Show Me the Incentives for Blogging: 
A Dynamic Structural Model of Employee Behavior

Yan Huang*
Param Vir Singh**
Anindya Ghose***
{yanhuang,psidhu}@cmu.edu; aghose@stern.nyu.edu

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*Yan Huang is a Doctoral Student at the Heinz College, Carnegie Mellon University. **Param Vir Singh is Assistant Professor of Information System at the Tepper School of Business, Carnegie Mellon University. ***Anindya Ghose is Associate Professor at the Stern School of Business, New York University. All the authors contributed equally and the order is in reverse of seniority. All the authors thank Ilab at the Heinz College, Carnegie Mellon University for their help in providing us with the data for this study.
Abstract

Many firms believe that enterprise blogging forums can be used to help build the structured platform required for an environment that supports emergent innovation. While some employees tend to be 'consumers' of content created by others, some others contribute by acting as 'creators'. In this paper, we build and estimate a theory-based dynamic structural model towards understanding the mechanisms that incentivize users to contribute to blog forums that are consumed by employees across the organization. We find strong evidence of competitive dynamics in our enterprise wide data setting. Our results demonstrate why employees contribute to blog forums and how these effects vary based on whether these are senior management employees or junior-level employees. We find that employees derive higher utility from readership of their work-related posts than their leisure-related posts. The low status employees derive higher self-expression utility from posting than high status employees. Further, in comparison to low status employees, high status employees continue to benefit more from past reputation. We also find that knowledge-based benefits are higher for low status employees and that low status employees feel higher levels of peer pressure to hold or generate knowledge than high status employees. Our results suggest that enterprises would benefit more from feedback systems that provide a picture of how knowledge workers in the organization are interacting with the tools are made available to them. We discuss implications for implementing feedback systems that quantify the reputation of the content creator and incentivize employees to engage in this practice.
SHOW ME THE INCENTIVES FOR BLOGGING: A DYNAMIC STRUCTURAL MODEL OF EMPLOYEE BEHAVIOR

Introduction

Over the last few years, blogs have become one of the most prominent web 2.0 technologies. Blog search engine Technoratti reports that there were more than 113 million blogs by April 2010, with 7.5 million of them active. Increasingly several leading organizations are encouraging their employees to blog (Aggarwal et al. 2009, Lee et al. 2006, Singh et al. 2010). Many firms believe that enterprise blogging forums can be used to help build the structured platform required for an environment that supports emergent innovation. Prominent among them are Sun Microsystems, Microsoft, Infosys, Cognizant, Google, etc. Thus, the success of corporate and industry blogs that actually provide updated and useful information has increased interest in blogs as a communication and discussion mechanism within the enterprise.

This drive by corporations to encourage employees to blog is because employee blogs have emerged as new sources of knowledge sharing within the enterprise (Lee et al. 2006, Singh et al. 2010, Yardi et al. 2009, Huh et al. 2007). However, employees’ motivation to blog may not always be in alignment with the firm's objective. Employee motivations determine whether they blog or not, what kind of information they share through their blogs, and what kind of blogs they read in turn. These activities have implications for their reputation within the firm and could potentially influence their career path and internal progress. Because of the increasing pervasiveness of this phenomenon, it is becoming increasingly important to understand the employee motivations to blog in an enterprise setting. Such an understanding would help devise strategies for a firm to influence employee blogging behavior.

In this paper, we aim to present an empirical framework to analyze dynamics in enterprise blogging using a unique individual-level dataset that maps the dual role of blog posting and reading behavior by employees. Our proposed model considers the employee motivations for reading and writing posts within an enterprise setting. The model is flexible enough to handle the inherent desire for self-expression, reputational concerns, knowledge holding, and seeking concerns, and the tradeoff between sharing pure entertainment-related knowledge (leisure) and work-related knowledge along with the time constraints. The model explicitly incorporates dynamics induced by these aspects of the employee behavior. We apply the model to a rich dataset that comprises the complete details of blog posting, blog reading, post content, and employee demographics for a large dataset of more than 5000 employees over a period of two years at a Fortune 1000 IT services and consulting firm.

We classify information in blogs into two types: work-related and non-work (leisure) related. In our model, employees are forward-looking and they make their decisions to maximize their long term utility instead of being myopic. Employees also compete with their peers and their actions are their best response to the peers' actions. We then formulate an employee's decision on when to write or read, what to write or read (in terms of work-related or leisure-related), and how much to write or read as a dynamic competition game in the tradition of structural dynamic competition games such as Bajari et al. (2007), Pakes and McGuire (1994, 2001), Gowrisankaran and Town (1997), Benkard (2004) and Erickson and Pakes (1995). Following Erickson and Pakes (1995) and Bajari et al. (2007) we focus on Markov Perfect Equilibrium as a solution concept.

There are four main components of the employee's utility function, which forms the core of this paper. The first component is the utility from self-expression. Several studies which have investigated why people blog reflect upon the desire to self-express as a dominant reason (Nardi et al. 2004, Miura and Yamashita 2007, Pederson and Macafee 2007, Furukawa et al. 2007, Kumar et al. 2004, Ali-Hasan and Adamic 2007). Individuals gain self-expression utility only from writing posts and not from reading. The second component of an employee's utility function is reputation. Individuals gain reputational benefits from writing posts in an enterprise setting. Blog writing allows individuals to express their expertise to a broad audience at a low cost. Hence, individuals may receive opinion leadership status, self-satisfaction, or indirect economic incentives, such as promotion, salary hike, etc. from writing posts (Aggarwal et al. 2009, Kavanaugh et al. 2006). The reputation incentive is proportional to the readership of an employees' blog. This is important because if an employee writes a post and no one reads it then he
does not receive any reputational benefit from that investment. Further, the work-related and leisure-related posts may provide different kinds and size of incentives. Individuals also derive utility from the knowledge they can acquire from reading posts (Singh et al. 2010, Yardi et al. 2009, Huh et al. 2007). This knowledge base forms the third component. We allow the knowledge-based utility derived from the work and leisure-related posts to be different. The work-related knowledge increase may help them in becoming more productive, be more informed about new ideas or technologies, open up new opportunities for collaborations, etc. (Yardi et al. 2009, Huh et al. 2007). The leisure-related information feeds to an employee's interests, allows him to relax, and updates him about current affairs, sports activities, cultural information, etc (Singh et al. 2010). Studies on employee knowledge sharing literature state that employees use work specific knowledge for both power and defense and power comes from knowledge holding (Ipe 2003, Davenport 1997; Gupta and Govindarajan 2000). At the same time, when employees do not share work relevant knowledge in an organization, which implicitly promotes knowledge sharing, they are penalized and ostracized (Pfeffer 1980, Brown and Woodland 1999). As a result employees pick cues from their peers, who they think are their social equivalents within the organization, and adjust their work relevant knowledge sharing to their peers' extent of work relevant knowledge sharing. The fourth component of the utility function captures this aspect of blogging. Specifically, if an employee were to share less than his peers did, his utility would increase with additional sharing. In addition, if he were to share more than his peers did, his utility would decrease with additional sharing. Besides these, the model involves an employee specific blogging time constraint and the employee maximizes his utility subject to this constraint. This captures the inherent tradeoff between devoting time to work relevant blogging and leisure relevant blogging.

