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A Structural Model of Employee Behavioral Dynamics in Enterprise Social Media

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We develop and estimate a dynamic structural framework to analyze the social-media content creation and consumption behavior of employees within an enterprise. We focus, in particular, on employees' blogging behavior. The model incorporates two key features that are ubiquitous in blogging forums: users face (1) a trade-off between blog posting and blog reading; and (2) a trade-off between work-related and leisure-related content. We apply the model to a unique data set comprising the complete details of the blog posting and reading behavior of employees over a 15-month period at a Fortune 1000 IT services and consulting firm. Despite getting a higher utility from work-related blogging, employees nevertheless publish a significant number of leisure posts. This is partially because the creation of leisure posts has a significant positive spillover effect on the readership of work posts. Counterfactual experiments demonstrate that leisure-related blogging has positive spillovers for work-related blogging, and hence a policy of abolishing leisure-related content creation can inadvertently have adverse consequences on work-related content creation in an enterprise setting. When organizations restrict leisure blogging, the sharing of online work-related knowledge decreases and this in turn can also reduce employee performance rating. Overall, blogging within enterprises by employees during their work day can have positive long-term benefits for organizations.

Keywords: structural modeling; dynamics; enterprise social media; blog posting; blog reading; work-related content; leisure-related content
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1. Introduction

A number of organizations are grappling with the challenge of devising a "social-media strategy." For many of these companies, such thinking has been externally focused and restricted to an analysis of how social-media outlets might be integrated into their marketing and advertising strategies. Over the last two to three years, however, several firms have adopted various types of social-media technologies, such as blogs and wikis, for internal use. Increasingly, several leading organizations have systems in place to encourage their employees to blog (Lee et al. 2006, Aggarwal et al. 2012, Singh et al. 2014). Prominent adopters include General Motors, IBM, HP, Microsoft, Infosys, Google, and Charles Schwab, among others. From an internal perspective, some have argued that the organizational adoption of social-media outlets such as enterprise blogs will improve access to knowledge experts, increase the rates of problem solving and new-product development, and reduce the costs of internal communication (McAfee 2006). The general thinking within such firms is that enterprise blogging forums can provide a structured platform to support employee participation in brainstorming and idea sharing, thus deepening a company's pool of knowledge. Therefore, the use of blogs as a mechanism for knowledge creation and dissemination has increased their adoption in enterprises (Lee et al. 2006, Huh et al. 2007, Yardi et al. 2009).

However, employees' motivations to blog may not always align with a firm's objectives. In enterprise blogging platforms, work- and leisure-related content often coexist on the same page.[1] Thus, some employees' blog posts may not be relevant to their work-related knowledge or professional expertise. Some firms believe that such behavior can undermine the purpose of enterprise blogging. Therefore,

[1] In this paper, by leisure-related blogs, we refer to all blog content that is not work related. This includes topics such as travel, sports, entertainment, photography, etc. Additional details are provided in Table 2 (see §4.1).

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it is increasingly important to understand employees' blogging behavior in an enterprise social-media setting to gain insights into how firms' policy interventions can influence employee behavior. Typically, employees' propensity to create or consume content on a blog is constrained by the time available for such activities. Thus, the utility they derive from blogging is determined by a trade-off between work- and leisure-related content. Employees also face another trade-off: how much time to spend on content generation (i.e., posting to blogs) versus content consumption (i.e., reading blogs).

Employees can benefit from the readership they gain from blogging on an enterprise social-media platform in a variety of ways. Work-related blogging allows individuals to communicate their expertise to a broader audience at a relatively low cost and develop their reputations. Once employees are identified as "experts" in certain domains, they may benefit from economic incentives, such as promotions and salary increases (Kavanaugh et al. 2006, Aggarwal et al. 2012). Leisure-related blog posting, on the other hand, can improve employees' popularity among their peers and make them "opinion leaders" on select topics. Reading blogs also provides benefits. An increase in work-related knowledge from reading blogs may help employees become more professionally productive, more informed about new ideas, create new opportunities for collaboration, and so on (Huh et al. 2007, Yardi et al. 2009). Leisure-related information can satisfy employees' interests and allow them to relax (Singh et al. 2014), thereby indirectly potentially improving their subsequent productivity.

Blog readership is typically a measure of the quality of one's contribution over a period of time. An employee with a high work-related readership accumulated over time can gain readership-based reputational benefits even if the employee does not post in the current period. In contrast, an employee with a low work-related readership will find it much more difficult to develop a substantial readership based solely on current-period posting. As posting-related readership accrues based on employees' blogging contributions over a longer time horizon, the reputational benefits of blogging depend on an employee's "cumulative readership" over time. Similarly, the knowledge an employee gains from reading blogs can improve productivity and performance not only in the current period but also over a longer time horizon (McAfee 2006).[2] Therefore, we theorize that employees in an enterprise setting need to maximize lifetime utility rather than immediate utility, when making their decisions regarding the trade-offs described above.

Although "cumulative work readership" and "cumulative leisure readership" provide employees with very different benefits, these two types of readership can have strong positive or negative relationship. Readers may follow particular bloggers, rather than specific topics or posts. Work or leisure posts by a given blogger appear on the same forum. Thus, employees with high levels of cumulative leisure readership can attract readers to their work-related posts, and vice versa. If this occurs, there may be positive spillovers between work and cumulative leisure readership. However, employees with high cumulative leisure readership may be regarded as "unprofessional" in a work context. In this case, readers would not expect their work-related posts to be of high quality; thus a high leisure readership can have a negative impact on an individual's work readership. Because of these two countervailing effects, it is interesting to understand the direction and magnitude of the relationship between cumulative work and leisure readership.

In this paper, we examine the following three questions: (1) How do employees allocate their time to the different types of blogging activities in an enterprise setting when facing the trade-offs between work- and leisure-related content and between posting and reading content? (2) Is there any relationship between work- and leisure-related readership accruing from blogging dynamics, and if so, are these spillovers positive or negative? (3) What would be the impact of a policy that prohibits employees from creating leisure-related blogs on the creation and consumption of work-related blogs? We formulate an employee's decision on when to write or read and what to write or read (in terms of work-related or leisure-related content) as a dynamic structural game.

There are two main components of the employee's utility function, which forms the core of this paper. The first is the cumulative readership of an employee's blog. In each period, an employee receives utility from her cumulative readership, separately for work- and leisure-related posts. Individuals also derive utility from their "knowledge state," which can be improved by reading blog posts (Huh et al. 2007, Yardi et al. 2009, Singh et al. 2011). This knowledge state forms the second component. Similar to readership-based utility, we allow the knowledge-based utility derived from work- and leisure-related posts to differ.[3]

[2] In addition, the CEO of the Fortune 1000 firm that provided us with our data stated that "[e]mployees' blogging activities are strongly correlated with their productivity."

[3] Note that in this paper, an employee's knowledge state measures the knowledge she gains from blogging internally. The knowledge that the employee obtains from external or offline activities are not included, because we do not observe this in our data.

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We apply the model to a unique data set comprising the complete details of blog posting and reading behavior for a large data set of 2,396 employees over a 15-month period at a Fortune 1000 IT services and consulting firm. Our results reveal that employees derive approximately 27%–71% greater utility from cumulative work readership than from the same amount of cumulative leisure readership. Although the readership of leisure posts provides less direct utility than work posts, employees nevertheless create leisure-related posts, as the publication of leisure posts has a significant positive spillover effect on the readership of work posts. We find that if there were no readership spillover effect from leisure to work, leisure posting would decline by approximately 33%. On average, we find that reading and writing work-related posts is more costly than reading and writing leisure-related posts. We also find that the joint cost of reading work and leisure posts is lower than the sum of reading the two posts separately. This may be the result of reduced search costs.

There is also evidence of competition among employees to attract readership for their posts. This leads to an interesting tension for an individual as a blogger and as a reader. As a blogger, the individual would like peers to produce fewer posts to allow her to attract a larger readership base. In contrast, as a reader, she would like peers to produce more posts, as she can gain additional knowledge from them. We find that even a 10% decrease in competition could increase work-related posting by approximately 18% and work-related reading by approximately 13%.

Using the point estimates of the parameters, we conduct a counterfactual experiment to analyze the effects of prohibiting leisure-related posting. Interestingly, this policy does not increase work-related posting. Instead, it reduces the probability of work-related posting from 6.5% to 0.65%. This suggests that a policy of prohibiting leisure-related activities can hamper work related knowledge sharing in an enterprise setting. Intuitively, two countervailing forces exist under such a policy. On the one hand, a policy of prohibiting leisure posting can provide employees with additional time to generate work-related posts. On the other hand, this policy can also eliminate readership spillover effects from leisure to work posting and, hence, reduce employees' incentives to create work-related posts. In our setting, the second force dominates the first, leading to an overall reduction in work-related posting. A potential measure of the external validity of our "knowledge gained from blogging activities" is that the knowledge an employee gains from reading blogs leads to an increased performance rating for that employee. Using data on performance evaluations on a subset of employees in our sample, we also find that individuals who are in a higher knowledge state receive higher job performance evaluations on average.

The overall aim of our study is to make the following contributions. First, to our knowledge, this is the first study to employ a dynamic structural framework to analyze employee blogging activities to derive insights into the trade-offs between work- and leisure-related blogging and between content creation (blog writing) and content consumption (blog reading). Although prior studies have investigated why individuals create content on blogs, they are based on surveys/questionnaires, which can be affected by self-reporting bias. In contrast, our study uses actual microlevel blogging activity data from a large, enterprise-wide setting to shed light on why individuals blog and model employee behavior accordingly. Further, a key benefit of structural models is that they do not suffer from the Lucas critique and can be used to analyze the impact of policy interventions (Lucas 1976). As a result, our framework can be used to analyze the potential impacts of policy interventions. Second, our model generates important managerial implications for firms that may be contemplating prohibiting leisure-related blogging within the enterprise. By demonstrating that there are positive spillovers from leisure-related blogging to work-related blogging, and vice versa, our results suggest that a policy prohibiting leisure-related content creation can have unintended, adverse consequences on work-related content creation. Finally, our study's methodological contribution is to provide a way of accounting for unobserved states in the Weintraub et al. (2008) framework through the use of a hidden Markov model (HMM) framework. We combine the method proposed in Weintraub et al. (2008) with the Arcidiacono and Miller (2011) framework to benefit from the computational simplicity of one approach and the other's ability to account for unobserved state variables.

