Management Science

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http://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 66, No. 2, February 2020, pp. 587–604
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

What Makes Geeks Tick? A Study of Stack Overflow Careers

Lei Xu,[a] Tingting Nian,[b] Luís Cabral[c]

[a] Toulouse School of Economics, 31000 Toulouse, France; [b] The Paul Merage School of Business, University of California, Irvine, California 92697; [c] Department of Economics, Stern School of Business, New York University, New York, New York 10012

Contact: lei.xu@tse-fr.eu, http://orcid.org/0000-0002-2662-946X (LX); tnian@uci.edu, http://orcid.org/0000-0003-3398-5064 (TN); luis.cabral@nyu.edu, http://orcid.org/0000-0003-2763-2422 (LC)

Received: February 27, 2017
Revised: February 2, 2018; August 22, 2018
Accepted: November 19, 2018
Published Online in Articles in Advance: August 6, 2019

https://doi.org/10.1287/mnsc.2018.3264

Abstract. Many online platforms rely on users to voluntarily provide content. What motivates users to contribute content for free, however, is not well understood. In this paper, we use a revealed-preference approach to show that career concerns play an important role in user contributions to Stack Overflow, the largest online question-and-answer community. We investigate how activities that can enhance a user's reputation vary before and after the user finds a new job. We contrast this reputation-generating activity with activities that do not improve a user's reputation. After finding a new job, users contribute 23.7% less in reputation-generating activity; by contrast, they reduce their non–reputation-generating activity by only 7.4%. These findings suggest that users contribute to Stack Overflow in part because they perceive such contributions as a way to improve future employment prospects. We provide direct evidence against alternative explanations such as integer constraints, skills mismatch, and dynamic selection effects.

History: Accepted by Chris Forman, information systems.
Supplemental Material: Data files and the online appendix are available at https://doi.org/10.1287/mnsc.2018.3264.

Keywords: career concerns • online public goods • signaling • voluntary contribution

1. Introduction

A fascinating and economically important consequence of the rise of the Internet is the growing prevalence of private contributions to collective projects such as Wikipedia, bulletin boards, or open-source software. As Lerner and Tirole (2002) put it, to an economist, the behavior of individual contributors appears somewhat puzzling: Is it a case of altruism, or are there ulterior motives behind private contributions to a public good?

Our paper addresses this research question using data from Stack Overflow (SO), the largest online question-and-answer (Q&A) platform for programming-related matters. We consider a hypothesis put forward by Lerner and Tirole (2002)—namely, that contributions are motivated by career concerns: the desire to signal one's ability so as to obtain better employment.[1]

Affiliated with SO, the Stack Overflow Careers (SOC) site hosts job listings and contributors' curricula vitae (CVs) so as to match employers and employees.[2] The data from SO and SOC allow us to link online activity to real-world individuals. We construct complete histories of each individual's online trajectory, including contributions to SO, individual characteristics, and employment history. Following previous empirical testing of the career-concerns hypothesis (Chevalier and Ellison 1999, Miklós-Thal and Ullrich 2015), we test the hypothesis by identifying shifts in behavior following employment changes. We find that before changing to a new job, a contributor provides more and better Answers. However, immediately following the job change, we observe a significant drop in both the quantity and quality of Answers activity. This pattern is consistent with a career-concerns theory of contributions to SO: Before a job change, a contributor's reputation has an effect on employment prospects, whereas after the job change has taken place, the reputation–employment link disappears or at least is significantly weakened.

The causal link inherent to the career-concerns hypothesis cannot be established based on this piece of evidence alone. A job seeker's behavior can be explained by multiple confounding factors. Most importantly, users starting new jobs may have busier work schedules, which prevents them from contributing to SO. Accordingly, we adopt a modified version of the difference-in-differences (DD) approach: We compare each individual's behavior across different types of activities before and after a job change.

To show the rationale behind this approach, we first build a theoretical model of user contributions. We assume that agents derive utility from different activities and are subject to an aggregate time constraint. Specifically, the activities are online contributions that improve an agent's reputation, online contributions that have no effect on an agent's reputation, and work (revenue-generating) activities. Finally, we assume that the probability of finding a new job (or a better revenue-generating activity) increases in an agent's reputation.

