User-Generated Content and Employee Creativity: Evidence from Salesforce IdeaExchange Community

Completed Research Paper

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Abstract

This study investigates how accessing user-generated content in online user innovation communities (OUICs) may influence employee creativity. By analyzing a longitudinal dataset obtained from the IdeaExchange community of Salesforce.com, we find that employees who frequently access diverse and well-codified idea content contributed by external product users are likely to generate more ideas than those who do not; however, the marginal effects of diverse and well-codified content decrease as employees access increasing amounts of community content. Moreover, our findings illustrate that the number of implemented ideas from an employee is positively associated with the number of new ideas s/he generates. We discuss important implications of our study for online innovation communities and for employee creativity in organizations. We also provide insights for firms on how to build a thriving community via increasing the scope and level of employee participation.

Keywords: Online User Innovation Communities, User-generated Content, Employee Creativity, Crowdsourcing, Co-creation

Introduction

Firm-hosted online user innovation communities (OUICs) refer to firm-sponsored initiatives designed to co-create value with firms' product users and customers. In OUICs, product users voluntarily contribute their ideas about host firms' new and existing products/services and have their ideas discussed and evaluated by other users and internal employees of the host firms. Over time, this user-generated content – i.e., ideas, comments and suggestions – forms the collective content shared across the community for new product development (Holmström and Henfridsson 2006).

Prior research has shown that accessing collective community content has significant effects on product users' subsequent participation and contribution. Porter and Donthu (2008), for example, find that host firms' efforts to foster users' community embeddedness and thereby facilitate their access to quality content have significant trust-building effects on product users. Such trust in host firms is found to be positively and significantly related to product users' intention to share knowledge in the communities (Kosonen et al. 2013). Dahlander and Frederiksen (2012) find that spanning multiple OUICs to access different community content is consequential for product users' innovativeness. Other studies document how product users learn from their participation and develop their sense of responsibility to the community (Nambisan and Baron 2010) and develop abilities to come up with high potential ideas (Huang et al. 2014).

While these studies provide valuable insights on how community content influences product users' behavior and its subsequent outcomes, we know little about its impacts on host firms' employees who also participate in the communities. Understanding the influences of community content on internal employees is important for several reasons. First, internal employees and external product users, while all participating together in the communities, are two inherently different groups of people having distinct relationships with the host firms. As such, the findings of prior research focusing on product users may not apply to internal employees. Specifically, accessing community content might have positive effects, such as learning (Schlagwein and Bjørn-Andersen 2014) or negative effects, such as information overload (D'Arcy et al. 2014) or no effects on participating employees. Second, despite the wide adoption of open innovation with external product users, *internal employees* are still considered by firms as the most important innovation partners (Chesbrough and Brunswicker 2014). As such, if accessing community content affects employee creativity positively, host firms will be able to enhance their employees' creativity through mobilizing more employees to engage in the communities. Third, and more importantly, employees' participation from various job levels and functions is imperative for achieving long-term community success (Whelan et al. 2011; Ogneva and Kuhl 2014). Thus, examining the effects of community content on participating employees will contribute toward an understanding of the consequences of their participation in OUICs.

Scholars have called for empirical studies to better understand internal employees' participation in OUICs (e.g., Chesbrough and Brunswicker 2014; Nambisan and Baron 2010; Jeppesen and Frederiksen 2006). Nambisan and Baron (2010), for example, highlight that an important organizational decision relates to the choice of employees assigned to participate in an OUIC and the nature of their participation. Other studies emphasize the importance of proactive and active attention from internal employees for eliciting more suggestions and ideas from external product users (Di Gangi et al. 2010; Dahlander and Piezunka 2014). In the present study, we focus on employees of the host firms and investigate *how accessing user-generated content in OUICs impacts employee creativity*.

We develop our hypotheses by drawing upon organizational knowledge creation theory (Nonaka 1994) in concert with previous literature on OUICs. We then examine our hypotheses in the context of IdeaExchange, an OUIC hosted by Salesforce.com. We combine qualitative coding on 8,088 user ideas that have been commented and/or voted on by 122 employees of Saleforce.com with quantitative participation data of these employees. Overall, our study shows that accessing user-generated content in OUICs affects employee creativity positively. Specifically, employees who frequently read diverse and well-codified idea content contributed by product users are likely to generate more ideas than those who do not; however, the marginal effects of diverse and well-codified content decrease as employees access increasing community content. In addition, our results show that for an internal employee, the number of implemented ideas is positively associated with the number of new ideas s/he generates. This contrasts with the findings of prior research that most product users tend to have none or only a few of their ideas implemented by the host firms; ideas of product users on average have a much lower adoption rate. With these results, our goal is to understand the innovation benefits employees might obtain from OUICs, and offer specific suggestions for developing overall employee engagement in OUICs.