The remainder of this paper is organized as follows. In §2, we review the literature relevant to this paper. Section 3 presents our model of employee blogging dynamics. Section 4 describes our data and estimation strategies. We report estimation results in §5, followed by the policy experiment and post hoc analysis in §6. Section 7 summarizes and concludes our study.

2. Literature Review

Our research is related to multiple streams of the literature. The first stream of relevant literature relates to the impact of blogs. Several studies have focused on how different aspects of user-generated blogs affect product sales and market structure. Dhar and Chang (2009) find that the volume of blog posts on a musical album is a significant predictor of the album's

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future sales. Gopinath et al. (2013) find that postrelease blog valence has a statistically significant effect on the postrelease box-office performance of films in local geographical markets, whereas postrelease blog volume does not. Dewan and Ramaprasad (2012) demonstrate that the intensity of music sampling is positively associated with the popularity of a blog among previous consumers. Dewan and Ramaprasad (2014) study the interplay between blog buzz, radio play, and music sales. Sun and Zhu (2013) analyze blog posts on a Chinese portal site after the launch of an ad-revenue-sharing program and find that popular content in blog posts increased after the introduction of the program. Shriver et al. (2013) study the causal effect of blog content on users' ability to form social ties and find that social ties affect content creation, and vice versa.

Furthermore, a number of papers investigate the effect of enterprise social media on firm performance. For example, Huh et al. (2007) reveal that blogs facilitate 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 an enterprise. Studying a large internal corporate blogging community using log files and interviews, Yardi et al. (2009) find that employees expect to receive attention when they contribute to blogs, but the results are often not commensurate with these expectations. Singh et al. (2014) study the blog reading dynamics of employees within a large firm and find that most of the employees' time is devoted to reading and writing leisure-related posts. Aggarwal et al. (2012) find that negative blog posts act as a catalyst for increasing overall blog readership, and the effect of this increased readership of positive posts is generally sufficient to offset the adverse effect of a few negative posts regarding firm value. Wattal et al. (2010) study the role of network externalities on the use of blogs in an organization and demonstrate that the use of blogs in an individual's network is associated with an increase in own usage and this network effect is stronger for members of younger generations.

To our knowledge, no prior work has investigated the incentives for individuals to participate in blogging activities while examining the outcomes of firms' internal social-media policies. In online settings, users need to allocate resources between content-generation and content-usage activities, as they can take on the dual role of creators and consumers (Trusov et al. 2010, Ghose and Han 2011). However, there is little research quantifying the relationships between how content on a social-media platform is created and consumed. The primary reason for such a gap is that, whereas data on content creation are easily available, data on content consumption are typically not available to researchers. However, consumption information can be retrieved from proprietary access logs. A small but emerging stream of work has begun to examine both content-creation and content-consumption data (Ghose and Han 2010, 2011; Ahn et al. 2011; Albuquerque et al. 2012). Ghose and Han (2010) find evidence of dynamic learning in multimedia content created using mobile devices. Ghose and Han (2011) analyze a data set encompassing users' content creation and consumption behavior on mobile devices and find a negative relationship between content generation and consumption behavior for a given user. Using an "approximation aggregation" rational-expectations equilibrium framework, Ahn et al. (2011) find that enhancing content durability and reducing content consumption costs appear to be the most effective strategies for increasing site visitation. Albuquerque et al. (2012) use data from a print-on-demand service for user-created magazines and find that content price and content creators' marketing actions each has a strong effect on purchases.

Regarding methodology, our paper follows the literature on dynamic structural models. We employ a dynamic game model to capture the key features of individuals' blogging behavior. The dynamic game model, in which multiple agents make decisions and the utility each agent obtains depends on others' decisions, is a specific type of dynamic structural model. It has been widely adopted and applied in industrial organization and marketing literatures (see Dubé et al. 2005 for a detailed review). Pakes and McGuire (1994) and Ericson and Pakes (1995) were the first to introduce the Markov perfect equilibrium concept in dynamic games, and this equilibrium concept has been widely adopted since. However, estimating the dynamic game model is computationally burdensome. In fact, the Markov perfect equilibrium (MPE) is computationally intractable for dynamic games with a very large number of agents, as is the case in our setting. Recently, Weintraub et al. (2008) proposed the concept of an oblivious equilibrium, which approximates the MPE under fairly general restrictions. Another challenge in dynamic game estimation concerns accounting for unobserved heterogeneity. Recently, Arcidiacono and Miller (2011) proposed a strategy employing a mixture model framework to account for unobserved heterogeneity in dynamic game models.

The most closely related studies to our work are by Kumar et al. (2010), who use a dynamic game to examine why users contribute to connected goods in social-networking sites, and Lu et al. (2010), who study how the social structure of individuals on a social-media platform affects their willingness to share knowledge with peers. However, none of these papers examines the implications that a firm's adoption of enterprise social media has for internal employee behavior, nor do they examine employees'

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incentives to create and consume content internally. In our study, we apply a dynamic game model to answer these questions, and this is among the first papers to adopt a structural-modeling approach to address these questions.

3. Model

3.1. Per-Period Utility

Employees $i = 1, \ldots, I$ make blogging decisions on a periodic basis for time periods $t = 1, \ldots, T$. We define a period as one week. In enterprise blogging, there are two types of blog posts that employees can generate represented by $j = \{w, l\}$, where w represents work-related posts and l represents leisure-related posts. In each period, an employee decides whether to read (or post a blog of type j). We use p to denote "post" and r to denote "read." In other words, the action that an employee takes in each period comprises four discrete elements, i.e., d_{itwp}, d_{itlp}, d_{itwr}, and d_{itlr}, where d_{itjp} is an indicator variable, which equals 1 if employee i posts one type j post at time t, and d_{itjr} is a count variable, which takes values 0, 1, 2, and 3. We allow individuals to publish up to one blog posting in each period, but read up to three blogs in each period. If an individual publishes more than one blog post or reads more than three blogs, the number will be truncated to the maximum number.[4] Thus, in total, an employee can make 64 possible combinations of choices. For notational convenience, we convert the four-dimensional action space into a one-dimensional action space A_i, which is defined as $A_i = \{1, 2, \ldots, 64\}$, a finite set of 64 elements. In every period, every employee chooses an action $a_{it} \in A_i$. In addition, $a_t = (a_{1t}, \ldots, a_{It})$ denotes the set of actions that all employees choose at time t.

Note that each value of a_{it} is associated with a single combination of the four activities. For instance, $a_{it} = 1$ corresponds to the situation in which $d_{itwp} = 0$, $d_{itlp} = 0$, $d_{itwr} = 0$, and $d_{itlr} = 0$; $a_{it} = 2$ indicates the situation in which $d_{itwp} = 0$, $d_{itlp} = 0$, $d_{itwr} = 0$, and $d_{itlr} = 1$ etc. In other words, knowing a_{it} is equivalent to knowing $(d_{itwp}, d_{itlp}, d_{itwr}, d_{itlr})$. We assume that an employee's per-period utility function at time t comprises the utility from cumulative readership (denoted R), utility from knowledge gained through blogging activities (denoted K), an unobserved private shock, and everything else in the form of an outside good. An employee's utility at time t, U_{it}, is given by

$$U_{it} = \omega_{it}(R_{itw}, R_{itl}, \theta_1, \theta_2) + \tau_{it}(K_{itw}, K_{itl}, \theta_3, \theta_4) + O_{it} + \gamma_{it}(a_{it}). \quad (1)$$

Here ω_{it} denotes cumulative readership-based utility and τ_{it} denotes the knowledge-based utility from blogging. The parameter R_{itj} reflects the discounted cumulated readership employee i receives from type j posts until period t, and θ_1 and θ_2 are corresponding parameters that capture the effect of readership on utility. The parameter K_{itj} is the blog-related knowledge level of type j for an employee i at the end of period t, and θ_3 and θ_4 are corresponding parameters that capture the effect of knowledge on utility. The consumption of outside goods is indicated by O_{it}, with the utility from per-unit consumption of the outside good being normalized to one. The outside good option denotes different types of activities that an employee can engage in other than blogging. The action-specific random shock associated with the utility that may affect an employee's decisions is denoted $\gamma_{it}(a_{it})$. Before choosing her actions, employee i receives a vector of choice-specific shocks, $\gamma_{it} = (\gamma_{it}(0), \gamma_{it}(1), \ldots, \gamma_{it}(63))$. To achieve identification, we assume that each element in γ_{it} has a type 1 extreme value distribution and is independent and identically distributed across individuals and actions. When employee i chooses an action a_{it}, the choice-specific shock associated with this particular action, i.e., $\gamma_{it}(a_{it})$, is realized and contributes to the individual's current period utility. A summary of all variables and notations is presented in Table 1.

3.1.1. Cumulative Readership. Prior work has shown that individuals who are considered to possess expertise are often accorded power and status within an organization (French and Raven 1959). In the context of digital spaces, Levina and Arriaga (2014) have proposed an analytical lens for studying social status production processes across a wide variety of user-generated content (UGC) platforms and elaborated on what role status markers may play in shaping social dynamics in online platforms. Thus, sharing expertise can produce significant personal benefits in terms of increased recognition within the organization (Constant et al. 1994, Argote et al. 2003, Thomas-Hunt et al. 2003, Roberts et al. 2006, Lu et al. 2010). These benefits are also applicable in blog settings, as intuitively, when employees blog they are sharing their expertise with others. The readership of a blog indicates the extent to which a blogger shares her expertise and readers consider her an expert (Nardi et al. 2004). Thus, the utility a blogger derives from posting would be proportional to the cumulative readership of her posts. In the utility function, the readership-based utility is incorporated as ω_{it}, where

$$\omega_{it}(R_{itw}, R_{itl}, \theta_1, \theta_2) = \theta_1 \log(R_{itw}) + \theta_2 \log(R_{itl}). \quad (2)$$

We argue that employees derive readership-based utility from their cumulative readership (accumulated over time), and not simply from contemporaneous readership (readership they receive in the current

[4] This assumption is based on the descriptive statistics of the data. It is motivated by the observation that less than 0.1% of users publish more than one blog post or read more than three posts of type j in a period. Further, it is also necessary for computational tractability.