The model's equilibrium implies that, upon obtaining a new job, the relative time spent on reputation-increasing online activities (relative to non–reputation-increasing online activities) decreases. This theoretical result forms the basis of our empirical identification strategy.

In particular, the DD approach compares reputation-increasing to non–reputation-increasing activities from the same sample of job changers before and after a job switch.[3] We conclude that contribution levels decrease by 23.7% right after a job change, of which 12.4%–16.3% is due to (the removal of) career concerns. Apart from examining both short- and long-term activity changes over time, we also consider the heterogeneous responses to job changes for users with different characteristics, such as levels of education, types of degrees, work experience, and existing online reputation. All of the results are consistent with the career-concerns hypothesis. As with any other DD specification, the validity of our identification hinges on the parallel-trend assumption. We address several major alternative explanations that can potentially invalidate this assumption, including integer constraints, skills mismatch, and dynamic selection effects.[4] We test the external validity of our results by using a different data set, comprising information from LinkedIn pages rather than SOC.[5]

To be clear, we do not claim that career incentives are the only motivation behind the contributions to SO. In fact, many previous studies have shown other types of motivations that drive private contributions to online public goods, such as social effects (Zhang and Zhu 2011, Algan et al. 2013), learning (Lakhani and von Hippel 2003), reciprocity (Athey and Ellison 2014), financial rewards (Hann et al. 2013, Luca and Zervas 2016), and goal achievement and online status (Goes et al. 2016).[6]

Our results complement the existing literature by showing clear evidence of a widely held hypothesis: Career concerns matter. To the best of our knowledge, this paper is the first to empirically identify and estimate the causal relation between changes in career status and voluntary contributions to online public goods as an indirect measure of career concerns. We believe our methodology is helpful in other contexts, and we believe our empirical results are important, considering the increasing use of online activity in hiring decisions.

Our results also have important policy implications for platform companies. The prevalence of online platforms has attracted many firms to adopt a platform-based business model. Many have tried but failed to launch a successful platform, mostly due to insufficient user participation from one or multiple sides. Because of network effects, a user will not participate without the participation of others. A thorough understanding of the motivations behind user participation is therefore crucial for the success of a platform, especially a platform that relies on voluntary contributions of user-generated content (i.e., a crowdsourcing-based platform). Our results imply that career concerns could be a way through which platforms encourage active user engagement. In Section 8, we develop this and other managerial implications in greater detail.

2. Background

Stack Overflow is the largest online Q&A site where programmers ask and answer programming-related questions (Figure 1).[7] It provides for Wikipedia-style editing (Figure 2), and it includes a system of votes, badges, and user reputation that ensures high-quality, peer-reviewed answers. SO is widely used by programmers.[8] Asking or answering questions requires a simple registration process. The majority of users have anonymous usernames.

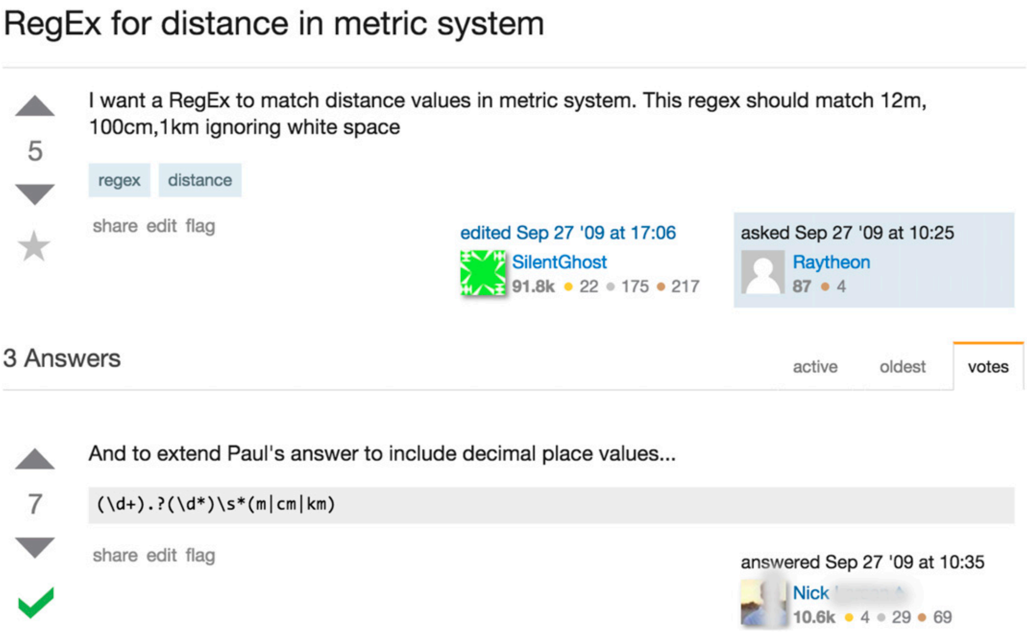
Measures of user activity: users on SO engage in four major activities:

- Questions: Any registered user can ask a Question. A Question can be voted up or down. A hard but important Question is usually voted up to get attention from more contributors. A duplicate or unclear Question is usually voted down.[9]
- Answers: Any registered user can provide Answers to existing Questions.[10] A Question can have multiple Answers, and the latter are ranked by total Votes.
- Edits: Registered users can also make or suggest minor changes to a Question or Answer: Edits. Edits help make the Questions and Answers more readable and understandable to future viewers.
- Votes: Registered users can give upvotes or downvotes to Questions and Answers *but not to Edits*. Votes reward reputation points of the owner of a post: Each upvote on a Question gives the asker 5 points, whereas each upvote on an Answer is worth 10 points.[11]

Stack Overflow Careers is a job-matching website that hosts programming-related job listings as well as resumes of job candidates.[12] For contributors, creating a resume on the website is free of charge but by invitation only, and the invitation is based on the contributors' recent activity on the site as well as their fields of expertise.[13] On the resume, contributors can easily provide a link to their SO profiles, through which employers can learn more about the job applicants' expertise: That is, potential employers observe the user's reputation score, a reflection of the quantity and quality of the user's contribution to SO.

Through a paid subscription, SOC helps employers by reducing their hiring search costs. First, SOC provides a select sample of high-level contributors invited by SO. Second, SOC includes a wealth of information regarding the job applicants' skill sets, including, in particular, their contribution history to SO.

Figure 1. (Color online) A Question with Its Answers on Stack Overflow



Notes. One Question can receive multiple Answers, which are ranked by Votes by default. The asker can select one Answer as the "correct" Answer. Both Questions and Answers receive upvotes or downvotes. One upvote to a Question rewards 5 points to the asker; one upvote to an Answer rewards 10 points to the contributor.

Finally, employers who access SOC may post their openings as well as search candidates by location, skills, and so on.[14]

3. Theoretical Model of User Contribution

We propose a simple dynamic model of user contributions. Consider an infinite-period, discrete time line, and suppose agents discount the future according to the factor δ. Each agent is an SO contributor and a job seeker. The agent's state space is limited to $s \in \{0, 1\}$, where $s = 0$ stands for current (or old) job and $s = 1$ stands for future (or new) job. We assume $s = 1$ is an absorbing state. To the extent that this is not the case, our estimates of career concerns should be regarded as a lower bound of the real size of career concerns.

A fundamental hypothesis that we propose to test is that the probability of job transition—that is, the transition from $s = 0$ to $s = 1$—is endogenous, specifically, a function of the agent's reputation r_t:

$$\mathbb{P}(s_t = 1 \mid s_{t-1} = 0) = p(r_t).$$

In each period, agents must decide how to allocate their time. We consider three types of tasks: Work, Answers, and Edits. Let w_t, a_t, and e_t be the time devoted to each of these tasks, respectively. Each agent's time constraint is then given by

$$w_t + a_t + e_t = T.$$

Consistent with the structure of SO, we assume r_t is a function of past values of a_t *but not* of past values of e_t. In fact, a crucial difference between Answers and Edits is that the former is a Vote-generating activity, whereas the latter is not.[15]