Our results show that blog posting does provide self-expression utility to employees. Employees derive higher utility from readership of their work-related posts than their leisure-related posts. The knowledge-based utility an employee derives from reading work-related posts comes from both the cumulative knowledge at the beginning of the period and the knowledge acquired in the period. However, only current component of leisure-related knowledge provides a positive and significant utility to an employee. We find that employees in fact deal with their knowledge holding/sharing concerns by comparing their extent of work relevant knowledge sharing with that of their peers.

In addition we find some interesting results when we stratify the sample into low status and high status employees. The low status employees derive higher self-expression utility from posting than high status employees. Further, reputation depreciation factor is higher for low level employees as compared to high level. This indicates that, in comparison to low status employees, high level employees continue to benefit more from past reputation. Knowledge-based utility from work is also higher for low status employees. Results also show that low status employees feel more peer pressure to hold/share than high status employees.

Our study aims to makes a number of contributions. First, it provides insights into a very important but confusing phenomenon of why individuals incur the cost of reading and writing blogs when there appear to be no explicit monetary incentives for doing so. Second, we provide a structural framework to analyze employee blogging activities. An advantage of structural model is that it explains the reasons for user behavior rather than fitting the data as a reduced model would do. Our econometric framework captures theoretical arguments of psychological, economic, and social motivations for participating in these activities. Third, while prior studies have investigated why individuals blog, the results from those studies are based on surveys/questionnaires which can be affected by self-reporting bias. In contrast, our study uses actual micro-level blogging activity data from a large enterprise-wide setting to shed light on why individuals blog and model employee behavior accordingly.

**Literature Review**

In the last few years, the research on the different aspects of blogs has exploded. Recent studies have focused on understanding why people blog. Nardi et al. (2004) find that bloggers are driven to document their lives, provide commentary and opinions, express deeply felt emotions, and articulate ideas through writing. Miura and Yamashita (2007) surveyed a large number of bloggers to understand why blogger continue writing posts. They found that bloggers who are satisfied with the benefits their posts provide them within terms of self-expression, and relationship with others are more inclined to continue blogging. Cummings et al. (2002) and Mishne and Glance (2006) study why bloggers cite others posts.

Lin et al. (2006) provide a method to detect communities in blogosphere. Nakajima et al. (2005) develop methods to detect influential bloggers. Adar and Adamic (2005), Leskovec et al. (2007), and Todeva and Kaskinova (2009) study large scale blog datasets and shed light on how information diffuses in a blogosphere. Recently, there has been
an impetus to study blog reading behavior (Furukawa et al. 2007, Adamic and Glance 2005). These studies explain why individuals cite and comment on other posts, and join blog-rolls. They focus on readers who are also bloggers.

Since the adoptions of blogs within enterprises, some studies have begun to explore aspects of employee blogs. Aggarwal et al. (2009) study how negative posts by its employees can actually benefit a firm. They find that small number of negative posts are most beneficial to a firm. They argue that negative posts bring in more readers who are also exposed to the larger fraction of positive posts on the blog. Huh et al. (2007) conducted semi-structured interviews with fourteen active employee bloggers to investigate the role of blogging and its effects on work processes. They reveal that blogs facilitates access to tacit knowledge and resources vetted by experts, and, most importantly, contribute to the emergence of collaboration across a broad range of communities within the enterprise. Yardi et al. (2009) studied a large internal corporate blogging community using log files and interviews and found that employees expected to receive attention when they contributed to blogs, but these expectations often went unmet. Employees expected returns from their blogging activities and they expressed frustration if they invested time and received little or no perceived return on investment. Singh et al. (2010) study blog reading dynamics of employees within a large firm. The find that most of the employees' time is devoted to reading and writing leisure-related posts. They also find that employees typically focus on one or two categories for some time and then switch to an exploratory phase where they read small amount in a number of categories after which they again switch to a reading heavily in a few categories.

Finally, this paper is also related to the emerging literature on the economic and social implications of user-generated content based on Web 2.0 technologies. Existing research focuses on the various factors that motivate users to generate content, especially in the digital media environment. Nov (2007) surveys Wikipedians and finds that fun and ideology are the major motives for UGC in a collaborative environment. A related stream of work has examined the economics of UGC in online communities using different media such as PC and mobile by modeling their impact on inter-temporal dependencies in user behavior (Ghose and Han 2009) as well as modeling the presence of dynamic learning in such two-sided forums (Ghose and Han 2010). From a social standpoint, the impact of blogs on outcome of important events such as political elections has been studied by Adamic and Glance (2005), Drezner and Farrell (2004), and Farrell et al. (2008).

**Dynamic Game Model**

**Model Setup**

Employees $i=1,...,I$ decide about blogging decisions on a periodic (e.g. weekly) basis for $t=1,...,T$. In the enterprise blogging there are two types of posts $j \in \{w, l\}$ where $w$ represents work-related posts and $l$ represents leisure-related posts. At each period, employee decide how many posts of type $j$ to write and read. For each post type $j$, the employee can choose among a discrete set of available post quantity $n$. Let $a_{it} \in A_i$ denote consumer $i$'s actions at time $t$ and let $a_t = (a_{i1}, ..., a_{iI})$ denote the set of time $t$ actions. Hence, $a_{it} = (n_{itwp}, n_{itlp}, n_{itwn}, n_{itlr})$.

We assume that the employee's per period utility function at time $t$ comprises of utility from self-expression, reputation, knowledge, peer pressure for knowledge holding/sharing, and the costs of reading and writing. All these factors are explained and operationalized below.