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Table 1 Summary of Notations

$\log(R_{itw})$	Natural log of cumulative readership (measured by depreciated past readership and current period readership) of work-related posts for employee i in period t
$\log(R_{itl})$	Natural log of cumulative readership (measured by depreciated past readership and current period readership) of leisure-related posts for employee i in period t
K_{itw}	Work-related knowledge state from blogging (measured in levels); the number of levels is specified after HMM estimation
K_{itl}	Leisure-related knowledge state from blogging (measured in levels); the number of levels is specified after HMM estimation
d_{itwp}	Binary variable with 1 denoting that employee i posts a work-related post in period t and 0 otherwise
d_{itlp}	Binary variable with 1 denoting that employee i posts a leisure-related post in period t and 0 otherwise
d_{itwr}	Number of work-related posts employee i read in period t
d_{itlr}	Number of leisure-related posts employee$i$ read in period t
i, j, t	Indices of employee, post types and periods (week)
$a_{it} s_{it}$	Employee i's action and states in period t
a_t, s_t	Vectors of actions and states of all employees in period t
r_{itj}	New readership employee i receives in period $t$from type j post in period t
β, δ	Discount factors in the lifetime utility function and the depreciation factor in the accumulation of the readership, respectively
$orgstatus_i$	Individual i's organizational status within the firm; it equals 1 if individual i's organizational status is high and 0 if individual i's organizational status is low

period). This is because employees' readership in previous periods can carry over to the next period with a certain discount rate. We apply a log transformation here to adjust the overdispersion in the cumulative readership distribution.[5] The log transformation also yields a concave relationship between readership-based utility and cumulative readership. This makes sense, as an additional unit of readership does not provide as much additional utility to individuals with very high levels of cumulative readership compared to those who have a low level of cumulative readership.

3.1.2. Knowledge. Blogs facilitate access to tacit knowledge and resources vetted by experts. The primary reason that corporations allow their employees to participate in blogging activities during their work hours is that the employee blogs act as a new channel for work-relevant knowledge sharing within the enterprise (Lee et al. 2006, Huh et al. 2007, Yardi et al. 2009, Singh et al. 2014). Employees can acquire knowledge by reading others' posts. By reading others' work-related posts, employees become more productive, more informed of new ideas, and more aware of their colleagues' expertise, all of which may create new opportunities for collaborations (Singh et al. 2011). Leisure posts can help the reader relax and refresh. Furthermore, individuals have an inherent need for leisure, which leisure reading and posting can provide. In the utility function, the knowledge-based utility is captured by τ_{it}, where

$$\tau_{it}(K_{itw}, K_{itl}, \theta_3, \theta_4) = \theta_3 K_{itw} + \theta_4 K_{itl}. \tag{3}$$

3.1.3. Budget Constraint. An employee has a limited amount of time in each week, y_{it}, to engage in different activities. Note that y_{it} is 24×7 hours per week. Let t_{jrm} be the cost of identifying and reading m type j posts and t_{jp} be the cost of developing and writing a type j post. Furthermore, let $t_{rr}(t_{pp})$ represent any cost spillover from reading (posting) both leisure and work posts in the same period; $t_{wrp}(t_{lrp})$ represents any cost spillover between work (leisure) writing and posting. Then, we have the following budget constraint:

$$\begin{aligned} y_{it} = {} & \sum_j t_{jp} d_{itjp} + \sum_j \sum_{m=1}^{3} t_{jrm}(d_{itjr} = m) \\ & + t_{rr}\log(d_{itwr} \cdot d_{itlr} + 1) + t_{wrp}\log(d_{itwr} \cdot d_{itwp} + 1) \\ & + t_{lrp}\log(d_{itlr} \cdot d_{itlp} + 1) + t_{pp}\log(d_{itwp} \cdot d_{itlp} + 1) \\ & + t_o O_{it}. \end{aligned} \tag{4}$$

Here, O_{it} is outside good consumption and t_o is the associated coefficient that captures the per-unit time cost of consuming the outside good. This budget constraint allows us to capture the trade-off that an individual would consider while selecting the time to allocate to blogging and nonblogging activities.

Let us define $\theta_5 = t_{wp}/t_0$; $\theta_6 = t_{lp}/t_0$; $\theta_7 = t_{wrm}/t_0$; $\theta_8 = t_{lrm}/t_0$; $\theta_9 = t_{rr}/t_0$; $\theta_{10} = t_{wrp}/t_0$; $\theta_{11} = t_{lrp}/t_0$; $\theta_{12} = t_{pp}/t_0$, which can be interpreted as the cost of participating in the four types of blogging activities relative to cost of participating in nonblogging activities. Note that θ_7 and θ_8 are both 3×1 vectors. Solving for O_{it}, we obtain

$$\begin{aligned} O_{it} = {} & \frac{y_{it}}{t_o} - \theta_5 d_{itwp} - \theta_6 d_{itlp} - \sum_{m=1}^{3} \theta_{7(m)}(d_{itwr} = m) \\ & - \sum_{m=1}^{3} \theta_{8(m)}(d_{itlr} = m) - \theta_9 \log(d_{itwr} \cdot d_{itlr} + 1) \\ & - \theta_{10}\log(d_{itwr} \cdot d_{itwp} + 1) - \theta_{11}\log(d_{itlr} \cdot d_{itlp} + 1) \\ & - \theta_{12}\log(d_{itwp} \cdot d_{itlp} + 1). \end{aligned} \tag{5}$$

[5] Throughout the paper, log denotes the natural logarithm.

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Combining Equations (5) and (1) yields

$$\begin{aligned} U_{it} = {} & \theta_1 \log(R_{itw}) + \theta_2 \log(R_{itl}) + \theta_3 K_{itw} + \theta_4 K_{itl} + \frac{y_{it}}{t_o} \\ & - \theta_5 d_{itwp} - \theta_6 d_{itlp} - \sum_{m=1}^{3} \theta_{7(m)}(d_{itwr} = m) \\ & - \sum_{m=1}^{3} \theta_{8(m)}(d_{itlr} = m) - \theta_9 \log(d_{itwr} \cdot d_{itlr} + 1) \\ & - \theta_{10} \log(d_{itwr} \cdot d_{itwp} + 1) - \theta_{11} \log(d_{itlr} \cdot d_{itlp} + 1) \\ & - \theta_{12} \log(d_{itwp} \cdot d_{itlp} + 1) + \gamma_{it}(a_{it}). \end{aligned} \tag{6}$$

Because y_{it}/t_o affects all choices in the same way, we drop it from the utility function and rewrite the utility function as

$$\begin{aligned} U_{it} = {} & \theta_1 \log(R_{itw}) + \theta_2 \log(R_{itl}) + \theta_3 K_{itw} + \theta_4 K_{itl} \\ & - \theta_5 d_{itwp} - \theta_6 d_{itlp} - \sum_{m=1}^{3} \theta_{7(m)}(d_{itwr} = m) \\ & - \sum_{m=1}^{3} \theta_{8(m)}(d_{itlr} = m) - \theta_9 \log(d_{itwr} \cdot d_{itlr} + 1) \\ & - \theta_{10} \log(d_{itwr} \cdot d_{itwp} + 1) - \theta_{11} \log(d_{itlr} \cdot d_{itlp} + 1) \\ & - \theta_{12} \log(d_{itwp} \cdot d_{itlp} + 1) + \gamma_{it}(a_{it}). \end{aligned} \tag{7}$$

Note here that y_{it}, the total time available, is exogenous, which is 24×7 hours per week. However, the blogging budget is endogenous. For example, one of the many (64) choices available to employees includes zero work-related postings, zero leisure-related postings, zero work-related reading and zero leisure-related reading. If an individual chooses this option, she spends the entire time budget on the outside good and none on blogging activities. If an individual chooses to publish both work-related and leisure-related blog posts and read multiple work-related posts and multiple leisure-related posts, she spends a substantial amount of time on blogging and less time on the outside good.

3.2. Dynamic Game

3.2.1. State Variables. We define $s_{it} = (R_{itw}, R_{itl}, K_{itw}, K_{itl}, orgstatus_i)$ as the set of the state variables for employee i in period t. The state $orgstatus_i$ denotes individual i's organizational status within the firm. The organizational status of an individual does not change in our data set. We further define $s_{-it} = (R_{-itw}, R_{-itl}, K_{-itw}, K_{-itl}, orgstatus_{-i})$ as the set of state variables of i's peers. Although we can observe the readership levels and organizational status of employees, we cannot observe their knowledge levels. However, employees could learn about others by reading their posts or by interacting with them. Hence, we allow individual decisions and state transitions to be a function of peer knowledge states. That is we assume that employees can observe knowledge levels of their peers. However, we let the data reveal whether peer knowledge states affect the individual decisions and state transitions. All of the firm's employees constitute the group of peers for a given employee. Then, the strategy profile for i depends on $s_t = (s_{it}, s_{-it})$.

Cumulative Readership Evolution. The first four elements in the utility function (Equation (7)) are all state variables that evolve according to the actions employees take in each period. The readership states evolve as follows[6]:

$$R_{itj} = \delta R_{it-1j} + d_{itjp} r_{itj}. \tag{8}$$

Here, δ is a depreciation factor, which is set at 0.95.[7] This depreciation factor accounts for the fact that the contribution of past cumulative readership to current cumulative readership declines as time passes. Individuals will have to regularly post to maintain a high cumulative readership. The parameter r_{itj} is the readership that blogger i receives for the type j post she wrote in period t and is determined as follows:

$$\begin{aligned} r_{itj} = f\Bigg(& R_{itw}, R_{itl}, K_{itw}, K_{itl}, orgstatus_i, \sum_{x:x\neq i} d_{xtwp}, \\ & \frac{\sum_{x:x\neq i} d_{xtwp} R_{xtw}}{\sum_{x:x\neq i} d_{xtwp}}, \frac{\sum_{x:x\neq i} d_{xtwp} R_{xtl}}{\sum_{x:x\neq i} d_{xtwp}}, \\ & \frac{\sum_{x:x\neq i} d_{xtwp} K_{xtw}}{\sum_{x:x\neq i} d_{xtwp}}, \frac{\sum_{x:x\neq i} d_{xtwp} orgstatus_x}{\sum_{x:x\neq i} d_{xtwp}}, \\ & \sum_{x:x\neq i} d_{xtlp}, \frac{\sum_{x:x\neq i} d_{xtlp} R_{xtw}}{\sum_{x:x\neq i} d_{xtlp}}, \frac{\sum_{x:x\neq i} d_{xtlp} R_{xtl}}{\sum_{x:x\neq i} d_{xtlp}}, \\ & \frac{\sum_{x:x\neq i} d_{xtlp} K_{xtl}}{\sum_{x:x\neq i} d_{xtlp}}, \frac{\sum_{x:x\neq i} d_{xtlp} orgstatus_x}{\sum_{x:x\neq i} d_{xtlp}}, \\ & \sum_{x:x\neq i} d_{xtwr}, \sum_{x:x\neq i} d_{xtlr}, \varepsilon_{itj} \Bigg). \end{aligned} \tag{9}$$

The readership of a new type j post is affected by a blogger's own cumulative work (R_{itw}) and leisure (R_{itl}) readership levels, knowledge levels (K_{itw} and K_{itl}), and her organizational status ($orgstatus_i$). It is also affected by the number of work and leisure posts read ($\sum_{x:x\neq i} d_{xtwr}$ and $\sum_{x:x\neq i} d_{xtlr}$) and written ($\sum_{x:x\neq i} d_{xtwp}$ and $\sum_{x:x\neq i} d_{xtlp}$) by her peers in period t and the average work and leisure readership value, knowledge level, and organizational status of peers' who posted work and leisure posts in period t. The average work and leisure readership, associated knowledge levels

[6] Although the readership states are considered continuous here, for estimation purposes we will discretize the readership states in §4.2.

