the discussions and threads they have participated, the profiles of people following them, and the entire ranking list of the community.

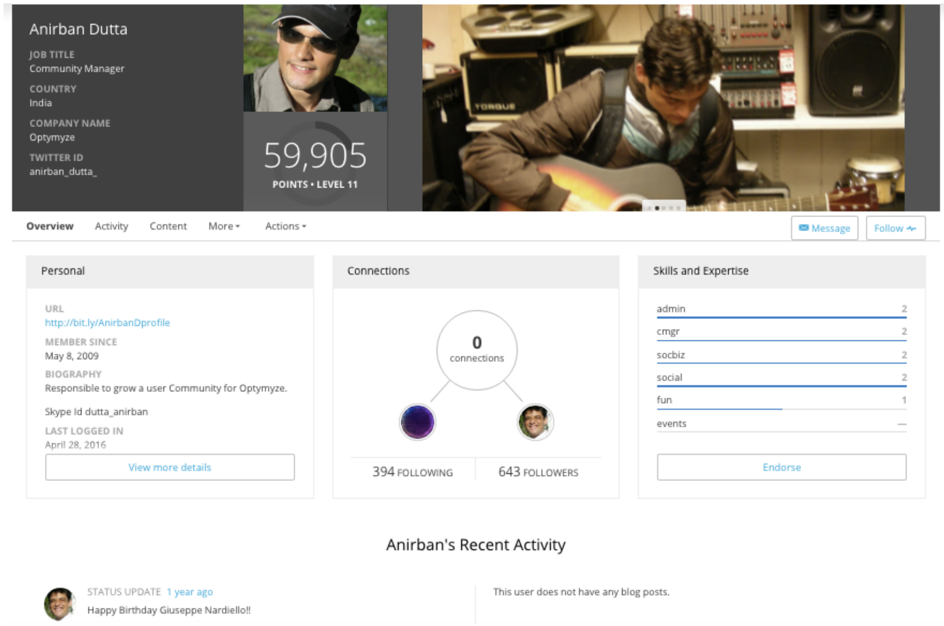

Figure 6. An Example of Online Member Profile

To measure the initial structural capital, I utilized the total number of followers a member has in the community. The more followers a member has, the more closely s/he moves toward the core structure of an online community (Ahuja & Carley, 1999; Borgatti, 2005). To measure the initial cognitive capital, I recorded and coded all the helpful and correct answers a member had contributed before March 2016. I coded the answers as follows: an answer would receive 2 points if it was marked as "correct", 1 points if marked as "helpful", and 0 points if no marks. I then summed up the points for each member and used this cumulative score to represent the initial cognitive experience (knowledge and expertise) a member had had in the community. I measured initial cognitive capital in this way considering that members' knowledge contribution should be positively associated with members' level of knowledge and expertise (Wasko and Faraj, 2005). Drawing upon previous studies (Borgatti et al., 2009; Borgatti & Cross, 2003), the initial relational capital was measured by counting the number of ties where two members followed each other. For example, if a member had 5 connections where s/he and the other member followed each other, s/he would receive a relational score of 5. Research on social media indicates that when individuals choose to follow each other, they tend to trust each other to an extent and are willing to interact for reciprocity (Ellison et al., 2011; Coleman, 1988).

Then at the end of each month (i.e., the beginning of the next month), I measured knowledge contribution as well as the gain (or loss) of structural, cognitive and relational capital for each member. I measured knowledge contribution using each member's participation data during the current month (i.e., the past 30/31 days). Specifically, I categorized each member's discussion contributions into: 1) correct answers, 2) helpful answers and 3) others. A member would receive 2 points if one of his/her answers was marked as correct, and 1 points if marked as helpful, and 0 if it had received no marks. I then summed up the points and used this score as one's knowledge contribution in the current month.