Theoretical Development

We define employee creativity as the extent to which an employee actively generates valuable ideas – i.e., ideas that are both useful and novel, concerning products, services, processes and procedures (Dean et al. 2006; Amabile 1996). Creativity is generally considered to be a continuous concept with ideas ranging from minor adaptations to major contributions. Research on employee creativity in organizations shows that employee creativity is a function of both individual ability and organizational context (Anderson et al. 2014; Amabile 1983; Amabile 1988). Different aspects of social context have been linked to employee creativity at work, including organizational climate (Tushman and O'Reilly 1996), leadership (Mumford et al. 2002), work group relations (Scott and Bruce 1994) and human resource management practices (De Stobbeleir et al. 2011). A growing research stream focuses specifically on the informational advantages associated with access to external sources of knowledge and information. It builds on the assumption that communications and interactions with diverse others is an important driver of individual creative performance (Burt 2004; Perry-Smith 2006). Drawing upon this stream of research and organizational knowledge creation theory, we next develop three hypotheses related to employee creativity in the context of OUIC. Specifically, we investigate how accessing diverse and well-codified knowledge contained in user idea content may stimulate and facilitate the generation of new ideas by internal employees. In addition, we investigate the value of ideas generated by employees in OUICs by examining their implementation.

Knowledge Creation and Employee Creativity in OUICs

A core dimension of new knowledge creation in organizations is referred to as the "ontological" dimension – i.e., the level of social interaction between individuals (Nonaka 1994). Specifically, 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). Such a knowledge-creating place can be formal or informal, physical or virtual, and inside or outside organizational boundaries (Nonaka and Toyama 2003; Nonaka et al. 2000). In the present study, we treat firm-hosted OUICs as such communities of interaction that are virtual and span organizational boundaries. In addition to the context for knowledge creation, 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.

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. Beyond conducting formal task-related procedures specified by the organization, regularly accessing user-generated content may facilitate the creativity of employees by linking their routine work to active learning and innovation (Nonaka 1994). While accessing user-generated content in OUICs is likely to facilitate employee creativity, 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 influences of community content on employee creativity, we focus on two traits of knowledge that may affect individual creativity 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 and Levinthal 1990). A wide variety of studies have recognized the importance of knowledge diversity for individual creativity (e.g., Burt 2004; Rodan and Galunic 2004; Faniel and Majchrzak 2007; Jeppesen and Laursen 2009; 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. We thereby 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 creativity 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 creativity because a wealth of information creates a substantial information-processing burden (Simon 1971; Ocasio 1997). 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) (Simon 1971; Koput 1997; Laursen and Salter 2006). Taken together, we posit:

Hypothesis (H1a): *Employee creativity in an OUIC is positively associated with the degree of diverse content an employee has accessed; however, the marginal effect of diverse content should decrease as the employee accesses increasing community content.*

In addition to diversity, knowledge has different levels of codifiability. 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 creativity because they are less ambiguous and hence more readily integrated into one's existing knowledge plans (Mahr and Lievens 2012; Sosa 2011; Finke et al. 1992). 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). We 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, we expect that the creativity 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, we hypothesize that the effect of well-codified idea content on employee creativity is nonlinear as follows:

Hypothesis (H1b): *Employee creativity in an OUIC is positively associated with the degree of well-codified content an employee has accessed; however, the marginal effect of well-codified content should decrease as the employee accesses increasing community content.*

Creativity relates not only to the generation of new ideas, but also to their value. In the context of OUIC, the goal of host firms is to crowdsource not only new ideas but ideas that are worthy of implementation. We therefore examine the value of employee ideas by investigating their implementation. We expect that internal employees who frequently access community content are likely to generate valuable ideas for the following reasons. First, since employees possess deep knowledge of the products of the host firms, they are likely to generate ideas that are compatible with existing products, reducing the strain on the host firm's innovation efforts (Di Gangi and Wasko 2009). Second, being familiar with the new product development processes as well as the internal resources of the firm, employees are more likely to generate new ideas that are viable. Third, employees are likely to generate novel ideas when linking their routine work to active learning by regularly accessing community knowledge outside organizational boundaries (Nonaka 1994). In addition, as insiders, employees are able to facilitate internal communication and thereby diffuse their ideas to the appropriate departments and teams without community promotions (Foss et al. 2011; Whelan et al. 2011). Ideas that have been channeled to the people possessing the influence and expertise to exploit them are more likely to be fulfilled and implemented (Howell and Boies 2004; Whelan et al. 2011). Taking H1 and the above discussion together, we expect that, compared to product users, employees who frequently access community content may not only generate more new ideas, but generate more ideas that are valuable and would be implemented by the host firm. We thereby expect that for an internal employee, the more ideas s/he generates, the greater the number of her/his ideas that will be implemented, leading to the following hypothesis:

Hypothesis (H2): *The number of implemented ideas from an employee is positively associated with the number of new ideas generated by that employee in an OUIC.*

Methodology

Context: Salesforce.com's IdeaExchange Community

We selected IdeaExchange, the OUIC of Salesforce.com, as our empirical setting. Salesforce.com launched IdeaExchange in 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 our interview with the community manager, IdeaExchange was launched as a forum to gather users' suggestions and ideas for new product development and to enable community members to discuss and vote on the best ones. Employees of Salesforce.com are encouraged to participate in the community to help facilitate the implementation of valuable ideas. Notably, while Salesforce employees from different levels/functions might possess different motives for participating in the community, their participation remains voluntary.

Data Collection

We applied a longitudinal data collection and collected two-year interaction data of the community from July 2012 to June 2014. The dataset includes 4,472 user ideas that were created during this two-year period. To identify employees participating in the community, we analyzed all the ideas in the dataset. For each idea we accessed, we 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 ideas – that a member has made to the community. Table 1 summarizes the demographic characteristics of these employees as of June 2014.