We assume each agent's utility each period is additively separable between work tasks and SO-related tasks:

$$u_t = g_s(w_t) + f(a_t, e_t),$$

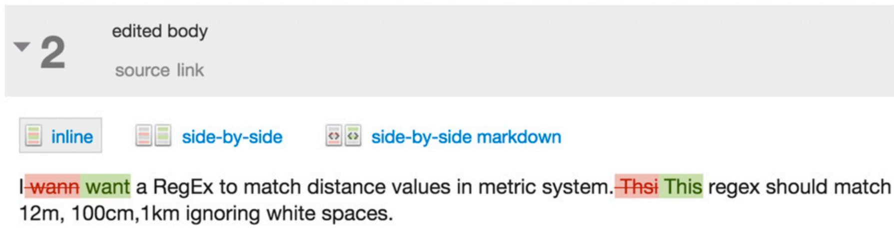
where $f(\cdot,\cdot)$ is a homothetic function and both $f(\cdot,\cdot)$ and $g(\cdot)$ are twice differentiable functions such that $f', g' > 0$ and $f'', g'' < 0$. The homotheticity of $f(\cdot,\cdot)$ means a constant marginal rate of substitution along rays, which implies the time elasticity of a and e are the same—namely, $\eta_a = \eta_e$ where $\eta_x = \frac{dx/dT}{x/T}$. Many commonly used utility functions satisfy these assumptions, including constant elasticity of substitution functions where $f(a, e) = (\alpha a^\rho + (1-\alpha)e^\rho)^{\frac{1}{\rho}}$.

Notice that we allow the utility from work to be state-dependent. In fact, the agent's demand for a new job results from our assumption that $g_1(w) > g_0(w)$.

In this model, $f(a_t, e_t)$ is the utility function derived from intrinsic motivations. The career incentive of a_t activity is not included in the f function; rather, it enters through a higher $p(r_t)$ in order to transition to a job with a higher value of $g(w)$.

Agents are forward looking: In each period t, they choose w_t, a_t, e_t so as to maximize value $V_t(s)$, where

Figure 2. (Color online) An Edit on Stack Overflow



Notes. Most Edits correct grammar or spelling mistakes, clarify the meaning of a post, or add related information. Users with reputation under 2,000 can suggest edits, which rewards them two points if accepted. Users with over 2,000 reputation points do not get the two-point reward.

$s = 0, 1$. The value functions are determined recursively as follows:

$$V_t(s) = \max_{w_t, a_t, e_t} g_s(w_t) + f(a_t, e_t) + \delta\, E\, V_{t+1}(s')$$
$$\text{subject to: } w_t + e_t + a_t = T.$$

Our main theoretical result is as follows:

Proposition 1. *Suppose $g_0(w) < g_1(w)$ and $g_0'(w) < g_1'(w)$. Then*

$$a_t|_{s=1} < a_t|_{s=0}. \tag{1}$$

Moreover,

$$\left.\frac{a_t}{e_t}\right|_{s=1} < \left.\frac{a_t}{e_t}\right|_{s=0} \quad \textit{iff} \quad p'(\cdot) > 0. \tag{2}$$

Proof. See the online appendix.

Proposition 1 establishes two effects of a job change: a decline in the time spent providing Answers and a decline in the relative time spent on Answers vis-à-vis Edits. The first effect (decline of Answers activity) can be decomposed into two effects: an increase in the marginal utility of time spent at work and a decline in the utility of Answers due to diminished career incentives. Because two effects arise, a decline in Answers is a necessary but not sufficient condition for our career-concerns hypothesis. By contrast, the second effect takes place if and only if career concerns are present. It therefore provides a sharper test of our central hypothesis.

Our model is fundamentally different from the classic models of career concerns, starting with the seminal works by Holmström (1999) and Gibbons and Murphy (1992): It abstracts away from the principal–agent problem and instead focuses on the time-allocation decisions of a job seeker.

One advantage of such a theoretical model is that it helps clarify the assumptions underlying an empirical identification strategy. The assumption that the Edits and Answers components in the utility function share the same elasticity with respect to changes in T plays an important role. As individuals work for longer hours, the assumption is necessary to prevent Edits from responding disproportionally to changes in time availability. In Section 7, we provide several tests to test the validity of this assumption.