I also used each member's participation data to measure the change of cognitive capital. Specifically, I browsed through all the discussions a member had participated in the current month and determined whether the correct answer and/or the helpful answers were contributed by the focal member or others. Because members usually choose to follow (i.e., bookmark) the discussions in which they participated, a member should learn from the correct and/or helpful answers if they appear in the discussion threads[5]. I therefore utilized this process to measure the change of cognitive capital. To quantify the

[5] After choosing to follow a discussion, a member will receive a notification (via email and on community app) if a helpful or a correct answer is marked by the asker.

cognitive change, I again coded a correct answer as 2 points, a helpful answer as 1 points and 0 points if no correct/helpful answers were marked in the discussion. I then used the cumulative score as a member's cognitive change in the current month.

The change of structural capital was measured by recording the number of new followers of each member at the end of each month. However, whether the new followers resulted from a member's knowledge contribution is unobservable. To overcome this issue, I checked each new follower's online profile to determine whether the follower and the focal member had participated in the same discussion threads. I suggest that the following action should, to some extent, result from the knowledge contribution if the two members had participated in the same discussions. Based on this criterion, I was able to remove those new followers whose motives were "unidentifiable". I then recorded the number of new ties where the focal member and the new follower followed each other as the change of relational capital.

Community growth was measured at the end of each month by counting the number of new members. By sorting the community people list, I was able to determine who joined the community during the current month. Table 26 summarizes the variables in this study and Table 27 further describes the discussion data I collected during the 5-month observation period.

Table 26. Variable Definitions and Measures

Variable	Definition	Source of Measurement Data
Social capital – structural (*Structural*)	The connections and structural links between a member and others in the community	Online profile data of each member: connections
Social capital – cognitive (*Cognitive*)	The capability of a member to understand and apply the knowledge when connecting with others in the community	Online profile data of each member: participated discussions
Social capital – relational (*Relational*)	The characteristics of the relationship (such as mutual respect, trust and generalized reciprocity) between a member and others in the community	Online profile data of each member: connections
Change of social capital – structural (*StructuralDelta*)	The degree of the change of connections and structural links between a member and others in the community	Online profile data of each member: connections
Change of social capital – cognitive (*CognitiveDelta*)	The degree of the change of capability of a member to understand and apply the knowledge when connecting with others in the community	Online profile data of each member: participated discussions
Change of social capital – relational (*RelationalDelta*)	The degree of the change of characteristics of the relationship (such as trust and generalized reciprocity) between a member and others in the community	Online profile data of each member: connections
Knowledge contribution (*Contribution*)	The number of helpful and/or correct answers contributed by a member in the community	Online profile data of each member: participated discussions
Community growth (*Growth*)	The number of new members joining the community during each month	Community data: people

Note: Variable abbreviation is in parentheses.

Table 27. Characteristics of the Discussion Data

Number of distinct discussions	6,127
Number of answered discussions	3,042
Number of answers marked helpful	1,580
Number of discussions answered by new members	67

Modeling and Estimation Approach

My empirical study fits with panel data models. Applying panel models allows us to take account of potential endogeneity issues such as omitted variable bias and reverse causality (Greene, 2011). For example, some members may contribute more knowledge than others not merely because of difference in social capital but because of different levels of motivations arising from personal characteristics. These omitted variables may bias the results and building a panel data allows us to control for these individual fixed-effects (Greene, 2011). The endogeneity of reverse causality is largely minimized because of the inclusion of recursive relationship between social capital and knowledge contribution in my empirical model. In addition, the inclusion of community tenure helps us control for time effects.