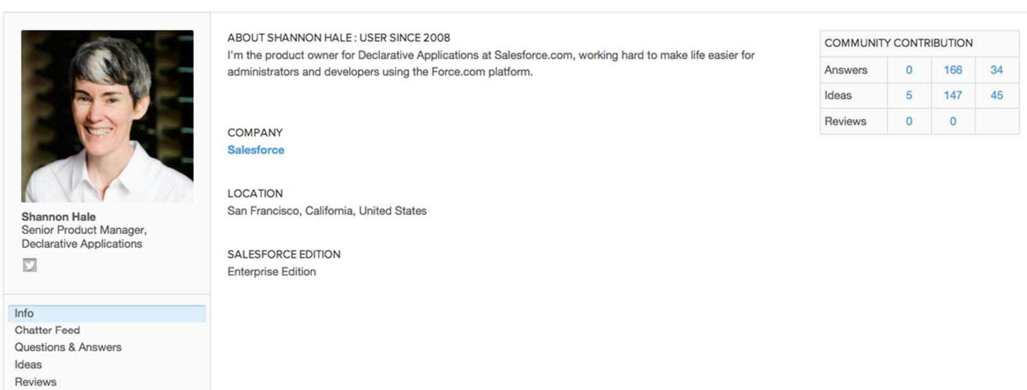

Figure 1: An Example of Online Employee Profile[1]

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

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)

Table 1. Demographic Characteristics of the Employees (N=122)

Measures

In order to measure *knowledge diversity* and *knowledge codifiability*, we applied qualitative coding on all the user ideas that had been commented and/or voted on by the 122 employees (we 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, we 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[2] user ideas were recorded (in a word document ordered by employee) to be qualitatively coded.

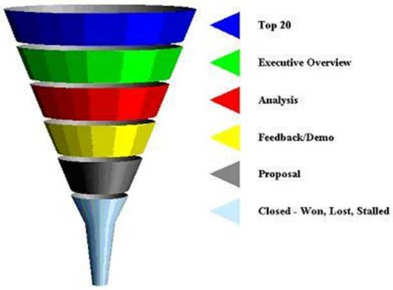
Knowledge codifiability reflects how well product users have converted their tacit knowledge into explicit knowledge posted as idea content. In other words, a higher degree of knowledge codifiability implies that the product users have codified their ideas to a much fuller extent, which may hinge on 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, we discussed and developed a coding scheme before coding the idea content. Table 2 details our 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 3 shows some user ideas representing different levels of codifiability according to our coding scheme.

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 2 Coding Scheme for Codifiability of Idea Content

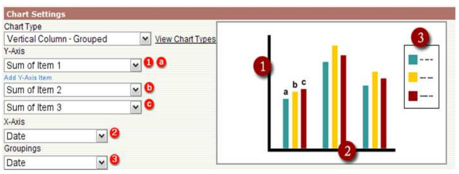
[2] Many user ideas were commented and/or voted on by multiple employees; thereby the distinct ideas are less than 8,088.

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."

Table 3: Selected Ideas at Different Levels of Codifiability

To evaluate the reliability of our coding scheme and results, we conducted an iterative sample coding process suggested by Lombard et al. (2002) and calculated the Cohen's kappa accordingly. Specifically, the authors independently coded a subset of 150 ideas. After categorizing the first 100 ideas, we achieved a Cohen's (1960) kappa of 0.71. We 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[3] on the remaining 50 ideas ensured the level of reliability between the coders. Then one of the coders continued with the remainder of the ideas and assigned a final score for each of the 8,088 ideas.

Knowledge diversity reflects how diverse the idea content is. To measure this variable, we utilized the *idea tags* assigned to each idea (Bayus 2013; Di Gangi and Wasko 2009). As shown in Table 3 above, Salesforce.com assigns different idea tags 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, we created an idea/category matrix – 8,088 rows (ordered by ideas accessed by each employee) x 41 columns. Each row represents an idea where we marked "1"

[3] A Cohen's kappa of 0.80 or greater is usually considered a good score of inter-coder reliability (Cohen 1960).

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".

Regarding the dependent variables, the *number of new ideas* generated by an employee was collected from the records in his/her online profile. To calculate the *number of implemented ideas*, we utilized the *idea status* tags. As shown in Table 3, each idea posted in the community is also assigned a status tag to indicate the status of that idea. Accordingly, for each employee we calculated the total number of tags indicating a status of "partially implemented" or "implemented". Table 4 summarizes all the variables discussed.

Variable	**Definition**	**Source of Measurement Data**
Number of new ideas (*New_Ideas*)	Number of new ideas generated by an employee in the community	Employees' community profiles
Number of implemented ideas (*Imp_Ideas*)	Number of implemented ideas from an employee	Status tags of employee ideas
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

Note: Variable abbreviation is in parentheses.

Table 4. Variable Definitions and Measures

Modeling Strategy

In the present study, we are interested in examining how accessing user-generated content (i.e., diverse and well-codified ideas) impacts employee creativity. Instead of conducting a cross-sectional analysis, we constructed a panel dataset in order to take potential endogeneity into account. For example, one employee may be more creative 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 generate more ideas than others simply because s/he is interested in generating ideas. We therefore measure knowledge diversity and codifiability before measuring employees' behavior of idea generation to take this and other potential reverse causality into account. We also include employees' community tenure to help eliminate time effects.