**Self-expression**

One consensus in the information sharing literature is that knowledge sharing behavior is motivated by both employees’ personal belief structure (internal factors) (Szulanski 1996). Among internal factors, self-expression and self-esteem are considered the most important. An important motivation for bloggers has been reported to be their desire for self-expression (Nardi et al. 2004, Miura and Yamashita 2007, Pederson and Macafee 2007, Furukawa et al. 2007, Kumar et al. 2004, Ali-Hasan and Adamic 2007). An employee's desire to self express by writing a blog post is captured in the utility function via the function $\phi_{ijt}$ where

$$\phi_{ijt} = \theta_1 \sum_j n_{ijtwp} - \theta_2 \left( \sum_j n_{ijtwp} \right)^2 - \theta_3 k_{itw}.$$
Here, $\theta_1$ and $\theta_2$ are parameters that capture the extent to which each additional post affects an employee's self-expression satisfaction. Each additional post provides a decreasing marginal self-expression utility as indicated by the quadratic function. $h_{it}$ is a state variable that indicates the number of periods since the employee last wrote a post, and $\theta_3$ is the associated parameter. $\theta_3 > 0$ would indicate that the individual feels higher desire to self express as the time since she last wrote a post increase. The formulation of $h_{it}$ to capture desire to self express is consistent with the work by Kumar (2010) who considers this in the case of connected goods.

**Reputation**

Constant (1994) points out that sharing expertise may produce significant personal benefit in terms of increase in personal identification with workers and organizations. These benefits can be applied in blog settings, as intuitively, expected reputation gain is one of the most important motivations for individuals to write blogs. Employees derive reputation benefits from the posts they write. When an employee writes a post it indicates her expertise in an area. The employee derives reputational benefit consistent with her readership. In the utility function, the reputation-based utility is incorporated as $\omega_{it}$ where

$$\omega_{it} = \theta_4 R_{ijtp} + \theta_5 R_{ijtp}.$$  

Here, $R_{ijtp}$ is the number of readers for type $j$ posts written by employee $i$ in period $t$. We allow for the readership of the two types of posts to enter separately into the model as they may lead to different kind and size of incentives. Work-related posts may express a reader's expertise in work-related knowledge, which may help an employee derive indirect/direct economic incentives within the enterprise. The leisure-related posts may benefit the individual getting a fan following and becoming more popular among the employee who read her posts.

**Knowledge**

Blogs facilitate access to tacit knowledge and resources vetted by experts (Huh et al. 2007). The primary reason why corporations allow their employees to participate in blogging activities during their work hours is because the employee blogs act as a new source of work relevant knowledge sharing within the enterprise (Lee et al. 2006, Singh et al. 2010, Yardi et al. 2009, Huh et al. 2007). In the knowledge economy, knowledge is a key resource for both the firm and for employees. It makes a knowledge worked more productive leading to associated benefits. Employees can acquire knowledge by reading other's posts. When employees read others posts they become more aware of their (blogger) expertise, which opens up new opportunities for collaborations. As in the case of reputation the two types of posts affect the type and size of incentives differently. Hence, we enter them separately. In the utility function, the knowledge-based utility is captured by $\tau_{ijt}$ where

$$\tau_{ijt} = \theta_6 K_{ijt} + \theta_7 K_{ijt}.$$  

Here $K_{ijt}$ is the knowledge of type $j$ for a employee $i$ at the end of time period $t$.

**Peer Pressure for Knowledge Holding/Sharing**

Individuals are also concerned about disclosing their work relevant knowledge because knowledge is considered a key resource and the individuals are likely to be valued more for only what they know (Ipe 2003, Davenport 1997, Gupta and Govindarajan 2000). However, the individuals who do not share knowledge within an enterprise which promote sharing knowledge also face a disutility by breaking enterprise norms (Singh et al. 2009, Pfeffer 1980, Brown and Woodland, 1999). Hence, the employee compares itself to its peers and see how much work relevant knowledge they are sharing (Pfeffer 1980, Brown and Woodland 1999). In essence, employees do not worry about the total amount of work relevant knowledge that they are sharing and are only concerned about the relative level of knowledge that they share as compared to their peers. Let $m_i$ be the set of employee $i$’s peers. We construct an index $x_{it}$ as:

$$x_{it} = \sum_{s=1}^{t-1} n_{iswp} - \left( \frac{\sum_{s=0}^{t-1} n_{kswp}}{|m_i|} \right), k \in m_i.$$
Note that $x_{it}$ will be positive when $i$ is sharing more work-related knowledge than its peers are and negative otherwise. The utility from disclosing knowledge is then incorporated into the utility function as $\theta_{it} = \theta_{it}^p n_{itwp}$. $\theta_{it} < 0$ would indicate that sharing more knowledge than peers would lead to a greater disclosure disutility but sharing less than peers would lead to disutility due to breaking of sharing norms. Hence, when an individual is sharing more than the peers he would like to lessen his sharing to reduce the disclosure disutility. However, when sharing less than peers he would like to increase the amount of sharing to decrease the disutility from breaking sharing norms.

**Budget Constraint and Blogging Costs**

At time $t$, employee $i$ has an exogenous time budget $y_{it}$ allocated for blogging activities. Let $t_{it}$ be the cost of identifying and reading one post and $t_{pt}$ be the cost of developing and writing one post. Then we have the following budget constraint:

$$y_{it} = t_{it} \sum_j n_{itjp} + t_{pt} \sum_j n_{itjp}.$$  

This budget constraint allows us to capture the tradeoff that an individual would consider while deciding time to allocate to pure leisure or work activities.

The blogging costs enter the utility function as $c_{it}$:

$$c_{it} = \theta_9 \sum_j n_{itjp} + \theta_{10} \sum_j n_{itjp}.$$  

Here, $\theta_9$ and $\theta_{10}$ represent the per unit cost of reading and writing posts respectively. A point to be noted here is that the time cost is only a subset of the total cost of blogging.