I therefore constructed a panel data based on member-month pairs, resulting in 17,560 observations (3,512 members x 5 months). For each member-month pair, variables include social capital (time t), the change of social capital – structural, cognitive and relational (time t), knowledge contribution (time t), community growth and tenure (time t). To estimate the interactions (i.e., the spiral relationship) between social capital and knowledge contribution, I ran a series of linear regression models suggested by (Baron & Kenny, 1986). I first estimated the relationship between social capital change and social capital as follows:

$$\mathrm{StructuralDelta}_{it} = \beta_0^1 + \beta_1^1 * \mathrm{Structural}_{it} + \varepsilon_{it}^1 \qquad (11)$$

$$C\mathrm{ognitiveDelta}_{it} = \beta_0^2 + \beta_1^2 * \mathrm{Cognitive}_{it} + \varepsilon_{it}^2 \qquad (12)$$

$$\mathrm{RelationalDelta}_{it} = \beta_0^3 + \beta_1^3 * \mathrm{Relational}_{it} + \varepsilon_{it}^3 \qquad (13)$$

Then the relationship between knowledge contribution and social capital was estimated using the following models:

$$\mathrm{Contribution}_{it} = \beta_0^4 + \beta_1^4 * \mathrm{Structural}_{it} + \varepsilon_{it}^4 \qquad (14)$$

$$\mathrm{Contribution}_{it} = \beta_0^5 + \beta_1^5 * \mathrm{Cognitive}_{it} + \varepsilon_{it}^5 \qquad (15)$$

$$\mathrm{Contribution}_{it} = \beta_0^6 + \beta_1^6 * \mathrm{Relational}_{it} + \varepsilon_{it}^6 \qquad (16)$$

As the last step, the relationship between social capital change and knowledge contribution as well as the moderating role of community growth were estimated as follows[6]:

$$\mathrm{StructuralDelta}_{it} = \beta_0^7 + \beta_1^7 * \mathrm{Contribution}_{it} + \beta_2^7 * \mathrm{Contribution}_{it} * \mathrm{Growth}_t + \varepsilon_{it}^7 \quad (17)$$

$$\mathrm{CognitiveDelta}_{it} = \beta_0^8 + \beta_1^8 * \mathrm{Contribution}_{it} + \beta_2^8 * \mathrm{Contribution}_{it} * \mathrm{Growth}_t + \varepsilon_{it}^8 \quad (18)$$

$$\mathrm{RelationalDelta}_{it} = \beta_0^9 + \beta_1^9 * \mathrm{Contribution}_{it} + \beta_2^9 * \mathrm{Contribution}_{it} * \mathrm{Growth}_t + \varepsilon_{it}^9 \quad (19)$$

Results

Table 28 presents the descriptive statistics of my dataset. Table 29 summarizes the results estimating the relationship between social capital and social capital change of community members. The result of Hausman test ($p<0.001$) favors fixed-effects over random effect. The rho parameters (24.5%, 90.6% and 13.2%) represent the percentage of variance explained by the individual fixed-effects. The positive and significant coefficients in all three models (structural: $\beta=0.226$, $p<0.001$; cognitive: $\beta=0.388$, $p<0.001$; relational: $\beta=0.479$, $p<0.001$) indicate that community members' existing social capital positively affects social capital change of members. Put differently, there is a direct relationship between existing social capital level and social capital change. My results from Table 30 (structural: $\beta=0.210$, $p<0.001$; cognitive: $\beta=0.351$, $p<0.001$; relational: $\beta=0.288$, $p<0.001$) are consistent with previous studies (e.g., Wasko & Faraj,

[6] The relationship between social capital change and social capital does not need statistical estimation because the new social capital is predetermined by social capital change.

2005), confirming the positive effect of social capital on members' knowledge contribution behavior. Members with a higher degree of social capital are more likely to continue to participate in the discussions and contribute knowledge.