Given the above, we 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. We 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 we observed how many ideas the employee generated in the subsequent 30 days and used this number as the dependent variable of *number of new ideas* for each unit of observation. We also recorded the number of implemented ideas from all the ideas generated by the employee in a particular month.

Estimation Approach

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. Our subsequent model tests show that the over-dispersion parameter α is larger than 0, indicating a NB panel model fits better with our data (Greene 2011). We 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 our 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, we added a zero inflation part to estimate a full zero-inflated negative binomial fixed-effects (ZINB) panel model (Greene 2011)[4].

The ZINB model assumes that excess zeros in the dependent variable are generated by two distinct processes. For example, in our study the excess zero outcomes might be attributed to two different processes – namely, participants vs. lurkers[5]. 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).

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

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

Under this estimator, the model framework is:

$$E[y_{it}|\boldsymbol{x_{it}}] = \exp(\delta_i + \boldsymbol{\beta}'\boldsymbol{x_{it}}) = \lambda_{it} \quad (2)$$

Where $\boldsymbol{x_{it}}$ 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); δ_i 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, we have $y_{it} = 0$ with probability φ_{it} (behaving as lurkers), and have $y_{it} = \lambda_{it}$ (negative binomial estimate from formula (2)) with probability $1 - \varphi_{it}$:

$$\varphi_{it} = \frac{\exp(\boldsymbol{\gamma}'\boldsymbol{Z_{it}})}{1+\exp(\boldsymbol{\gamma}'\boldsymbol{Z_{it}})} \quad (3)$$

Where $\boldsymbol{Z_{it}}$ is a q x 1 vector of explanatory variables in the logit model and $\boldsymbol{\gamma}'$ is a q x 1 vector of corresponding coefficients (Hausman et al. 1984).

To test the ZINB panel models, we used the NLOGIT 5 econometric software developed by Greene (2011) and followed a two-step procedure. We first fitted the ZINB model without fixed-effects to obtain a set of starting values for the panel model; we then fitted the panel model again with zero-inflated Poisson fixed-effects (Greene 2011). To test the relationship between new ideas and implemented ideas, we chose the linear regression panel estimation. Given the small and insignificant value of Hausman test, we ran the linear panel regression with both fixed-effects and random effects.

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

[5] Lurkers refer to individuals who only read others' posts without participating and contributing in the community (Wasko et al. 2004).

Results

Table 5 presents descriptive statistics and correlations. Tables 6 and 7 show the results based on the balanced and unbalanced panel data, respectively. The α in both tables are larger than 0, indicating the over-dispersion in our 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.

Variable	Mean	S.D.	Min	Max	1	2	3	4	5
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. New_Ideas	0.15	0.42	0.0	4.0	0.03	0.46	0.57	1.00	
5. Imp_Ideas	0.08	0.28	0.0	2.0	0.03	0.35	0.43	0.77	1.00

Table 5: Descriptive Statistics and Correlations Matrix (N=122 by month)

Variables	ZINB Fixed-effects Panel		Linear Panel (DV: Imp_Ideas)	
	NB	Logit	Fixed-effects	Random Effects
Constant		5.938*** (0.010)		0.001 (0.004)
Tenure	-0.031*** (0.007)			
KC	0.058*** (0.010)	-0.431*** (0.030)		
KD	0.145*** (0.024)	-0.340*** (0.0001)		
KC*KC	-0.0004*** (0.0001)			
KD*KD	-0.0018*** (0.0005)			
New_Ideas			0.548*** (0.010)	0.541*** (0.008)
Vuong	6.78			
Hausman	107.38***		1.64	
Alpha	> 0			
Log-likelihood	-661.86			
R-squared			61.5%	61.1%

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

Table 6: Results from Balanced Panel Data (N=106; Observations = 2,544)

Variables	ZINB Fixed-effects Panel		Linear Panel (DV: Imp_Ideas)	
	NB	Logit	Fixed-effects	Random Effects
Constant		4.778*** (0.010)		0.001 (0.004)
Tenure	-0.030*** (0.007)			
KC	0.060*** (0.010)	-0.497*** (0.028)		
KD	0.149*** (0.023)	-0.360*** (0.0001)		
KC*KC	-0.0004*** (0.0001)			
KD*KD	-0.0019*** (0.0005)			

New_Ideas			0.540*** (0.010)	0.534*** (0.008)
Vuong	7.00			
Hausman	114.94***		1.41	
Alpha	> 0			
Log-likelihood	-708.24			
R-squared			60.6%	60.0%

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

Table 7: Results from Unbalanced Panel Data (N=122; Observations = 2,784)

The positive and significant coefficients of *knowledge diversity* in the NB models in Table 6 (β=0.145, p<0.001) and Table 7 (β=0.149, p<0.001) indicate that accessing diverse content affects employee creativity 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 30 days. Likewise, the positive and significant coefficients of *knowledge codifiability* in Table 6 (β=0.058, p<0.001) and Table 7 (β=0.060, p<0.001) indicate that accessing well-codified content affects employee creativity positively. Using the balanced model as an example again, it shows that on average, a one unit increase in content codifiability is associated with an increase in employee creativity by about 5.9%. In addition, the coefficients of quadratic terms are all negative and significant in both tables (β=-0.0004, p<0.001; β=-0.0018, p<0.001 in Table 6, and β=-0.0004, p<0.001; β=-0.0019, p<0.001 in Table 7). 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, our results show 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. Therefore, hypotheses 1a and 1b are supported.