[7] The qualitative nature of the results is robust to several other values of the depreciation factors.

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and organizational status for peers who posted a type j post in period t are represented by

$$\frac{\sum_{x:x\neq i} d_{xtjp}R_{xtw}}{\sum_{x:x\neq i} d_{xtjp}}, \frac{\sum_{x:x\neq i} d_{xtjp}R_{xtl}}{\sum_{x:x\neq i} d_{xtjp}}, \frac{\sum_{x:x\neq i} d_{xtjp}K_{xtj}}{\sum_{x:x\neq i} d_{xtjp}}, \frac{\sum_{x:x\neq i} d_{xtjp}orgstatus_x}{\sum_{x:x\neq i} d_{xtjp}}.$$

These variables that capture peer posting activity and the characteristics of the posters account for the effect of competition. The level of reading represents the total size of readership "pie" and the level of posting represents the number of posts among whom the pie will be distributed.

Further, to account for unobserved or latent factors that may affect r_{itj}, we include the term ε_{itj}. An example of this latent factor is the timeliness of one's blog postings. A highly timely post may increase its poster's readership level. Note that posting is a necessary but not sufficient condition for obtaining readership. As described above, a number of variables affect the readership of a post. To summarize, there are two drivers of an employee's readership in our context: (i) state variables of the blogger and the blogger's peers, and the amount of reading and posting in the category; and (ii) latent or hidden factors such as the timeliness of a post.

Knowledge Evolution. The third and fourth state variables are the knowledge levels of employee i, K_{itw}, and K_{itl}, for work and leisure, respectively. The knowledge of an employee is unobservable to us. In our model, work-related knowledge has $1, \ldots, kw$ ordered discrete levels and leisure-related knowledge has $1, \ldots, kl$ ordered discrete levels. In period t, an individual probabilistically belongs to a knowledge state based on her knowledge stock, 1 being the lowest knowledge state and $kj; j \in \{w, l\}$ being the highest. She can transition from one state to another by participating in learning activities, some of which are observed, over a given period. This allows the transition probability from a given state to another to differ across individuals and across time periods for the same individual. In our setting, the two learning activities we observe are the amount of reading and posting activities of an employee in a period. The probability that individual i will transition from knowledge state K_{it} at time t to K_{it+1} at time $t+1$ is given by

$$P(K_{it+1j} \mid K_{itj}, s_{it}, s_{-it}) = f\left(K_{itj}, d_{itjp}, d_{itjr}\left(\sum_{x:x\neq i} d_{xtjp}\right), d_{itjr}\left(\frac{\sum_{x:x\neq i} d_{xtjp}R_{xtj}}{\sum_{x:x\neq i} d_{xtjp}}\right), d_{itjr}\left(\frac{\sum_{x:x\neq i} d_{xtjp}K_{xtj}}{\sum_{x:x\neq i} d_{xtjp}}\right), d_{itjr}\left(\frac{\sum_{x:x\neq i} d_{xtjp}orgstatus_x}{\sum_{x:x\neq i} d_{xtjp}}\right), \kappa_{itj}\right). \tag{10}$$

Thus, in our model, the type j knowledge state transitions depend on the current knowledge state of the individual (K_{itj}) and both the reading (d_{itjr}) and posting (d_{itjp}) activities of type j. The effect of reading on knowledge transitions is moderated by the average readership ($\sum_{x:x\neq i} d_{xtjp}R_{xtj}/\sum_{x:x\neq i} d_{xtjp}$), knowledge level ($\sum_{x:x\neq i} d_{xtjp}K_{xtj}/\sum_{x:x\neq i} d_{xtjp}$), and organizational status ($\sum_{x:x\neq i} d_{xtjp}orgstatus_x/\sum_{x:x\neq i} d_{xtjp}$) of peers who wrote type j posts in period t. The knowledge state of an individual would influence her ability to learn (Cohen and Levinthal 1990). Reading and posting are learning activities that should affect knowledge state transitions. The number of posts written by peers represents the richness of the content from which a reader could learn. Further, the posts written by bloggers with higher cumulative readership, knowledge, and organizational status are likely to be of higher quality, thereby influencing the learning of readers. Finally, the knowledge state transition could also be affected by other hidden or latent factors unobserved to us that are captured by the term κ_{itj}.

3.2.2. Sequence of Events. The specific sequence of events in our model is as follows:

1. Employees observe their states s_{it} and their peers' states s_{-it}.
2. Employees observe their set of choice-specific random shocks ($\gamma_{it}(a_{it})$).
3. Employees calculate their action-specific expected utility.
4. Employees execute their decisions, the choice-specific random shock is realized, and they receive utility.
5. Employee states evolve to s_{it+1} because of their and their peers' actions.

3.2.3. Lifetime Utility Function. We model an employee's posting and reading decisions as a dynamic optimization problem. The employee's tasks are to decide if and when to read work posts, read leisure posts, write a work post, and write a leisure post to maximize the sum of discounted expected future utility U_{it} over an infinite horizon:

$$\max_{a_{it}} E\left(\sum_{t=1}^{\infty} \beta^t U_{it}(a_{it}, s_t, \gamma_{it}) \,\middle|\, s_t, \gamma_{it}\right). \tag{11}$$

Here, β is the common discount factor. The operator $E_t[\cdot]$ denotes the conditional expectation operator given the employee's information at time t. Three components of the model must be emphasized. First, in our model, an individual's states evolve over time, and as a result, her decisions vary over time, which makes the model dynamic. Second, the employee balances her time between reading and writing, and work and leisure due to the budget constraint. Thus, her actions are interdependent. The work and leisure activities may also be interdependent because of cost

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and readership spillovers. Third, an employee's utility is a function of the decisions made by her peers (through readership and knowledge state transitions), making this a multiagent dynamic game.

3.2.4. Equilibrium Concept. Ericson and Pakes (1995) proposed the MPE as a solution concept for dynamic structural games. In an MPE, each employee's behavior exclusively depends on the current states and on the employee's current private shock. Formally, a Markov strategy for employee i is a function σ_i: $S \times \Gamma_i \to A_i$, where S denotes the states of all individuals, Γ_i denotes employee i's private random shock, and A_i denotes the set of individual i's actions. A profile of Markov strategies is a vector, $\boldsymbol{\sigma} = (\sigma_1, \ldots, \sigma_I)$, in which $\boldsymbol{\sigma}$: $S \times \Gamma_1 \times \cdots \times \Gamma_k \to A$. Here, we drop the time index because the strategy profile is time invariant. If behavior is driven by a Markov strategy profile $\boldsymbol{\sigma}$, employee i's expected lifetime utility given state $\mathbf{s}$ can be written recursively as a Bellman equation:

$$V_i(\mathbf{s}; \boldsymbol{\sigma}) = E_\gamma\bigg[U_i(\boldsymbol{\sigma}(\mathbf{s}, \boldsymbol{\gamma}), \mathbf{s}, \gamma_i) + \beta \int V_i(\mathbf{s}'; \boldsymbol{\sigma})\, dP(\mathbf{s}' \mid \boldsymbol{\sigma}(\mathbf{s}, \boldsymbol{\gamma}), \mathbf{s}) \mid \mathbf{s}\bigg]. \quad (12)$$

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

$$V_i(\mathbf{s}; \boldsymbol{\sigma}, \boldsymbol{\sigma}\_i) \geq V_i(\mathbf{s}; \sigma_i', \boldsymbol{\sigma}\_i). \quad (13)$$

However, given the large number of agents and the huge state space, the MPE is computationally intractable in our setting. Recently, Weintraub et al. (2008) developed the concept of oblivious equilibrium (OE), which approximates MPE under fairly general assumptions. Farias et al. (2012) find that if the market is not overly concentrated and the number of agents is large, which is the case in our setting, OE approximates MPE very well.

OE is based on the notion that in a market with a large number of agents, simultaneous changes in the states of a large number of actors would average out and the industry state would remain roughly constant over time (Weintraub et al. 2008). As a result, an agent can make near-optimal decisions by considering her own state and the steady state average industry state. OE is also a more reasonable equilibrium concept in our setting, as individuals are unlikely to know the states of each of their peers, which they are required to do in MPE. Further, in our data set, we observe that the average peer states are relatively stable and are not trending. Thus, we use OE to approximate MPE in our setting.

4. Empirical Estimation

4.1. Data

Our data come from a large Fortune 1000 IT services, business-process outsourcing, and consulting firm. It is a U.S.-based firm with significant presence and operations in several other countries across multiple continents: Europe, Asia, and the Americas being the major areas. *Fortune* magazine named this firm one of the fastest-growing companies in 2009, with several billion dollars in annual revenue. The firm has undertaken several strategies to encourage greater knowledge and information sharing across and within locations. Prominent among these measures is the use of Web 2.0 technologies such as blogs for use within the enterprise.