Table 28. Descriptive Statistics and Correlations Matrix (N=17,560)

Variable	Mean	S.D.	Min	Max
Structural	4.67	6.01	0	343
StructrualDelta	1.95	4.40	-2	451
Cognitive	16.97	10.98	0	182
CognitiveDelta	1.62	2.10	0	18
Relational	3.27	4.20	0	249
RelationalDelta	1.25	3.31	-1	354
Contribution	1.98	2.52	0	71
Growth	580.2	53.8	478	629

Table 28 (cont'd). Descriptive Statistics and Correlations Matrix (Panel: by month)

Variable	1	2	3	4	5	6	7	8
Structural	1.00							
StructrualDelta	0.63	1.00						
Cognitive	0.23	0.15	1.00					
CognitiveDelta	-0.01	0.06	0.12	1.00				
Relational	0.81	0.65	0.23	-0.01	1.00			
RelationalDelta	0.64	0.83	0.13	0.05	0.70	1.00		
Contribution	0.05	0.14	0.11	0.59	0.06	0.13	1.00	
Growth	0.27	0.06	0.18	-0.37	0.25	0.04	-0.38	1.00

Table 29. Fixed-effects Results of Social Capital and Social Capital Change

	Model 1 (N=17,560) *Dependent Variable = StructuralDelta*	Model 2 (N=17,560) *Dependent Variable = CognitiveDelta*	Model 3 (N=17,560) *Dependent Variable = RelationalDelta*
Structural	0.226*** (0.007)		
Cognitive		0.388*** (0.003)	
Relational			0.479*** (0.008)
Constant	0.900*** (0.044)	8.209*** (0.067)	-0.313*** (0.032)
Hausman	1,368***	12,510***	117***
rho	24.5%	90.6%	13.2%

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$

Table 30. Fixed-effects Results of Social Capital and Knowledge Contribution

	Model 1 (N=17,560)	Model 2 (N=17,560)	Model 3 (N=17,560)
Structural	0.210*** (0.004)		
Cognitive		0.351*** (0.004)	
Relational			0.288*** (0.007)
Constant	2.969*** (0.027)	7.955*** (0.085)	2.930*** (0.028)
Hausman	3,139***	6,017***	2,702***
rho	50.4%	84.1%	49.3%

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$

Table 31. Fixed-effects Results of Knowledge Contribution and Social Capital Change

	Model 1 (N=17,560) *Dependent Variable = StructuralDelta*	Model 2 (N=17,560) *Dependent Variable = CognitiveDelta*	Model 3 (N=17,560) *Dependent Variable = RelationalDelta*
Contribution	0.834*** (0.075)	0.829*** (0.032)	0.563*** (0.057)
Contribution Growth*	0.001*** (0.0001)	0.0005*** (0.00006)	0.0009*** (0.0001)
Constant	1.940*** (0.040)	0.559*** (0.017)	1.295*** (0.031)
Hausman	1,105***	284***	1,064***
rho	41.9%	29.2%	40.9%

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$

More importantly, the results in Table 31 suggest that the knowledge contribution of members will, in turn, impact their social capital levels. Using the structural capital dimension as an example, the results (β=0.834, p<0.001) show that with each one unit increase in knowledge contribution, a member will on average receive 0.8 more incoming ties (e.g., following). Combined, the results from Tables 29, 30 and 31 support my spiral perspective regarding the relationship between knowledge contribution and social capital of individuals in OUCs. In addition, regarding the moderating role of community growth, the positive and significant coefficient estimates of the interaction terms (structuraldelta: β=0.001, p<0.001; cognitivedelta: β=0.0005, p<0.001; relationaldelta: β=0.0009, p<0.001) in all three models indicate that the impact of knowledge contribution on social capital change hinges on community growth. In other words, communities with large and increasing members further facilitate the increase of social capital of members resulting from their knowledge contribution.