Regarding the implementation of employee ideas, the results of our linear panel models (both fixed-effects and random effects) in Table 6 and Table 7 support our hypothesis (H2). The positive and significant coefficients of *new ideas* show that the number of implemented ideas from an employee is positively associated with the number of new ideas s/he generates. Specifically, using the fixed-effects model in Table 6 as an example (β=0.548, p<0.001), our results show that on average, for every 10 new ideas an employee generates, over half of them will be ultimately implemented by the host firm. This not only supports our expectation that there is a positive relationship between new ideas and implemented ideas, but indicates that the majority of employee ideas will be implemented.

With respect to the logit section, 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 have a higher likelihood of behaving as lurkers and are less likely to contribute their ideas.

Robustness Checks

We conducted two robustness checks on our panel data. First, instead of building monthly observations for each employee, we broke down the panel and restructured our 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. We then ran the ZINB fixed-effects on both models; the results are highly consistent with those from the employee-month pairs. Table 8 and Table 9 show the results in details. Second, after breaking down the panel into biweekly observations, a majority of employees only generate one or no idea in most bi-weeks. We therefore modified our panel to fit a logit model estimated by unconditional fixed-effects. The results are also shown in Tables 8 and 9 for the balanced and unbalanced model, respectively.

Overall, the results (column 5 in both tables) 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 accessing community content on employee creativity.

Variables	**ZINB Fixed-effects Panel (Bi-week)**		**Linear Fixed-effects Panel**	**Logit Fixed-effects Panel**
	NB	**Logit**		
Constant		16.40*** (0.040)		
Tenure	-0.013*** (0.003)			-0.024*** (0.005)
KC	0.189*** (0.022)	-1.806*** (0.0003)		0.636*** (0.041)
KD	0.367*** (0.044)	-1.779*** (0.0015)		0.994*** (0.070)
KC*KC	-0.002*** (0.0003)			-0.007*** (0.0005)
KD*KD	-0.009*** (0.0016)			-0.023*** (0.0026)
New_Ideas			0.552*** (0.007)	
Vuong	10.43			
Hausman	138.99***		2.30	210.33***
Alpha	> 0			
Log-likelihood	-712.25			-571.84
R-squared			56.4%	

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

Table 8: Results from Balanced Panel Data (N=106; Observations = 5,512)

Variables	**ZINB Fixed-effects Panel (Bi-week)**		**Linear Fixed-effects Panel**	**Logit Fixed-effects Panel**
	NB	**Logit**		
Constant		14.44*** (0.040)		
Tenure	-0.013*** (0.003)			-0.025*** (0.005)
KC	0.197*** (0.022)	-1.665*** (0.0003)		0.660*** (0.041)
KD	0.366*** (0.044)	-1.675*** (0.0015)		1.011*** (0.070)
KC*KC	-0.002*** (0.0003)			-0.007*** (0.0005)
KD*KD	-0.009*** (0.0016)			-0.024*** (0.0026)
New_Ideas			0.556*** (0.006)	
Vuong	10.22			
Hausman	151.56***		2.99	249.87***
Alpha	> 0			
Log-likelihood	-712.25			-590.47
R-squared			56.7%	

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

Table 9: Results from Unbalanced Panel Data (N=122; Observations = 6,025)

Discussion

The present study focuses on internal employees who participate in OUICs. Our study extends the existing literature by examining the creativity effects on internal employees who access user-generated content in OUICs. Employees who frequently access diverse and well-codified content in the community generate more ideas than those who do not. Nevertheless, the marginal effects of diverse and well-codified content decrease because of potential attention problems and the negative effects of overabundant information. Moreover, our findings indicate that the majority of new ideas generated by an internal employee will be adopted and implemented by the host firm. This finding contradicts prior studies on product users that many user ideas do not receive enough community votes to garner the attention of product review teams (Bayus 2013) and tend to not be implemented by the host firm (Di Gangi and Wasko 2009; Bayus 2013; Chen et al. 2012). Even for some ideas that are popular in the community, they are rejected by the product review teams because of low feasibility and/or high project risk (Di Gangi et al. 2010). In contrast, as insiders who possess particular knowledge on existing products and new product development process and have close relationships with the host firm, employees are likely to have more of their ideas implemented than product users. This indicates that in the context of OUIC, ideas generated by internal employees are on average more valuable for the host firm than those of product users.

Our findings hold implications for research on employee creativity in organizations. Specifically, our study suggests that organizations could harness the OUIC as a secondary, informal context to balance the primary contexts – e.g., team structure and composition (Anderson et al. 2014) – that have been developed to facilitate employee creativity. By doing so, organizations will enable employees to rely on the primary contexts to conduct routine tasks and switch to the secondary contexts such as OUICs to support non-routine tasks and innovations. Over time, combining participation in different contexts – formal (i.e., task forces and teams) and informal (i.e., OUICs) – will stimulate employees' exploration/exploitation behaviors (Mom et al. 2009). This is consistent with Nonaka (1994)'s view that linking employees' routine work to active learning and innovation is an integral part for facilitating employee innovativeness.