These blogs are hosted on an internal platform and are not accessible to individuals outside the organization. This platform allows every employee to host her own blog, which is accessible to all of the firm's employees across the entire hierarchy. The identity of the blogger is disclosed on the blog. A brief description of an employee's most recent posts is displayed on the employee's blog homepage in the order in which they were posted (the most recent post appears at the top). This listing is done irrespective of the category or topic of the post. That is, both work- and leisure-related posts appear on the homepage. The titles of these posts contain hyperlinks that users can click to view the full content of the post. Notably, the firm offers no explicit reward structure.

Bloggers classify their posts into one of several categories (for example, software testing, films, history, knowledge management, senior management, etc.). To be able to measure the knowledge-sharing component, the firm tracks the blogs that an employee reads at a given point in time; the readership count of each post is displayed along with the blog post and is observable to everyone. As the blogs are only internally accessible, the firm does not impose any restrictions on the types of posts that employees can write. To analyze the type of content shared on the internal blogosphere, the firm broadly classifies the blog-article categories into two topics: work related (w) and leisure related (l). Table 2 presents the subcategories that constitute each topic.

Our data consist of the blog reading and writing activities of 2,396 employees over a 64 week period. These include employees who both publish and read at least one post during the sample period. We have data on the precise timestamps of blog-reading and blog-posting activities. For the purposes of estimation, we define a period as one week. This provides us with data for 64 periods in total. We treat the first 16 weeks as the holdout period for calculating the initial state variable values. We estimate and test the model using

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Table 2 Blog-Post Classification

Topics	Leisure related	Work related
Subcategories	Fun; movies-TV-music; sports; puzzles; chip-n-putt; religion-spiritual-culture; history-culture; photography; arts; poetry-stories; books; geographies	FLOSS; technology; testing; domains; corporate functions; knowledge management; project management; business development; senior management; practices-programs-accounts

data from the remaining 48 weeks (week 17–64). We use the data from week 17 to 56 to estimate the model parameters. We use data from week 57 to 64 to test model performance.

Table 3 contains high-level descriptive statistics on our data. These employees wrote 25,981 posts during the 64-week period, indicating that not every employee published a blog post in every period. Of these, 9,934 posts were work related and 16,047 leisure related. There were 26,784 readings of work posts and 37,232 readings of leisure posts by these employees during the 64-week period. We classify the organizational status of an employee into "high" and "low" categories based on her position in the organizational hierarchy. Because this firm is in the IT industry, anyone at or above the rank of a director in the company is classified as a "high-status" individual. Of the 2,396 employees in our sample, 214 employees are classified as "high-status" and the remaining 2,182 are classified as "low status."

The descriptive statistics for the key variables used to construct the model's variables are presented in Table 4. On average, each week, 6.50% of employees publish a work-related blog post; 10.60% publish a leisure-related blog post; 17.58% read work-related blog posts; and 24.39% read leisure-related blog posts. On average, 40.03 employees read a given work-related post, and 107.48 employees, on average, read a given leisure-related post.

4.2. Estimation Strategy

Our model and data raise several challenges for estimation. First, the readership states are continuous. We derive the continuous cumulative readership states using Equation (8). However, the continuous states make the estimation computationally difficult. As a result, we discretize the log of cumulative readership states (from 0 to 7.7) into seven equally sized intervals.[8] We selected seven intervals, as it allows us to have sufficient data in each discrete interval and meaningful transitions from each state. This allows us to calculate the state transitions appropriately.

[8] Log cumulative readership observations above 7.7 were added to the last bin.

Table 3 Overall Sample Statistics

Number of employees	2,396
Number of high-status employees	210
Number of low-status employees	2,179
Period length (week)	1
Number of periods	64
Total posts written	26,075
Work-related posts written	9,967
Leisure-related posts written	16,108
Work-related post reading	398,979
Leisure-related post reading	1,731,288

Notes. In total, 45,287 employees participated in blogging over the 64-week period. However, most of these employees were not active users of blogging. Only 2,396 employees created at least one post and read at least one post during the 64-week period. These 2,396 employees constitute the full set of employees who ever wrote a post. However, these employees only form a subset of the total readership. In the main text, we model the reading and posting decisions of these 2,396 employees. However, because all employees know how many readers each post received, the readership equation in the main text uses the true readership data (from the full sample of 45,287 potential readers). We also conducted a robustness check, in which we only consider reading by the 2,396 employees in the estimation of readership Equation (9). The qualitative nature of all our results remains unchanged. In this table the number of work and leisure readings correspond to those by all employees and not just the 2,396 employees in the sample.

Table 4 Descriptive Statistics of Key Variables

Variable	Mean[a]	Minimum	Maximum
R_{itw}	16.281	0	4,043.83
R_{itl}	86.192	0	7,438.58
K_{itw}	0.120	0	1
K_{itl}	0.159	0	1
d_{itwp}	0.065	0	1
d_{itlp}	0.106	0	1
$d_{itwr} = 1$	0.080	0	1
$d_{itwr} = 2$	0.034	0	1
$d_{itwr} = 3$	0.008	0	1
$d_{itlr} = 1$	0.124	0	1
$d_{itlr} = 2$	0.037	0	1
$d_{itlr} = 3$	0.016	0	1
$orgstatus_i$	0.089	0	1

[a]We first calculate the average of each variable across individuals in each period and then calculate the mean across periods.

Because we discretized the readership states, we also discretize the corresponding parameters in the utility function. We have seven parameters for each readership state, one corresponding to each level of the readership state. That is θ_1 and θ_2 are now vectors of size 7×1 each. The state size (NS) for an individual's own state is $7 \cdot 7 \cdot 2 \cdot kw \cdot kl$. The size of the individual-specific state transition matrix would be $NS \times NS$. Second, knowledge states are unobserved to us. Thus, as mentioned above, we use the procedure proposed by Arcidiacono and Miller (2011) for models with unobserved state variables.

The estimation procedure operates as follows.

Step 1. Estimate the transition probabilities for $\log(R_{itw})$, $\log(R_{itl})$, K_{itw}, and K_{itl}.

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All the states have discrete ordered levels. As a result, we model the state transition as an ordered logistic regression. We allow the regression parameters to be current state specific. The conditional choice probabilities (CCP) are the probabilities of choosing actions given the state values. Given the states, we can estimate the CCP through a multinomial logistic regression of actions on state variables. The *CCP* and the state transitions are jointly estimated through a *HMM*.

The *HMM* operates as follows: The state transition probabilities for $\log(R_{itw})$ and $\log(R_{itl})$ are a function of the variables given in Equation (9). Further, the state transitions for K_{itw} and K_{itl} are functions of the variables given in Equation (10). In Equations (9) and (10), we employ the discretized values of cumulative readerships when calculating the readership-specific variables. Let $D_i = \{a_{i1}, a_{i2}, \ldots, a_{iT}\}$ represent the sequence of choices for individual i, $S_i = \{s_{i1}, s_{i2}, \ldots, s_{iT}\}$ represent the state sequence over time for individual i, π_i represent the initial state distribution ($1 \times NS$) for individual i, and λ represent the set of parameters that govern the state transition probabilities and the *CCP* ($NS \times 64$). An element jk of *CCP* represents the probability of action k given state j. For simplicity, let us represent the observed state by O and the unobserved/hidden state by H. Further, let O_i and H_i represent the observed and unobserved state sequences for individual i.

Then, the probability of the observed outcome sequence D_i and observed state sequence O_i is obtained (Rabiner 1989) as follows:

$$\begin{aligned} L(D_i, O_i) &= P(D_i, O_i \mid \lambda) \\ &= \sum_{\forall H_i} (P(D_i \mid \lambda, O_i, H_i) \cdot P(O_i \mid \lambda, H_i) \\ &\quad \cdot P(H_i \mid \lambda)). \end{aligned} \tag{14}$$

We maximize Equation (14) to obtain parameter set λ. The initial state distribution is analytically derived by solving the equation $\pi_i = \pi_i \bar{Q}$, where $\bar{Q}$ is the state transition matrix calculated at the mean value of covariates for individual i. The number of levels in the knowledge states is determined by comparing the Akaike information criterion from models with different numbers of levels in the knowledge states.

Step 2. Estimate utility parameters.

In this step, we estimate the structural parameters: $\rho = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \theta_9, \theta_{10}, \theta_{11}, \theta_{12})$. In an OE, the *CCP* is a function of an individual's own state. Peers influence the utility of an individual because the *CCP* and the state transition probabilities determine the steady state peer state distribution.[9] The main computational advantage that OE provides is to convert the multiagent dynamic game problem into a single agent dynamic optimization problem. Moreover, one can use any one of several methods proposed in the literature to solve this single agent dynamic optimization problem. We follow the Aguirregabiria and Mira (2007) nested pseudo maximum likelihood procedure to solve the single agent dynamic optimization problem.

4.3. Identification and Normalization

A few identification issues must be addressed before the model can be consistently estimated. First, we assume that the private shocks are extreme value type 1 distributed, as is common in the literature. Second, we cannot jointly identify t_o and the cost-specific parameters. Thus, we normalize $t_o = 1$. Third, for identification, we specify the utility parameter corresponding to the lowest level of the readership state as zero. To ensure that only data from periods after the equilibrium is reached are used in the estimation, we consider a subset of our data (16 weeks) as the preestimation sample and estimate and test our model using the remaining data (48 weeks). We also perform a robustness check with a 30-week holdout period and observe no change in the qualitative nature of the results.

5. Results

The results reveal that peer knowledge states significantly affect employee decisions. Note that in an OE, an individual's decisions are based on steady state peer state distribution, an individual does not need to know every peer's individual knowledge state. In the subsequent discussion, we assume that individuals consider their peers' knowledge states in making decisions. In Step 1 of the estimation, we identify the number of levels in the knowledge states. We compared several models with different numbers of knowledge state levels from 1 to 5. The results indicate that a model with two levels of knowledge for both work and leisure perform the best with respect to the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Thus, from here on the remaining discussion assumes there are only two state levels for both the work and leisure knowledge states. In Step 1, we also estimated the state transition probabilities. These transition probabilities reveal several insights that we discuss in the following subsection. Because space limitations, we only discuss the work readership and knowledge transitions.

5.1. Readership State Transitions

5.1.1. Readership Spillover from Leisure to Work. In Table 5, we report the cumulative work readership state transitions from posting a work-related post at time t for a low-organizational-status

[9] The peer state distribution indicates the number of peers in each state.