Proposition 2. *Suppose $p'(\cdot) > 0$ and $p''(\cdot) < 0$. Then*

$$\left.\frac{a_t}{e_t}\right|_{s=0, r_{t-1}} > \left.\frac{a_t}{e_t}\right|_{s=0, r'_{t-1}} \quad \textit{for} \quad r_{t-1} < r'_{t-1}. \tag{3}$$

Moreover, let $p(\cdot)$ take on more arguments and become $p(x_t, r_t)$. Assuming $\frac{dp(x_t,r_t)}{da_t} > 0$, $\frac{dp(x_t,r_t)}{dx_t} > 0$, and $\frac{d^2p(x_t,r_t)}{da_t dx_t} < 0$,

$$\left.\frac{a_t}{e_t}\right|_{s=0, x_t} > \left.\frac{a_t}{e_t}\right|_{s=0, x'_t} \quad \textit{for} \quad x_t < x'_t. \tag{4}$$

Proof. See the online appendix.

Proposition 2 shows the heterogeneous effects of career concerns on online activities for those with different online reputation and other characteristics (e.g., education, work experience, etc.), respectively. The first part of Proposition 2 shows that if $p(\cdot)$ is a concave function—that is, if the marginal benefit of additional reputation on job offers is smaller for those already enjoying a good reputation—the effect of career concerns would be smaller. Similarly, the second part of Proposition 2 says the effect of career concerns would also be smaller if the marginal benefit of online reputation is smaller for those with better characteristics.

The two parts of Proposition 2 correspond to the two predictions made by Lerner and Tirole (2002) that the behavioral responses due to career concerns are more pronounced when (i) effort has a stronger impact on performance, and (ii) performance becomes more informative about talent. Additional empirical tests and discussions of the results of Proposition 2 will be provided in Section 6.

4. Data

Our data set is derived from the Stack Overflow and Stack Overflow Careers sites.

We focus on a set of users who satisfy a series of criteria required by our empirical test:[16] located in the United States and Canada (65,179 users), profiles with links to SO (24,519), job switchers (moving from one job to another), some work information (19,088), clean job switchers (with gaps no greater than 1 month between two jobs and no job overlapping) (10,226), and active users (at least one Answer and at least one Edit within the 4-month period around a job change) (1,301).

Applying this series of criteria results in a sample of 1,301 users with 1,520 job switches. A vast majority are dropped due to inactivity. Our identification strategy requires a minimum level of SO activity, and the majority of users have zero activities in periods surrounding job changes, which does not provide much useful information.

Obviously, the sample is not representative of the whole population, because the vast majority do not give any Answers (77.3%). On the other hand, the most active 7.9% contribute 91.2% of all the Answers. We believe it is a representative sample of the active contributors.

For each user in our sample, we associate their user resumes (which include dates of job changes) to user identifications (IDs) on SO. With the user IDs at hand, we then collect their activities on SO.

Table 1 provides descriptive statistics comparing different groups: the whole SO population, SOC users, and the sample we use in our research. All the statistics show that our analysis focuses on a sample of users who are considerably more active than average. A more detailed analysis and comparison can be found in the online appendix.

5. Identification Strategy

Conceptually, our identification strategy is straightforward: Job seekers are active on SO to signal their ability and thus obtain a better job. If career concerns are important to incentivize user activity, we expect a drop in such activity once the goal (a better job) is attained. Because career aspirations may not be satisfied by a single advancement, career concerns might not entirely disappear, but at least they are diminished at the start of a new job.

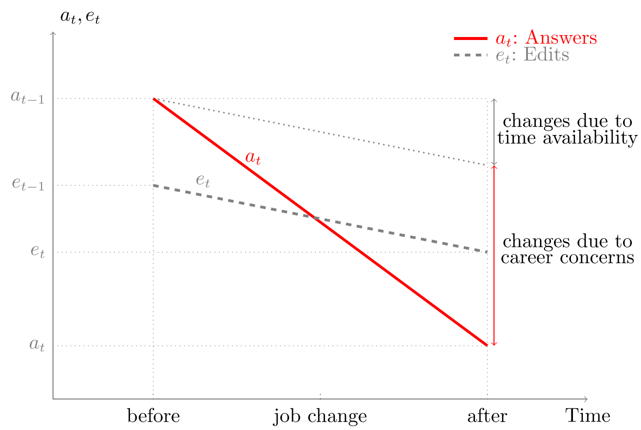
In practice, various confounding factors make the measurement of career-concern effects difficult. In particular, a reduction in online activity following a job change may simply result from a reduction in time availability: A new job often requires training and familiarization with a new environment. In fact, as the first part of Proposition 1 states, we expect a drop in a_t through two effects: a drop in career concerns (measured by $p(r_t)$ in the model) and an increase in work activities (measured by the shift from $g_0(w)$ to $g_1(w)$ in the model).