Our findings also support the view that online community interactions are no longer text based but increasingly rely on figures/pictures and other media (Jarvenpaa and Majchrzak 2010). This phenomenon becomes particularly prominent in OUICs where users are increasingly depending on figures/pictures, video/web page links and other personal drawings to help 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 processed by others to become part of their new ideas. The result is that in the context of OUIC, individuals are able to achieve "externalization" (creating explicit knowledge from tacit knowledge) and "combination" (the reconfiguring of existing explicit information into new knowledge) of knowledge for innovation without face-to-face interactions (Nonaka and von Krogh 2009).

Furthermore, by focusing on the participation of internal employees and analyzing its innovation outcomes, we hope to catalyze research on the role of internal employees in OUICs. Doing so will help address the failure of many innovation communities to yield solutions that provide competitive advantage (Whelan et al. 2011; Ogneva and Kuhl 2014). While prior research has extensively studied the factors and mechanisms that influence sustainable user participation and contribution in OUICs (Chen et al. 2012; Nambisan and Baron 2010; Jeppesen and Frederiksen 2006; Wasko et al. 2004), the findings of these studies may not apply to internal employees. For example, the role of *lead employees* in OUICs differs from that of *lead users*. While lead users enjoy revealing their knowledge and ideas to other users (Jeppesen and Laursen 2009; Mahr and Lievens 2012), lead employees may share ideas in order to motivate more external users to post their opinions and knowledge. Similarly, community-specific commitment (Wiertz and De Ruyter 2007) and fairness expectations (Franke et al. 2013) may influence employee participation and contribution differently than users. Overall, the nature of employee participation and contribution in firm-hosted online innovation communities has been neglected in the extant literature. Further research is needed to determine the drivers that motivate or hinder employees to engage in OUICs and illustrate how their behavior and individual actions shape innovative outcomes. Our research is a first step toward this direction.

From a practical perspective, our study highlights the benefits of having employees participate in OUICs. Their participation will not only facilitate the contributions from product users, but help enhance host firms' innovative performance via contributing ideas from employees. More importantly, having sustainable participation from both external product users and internal employees is imperative for the long-term success of any OUICs. It serves as the foundation upon which firms can further design, invest, build and grow their communities (Butler 2001; Faraj et al. 2011; Grant 2012). We therefore suggest that host firms should develop a strategic vision and action plan to increase the scope and level of employee participation in the communities.

Our investigation of Salesforce.com's OUIC also allows us to obtain valuable insights and knowledge to provide advice on when and how host firms should develop employee participation. Specifically, we 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. Our 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 and Kuhl 2014). Communicating the importance and value of building a thriving OUIC will help enable these internal champions. For example, community managers may use our results and the positive effects associated with employee creativity 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, we are unable to capture and investigate other important community properties such as social relationships that may affect individual creativity. Hence, future studies taking a social network perspective may be able to uncover other outcomes and factors in explaining knowledge creation and employee creativity in OUICs. 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. Third, as in any other empirical study based on a single setting, the generalizability of our findings is limited. Therefore, future studies applying multi-community analysis in other contexts will be valuable to deepen and extend our understanding of employee participation and contributions in OUICs. Fourth, a large number of employees in our sample are from the PPM and CS&UX functions. This over representation might relate to the five functions' different motives for participating in the community. For example, employees of the CS&UX function aim to receive industry insights and best practices from users and then convert these into new product features. On the other hand, product management teams tend to filter, collect and analyze user ideas for new product development. As a result, employees of these two functions may be more motivated to participate in the community compared to those of other functions.

Notwithstanding these limitations, our study extends prior research on firm-hosted OUICs by focusing on internal employees, examining their participation and related outcomes. Our study offers preliminary evidence that accessing user-generated content in OUICs significantly influences employee creativity. We thus suggest that host firms should 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.

References

Amabile, T. M. 1983. *The social psychology of creativity*. Springer-Verlag, New York, NY.

Amabile, T. M. 1988. "A model of creativity and innovation in organizations," In Staw, B., and Cummings L.L. (Eds.), *Research in organizational behavior* 10: 123–167.

Amabile, T. M. 1996. *Creativity in context: Update to "the social psychology of creativity"*. US: Westview Press, Boulder, CO.

Anderson, N., Potočnik, K., and Zhou, J. 2014. "Innovation and Creativity in Organizations a State-of-the-Science Review, Prospective Commentary, and Guiding Framework," *Journal of Management* 40 (5): 1297–1333.

Bayus, B. L. 2013. "Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community," *Management Science* 59 (1): 226–44.

Burt, R. S. 2004. "Structural Holes and Good ideas," *American Journal of Sociology* 110 (2): 349–99.

Butler, B. S. 2001. "Membership Size, Communication Activity, and Sustainability: A Resource-Based Model of Online Social Structures," *Information Systems Research* 12 (4): 346–62.

Chen, L., Marsden, J. R., and Zhang, Z. 2012. "Theory and Analysis of Company-Sponsored Value Co-Creation," *Journal of Management Information Systems* 29 (2): 141–72.

Chesbrough, H., and Brunswicker, S. 2014. "A Fad or a Phenomenon?: The Adoption of Open Innovation Practices in Large Firms," *Research-Technology Management* 57 (2): 16–25.