Additional Analyses

I conducted several additional analyses. First, I estimated a set of full models as follows to consider the mediating effect of knowledge contribution on the change of social capital:

$$\mathrm{StructuralDelta_{it}} = \beta_0^{10} + \beta_1^{10} * \mathrm{Contribution_{it}} + \beta_2^{10} * \mathrm{Structural_{it}} + \varepsilon_{it}^{10} \quad (20)$$

$$\mathrm{CognitiveDelta_{it}} = \beta_0^{11} + \beta_1^{11} * \mathrm{Contribution_{it}} + \beta_2^{11} * \mathrm{Cognitive_{it}} + \varepsilon_{it}^{11} \quad (21)$$

$$\mathrm{RelationalDelta_{it}} = \beta_0^{12} + \beta_1^{12} * \mathrm{Contribution_{it}} + \beta_2^{12} * \mathrm{Contribution_{it}} + \varepsilon_{it}^{12} \quad (22)$$

Table 32 summarizes the results. Comparing these results in Table 32 with those in Table 29 indicates that knowledge contribution plays as a partial mediator only for the cognitive social capital. There is a 0.131 decrease in the cognitive coefficient (Table 29, Model 2 vs. Table 32, Model 2, two-tailed test: t=3.21, p<0.01), indicating about 33.7% of the impact of existing cognitive capital on cognitive capital change is mediated by knowledge contribution.

Table 32. Fixed-effects Results of Full Models

	Model 1 (N=17,560) *Dependent Variable = StructuralDelta*	Model 2 (N=17,560) *Dependent Variable = CognitiveDelta*	Model 3 (N=17,560) *Dependent Variable = RelationalDelta*
Structural	0.239*** (0.008)		
Cognitive		0.257*** (0.004)	
Relational			0.511*** (0.008)
Contribution	0.063*** (0.013)	0.370*** (0.005)	0.111*** (0.009)
Constant	0.713*** (0.060)	5.259*** (0.075)	-0.641*** (0.042)
Hausman	1,019***	2,494***	43***
rho	22.8%	84.9%	12.0%

Standard errors are in parentheses. *** Sig. at $p < 0.001$; ** Sig. at $p < 0.01$; * sig. at $p < 0.05$

Second, I recalculated the cognitive capital change by including only those discussions followed by the focal member. I suggest that discussion updates (e.g., the mark of useful and correct answers contributed by other members) are more likely to be noticed (and thereby learned) by the member if s/he follows the discussions. I then reran the models and the results are consistent regarding the sign and significance of the variables.

Discussion and Conclusion

My study provides several implications for existing OUC literature as well as the design of OUCs. First and foremost, my study indicates that in OUCs, knowledge exchange not only hinges on but drives the forming of individuals' structural, cognitive and relational capital. For those individuals who actively engage in knowledge contribution and exchange, they are more likely to occupy the core structure with high connectedness by attracting and creating multiple social ties. It is these individuals who build the most structural capital in the network (Wasko et al., 2009; Faraj & Johnson, 2011). Therefore, while theories of social network and collective action have shown that network outcomes are determined by its structure (Burt, 1992; Nahapiet & Ghoshal, 1998;

Faraj & Johnson, 2011), a largely ignored dimension is how network outcomes (e.g., knowledge exchange) will in turn impact network structures.

For cognitive capital, my study shows that individuals also develop their expertise and skills by contributing knowledge in the community. As an individual contributes his/her own knowledge, s/he is involved in the knowledge exchange process, either actively or passively. A knowledge contributor may, for example, discuss with others regarding the correctness of his/her answers, read and comment on answers of others or simply receive a notification of the marking of a best answer. In other words, I suggest that in OUCs knowledge contribution itself motivates the contributor to interact with others who share the same practice and thereby learn the knowledge, skills and norms of the practice over time. This developed expertise or cognitive capital then drives the individual to continue to share his/her knowledge in the community. In contrast to previous studies largely assuming knowledge contribution depends on pre-determined cognitive capital (e.g., Wasko & Faraj, 2005), my study emphasizes the development of cognitive capital as a key outcome of knowledge contributions.