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Table 5 Expected Cumulative Work Readership State at Time $t+1$ Due to Publishing One Work-Related Post for an Employee in a Low Work Knowledge State

Cumulative work readership state at time t	Cumulative leisure readership state at time t: 1	2	3	4	5	6	7
1	1.120	1.153	1.193	1.243	1.303	1.374	1.457
2	2.116	2.155	2.196	2.246	2.307	2.379	2.464
3	3.099	3.134	3.170	3.215	3.270	3.336	3.414
4	4.084	4.115	4.146	4.186	4.234	4.295	4.366
5	5.050	5.071	5.091	5.116	5.148	5.188	5.238
6	6.019	6.029	6.038	6.048	6.062	6.080	6.103
7	7.000	7.000	7.000	7.000	7.000	7.000	7.000

Note. Low-organizational-status employee; peer-specific variables are set at mean levels.

individual in a low knowledge state. To construct this table, we set the peer-specific variables (from Equation (9)) at their mean values. An employee's leisure knowledge does not significantly influence the work readership transition. Thus, it is omitted in the construction of Tables 5–7.

Table 5 indicates that the expected work readership state is higher than an employee's current state if she posts a work-related post. That is, the new readership that a new work-related post will generate outweighs the depreciation in existing readership. Interestingly, the expected work readership resulting from posting a work-related post is higher for employees with higher leisure readership than otherwise. For example, for an employee with a work readership state of 4, the expected work readership state from posting a work-related post is 4.186 if her leisure readership state is 4 and 4.366 if her leisure readership state is 7. This indicates a positive and significant spillover from leisure to work readership. As mentioned above, several of a blogger's posts are displayed on the same homepage, irrespective of whether they are work or leisure related. As a result, when readers visit a blog, they are exposed to both work and leisure posts. Thus, some readers who may visit the blog to read a leisure post may also end up reading a work post. We also find a similar spillover effect from work readership to leisure readership.

Table 6 Expected Cumulative Work Readership State at Time $t+1$ from Publishing one Work-Related Post for an Employee in a High Work Knowledge State

Cumulative work readership state at time t	Cumulative leisure readership state at time t: 1	2	3	4	5	6	7
1	1.247	1.308	1.380	1.464	1.561	1.669	1.788
2	2.251	2.312	2.385	2.471	2.568	2.677	2.797
3	3.219	3.275	3.342	3.420	3.513	3.618	3.735
4	4.189	4.238	4.299	4.371	4.456	4.557	4.668
5	5.119	5.151	5.191	5.239	5.298	5.369	5.454
6	6.050	6.062	6.080	6.102	6.127	6.159	6.204
7	7.000	7.000	7.000	7.000	7.000	7.000	7.000

Note. Low-organizational-status employee; peer-specific variables are set at mean levels.

Table 7 Expected Cumulative Work Readership State at Time $t+1$ from Publishing One Work-Related Post When Competition Is 10% More Intense

Cumulative work readership state at time t	Cumulative leisure readership state at time t: 1	2	3	4	5	6	7
1	1.105	1.134	1.170	1.214	1.269	1.334	1.412
2	2.064	2.135	2.173	2.218	2.274	2.339	2.419
3	3.050	3.118	3.150	3.190	3.239	3.300	3.372
4	4.037	4.101	4.128	4.162	4.207	4.263	4.327
5	5.008	5.061	5.080	5.102	5.130	5.169	5.211
6	5.980	6.025	6.033	6.042	6.053	6.069	6.091
7	7.000	7.000	7.000	7.000	7.000	7.000	7.000

Note. Low-organizational-status employee in a high work knowledge state.

5.1.2. Spillover from Work Reading to Work Readership. In Table 6, we report the expected work readership state from posting a work-related post for a low-organizational-status employee who is in a high work knowledge state. The peer-specific variables used to construct Table 6 are set at their mean values. Work reading primarily affects a reader's work knowledge state. To determine the spillover effect from work reading to work readership, we can compare how work knowledge affects the evolution of the work readership state. By comparing the values in Table 5 to their corresponding values in Table 6, it is clear that the values are higher in Table 6. For example, the expected work readership from posting a work-related post for an employee with a work readership state of 4 and leisure readership state of 4 is 4.371 if she has high work knowledge and 4.186 if she has low work knowledge. This indicates there is a significant, positive spillover from work reading to work readership. As discussed earlier, bloggers with greater knowledge may be able to write better-quality posts that attract more readers. We also observe a similar spillover effect from leisure reading to leisure readership. Although not discussed here, we also find that employees with higher organizational status receive higher readership for their new work-related posts.

5.1.3. Effect of Competition on Work Readership. We find intense competition for readership. The readership state transition regressions reveal a negative and significant effect of variables related to peer posting behavior on an individual's transitions to higher readership states. To assess how competition for readership affects the evolution of work readership states, we calculate readership state transition probabilities at a higher level of competition. To conduct this analysis, we increase the peer-specific variables (other than the number of posts read by peers and the variables corresponding to peers' leisure posting) by 10%

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Table 8 Work knowledge Transition Probability from Reading (Peer-Related Variables at Mean Values and Zero Work-Related Posts Written by an Individual)

	(a)		(b)		(c)		(d)	
	Read zero work post		Read one work post		Read two work post		Read three work post	
	State at period $t+1$		State at period $t+1$		State at period $t+1$		State at period $t+1$	
State at period t	LWK	HWK	LWK	HWK	LWK	HWK	LWK	HWK
LWK	97.07%	2.93%	95.17%	4.83%	93.87%	6.13%	92.88%	7.12%
HWK	15.45%	84.55%	9.80%	90.20%	7.79%	92.21%	6.72%	93.28%

Note. LWK, low work knowledge; HWK, high work knowledge.

and recalculate the work readership state transition probabilities and report the results in Table 7. This table is constructed for a low-organizational-status employee in a work high knowledge state. In constructing Table 7, we assume that peers wrote 10% more work posts than average; the average work and leisure readerships, knowledge levels, and organizational status of these peers are 10% higher than average. This means that more peers are writing work posts and these peers have higher work and leisure readerships, knowledge levels, and organizational status than the mean levels of peers who wrote posts in a given period. All other peer-specific variables that affect changes in work readership are set at their mean levels.

By comparing Table 7 with Table 6, we observe that there is competition for readership. As competition increases, the expected new readership that an employee's new work-related post can obtain decreases. For example, the expected work readership state resulting from posting a work-related post decreases from 4.371 to 4.162 when competition increases by 10% from its mean level for a low-organizational-status employee in a high work knowledge state whose work and leisure readership states are both 4. We observe a similar effect of competition on changes in the leisure readership state.

5.2. Knowledge State Transitions

To determine how reading work-related posts affects work-related knowledge state transitions, we report four transition matrixes in Table 8. To construct the transition matrixes in Table 8, we set the peer-specific variables (from Equation (10)) at their mean values and assume that the employee has not written a work-related post in period t. Because an employee's organizational status and work and leisure readerships do not affect her work knowledge transitions, we ignore them when constructing these transition matrixes. Panel (a) of Table 8 reports a work knowledge transition matrix for an individual who has not read any work-related post in period t. Panels (b), (c), and (d) of Table 8 represent the work knowledge transition matrixes for cases in which an individual has read, respectively, 1, 2, and 3 work posts in period t.

From panel (a) of Table 8, we can see that the states are very sticky. It is difficult to move from one state to another. The probability that an individual in a low state will move to a high state is only 2.93% if he does not read or write a work-related post. However, reading work-related posts increases an employee's work-related knowledge. Table 8 indicates that reading one, two, and three work posts increases the probability that an employee in a low work knowledge state will transition to a high work knowledge state from 2.93% to 4.83%, 6.13%, and 7.12%, respectively. Reading work-related posts also helps an employee in a high work knowledge state to remain in a high work knowledge state.

An individual can also learn while composing her blog post. When an individual develops a post it helps her in thinking through her ideas, combine information from multiple resources, and provide a good analysis. Going through this process should help an individual improve her knowledge. Further, readers may also benefit if a larger number of posts were available to read. A reader would have a greater variety of content from which to choose. Moreover, work-related posts by employees who have higher levels of work readership, knowledge, or organizational status may represent higher-quality content.[10] Readers could benefit from access to such high-quality content.

In panel (a) of Table 9, we present the state transition matrixes for an employee who posted one work-related post in period t and read zero work-related posts in period t. Comparing panel (a) of Table 9 with panel (a) of Table 8, we observe that an individual is also able to gain work-related knowledge by writing a work-related post. Writing a work-related

[10] We find that posts written by individuals with higher knowledge or readership are more likely to be cited by others. Further, we solicited assistance from experts to classify software-testing posts in terms of quality of the content. The results indicated that posts written by individuals with higher levels of knowledge or readership were more likely to be classified as high quality than otherwise. We report these results in the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mnsc.2014.2125).

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Table 9 **Work Knowledge Transition Probabilities from Posting and Reading Posts with Increased and Better Content**

	(a)		(b)		(c)		(d)	
	Post one work post		Read one work post		Read two work posts		Read three work posts	
	State at period $t+1$		State at period $t+1$		State at period $t+1$		State at period $t+1$	
State at period t	LWK	HWK	LWK	HWK	LWK	HWK	LWK	HWK
LWK	94.10%	5.90%	93.83%	6.17%	91.70%	8.30%	89.25%	10.75%
HWK	8.13%	91.87%	7.65%	92.35%	5.46%	94.54%	4.78%	95.22%

Notes. LWK, low work knowledge; HWK, high work knowledge. Panel (a): zero work-related posts read by individual. Panels (b)–(d): zero work-related posts written by an individual when peer-related variables are 10% higher than their mean values.

post yields a greater increase in work-related knowledge than reading one. Specifically, writing a work-related post increases an employee's probability of moving from a low work knowledge state to a high work knowledge state from 2.93% to 5.90%.