**Utility Function**

An employee’s utility at time $t$ is given by $U_{it}$ as:

$$U_{it} = \varphi_{ijt}(\theta_1, \theta_2, \theta_3, R_{itwp}, n_{itwp}, n_{itw}, n_{it}) + \omega_{it}(\theta_4, \theta_5, R_{itwp}, R_{itlp}) + \tau_{ijt}(\theta_6, \theta_7, K_{itw}, K_{itl}) + \varphi_{it}(\theta_8, x_{it}, n_{itjp}) - c_{it}(\theta_9, \theta_{10}, n_{itwp}, n_{itlp}, n_{itw}, n_{itl}) + \gamma_{it}.$$  

$\gamma_{it}$ is the random shock to the utility that may affect an employee’s decisions. We assume that the error $\gamma_{it}$ $\gamma_{it} = \sum_{j,q} \gamma_{itjqn} \times d_{itjqn}$, and $\gamma_{itjqn}$ has an i.i.d normal distribution and

$$d_{itjp} = \begin{cases} 1, \text{if employee } i \text{ writes } n \text{ type } j \text{ post in period } t \\ 0, \text{otherwise} \end{cases}$$  

$$d_{itjn} = \begin{cases} 1, \text{if employee } i \text{ reads } n \text{ type } j \text{ post in period } t \\ 0, \text{otherwise} \end{cases}$$  

The utility function can be further written as:

$$U_{it} = \theta_1 \sum_j n_{itjp} - \theta_2 \left( \sum_j n_{itjp} \right)^2 - \theta_3 x_{it} + \theta_4 R_{itwp} + \theta_5 R_{itlp} + \theta_6 K_{itw} + \theta_7 K_{itl} + \theta_8 x_{it} n_{itwp} - \theta_9 \sum_j n_{itjp}$$  

Substituting the budget condition into the utility function gives:
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State Variables

There are six state variable is in our model. The first state variable is $h_{it}$. It evolves as follows:

$$h_{it} = \begin{cases} h_{it-1} + 1, & \text{if } \sum_j n_{itjp} = 0 \\ 0, & \text{otherwise} \end{cases}$$

This updating rule implies that the value of $h_{it}$ will keep on increasing as the time since last post written elapses, and $h_{it}$ is reset to zero as soon as a new post is written.

The second and third state variables are the cumulative knowledge of employee $i$, $\sum g|830\sum g303<\sum g3040\sum g3030\sum g3043\sum g3030$ and $\sum g|830\sum g303<\sum g3040\sum g3039\sum g3043$.

The knowledge of an individual evolves according to the following:

$$K_{it} = K_{it-1} + \alpha n_{itjp}$$

Here, $\alpha$ denotes a parameter that needs to be estimated.

The fourth state variable is the index $x_{it}$. It evolves as shown above. The fifth and the sixth state variables are the readership variables $R_{itwp}$ and $R_{itlp}$. The readership variables evolve as follows:

$$R_{itjp} = \delta R_{it-1jp} + r_{itjp}$$

Here, $r_{itjp}$ is the number of people who read $i$'s $n_{itjp}$ type $j$ posts in period $t$. In addition, $\delta$ is a parameter that needs to be estimated. At the beginning of period $t$ an employee will not know $r_{itjp}$. However, given that the behavior observed in the data is an equilibrium behavior, and the rational expectation equilibrium would suggest that the employee's ex ante expectation of readership would match ex post realization of readership.

We define $s$ as the set of the state variables for an employee. Then $s_{it} = (h_{it}, R_{itwp}, R_{itlp}, K_{itw}, K_{itl}, x_{it})$ is value of the state variables for an employee $i$ at time $t$.

Sequence of Events

The specific sequence of events in our model is as follows:

1. Employees observe their state $s_{it}$ and are allocated a time budget $y_{it}$.
2. Employees receive random shocks ($y_{it}$) for the reading and writing decisions.
3. Employees make expectation of the readership ($r_{itjp}$) they may get in the current period if they write a post. Note that other than reputation all other state variables are deterministic at the beginning of the period.
4. Employees make decisions as to how much to write ($n_{itwp}, n_{itlp}$) and read ($n_{itwr}, n_{itlr}$) in the current period.
5. Employees receive utility because of their decisions.
6. Employee states evolve because of their decisions.
Long Term Utility Function

We model the employee's writing and reading decisions as a dynamic optimization problem. The employee's tasks are to decide how many posts to read for work, how many posts to read for leisure, how many posts to write on work, how many posts to write on leisure to maximize the sum of the discounted expected future utility $U_{it}$ over the infinite horizon.

\[
\max_{\pi(\text{work}, \text{leisure}, \text{unrestricted})} E_t \left( \sum_{t=0}^{\infty} \beta^{t-t} U_{it} \right)
\]

The variable $\beta$ is the common discount factor. The operator $E_t[\cdot]$ denotes the conditional expectation operator given the employee's information at time $t$. There are two components of the model that need to be emphasized. The employee in our model maximizes his life time utility, which makes the model dynamic. At the same time, the utility of an employee is a function of the decisions made by his/her peers (through $x_{it}$) making it a multi-agent dynamic game.

Empirical Estimation

The model parameters that need to be estimated are: $\theta = \{\theta_y, \theta_\theta, \theta_\beta, \theta_0, \theta_\theta, \theta_\gamma, \theta_\theta, \theta_0, \theta_\theta, \theta_\gamma, \theta_\delta, \delta, \beta\}$. The long term utility function can be converted to a Bellman equation. Ideally, one would like to estimate the model with a backward induction process. One would also need to consider the complexity raised by the presence of dynamic competition. As shown by research on dynamic competition, by Erickson and Pakes (1995), Pakes and McGuire (2001), and Benkard (2004), computing an equilibrium for even relatively simple models is all but prohibitive. Hence, estimating the dynamic parameters is all but prohibitive.

To estimate the structural model, we follow the two-step estimation procedure suggested by Bajari et al. (2007) (hereafter BBL) for this scenario. The BBL estimator builds on the work by Rust (1987) which proposes an estimation strategy for single agent dynamic discrete choice models. There are several other estimation procedures suggested by for example Pakes et al. (2007), Pesendorfer and Schmidt-Dengler (2003), and Aguirregabiria and Mira (2007). However, all of them apply only to the case of discrete choice dynamic games. However, the BBL estimator applies to both the discrete and continuous choice cases.