Likewise, my findings indicate that individuals' relational capital is related to knowledge contribution. As individuals receive incoming ties and derive expertise and skills resulting from their knowledge contribution, they are willing to develop trust and a sense of reciprocity with others. A strong norm of reciprocity and trustworthiness in the collective will, in turn, reward individual efforts and ensure continual contributions (Nov et al., 2012; Dholakia et al., 2004). Taken together, my study highlights the importance of examining knowledge contribution and individuals' social capital as a spiral process in the OUC context. While the relationship of social capital to knowledge contribution is well-explained in the existing literature, little attention has been paid to the change of social capital arising from the knowledge exchange among community members. My study is a first step toward this direction.

Second, my study adds a layer in explaining how knowledge contribution impacts individuals' social capital by including community growth, an important construct in the online community literature. Studies have conceptualized community growth and size as an aspect of communities' structural dynamics and described how it changes over time (e.g., Butler, 2001; Hsiao & Chiou, 2012). A major conclusion is that community growth and resulting size has both negative and positive influences on user contribution and community sustainability (Bock et al., 2015). As a community grows, for example, it can attract more members, but this may induce increasing free riding and social loafing behavior among community members (Wasko et al., 2004). In complementing existing research, my study indicates that community growth may determine the structure and sustainability of a community through its moderating impact on the relationship between knowledge contribution and social capital. When a community grows slowly, social ties and expertise are hard to increase and active members may perceive less benefits from their contributions. As a result, they may be unwilling to maintain strong social bonds to the community and continue their above-average contributions (Ren, 2007; Mehra et al., 2006). In contrast, a fast-growth community may achieve sustainability via quickly capitalizing members' knowledge contribution in the form of social capital, motivating continuous contribution.

Third, my study sheds lights on the emerging research on online community leadership. Studies in this stream of research focus on the formation of leadership and the role of leaders in online communities (Johnson et al., 2015; Faraj et al., 2015). It has been found that knowledge contribution and structural social capital of individuals are two key antecedents of leadership in online communities (Faraj et al., 2015). Individuals with central network position and contributing frequently are more likely to be identified as leaders (Faraj et al., 2015). Nevertheless, my study illustrates that the path to leadership may entail ongoing interactions between individuals' knowledge contribution and network position. As one changes, so does the other. I therefore suggest that while both affect leadership independently, it is essential to account for the reciprocity between knowledge contribution and network positon and examine how such dynamics determine the emergence of leadership in online communities, an issue that has been largely neglected in the extant research.

Finally, my findings provide practitioners a valuable guideline for the design of OUCs. While reputation systems (e.g., member points, levels and statuses) have been largely implemented across various online communities as incentives for participation, few OUCs have integrated the systems with social networking features (Kane et al., 2012; Lau & Kwok, 2009). My empirical study demonstrates that implementing social network/media features will further motivate contribution by actualizing members' social capital in the community. The following/followers feature used by BMC, for instance, not only help visualize members' social ties and connections and thereby their positions in the network, but allow members to know who knows whom and their mutual friends. As a result, members are more likely to be motivated to participate in the community as they recognize the changes in their structural and relational capital. Also, the bookmark and notification features enable members to follow the discussions they participated or are interested in and receive real time updates on the discussion threads, such as new replies and the marking of correct answers. This allows participants to contemporaneously derive information and knowledge without logging into the community, facilitating the cognitive benefits perceived by community members. In short, my study shows that features of social networking highly relate to continual community participation and knowledge contribution, and managers and community designers should constantly adopt and implement new features and tools to enhance social exchange and connectedness within the communities.