Cohen, J. 1960. "A Coefficient of Agreement for Nominal Scales," *Educational and Psychological Measurement* 20 (1): 37–46.

Cohen, W. M., and Levinthal, D. A. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly* 35 (1).

Dahl, A., Lawrence, J., and Pierce, J. 2011. "Building an Innovation Community," *Research-Technology Management* 54 (5): 19–27.

Dahlander, L., and Frederiksen, L. 2012. "The Core and Cosmopolitans: A Relational View of Innovation in User Communities," *Organization Science* 23 (4): 988–1007.

Dahlander, L., and Piezunka, H. 2014. "Open to Suggestions: How Organizations Elicit Suggestions through Proactive and Reactive Attention," *Research Policy* 43 (5): 812–27.

D'Arcy, J., Gupta, A., Tarafdar, M., and Turel, O. 2014. "Reflecting on the 'Dark Side' of Information Technology Use," *Communications of the Association for Information Systems* 35 (1): 109–18.

De Stobbeleir, K. E. M., Ashford, S. J., and Buyens, D. 2011. "Self-Regulation of Creativity at Work: The Role of Feedback-Seeking Behavior in Creative Performance," *Academy of Management Journal* 54 (4): 811–31.

Dean, D. L., Hender, J. M., Rodgers, T. L., and Santanen, E. L. 2006. "Identifying Quality, Novel, and Creative Ideas: Constructs and Scales for Idea Evaluation," *Journal of the Association for Information Systems* 7 (10).

Di Gangi, P. M., and Wasko, M. 2009. "Steal My Idea! Organizational Adoption of User Innovations from a User Innovation Community: A Case Study of Dell IdeaStorm," *Decision Support Systems* 48 (1): 303–12.

Di Gangi, P. M., Wasko, M., and Hooker, R. 2010. "Getting Customers' Ideas to Work for You: Learning from Dell How to Succeed with Online User Innovation Communities," *MIS Quarterly Executive* 9 (4): 213–28.

Faniel, I. M., and Majchrzak, A. 2007. "Innovating by Accessing Knowledge across Departments," *Decision Support Systems* 43 (4): 1684–91.

Faraj, S., Jarvenpaa, S. and Majchrzak, A. 2011. "Knowledge Collaboration in Online Communities," *Organization Science* 22 (5): 1224–39.

Finke, R. A., Ward, T. B., and Smith, S. M. 1992. "*Creative Cognition: Theory, Research, and Applications*," Published by Bradford, The MIT Press, paper 1996 (hard 1992).

Franke, N., Keinz, P., and Klausberger, K. 2013. "'Does This Sound Like a Fair Deal?': Antecedents and Consequences of Fairness Expectations in the Individual's Decision to Participate in Firm Innovation," *Organization Science* 24 (5): 1495–1516.

Grant, A. M. 2012. “Giving Time, Time after Time: Work Design and Sustained Employee Participation in Corporate Volunteering,” *Academy of Management Review* 37 (4): 589–615.

Greene, W. H. 2011. *Econometric Analysis*. Pearson Education, Inc.

Hausman, J. A., Hall, B. H., and Griliches, Z. 1984. "*Econometric Models for Count Data with an Application to the Patents-R&D Relationship*," National bureau of economic research Cambridge, Mass., USA.

Holmström, H., and Henfridsson, O. 2006. “Improving Packaged Software through Online Community Knowledge,” *Scandinavian Journal of Information Systems* 18 (1): 2.

Howell, J. M., and Boies, K. 2004. “Champions of Technological Innovation: The Influence of Contextual Knowledge, Role Orientation, Idea Generation, and Idea Promotion on Champion Emergence,” *The Leadership Quarterly* 15 (1): 123–43.

Huang, Y., Singh, P. V., and Srinivasan, K. 2014. “Crowdsourcing New Product Ideas under Consumer Learning,” *Management Science* 60 (9): 2138–59.

Jarvenpaa, S. L., and Majchrzak, A. 2010. “Research Commentary-Vigilant Interaction in Knowledge Collaboration: Challenges of Online User Participation under Ambivalence,” *Information Systems Research* 21 (4): 773–84.

Jeppesen, L. B., and Frederiksen, L. 2006. “Why Do Users Contribute to Firm-Hosted User Communities? The Case of Computer-Controlled Music Instruments,” *Organization Science* 17 (1): 45–63.

Jeppesen, L. B., and Laursen, K. 2009. “The Role of Lead Users in Knowledge Sharing,” *Research Policy* 38 (10): 1582–89.

Kohn, N. W., Paulus, P. B., and Choi, Y. 2011. “Building on the Ideas of Others: An Examination of the Idea Combination Process,” *Journal of Experimental Social Psychology* 47 (3): 554–61.

Koput, K. W. 1997. “A Chaotic Model of Innovative Search: Some Answers, Many Questions,” *Organization Science* 8 (5): 528–42.

Kosonen, M., Gan, C., Olander, H., and Blomqvist, K. 2013. “My Idea Is Our Idea! Supporting User-Driven Innovation Activities in Crowdsourcing Communities,” *International Journal of Innovation Management* 17 (03).

Laursen, K., and Salter, A. 2006. “Open for Innovation: The Role of Openness in Explaining Innovation Performance among UK Manufacturing Firms,” *Strategic Management Journal* 27 (2): 131–50.