In a MPE, each employee’s behavior depends only on the current state and his current private shock. Formally, a Markov strategy for an employee $i$ is a function $\sigma_i: S \times I_i \to A_i$. A profile of Markov strategies is a vector, $\sigma = (\sigma_1, \ldots, \sigma_n)$, where $\sigma: S \times I_1 \times \ldots \times I_n \to A$. If behavior is driven by a Markov strategy profile $\sigma$, employee $i$'s expected utility given state $s$ can be written recursively as Bellman Equation:

\[
V_i(s; \sigma) = E_t \left[ U_i(\sigma(s, \gamma), s, y_{it}) + \beta \sum_{s'} V_i(s'; \sigma) dP(s' | \sigma(s, \gamma), s) \right].
\]

Here, $V_i$ is a value function which reflects expected value for employee $i$ at the beginning of a period before private shocks are realized. Following the literature, a profile $\sigma$ is Markov perfect equilibrium if, given the opponent profile $\sigma_{-i}$, each employee $i$ prefers its strategy $\sigma_i$ to all alternate strategies $\sigma_i'$. That is, for $\sigma$ to be MPE

\[
V_i(s; \sigma, \sigma_{-i}) \geq V_i(s; \sigma_i', \sigma_{-i}).
\]

Two step approach for estimation suggested by BBL

In the first step we estimate the policy functions $(\sigma_i: S \times I_i \to A_i)$, the state transition probabilities $P: A \times S \to \Delta S$, and the Value functions. Our choice variables (the number of posts employee reads or writes) are continuous. In that case let $F_i(a_i|s)$ denote the probability that the employee takes an action less than or equal to $a_i$. Let $G_i$ be the distribution of the random shocks. Then the policy function is given by (BBL):

\[
\sigma(s, y_i) = F_i^{-1}(G_i(y_i | s; \rho) | s)
\]
Given this, we only need to estimate the distribution of actions at each state, which is obtained from the data. To estimate the state transitions, we use the observed values of state variables \((h, K_{m}, K_{t}, x)\). Note that we can observe the values of \(K_{m}\) and \(K_{t}\) only if we set the initial value (at \(t=0\)) of knowledge levels of an employee to some value. Also, note that our state transitions are deterministic.

The estimation strategy suggested by BBL is inspired by Hotz et al. (1994). The estimation process uses forward simulation to estimate an employee’s value functions for a given strategy profile (including the equilibrium profile) given an estimate of state transition probabilities. Let \(V_{i}(s; \sigma, \rho)\) denote the value function of employee \(i\) at state \(s\), assuming \(i\) follows Markov strategy \(\sigma_{i}\) and all its peers follow \(\sigma_{-i}\). Then

\[
V_{i}(s; \sigma, \rho) = E \left[ \sum_{t=0}^{\infty} \beta^{t} U_{it}(\sigma(s_{it}, y_{it}), s_{it}, y_{it}; \rho) \mid s_{0} = s; \rho \right].
\]

Given the first stage state transition probability estimates, we can use simulation to estimate the value function \(V_{i}(s; \sigma, \rho)\) for any strategy profile \(\sigma\) and parameter vector \(\rho\). A simulated path of play is obtained as:

Step 1: Starting at state \(s_{0} = s\), draw private shocks \(y_{it}\) from \(G_{i}(\cdot | s_{0}, \rho)\) for every employee \(i\).

Step 2: Calculate specified action \(a_{it} = \sigma_{i}(s_{0}, y_{it})\) for each employee \(i\) and the resulting utility \(U_{it}(a_{it}, s_{it}, y_{it}; \rho)\).

Step 3: Determine the new state \(s_{t+1}\) according to the state transition function.

Step 4: Repeat the steps 1-3 for \(T\) period.

If the policy profile used in this step is the policy profile estimated in the first stage then it is the resultant value over a number of simulated paths is an estimate of the payoff \((\tilde{V}_{i}(s; \sigma, \tilde{\sigma}_{-i}; \rho))\) from playing \(\tilde{\sigma}_{i}\) in response to all peers playing \(\tilde{\sigma}_{-i}\).

In the second step, we use the estimates from first stage combined with the equilibrium conditions of the model to estimate the underlying structural parameters.

Let \(z \in Z\) index the equilibrium conditions, so that each \(z\) denotes a particular \((i,s; \sigma_{i}')\) combination. Let us further define:

\[
g(z; \rho, K) = V_{i}(s; \sigma, \sigma_{-i}; \rho; K) - V_{i}(s; \sigma_{i}', \sigma_{-i}; \rho; K).
\]

Here, \(K\) reflects that \(\sigma\) and state transitions are parameterized by \(K\). The equilibrium condition is satisfied at \(\rho, z\) if \(g(z; \rho, K) \geq 0\). This estimated through simple simulated minimum distance estimator.

**Identification and Normalization**

There are several identification issues that need to be addressed before the model can be consistently estimated. Since both the utility from writing posts and the cost of writing consist of a linear term in the number of posts written by an employee, we cannot separately estimate the two associated parameters. Specifically, we cannot estimate \(\theta_{1}\) and \(\theta_{10}\) together. We can only estimate the difference between the two. Hence, we update the utility function as follows:

\[
U_{it} = \theta_{1}\left(\frac{y_{it} - \tau_{rt} \sum_{j} n_{it,j}}{\tau_{pt}}\right) - \theta_{2}\left(\sum_{j} n_{it,j}\right)^{2} - \theta_{3}r_{it} + \theta_{4}R_{itwp} + \theta_{5}R_{itip} + \theta_{6}K_{itw} + \theta_{7}K_{itl} + \theta_{8}x_{it}R_{itwp}
\]

Second, the time cost itself holds no meaning. It has meaning only in relative terms. Hence, we normalize the time cost of writing a post to 1, i.e. \(\tau_{pt} = 1\). For identification we also set \(\tau_{rt} = 1\). We impose few more restrictions on the parameters. The discount factor is restricted to be less than 1, i.e. \(\beta < 1\). We do not observe the true time budget for each employee in each period. To address this issue, we construct the empirical distribution of the budget for each employee from the observed data. The budget is calculated following the budget constraint equation described earlier. For the simulation in the first stage, we draw a budget value randomly from the empirical distribution. We
construct the readership by drawing a random number from the empirical distribution of her past readership. Note that due to these we have to take expectations over their distributions.

We do not know the initial values of the state variables, which raise the well known 'initial conditions' problem. The first observation in our sample may not be the true initial outcome of an employee's blog content generation and reading behavior. If one does not control for initial choice history, the implicit assumption is that every employee has the same beliefs across both kinds of activity (read and write) and across both kinds of blogs (work and leisure). However, it is possible that a employee that has engaged in an activity multiple times in the past would have more informed priors than another user who has engaged very little in that activity. Hence, one needs to account for the heterogeneity of priors in the sample. We follow an approach that is similar in spirit to that used in Erdem et al. (2008). We use a part of our data (4 months) as a pre-estimation sample to estimate the distribution of state variables.