To account for these effects, we use the differential change in Answers relative to Edits to test the hypothesis that Answers are motivated by career concerns. A crucial difference between Edits and Answers is that the latter give rise to Votes, whereas the former do not. Therefore, we expect Answers to decline by more than Edits after individuals switch jobs. Our DD approach assumes that, aside from changes in job status, Edits and Answers follow a parallel path. Because this assumption is so crucial, in Section 7, we provide supporting evidence.

Essentially, our DD approach corresponds to the second part of Proposition 1. Figure 3 illustrates the main idea: After starting a new job, the reduction in Answers activity results from two effects: career concerns and time availability (or, opportunity cost of work time); however, the reduction in Edits activity results exclusively from the time-availability effect. Therefore, the difference between the changes in Answers and in Edits identifies the effect of job change on career-concerns incentives for Answers.

Figure 4 provides preliminary evidence regarding our hypothesis. It plots the monthly average of the logarithm of user activities in a 20-month window centered around a contributor's job-change event. Both Answers and Edits activity experience a significant

Figure 3. (Color online) Graphical Illustration of Identification Strategy: Difference-in-Differences



Notes. Treatment group: Answers activity (a); Control group: Edits activity (e). All activity data come from the same sample of contributors. DD coefficient is calculated as $(a_t - a_{t-1}) - (e_t - e_{t-1})$, which measures the differences of the Answers–Edits gap before and after a job change.

Table 1. Comparison of User Activity and Characteristics

Variables	All SO users	SOC users	DD analysis
Number of users	7,753,765	24,550	1,301
User activity (monthly)			
Questions	1.88	16.44	42.32
Answers	2.95	85.12	255.59
Edits	1.57	51.51	114.48
User characteristics			
Profile views	14.64	481.37	1,282.81
Upvotes	12.32	375.45	1,150.87
Downvotes	1.56	56.39	129.59
Age	30.92	35.92	35.64

Notes. The SOC users only include those located in the United States and Canada who provide a link to their SO profiles. Without such a link, we are unable to trace back to the SO profiles.

drop when a user starts a new job (month 1); however, the drop in Answers activity is considerably larger than the drop in Edits activity.

Naturally, several other alternative hypotheses may explain these dynamics. In Section 7, we present and evaluate several hypotheses under which the parallel-trend assumption could be violated and evaluate the validity of each hypothesis.

6. Empirical Analysis

We now come to a more formal test of the hypothesis implied by Proposition 1. Our empirical analysis focuses on the sample of 1,301 users who were subject to 1,520 job switches during the November 2008–November 2014 period. For each of these job switches, we measure activity levels by activity type and by month. Specifically, we define period 1 as the month when a job change takes effect (that is, the month users start a new job as listed on their CV). We then consider 3 months prior to a job switch (−3, −2, −1) and 3 months subsequent to a job switch (+2, +3, +4). We exclude months 0 and 1; in this way, we get a clearer perspective on the periods before and after the job change without contaminating the data with noise stemming from the process of the job change.

6.1. Empirical Specification

As illustrated in Figures 3 and 4, our identification strategy is derived from a difference-in-differences approach. However, instead of comparing the behavior of different individuals, we focus on the same set of individuals and compare their behavior across different activities before and after a job change:

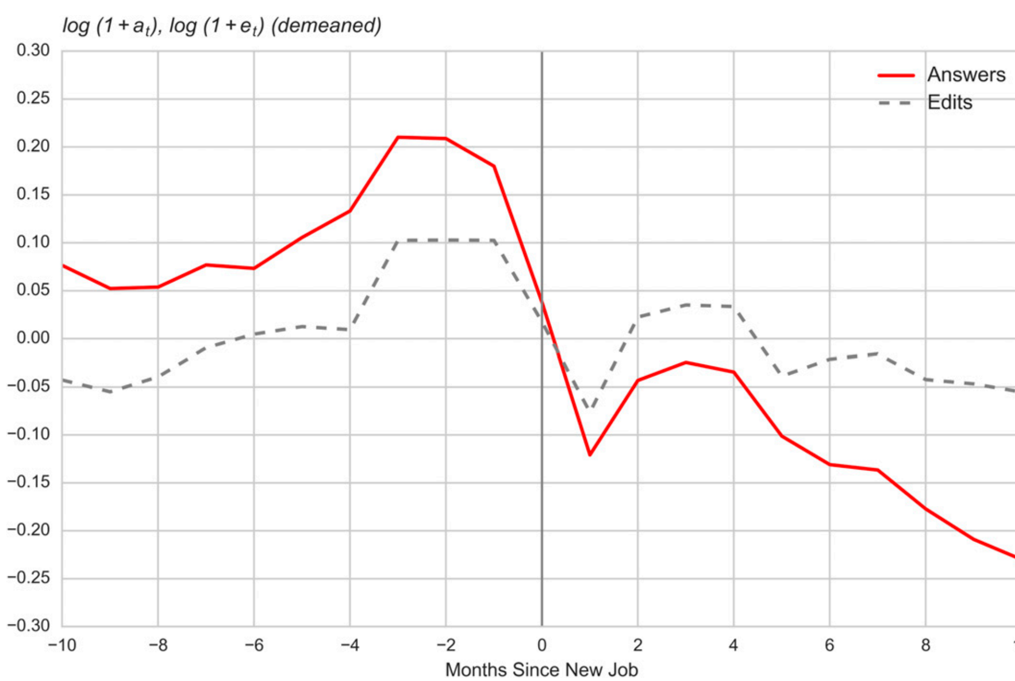
$$y_{ijt} = \alpha_{ij} + \beta S_{it} + \gamma J_j S_{it} + \lambda_{jt} + X_{ijt}\theta + \epsilon_{ijt}. \quad (5)$$

In regression (5), the dependent variable y_{ijt} includes two different types of online activities, including one Votes-generating activity (VGA) and one non-VGA, which are indicated by subscript j. VGAs can be Answers ($j = a$), Votes gained from Answers ($j = v$), or Questions ($j = q$); non-VGAs are Edits ($j = e$). All the activities are measured in logarithms. One advantage of this approach is that the coefficients can be readily interpreted as percent variations. S_{it} is the state dummy variable: $S_{it} = 0$ corresponds to the periods before a job change takes place for user i, whereas $S_{it} = 1$ corresponds to the periods after a job change takes place. J_j is a dummy variable that takes on value 1 if the activity is a VGA ($j = a, v, q$) and 0 otherwise ($j = e$).

α_{ij} are individual fixed effects for each type of activity, which can control for many individual characteristics that could influence online contribution levels, such as ability, personal preference, gender, age, and so on. The fixed effects are added at both the individual and activity level due to contributors' preference of one task over another. For example, some contributors ask many Questions but rarely give any Answers.

β measures changes in Edits activity before and after a job switch. The main parameter of interest is the DD coefficient γ. γ measures the additional

Figure 4. (Color online) Average Monthly Activity on Stack Overflow (Answers and Edits)



Notes. x-axis: number of months since a new job starts. $t = 1$ means the first month of a new job. People with different starting dates are normalized to the same timeline based on number of months since the new job. y-axis: log differences of activities.

change in a VGA (Answers or Questions) over the changes to a non-VGA (Edits) after a job change.

The two parts of Proposition 1 can be expressed by the regression coefficients β and γ. Specifically, we expect the level of SO activity to drop subsequently to a job shift; that is, we expect β and $\beta + \gamma$ to be negative. Moreover, we expect the drop in Answers to be greater than that of Edits, so that $\gamma < 0$, in addition to $\beta < 0$.

6.1.1. Seasonality and Duration Effects. To obtain a more accurate estimate of the effect of career concerns, we include additional activity data from a large sample of about 96,000 active SO users, which can control for variations due to seasonality and duration effects.[17]

Online contribution might be more active in certain months than others; job changes can also occur more often in certain months of the year. We include additional year and month dummies to control for such potential effects, denoted by λ_{jt} in regression (5). Duration effects include the initial excitement of discovering SO, which can change over time and have heterogeneous effects on Answers and Edits activity. We measure duration as the count of the number of months since the first activity on SO for each user and include dummies for all distinct values of duration, denoted by X_{ijt} in regression (5). A separate set of seasonality and duration dummies is added for each type of activity, in order to control for the heterogeneous effects of seasonality and duration on different activities.