Lombard, M., Snyder□Duch, J., and Bracken, C. C. 2002. “Content Analysis in Mass Communication: Assessment and Reporting of Intercoder Reliability,” *Human Communication Research* 28 (4): 587–604.

Ma, M., and Agarwal, R. 2007. “Through a Glass Darkly: Information Technology Design, Identity Verification, and Knowledge Contribution in Online Communities,” *Information Systems Research* 18 (1): 42–67.

Mahr, D., and Lievens, A. 2012. “Virtual Lead User Communities: Drivers of Knowledge Creation for Innovation,” *Research Policy* 41 (1): 167–77.

Maria, O., and Kuhl. E. 2014. “*Build a Thriving Community*,” Salesforce.com.

Mom, T. J. M., Frans A. J., Bosch, V. D., and Volberda, H. W. 2009. “Understanding Variation in Managers’ Ambidexterity: Investigating Direct and Interaction Effects of Formal Structural and Personal Coordination Mechanisms,” *Organization Science* 20 (4): 812–28.

Mumford, M. D., Scott, G. M., Gaddis, B., and Strange, J. M. 2002. “Leading Creative People: Orchestrating Expertise and Relationships,” *The Leadership Quarterly* 13 (6): 705–50.

Nambisan, S., and Baron, R. A. 2010. “Different Roles, Different Strokes: Organizing Virtual Customer Environments to Promote Two Types of Customer Contributions,” *Organization Science* 21 (2): 554–72.

Nonaka, I. 1994. “A Dynamic Theory of Organizational Knowledge Creation,” *Organization Science* 5 (1): 14–37.

Nonaka, I., and Toyama, R. 2003. “The Knowledge-Creating Theory Revisited: Knowledge Creation as a Synthesizing Process,” *Knowledge Management Research & Practice* 1 (1): 2–10.

Nonaka, I., Toyama, R., and Konno, N. 2000. “SECI, ‘Ba’ and Leadership: A Unified Model of Dynamic Knowledge Creation,” *Long Range Planning* 33 (1): 5–34.
Nonaka, I., and Von Krogh, G. 2009. “Perspective-Tacit Knowledge and Knowledge Conversion: Controversy and Advancement in Organizational Knowledge Creation Theory,” *Organization Science* 20 (3): 635–52.
Ocasio, W. 1997. “Towards an Attention-Based View of the Firm,” *Psychology* 1: 403–4.
Perry-Smith, J. E. 2006. “Social yet Creative: The Role of Social Relationships in Facilitating Individual Creativity,” *Academy of Management Journal* 49 (1): 85–101.
Porter, C. E., and Donthu, N. 2008. “Cultivating Trust and Harvesting Value in Virtual Communities,” *Management Science* 54 (1): 113–28.
Ren, Y., Harper, F. M., Drenner, S., Terveen, L. G., Kiesler, S. B., Riedl, J., and Kraut, R. E. 2012. “Building Member Attachment in Online Communities: Applying Theories of Group Identity and Interpersonal Bonds,” *Mis Quarterly* 36 (3): 841–64.
Rodan, S., and Galunic, C. 2004. “More than Network Structure: How Knowledge Heterogeneity Influences Managerial Performance and Innovativeness,” *Strategic Management Journal* 25 (6): 541–62.
Schlagwein, D., and Bjørn-Andersen, N. 2014. “Organizational Learning with Crowdsourcing: The Revelatory Case of LEGO,” *Journal of the Association for Information Systems* 15 (11): 754.
Scott, S. G., and Bruce, R. A. 1994. “Determinants of Innovative Behavior: A Path Model of Individual Innovation in the Workplace,” *Academy of Management Journal* 37 (3): 580–607.
Simon, H. A. 1971. “Designing Organizations for an Information-Rich World,” *Computers, Communication, and the Public Interest* 37: 40–41.
Sosa, M. E. 2011. “Where Do Creative Interactions Come from? The Role of Tie Content and Social Networks,” *Organization Science* 22 (1): 1–21.
The Community Roundtable. 2015. “The State of Community Management - Harvesting the Rewards of Community,” The Community Roundtable.
Tushman, M. L., and O’Reilly, C. A. 1996. “Ambidextrous Organizations: Managing Evolutionary and Revolutionary Change,” *California Management Review* 38: 4.
UCLA. 2014. “R Data Analysis Examples: Zero-Inflated Negative Binomial Regression”. UCLA: Statistical Consulting Group. http://www.ats.ucla.edu/stat/sas/notes2/.
Vuong, Q. H. 1989. “Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses,” *Econometrica: Journal of the Econometric Society*, 307–33.
Wasko, M. M., Faraj, S., and Teigland, R. 2004. “Collective Action and Knowledge Contribution in Electronic Networks of Practice,” *Journal of the Association for Information Systems* 5 (11): 2.
Whelan, E., Parise, S., De Valk, J., and Aalbers, R. 2011. “Creating Employee Networks That Deliver Open Innovation,” *MIT Sloan Management Review* 53 (1): 37–44.
Wiertz, C., and De Ruyter, K. 2007. “Beyond the Call of Duty: Why Customers Contribute to Firm-Hosted Commercial Online Communities,” *Organization Studies* 28 (3): 347–76.