Data Description

Our research setting is a large, Fortune 1000 information technology services, business process outsourcing, and consulting firm. Fortune named this firm one of the fastest growing companies in 2009 (Fortune 2009). Its annual revenues in year 2009 were a few billion dollars. It is a US-based firm with significant presence and operations in several other countries across multiple continents: Europe, Asia, and Americas being the major areas. To influence more knowledge and information sharing across as well as within locations, the firm has undertaken several measures. Prominent among these measures is the use of Web 2.0 technologies within the enterprise.

This firm adopted the use of employee blogs in late 2006. These blogs are hosted on an internal platform and are not accessible by people outside the organization. Every employee is allowed to host his/her own blog on this platform. These blogs are accessible to all the employees of the firm across the entire hierarchy. The identity of the blogger is also revealed on the blog. Bloggers classify their posts into one of the 25 categories (for example, software testing, movies, history, knowledge management, senior management, etc). To be able to measure the knowledge sharing aspect, the firm tracks who (which employee) reads which blog and at what time. Since the blogs are only internally accessible, the firm did not impose any restrictions on the kind of posts that can be written by the employees. To analyze the type of content that is being shared in the internal blogosphere, the firm broadly classifies the blog article categories into two topics: Work-related (w) and Leisure-related (l). Table 1 presents the sub-categories that constitute each topic.

<table>
<thead>
<tr>
<th>Sub Categories</th>
<th>Leisure Related</th>
<th>Work Related</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fun; Movies-TV-Music; Sports; Puzzles; Chip-n-putt; Religion-Spiritual-Culture; History-Culture; Education-Motivation; Photography; Arts; Poetry-Stories; Corporate Social Responsibility; Books; Geographies</td>
<td>FLOSS; Technology; Testing; Domains; Corporate Functions; Knowledge Management; Project Management; Business Development; Senior Management; Feedback; Practices-Programs-Accounts</td>
<td></td>
</tr>
</tbody>
</table>

For estimation purposes, we randomly selected 152 employees of the firm. We collected data about their blogging activities for approximately 2 years. We have data on exact timestamps of blog reading and posting activities. For the purpose of estimation, we define a period as one month. This provides us data for 23 months. The sample includes a number of employee designations, which are shown in Table 2.

High level descriptive statistics of our data are shown in Table 3. This set of employees wrote 7010 posts during the 2-year period. Out of these 2191 posts are work-related and 4819 posts are leisure related. Variable definitions along with associated parameters are shown in Table 4.
Table 2. Employee Designation Distribution in the Sample

<table>
<thead>
<tr>
<th>Designation</th>
<th>% in the Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Programmer Analyst</td>
<td>42.76%</td>
</tr>
<tr>
<td>Associate - Projects</td>
<td>11.18%</td>
</tr>
<tr>
<td>Programmer Analyst Trainee</td>
<td>9.87%</td>
</tr>
<tr>
<td>Sr. Associate Projects</td>
<td>7.89%</td>
</tr>
<tr>
<td>IT- Ops. Executive - ITIS</td>
<td>3.95%</td>
</tr>
<tr>
<td>Others</td>
<td>24.35%</td>
</tr>
</tbody>
</table>

Table 3. Overall Sample Statistics

<table>
<thead>
<tr>
<th>Overall Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Employees</td>
</tr>
<tr>
<td>Period length</td>
</tr>
<tr>
<td>Number of periods</td>
</tr>
<tr>
<td>Total posts written</td>
</tr>
<tr>
<td>Work-related posts written</td>
</tr>
<tr>
<td>Leisure-related posts written</td>
</tr>
<tr>
<td>Work-related post reading</td>
</tr>
<tr>
<td>Leisure-related post reading</td>
</tr>
</tbody>
</table>

* only includes posts written by the 152 employees in the dataset.
** includes all posts (even the one not written by the employees in the sample) read by the 152 employees.

The descriptive statistics for the key variables used to construct the model variables are presented in Table 5. On average there are 0.61 (1.36) work-related (leisure-related) blog posts written by an employee per month. An employee reads on average 2.08 (9.78) work-related (leisure-related) blog posts each month. A given work-related post by an employee is read by 33.2 employees on an average. Whereas the corresponding value for leisure-related post is 86.79. On average there is about a 5.75-month difference in the frequency of an employee's two work-related posts. Further, typically an employee publishes the same number of posts as his peers. (Note that there are other key variables for which statistics are not shown in Table 5. This is because the parameters needed to construct those variables need to be estimated).
Table 4. Variable Meaning and Corresponding Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Corresponding Parameter</th>
<th>Variable Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sum_{j} n_{itjp}$</td>
<td>$\theta_1$</td>
<td>Sum of the number of posts written by employee $i$ in period $t$.</td>
</tr>
<tr>
<td>$\left(\sum_{j} n_{itjp}\right)^2$</td>
<td>$\theta_2$</td>
<td>Square of sum of the number of posts written by employee $i$ in period $t$.</td>
</tr>
<tr>
<td>$h_{it}$</td>
<td>$\theta_3$</td>
<td>State variable at time $t$ that indicates the number of periods elapsed since the employee $i$ last wrote a post.</td>
</tr>
<tr>
<td>$R_{itwp}$</td>
<td>$\theta_4$</td>
<td>Cumulative reputation (measured through depreciated past readership and current period readership) of work-related posts for employee $i$ in period $t$.</td>
</tr>
<tr>
<td>$R_{itlw}$</td>
<td>$\theta_5$</td>
<td>Cumulative reputation (measured through depreciated past readership and current period readership) of leisure-related posts for employee $i$ in period $t$.</td>
</tr>
<tr>
<td>$K_{itw}$</td>
<td>$\theta_6$</td>
<td>Cumulative knowledge (measured through past and present knowledge acquired from reading) of work-related posts for employee $i$ in period $t$.</td>
</tr>
<tr>
<td>$K_{iti}$</td>
<td>$\theta_7$</td>
<td>Cumulative knowledge (measured through past and present knowledge acquired from reading) of leisure-related posts for employee $i$ in period $t$.</td>
</tr>
<tr>
<td>$x_{it} n_{itjp}$</td>
<td>$\theta_8$</td>
<td>$n_{itjp}$ multiplied with an index variable that measures the difference between the number of work-related posts written by employee $i$ and the average number of work-related posts written by his peers (employees at same designation as $i$) by time $t$.</td>
</tr>
<tr>
<td>$\sum_{j} n_{itjr}$</td>
<td>$\theta_9$</td>
<td>Sum of the number of posts read by employee $i$ in period $t$.</td>
</tr>
<tr>
<td>$n_{itjp}$</td>
<td>$\alpha$</td>
<td>Number of posts of type $j$ written by employee $i$ in period $t$.</td>
</tr>
<tr>
<td>discount rate</td>
<td>$\beta$</td>
<td>Rate at which an employee values future utility compared to current.</td>
</tr>
<tr>
<td>$R_{it-1jp}$</td>
<td>$\delta$</td>
<td>Cumulative reputation of type $j$ posts for employee $i$ in period $t-1$.</td>
</tr>
</tbody>
</table>