In panels (b), (c), and (d) of Table 9, we present the work-related knowledge transition matrixes where an individual has read one, two, and three work posts, respectively, while posting zero work-related posts, and peers have written 10% more posts than average and the average readership, knowledge and organizational status of peers who wrote work posts is 10% higher than average. Here, we can see that readers learn more as their peers write additional posts and a larger number of high-quality posts are available. For example, the probability of transitioning from a low work knowledge state to a high work knowledge state increases from 4.83% to 6.17% when peers have written 10% more posts and the posts are written by individuals with 10% higher work readership and knowledge levels and organizational statuses than the average. This finding highlights the countervailing effects of peer blogging. As we demonstrated above, as a blogger, an employee competes with her peers to attract readership to her posts. The value that a blogger may derive from her posts decreases when peers write additional posts or when peers with higher readerships, knowledge, or organizational statuses write posts. Thus, as a blogger, an employee would prefer peers to write fewer posts. However, as a reader, the same blogger benefits when her peers write additional posts.

5.3. Utility Function Parameters Results

The results for the second stage are presented in Table 10. For estimation purposes, the discount factor β is set to 0.95. The results indicate that employees gain positive utility from work-related cumulative readership and leisure-related cumulative readership. Employees also gain positive utility from work and leisure knowledge.

Comparing the parameters corresponding to the readership state variables, we can see that a given level of work readership provides greater utility than an equivalent level of leisure readership. For example, an individual with a work readership level of 4 obtains a one-period utility of 2.062 from having a work readership level of 4. In contrast, an individual with a leisure readership level of 4 obtains a one-period utility of 1.621 from having a leisure readership level of 4. Furthermore, this difference in utility for equal levels of work and leisure readerships is more pronounced at higher readership levels. Using t-tests, we find that the parameters corresponding to work readership are statistically significantly greater than the corresponding parameters for leisure readership.

The results for the knowledge-state-related parameters reveal that individuals derive greater utility from higher levels of work-related knowledge than higher levels of leisure-related knowledge. Specifically, the one-period utility from being in a high work

Table 10 **Estimated Utility Function Parameters**

	Work-related parameters	Leisure-related parameters
Readership-related parameters		
Cumulative readership level = 1	Fixed at zero	Fixed at zero
Cumulative readership level = 2	0.504***	0.331***
Cumulative readership level = 3	1.231***	0.890***
Cumulative readership level = 4	2.062***	1.621***
Cumulative readership level = 5	3.002***	2.153***
Cumulative readership level = 6	5.093***	3.295***
Cumulative readership level = 7	9.159***	5.358***
Knowledge-related parameters		
Knowledge level = *Low*	Fixed at zero	Fixed at zero
Knowledge level = *High*	1.351***	0.117**
Cost-related parameters		
Writing one post	5.699***	4.013***
Reading one post	2.431***	1.703***
Reading two posts	2.708***	2.260***
Reading three posts	3.789***	2.720***
Cost spillover parameters		
Reading × *Posting*	−0.113*	−0.015
Work posting × *Leisure posting*	−0.017	
Work reading × *Leisure reading*	−0.249***	

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

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knowledge state is 1.351. In comparison, the corresponding utility from being in a high leisure knowledge state is only 0.117.

The results for the cost parameters indicate that there are significant costs for posting and reading. The cost of only writing one work-related post is 5.669. The cost of only writing one leisure-related post is 4.013. This demonstrates that the cost of writing a work-related post is higher than writing a leisure-related post. We do not observe any significant spillover in posting costs if one posts both leisure- and work-related posts.

There are also significant costs for reading work- and leisure-related posts. The costs of reading only one, two, and three work-related posts are 2.431, 2.708, and 3.789, respectively. In comparison, the costs of reading only one, two, and three leisure-related post are 1.703, 2.260, and 2.720, respectively. The results show that reading work-related posts is more costly than reading leisure-related posts. A potential explanation for this is that work-related posts are technically dense and complex and would require significant effort from the reader to internalize.[11] We also find there are significant cost spillovers between reading work- and leisure-related posts. For example, the costs of reading one work-related and one leisure-related post are $2.431+1.703-0.249*\log(2)$. Similarly the costs of reading three work and three leisure posts are $3.789+2.720-0.249*\log(10)$. Thus, a reader incurs a lower cost from reading both work and leisure posts than the sum of their individual costs. One of the major components of the cost of reading is the search cost of finding an appropriate post to read. When an individual reads a blogger's work- or leisure-related post, she is also exposed to her other posts, and if she ultimately reads two different posts from a blogger, her search cost is reduced. In the data set, we observe a large number of instances in which readers read both leisure and work posts written by a blogger in a period.

We also find there is a significant cost spillover between work-related reading and posting. The cost of reading three work posts and writing one work post is $5.669+3.789-0.113*\log(4)$. A potential explanation for this cost spillover effect is that individuals may develop ideas they can use when writing a work post from reading work posts by others. The cost spillover between leisure posting and leisure reading is not significantly different from zero.

[11] To test this, we negotiated access to the exact content of the posts from the company and conducted a readability analysis of the textual content of the posts. This allows us to determine whether work-related posts are more difficult to read than leisure-related posts. The Flesch Reading Ease Score, which ranges from 0 to 100 ($0=$ very difficult and $100=$ very easy to read) was 45.62 for the average work post and 75.21 for the average leisure post (Kincaid et al. 1975). Thus, the readability analyses support our argument that work-related posts are more difficult to read than leisure-related posts, and therefore, the reader would have to expend a considerable amount of cognitive effort to understand them. This potentially explains the high cost of reading a work-related post observed in our data.

5.4. Model Performance

As noted above, we consider the last eight weeks of data to test the performance of our model. In this section, we report on how our model fits the holdout data. We apply four test statistics to measure the performance of our model: (1) distribution of the work posts written, (2) distribution of the leisure posts written, (3) distribution of the work posts read, and (4) distribution of the leisure posts read. We first calculate the values of the test statistics for the test period. We then simulate the posting and reading outcomes for each individual in the holdout period using our model and estimated parameters. We calculate the test statistics for our model by running the simulation 200 times. We compare the distributions obtained from our model with the true distributions in Figure 1. In the figure, the x axis depicts the test statistic, and the y axis depicts the percentage of individuals corresponding to the test statistic in the holdout sample (on a log scale). The solid black dots represent the test statistic from the actual data set, and the boxes and whiskers represent the corresponding statistics across the simulated data sets. The whiskers represent the upper and lower limits of the 200 corresponding simulated test statistics. The box represents the 25th and 75th percentiles.

From Figure 1, we can see that the distributions of all four test statistics from our model are very similar to that of the actual data. Thus, from Figure 1, we can conclude that our model performs very well in predicting key blogging behavior in the holdout sample.

5.5. Robustness Checks

We performed several tests to check the robustness of our results. We consider alternative measures of readership to assess whether the results are robust. We consider three different values for δ, the readership depreciation factor (0.9, 0.85, and 0.8). When the depreciation factor decreases, past readership depreciates rapidly. In all three cases, we find that the qualitative nature of the results remains unchanged across these different measures of readership and is consistent with those presented in Table 10. We also considered readership as average readership per post rather than the cumulative readership for each employee. We find that the results from this specification are qualitatively similar to those presented in Table 10.

We conducted a series of additional checks to examine the external validity of the readership and

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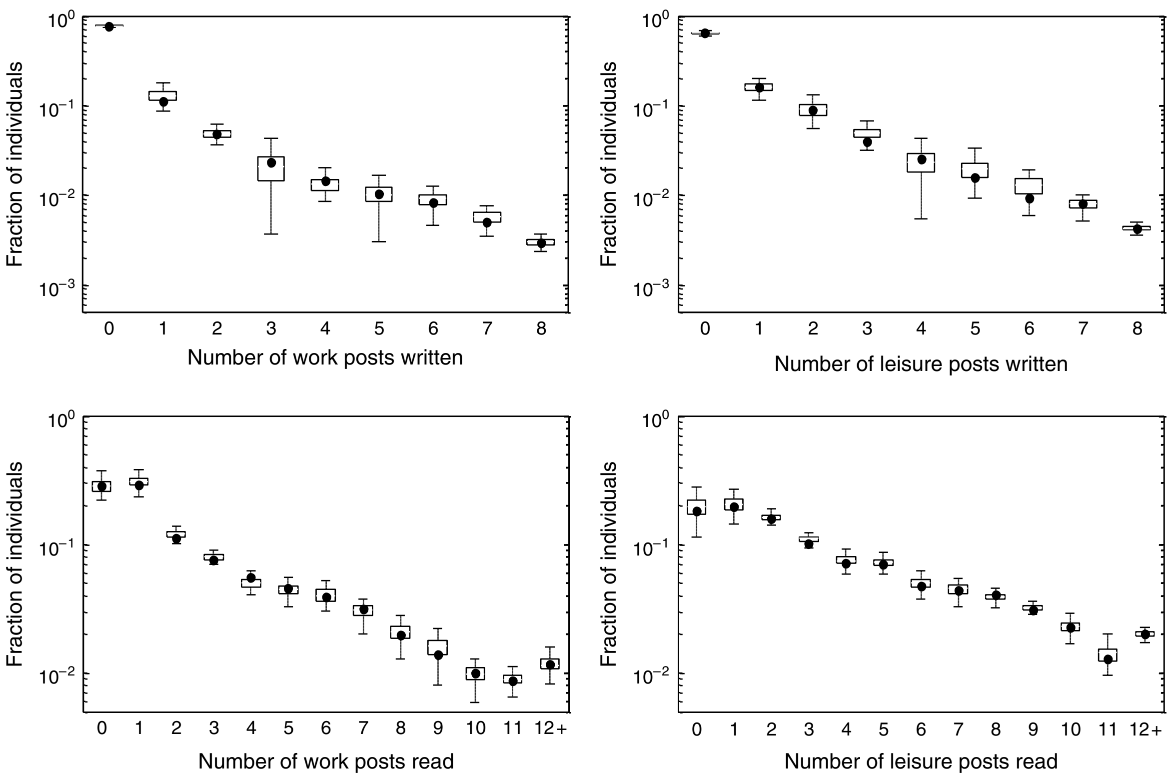
Figure 1 Test Statistics Distribution in the Holdout Data



knowledge measures. A potential measure of the external validity of our "knowledge gained from blogging activities" measure is that the knowledge an employee gains from reading blogs leads to an increased performance rating for that employee. We collected data on performance evaluations on a subset of employees in our sample. The employee is evaluated by her immediate superior and rated on a discrete scale from 1 to 4, with 1 being the lowest and 4 being the highest performance rating. We find that individuals who are in a higher knowledge state receive higher job performance evaluations on average.