CHAPTER FIVE

Summary and Conclusion

The first essay makes three key contributions. First, it extends the extant OUIC literature by revealing the role of participating employees and the benefits employee participation might yield. I find that employees' innovative work behavior such as voting and commenting positively impact user idea implementation. User ideas discovered and promoted by internal employees, versus those without receiving employee support (only promoted by other product users), are more likely to be implemented by the host firm. In addition, employees who frequently participate in the community and thereby access diverse and well-codified community content generate more ideas than those who do not, while the marginal effects of diverse and well-codified content decrease. Second, this essay opens paths for future OUIC research by differentiating internal employees from external product users. By comparing the community roles between users and employees, I theorize and highlight the unique role of employees in terms of community activities, participation motivation and required innovation knowledge. Further research is therefore needed to illustrate how the behavior and individual actions of participating employees shape innovative outcomes and contribute to the long-term success of OUICs. Third, my study sheds light on the types of behaviors and knowledge-creation processes that contribute to open innovation communities to innovate and the role of IT in enabling such knowledge creation. In the context of OUIC, my findings show that members are increasingly utilizing community platforms to innovate. Through figures/pictures, video/web page links, personal drawings and other media, ideators are able to convert their tacit knowledge and details related to personal experience into well-codified idea content. Such well-codified content constitutes the knowledge base of the community and is subsequently accessed and processed by others to become part of their new ideas. My study therefore indicates that, in the IT-enabled OUIC context, intellectual engagement with tacit-knowledge embedded IT artifacts (e.g., software codes and ideas) resides at the core of socialization aiming at new knowledge creation and innovation.

The second essay confers implications for both research and practice. Theatrically, this study indicates that examining the employee-user interaction is integral to understanding the dynamics and thereby the success of OSCs. On one hand, employees interact with users in various forms (e.g., community content, ongoing discussions) in the community aiming to meet users' needs and expectations toward product support. Employee participation thereby contributes to users' satisfaction toward the community as well as the host firm. This may further help build the community name among product users and attract more users to participate in and contribute to the community. On the other hand, as employees observe increasing positive outcomes resulting from their participation, they are more motivated to engage in the community and interact with users. Such a positive, spiral interaction pattern between employees and users is essential for the long-term success of any product support communities. Practically, this study highlights the necessity of having employee participation from different levels and functions to build a vibrant and thriving OSC. I suggest that overall engagement of employees is essential for several reasons. First, although users can usually derive answers from peers, they still prefer employees joining the discussion, helping identify incorrect answers, and elaborating or answering the most complicated questions. Therefore, not only could participating employees act as discussants and repliers but also as connectors and influencers to help members develop social connectedness and thereby a sense of community. More importantly, my study shows that the degree of employee-user interactions influences employees' contribution in terms of community blogs, articles and documents. Such contributed-knowledge, in turn, plays a critical role in facilitating user learning, self-support and peer exchange.

Finally, the third essay makes four theatrical and practical contributions. First, the essay indicates that in OUCs, knowledge exchange not only hinges on but drives the forming of individuals' structural, cognitive and relational capital. Second, the essay adds a layer in explaining how knowledge contribution impacts individuals' social capital by including community growth, an important construct in the online community literature. In complementing existing research, this study indicates that community growth may determine the structure and sustainability of a community through its moderating impact on the relationship between knowledge contribution and social capital. Third, this essay sheds lights on the emerging research on online community leadership. My findings illustrate that the path to leadership may entail ongoing interactions between individuals' knowledge contribution and network position. As one changes, so does the other. Fourth, my findings provide practitioners a valuable guideline for the design of OUCs. My empirical study demonstrates that implementing social networking features will further motivate contribution by actualizing members' social capital in the community. The following/followers feature used by BMC, for instance, not only help visualize members' social ties and connections and thereby their positions in the network, but allow members to know who knows whom and their mutual friends. Members are more likely to be motivated to participate in the community as they recognize the changes in their structural, cognitive and relational capital.

To conclude, building OUCs to complement existing product support and new product development has become increasingly popular across industries. However, many OUCs suffer from the "Empty Bar Syndrome" because they lack active external and/or internal participation. The studies outlined and summarized herein help to shed light on the behavior, performance and welfare of this external/internal duality – product users and host firm employees –, respectively. It is my hope that this dissertation will inform host companies, participating employees, customers/users and researchers about best practices, in design and management as well as policy and oversight, to ensure the sustainability and long-term success of OUCs.

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