Table 5. Descriptive Statistics of Key Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_{itwp}$</td>
<td>0.61</td>
<td>7.93</td>
</tr>
<tr>
<td>$n_{itlp}$</td>
<td>1.36</td>
<td>9.71</td>
</tr>
<tr>
<td>$n_{itwr}$</td>
<td>2.08</td>
<td>7.98</td>
</tr>
<tr>
<td>$n_{itlr}$</td>
<td>9.78</td>
<td>34.68</td>
</tr>
<tr>
<td>$h_{it}$</td>
<td>5.75</td>
<td>5.09</td>
</tr>
<tr>
<td>$r_{itwp}$</td>
<td>20.25</td>
<td>220.32</td>
</tr>
<tr>
<td>$r_{itlp}$</td>
<td>118.03</td>
<td>997.70</td>
</tr>
<tr>
<td>$x_{it}$</td>
<td>0.01</td>
<td>8.06</td>
</tr>
</tbody>
</table>

Results

Here we present two sets of results. The first set of results is for the full sample. The second set of results is for stratified sample where we separately estimate the parameters for high and low level employees.
Full Sample Results

The results for the structural model are presented in Table 6. The results show that $\theta_1$ is positive and significant while $\theta_2$ is negative and significant. This indicates a non-linear relationship between the utility from self-expression and the number of posts an employee writes in a period. Note that the estimated $\theta_1$ accounts also for the cost of posting as explained in the identification and normalization section. Even after counting for the cost $\theta_4$ is positive, it indicates that the true self-expression utility from posting may be higher than $\theta_1$. Considering both $\theta_1$ and $\theta_2$ together shows that the self-expression utility from posting at first increases at a decreasing rate with the number of posts made by an employee in a period up to a point after which it decreases at a decreasing rate. The parameter $\theta_3$ is negative and significant suggesting that as the time since an employee has posted elapses his desire to self express increases. The significance and direction of the three parameters together indicate that blog posting does provide self-expression utility to employees.

The parameters, $\theta_4$ and $\theta_5$, are both positive and significant. This indicates that employees derive reputation-based utility from their posts. On comparison one can see that $\theta_4 > \theta_5$. This inequality is also statistically significant at $p<0.1$. This reveals that employees derive a higher utility from readership of their work-related posts than their leisure-related posts. At the same time, $\theta_6$ is positive and significant. In addition, its value of 0.6811 indicating that utility from past readership decreases at a very high rate. It implies that employees who post infrequently derive lower reputational utility than ones who post frequently for same number of posts.

Individuals derive knowledge-based utility from reading other’s posts. It is important to consider both the component of knowledge-based utility (past knowledge and knowledge acquired in current period). The complete knowledge-based utility function is given by $\theta_8 K_{itw} + \theta_9 K_{itl} = (\theta_6 K_{it-1w} + \theta_7 a_{itw}) + (\theta_8 K_{it-1l} + \theta_9 a_{itl})$. Hence, the knowledge-based utility an employee derives from reading work-related posts comes from both the cumulative knowledge at the beginning of the period and the knowledge acquired in the period as indicated by positive and significant $\theta_6$ and $\alpha$. However, only current component of leisure-related knowledge provide a positive and significant utility to an employee.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimated values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_1$</td>
<td>12.3304***</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>-2.7321*</td>
</tr>
<tr>
<td>$\theta_3$</td>
<td>-7.2667*</td>
</tr>
<tr>
<td>$\theta_4$</td>
<td>1.2793***</td>
</tr>
<tr>
<td>$\theta_5$</td>
<td>0.6776*</td>
</tr>
<tr>
<td>$\theta_6$</td>
<td>3.5155***</td>
</tr>
<tr>
<td>$\theta_7$</td>
<td>0.0162</td>
</tr>
<tr>
<td>$\theta_8$</td>
<td>-0.7567**</td>
</tr>
<tr>
<td>$\theta_9$</td>
<td>-0.9969***</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.6811***</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.9517***</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.8359**</td>
</tr>
</tbody>
</table>

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ (two tailed $t$-test for all parameters)

The parameter $\theta_8$ is negative and significant confirming the presence of a dynamic game. This indicates that employees are in fact deal with their knowledge holding/sharing concerns by comparing their extent of work relevant knowledge sharing with that of their peers. If an employee has shared less than the peers have, he derives a higher knowledge/ holding/sharing utility by increasing his number of work-related posting. In contrast, if he has shared more that the peers he derives a lower knowledge holding/sharing utility by increasing his number of work-related posts. Due to identification and normalization issue, we are able to identify only one cost parameter $\theta_9$ which, is associated with the number of posts read. As expected, this parameter is negative and statistically significant. The discount rate $\beta$ is positive and significant. Its value of 0.9517 indicates that employees are in fact forward-looking.
Stratified Sample Results

We split our full sample into two groups, high and low, based on employee designations. Employees who are at the level of CEO/CIOs, VP’s, Directors, Executives, Senior Managers, etc. constitute the “high status” group. Employees who are at level of Analysts, Programmers, Trainees, etc constitute the “low status” group. The two resulting samples were estimated separately to investigate how the parameters may vary across employee status within the enterprise. The stratified sample estimates are provided in Table 7.

For both the high status and low status groups, \( \theta_1 \) is positive and significant and \( \theta_2 \) is negative and significant. In comparison to the low status group, high status employees have smaller \( \theta_1 \) and \( \theta_2 \). This implies that to begin with low status employees receive higher per unit post self-expression utility than the high status ones do, and their utility increases at a higher rate than up to a point than high status employees do and beyond the point decreases at a slower rate. At the same time \( \theta_3 \) is negative and significant for low status employees but negative and statistically insignificant for high status employees. This indicates that while the desire to express increases for low status employees as time increases since last post, the high status employees do not feel that effect. In sum, the low status employees derive higher self-expression utility from posting than high status employees.