6. Policy Experiment and Post-Hoc Analysis

6.1. Policy Experiment

Most enterprises believe that the primary purpose of workplace blogging is to promote work-relevant knowledge sharing. Thus, firms typically prefer that employees engage in work-related blogging as opposed to leisure-related blogging. In reality, firms can also implement policies to incentivize employees' blogging activities. In this section, we explore the effect of such a policy intervention: How do employees respond to a policy that prohibits leisure-related blogging?

We introduce the new policy by manipulating the parameter values in the utility function and then solve for the new equilibrium under the new policy. To execute this experiment, we set the cost of leisure-related posting and reading to be extremely high. In essence, this policy will eliminate leisure-blogging activities because the costs of leisure posting and reading are always higher than the benefits employees obtain from them. One would expect employees to switch from leisure-related activities to work-related activities because of the existence of the budget constraint, and thus, both work posting and work reading would increase. However, our simulation results suggest a different story. The "no leisure policy" column of Table 11 reports the probability of work-related posting and reading after the policy is implemented. The probability of work posting decreases from 6.59% to 0.65%. This result is, reassuringly, consistent with the readership spillover effect discussed in §5.1. When leisure activities are eliminated, bloggers can no longer benefit from the readership spillover effect. As a result, per post, they will receive smaller utility because of lower readership than before. Thus, their probability of publishing work-related posts will decline significantly. As fewer work posts are created, work reading also decreases. Specifically, work posting decreases by approximately 47% under the "no-leisure" policy. This result is consistent with our knowledge state transition results from §5.2, which

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Table 11 Policy Experiment Results

	Current policy	No-leisure policy
Mean probability of work reading		
Read one work post	8.04%	5.06%
Read two work posts	3.41%	1.66%
Read three work posts	0.87%	0.29%
Mean probability of work posting		
	6.59% (0.02)	0.65% (0.004)

showed that employees are able to learn more rapidly if their peers create more posts and those posts are created by employees with higher knowledge and readership. As work-related posting decreases, the reader's learning from reading slows down. As a result, the utility they derive from reading a work-related post declines, and hence they read even less. As bloggers write and read fewer posts than before, their own knowledge level decreases. As fewer people read posts, the average readership of bloggers further decreases.

These results have important managerial implications. Firms typically prefer a larger and more diversified internal knowledge pool. We observe that a policy of prohibiting leisure-related blogging can actually reduce the extent of knowledge creation and sharing within the firm. A decrease in the probability of work-related posting means that fewer employees are likely to post and read work-related content. As a result, less new knowledge is likely to be added to the knowledge pool.

6.2. Post-Hoc Analysis—Quantifying the Readership Spillover Effect

Using the structural parameter estimates, we now perform an analysis that quantifies the effect of the spillover from leisure readership to work readership, and vice versa, on number of leisure and work postings. To identify the effect of readership spillovers on blogging behavior, we set the parameter corresponding to readership spillovers in the readership state transition probabilities to zero. We then solve for the equilibrium. We consider two different state transition structures: (1) no spillover from leisure readership to work readership and (2) no spillover from work readership to leisure readership. In both scenarios, we also set the reading cost spillover parameter (θ_9) for leisure and work to zero. The results are reported in Table 12.

For comparison purposes, we also report the equilibrium probabilities for posting and reading under the real scenario (no change in readership spillovers). From the results of model (1) and model (0), we can see that if there were no spillovers from leisure to work readership, work-related posting would decrease by 90.44% (from 6.59% to 0.63%) and leisure-related posting would decrease by 33.37% (from 10.43% to 6.95%). It is easy to see how both work and leisure posting decrease if the spillover from leisure to work is removed. In the presence of a leisure to work readership spillover, leisure provides direct utility (from cumulative leisure readership) and indirect utility (by increasing cumulative work readership). Thus, employees derive greater utility from writing a leisure post in the presence of a spillover effect than otherwise. Similarly, in the presence of leisure to work readership spillover, employees derive greater utility from writing work posts compared to what they would derive in the absence of the spillover.

Table 12 Effects of Readership Spillovers on Blogging Behavior

Equilibrium probabilities	(0) No change (%)	(1) No readership spillover from leisure to work (%)	(2) No readership spillover from work to leisure (%)
Write work post	6.59	0.63	2.19
Write leisure post	10.43	6.95	7.98
Read one work post	8.04	6.05	6.29
Read two work posts	3.41	2.55	2.51
Read three work posts	0.87	0.64	0.75
Read one leisure post	12.41	10.28	11.09
Read two leisure posts	3.74	3.04	3.41
Read three leisure posts	1.60	0.87	0.87

We can see if there were no readership spillover from work to leisure, then work (leisure) posting would decrease by 66.77% (23.49%). These results indicate that the spillover from leisure to work readership has a larger impact on individual blogging behavior than the spillover from work to leisure. Also note that in all cases, both work and leisure reading would also decrease if there were no readership spillovers.

6.3. Post-Hoc Analysis—Quantifying the Effect of Competition

We now present an analysis that helps us to identify the effect of competition for readership on the blogging behaviors of individuals. To change the level of competition, we can artificially reduce or increase the number of peers who write posts. However, the number of peers who post per period is endogenously determined. Thus, artificially reducing or increasing the number of peers who post would make the model internally inconsistent. Therefore, to identify the effect of competition, we modify the parameters corresponding to the peer-related variables (other than the number of posts read by peers[12]) used to calculate cumulative readership state transitions (Equation (9)) and then solve for the equilibrium. We

[12] The competition-specific variables would be the variables that correspond to the characteristics of the peer bloggers. Hence, the competition-specific variables in Equation (9) are the ones that include the term d_{xtwp} or d_{xtlp}. A blogger competes with other

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Table 13 Effects of Competition on Blogging Behavior

Equilibrium probabilities	(0) No change (%)	(1) 10% lower competition for readership (%)	(2) 10% higher competition for readership (%)
Write work post	6.59	7.80	5.60
Write leisure post	10.43	11.98	8.81
Read one work post	8.04	8.95	7.11
Read two work posts	3.41	3.84	3.09
Read three work posts	0.87	0.99	0.70
Read one leisure post	12.41	13.46	11.32
Read two leisure posts	3.74	3.98	3.07
Read three leisure posts	1.60	1.66	1.30

consider two levels of competition and report the results in Table 13. We report results for a model in which (1) the parameters corresponding to competition are reduced by 10% and (2) the competition-specific parameters are increased by 10%. We can see that if the effect of competition on state transitions decreases by 10%, the equilibrium mean work posting and leisure posting probabilities increase by 18.36% and 14.86%, respectively. Similarly, a 10% increase in the effect of competition on state transitions decreases equilibrium mean work and leisure posting by 15.02% and 15.53%, respectively. Further, both work and leisure reading decrease as competition increases because less content is being generated from which employees can gain knowledge.

7. Conclusion

In recent years, we have seen that organizations have widely deployed enterprise social-media technologies for internal use. Companies can use blogs internally to initiate conversations between management and employees. If employees feel that they are involved in the conversation, one might observe greater loyalty and productivity. A blog is also useful for product development and informing the company of upcoming initiatives. Blogs can be more effective than email, as they eliminate the need to answer a given question multiple times and allow for feedback from the entire group as opposed to just the email recipient. Blogs can allow firms to trace employees' personal expertise and practices. Making these visible provides an understanding of who knows what, which is a starting point for collaboration and allowing knowledge to spread more effectively.

In this paper, we present a dynamic structural model in which the employees of an enterprise compete in the process of reading and writing blog posts. There are two types of blogs posts in our context: work-related and leisure-related posts. Users make choices concerning reading and writing based on their preferences for the two types of content. Our findings suggest that individuals derive a positive utility from increases in the cumulative readership of their work- and leisure-related posts. Work-related blogging allows employees to express their expertise, and once they are identified as "experts," this reputational gain can lead to economic benefits. In addition, leisure readership can indicate how popular employees are among their professional peers, and the more popular they are, the happier they are likely to be at work. However, for a given amount of cumulative readership for work and leisure posts, employees derive 27%–71% greater utility from work-related cumulative readership than from leisure-related cumulative readership. Further, reading and writing work-related posts is more costly than reading and writing leisure-related posts, on average.

We find evidence of competition among employees with respect to attracting readership for their posts. We identify a tension that peer blogging activity raises for an employee. As a blogger, an employee would prefer reduced readership competition and, hence, fewer of her peers to post. In contrast, as a reader, the same employee would prefer peers to post more, as this increases her rate of learning.

Although readership for leisure posts provides less direct utility than that of work posts, employees nevertheless post a significant number of leisure posts, because there is a significant spillover effect on the readership of work posts from the creation of leisure posts. Because the two types of blog posts coexist on the same platform, this spillover is bidirectional in nature. Our policy simulations suggest that prohibiting leisure-related posting would be counterproductive for organizations because it also leads to a reduction in work-related posting and reading. Overall, these results shed light on how enterprise adoption of social-media tools influences employee blogging behavior and choices.

An interesting implication of one of our robustness checks that considers the external validity of the cumulative readership and knowledge gained from blogging is that work-performance ratings are positively correlated with the knowledge states of employees. This indicates that employees who have gained higher levels of knowledge from their blogging activities tend to perform better in the organization. Although this correlation is merely suggestive, it is, nonetheless, a useful insight because many organizations have been concerned about the effects of blogging on employee performance and productivity.

Our paper has several limitations. First, in terms of reading, we only model whether an individual reads work-related or leisure-related posts. We do not

bloggers and not the readers. The number of posts read by peers is a reader-specific variable. Hence, we do not change the parameter specific to "the number of posts read by peers."

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model whose blog an individual reads.[13] Individual reading dynamics may be affected by the dynamics of the content created by the bloggers they follow. Future research could explicitly model this relationship. Second, commenting on blogs can be an important part of the knowledge-creation process, but we do not have sufficient information on the comments on the blog posts in our data to conduct any meaningful analyses. Third, because of data limitations, we only account for blog-reading behavior within the enterprise. Some of the blog creation and consumption dynamics may be affected by events outside of our data. For example, employees can also access external blogs and other social-media content. However, such data are not available to us. Notwithstanding these limitations, we hope that our work can pave the way for future research in this emerging area of enterprise social media.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2125.

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[13] There are multiple issues that make the estimation of a structural model with dyadic readership intractable. First, the state space would blow up. Second, the choice space would also blow up.

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