Table 7. Stratified Sample Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimated values (Low Status Group)</th>
<th>Estimated values (High Status Group)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_1 )</td>
<td>13.8399***</td>
<td>10.6052***</td>
</tr>
<tr>
<td>( \theta_2 )</td>
<td>-2.3926*</td>
<td>-3.0194*</td>
</tr>
<tr>
<td>( \theta_3 )</td>
<td>-10.8742***</td>
<td>-4.9906</td>
</tr>
<tr>
<td>( \theta_4 )</td>
<td>1.4478***</td>
<td>0.9147**</td>
</tr>
<tr>
<td>( \theta_5 )</td>
<td>0.6593*</td>
<td>0.7192*</td>
</tr>
<tr>
<td>( \theta_6 )</td>
<td>4.1798***</td>
<td>1.8149***</td>
</tr>
<tr>
<td>( \theta_7 )</td>
<td>0.0116</td>
<td>0.0217*</td>
</tr>
<tr>
<td>( \theta_8 )</td>
<td>-1.5742***</td>
<td>-0.3919*</td>
</tr>
<tr>
<td>( \theta_9 )</td>
<td>-0.9461***</td>
<td>-0.9984***</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.5124***</td>
<td>0.8472***</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.9519***</td>
<td>0.9514***</td>
</tr>
<tr>
<td>( \delta )</td>
<td>0.8392**</td>
<td>0.8314**</td>
</tr>
</tbody>
</table>

*** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \) (two tailed t-test for all parameters)

In comparison to high status employees, the low status employees derive more reputational utility from posting work-related posts as indicated by the estimated parameter \( \theta_4 \). This suggests that generating work-related posts in an organization matters much more for entry level employees than for those in senior management. While \( \theta_5 \) is greater for high level the difference is not statistically significant. Further, reputation depreciation factor, \( \alpha \) is smaller for low status employees as compared to high status ones. This indicates that, in comparison to low status employees, high status employees continue to benefit more from their past reputation. In other words, the reputation benefits are more robust for high status groups. This suggests that it is much more difficult to bring major changes in the internal reputation and credibility scores of the top-level management than that of the entry-level employees.

Knowledge-based utility from work is also higher for low status employees as indicated by \( \theta_6 \). A potential reason is that the blogs may be providing the kind of knowledge that may help low status employees as compared to high status employees. Whereas, \( \delta \) is same for both high and low status employees. While low status employees do not derive any knowledge-based utility from past reading of leisure posts, high status employees derive such. At the same time, both of them derive knowledge-based utility from current reading of both leisure and work-related posts.

Results also show that low status employees feel a higher level of peer pressure to hold/share than high status employees. This is consistent with the literature on social influence in the sociology literature, which finds that low status individuals are more susceptible to peer influence (Strang and Tuma 1993, Burt 1987, Singh and Phelps 2009).

Discussion and Conclusions

As enterprise blogs become an increasingly popular tool for generating and sharing information, this motivates the need to have a deeper understanding of users’ content generation and usage behavior in organizational settings.
While some employees tend to be 'consumers' of content created by others, especially their peers, some others contribute by acting as 'creators'. For a given user, content generation and usage may not be independent decision-making processes. Rather, they are likely to be inter-related processes. However, little is known about how content generation by users is related to their usage of such content, or vice-versa, and how these processes are associated with employees' organizational status within a firm. Moreover, this will vary based on the two prominent kinds of blogs that tend to exist within firms: work related and leisure-related blogs.

In an enterprise setting, success of a blog is even more important as there may be potential career and promotion-related benefits associated with increased visibility of an employee's blog posting. Blog post generation is a costly task where an employee can adopt a forward-looking decision-making rule keeping in mind long-term objectives of enhancing his internal reputation and knowledge, given the opportunity costs of time associated with these activities. In the same vein, a given employee is also likely to observe how his peers behave and then take actions in order to maximize the reputation and knowledge-related gains in this setting after considering how current actions can influence the future decisions of peers, which in turn can affect the future utility of the focal employee. This makes the interactions between users strategic. One can thus envision that enterprise blogging is a ripe area for a dynamic competitive game between employees.

In this paper, we build and estimate a theory-based dynamic structural model towards understanding the mechanisms that drive users to contribute to blog forums that are consumed by their peers and other employees across the organization. We find strong evidence of such dynamics in our enterprise wide data setting. Our model recognizes not only the possibility that employee contribution decisions are inter-related across peers within the organization, but also that content generation (blog writing) and usage (blog reading) decisions are inter-temporally related. Because we explicitly model the process of inter-temporal user decision-making, our approach illustrates the micro-mechanisms of contribution and usage decisions in an enterprise blog setting, rather than merely testing whether interdependence exists using a reduced form approach.

Our results establish why employees contribute to blog forums and how these effects vary based on whether these are top-level/senior management employees or entry level/junior level employees. Employees derive higher utility from readership of their work-related posts than their leisure-related posts. The low status employees derive higher self-expression utility from posting than high status employees. Further, reputation depreciation factor is also higher for low status employees as compared to high status. This indicates that, in comparison to low status employees, high status employees continue to benefit more from past reputation. We also find that knowledge-based utility from work is higher for low status employees and that low status employees feel higher levels of peer pressure to hold/share information than high status employees do.

So what can organizations do to spur knowledge creation through social media tools like blogs and wikis? Our results highlighting the effects of reputation, knowledge, and knowledge sharing suggest that enterprises would benefit more from feedback systems that provide a picture of how knowledge workers in the organization are interacting with the tools you make available to them. Better yet, these feedback systems should generate metrics that quantify the reputation of the content creator and incentivize people to engage in this practice. This can be done by adding some basic instrumentation to the knowledge sharing system. For example, they can make it simple to count things like blog posts made, comments made, documents contributed, documents consulted, and pointers shared and make these metrics salient and visible to all employees. Such metrics can thus help senior management evaluate junior employees on their knowledge sharing performance and use it as an additional tool in their annual evaluation. Furthermore, organizations can use such data to distill and identify patterns of content sharing practice that are worth emulating.

Our paper has some limitations, which could act as fruitful areas for future research. We have not explored the role of geographical location and physical proximity in our setting. It is plausible that distance from peers plays a role in the competitive dynamics within enterprises. We have also not examined the textual content of the blog postings. Future work can examine the sentiments and polarity of the blog content. Such information can be used by competitors to predict future readership, which will affect the decisions they take. Notwithstanding these limitations, we hope our paper, which provides the first known dynamic structural model of blogging, paves the way for future research in this important area.
Show me the incentives for blogging

References


Nov, O. "What motivates Wikipedians?" Communications of the ACM (50:11), November 2007, pp. 60- 64.