6.2. Main Effects of Career Concerns

Table 2 presents our core results. The results are organized into two panels, using the number of Answers and Votes gained from Answers as measures of Answers activity. For each panel, the first regressions (columns 1 and 3) show our base results without controlling for seasonality and duration effects. We thus have 18,192 observations (1,516 job switches from 1,301 contributors times 6 months (3 prior to the job switch and 3 subsequent to the job switch) and times 2 activities (Answers and Edits)). The second regressions in each panel (columns 2 and 4) shows the results while controlling for seasonality and duration effects, using activities from the above-mentioned 96,000 active SO users.

Column 1 shows that after a job switch, Edits activity experiences a significant drop of 7.38%. Moreover, the DD coefficient shows an additional drop of 16.27% in Answers activity, which we attribute to career concerns. The total changes in Answers activity can be calculated by −7.38% − 16.27% = −23.65%. The results confirm the predictions from Proposition 1 that both coefficients are negative. Column 2 adds a set of dummies that control for seasonality and duration effects, with which the coefficient estimate reduces slightly to a statistically significant 12.36% decline.

Columns 3 and 4 report the same set of estimates using Votes instead of Answers to measure the Vote-generating activity. Votes is a measure that includes both quantity and quality of Answers, and it can be a

Table 2. Effects of Career Concerns on Answers and Edits Activity

	Panel A: $y \in$ {Answers, Edits}		Panel B: $y \in$ {Votes, Edits}	
Variables	(1)	(2)	(3)	(4)
NewJob (*S*)	−0.0738***	−0.0742***	−0.0738***	−0.0742***
	(0.019)	(0.019)	(0.019)	(0.019)
NewJob (*S*) × *Answer*/*Vote* (*J*)	−0.1627***	−0.1236***	−0.1943***	−0.1536***
	(0.033)	(0.033)	(0.037)	(0.037)
Seasonality dummy		x		x
Duration dummy		x		x
Contributors	1,301	97,723	1,301	97,723
N	18,192	9,105,862	18,192	9,105,862
R^2	0.014	0.033	0.014	0.027

Notes. This table summarizes the DD estimates from regression (5). The DD coefficient measures the extent to which Answers activity changes relative to Edits activity in a 3-month period before and after switching to a new job. The dependent variables include both Answers and Edits activity. Panels A and B use distinct measures of Answers activity: Panel A uses the number of Answers, and Panel B uses the number of Votes received from Answers. All measures of activities are transformed by a logarithm of one plus the activity count. Independent Variables: S_{it} indicates whether the current state is a new or old job: $S_{it} = 0$ prior to job switch, $S_{it} = 1$ after job change. J_j indicates the different types of activities: $J_j = 1$ if $k = a, v$ (Answers or Votes activity), $J_j = 0$ if $k = e$ (Edits). The first row of the table presents the estimates of β, which measures the changes in Edits activity after switching to a new job. The second row presents the estimates of DD coefficient γ. The first column in each panel estimates the regression without extra controls; the second column adds seasonality (year and month) and duration (length of time since first activity on SO) dummies. To control these effects, we use the activity data of 96,000 SO users, which is shown in the "No. of contributors." Number of contributors for DD analysis, 1,301; number of job switches, 1,520; number of contributors used to control for seasonality and duration effects, 96,422. Robust standard errors are in parentheses, clustered at the individual-activity-type level.

***p < 0.01; **p < 0.05; *p < 0.1.

better measure of the amount of effort in contribution activities. The results using Votes give similar but slightly larger estimates than results using Answers. In Section 6.4, we investigate in depth the impact of increased effort on the quantity and quality of Answers.

6.3. Month-to-Month Comparison

Table 2 summarizes DD estimates by comparing the differential changes of Answers and Edits activity in the 3-month period before and after a job change. We also explore the effects of career concerns over a longer period of time. Using period −2 as the baseline period, we compare the activity of all other periods to period −2.[18] We also control for seasonality and duration effects using the same 96,000 SO users mentioned before. We do so by estimating two following specifications:

$$y_{it} = \alpha_i + \sum_{\tau=-20}^{20} \beta_\tau \, \mathbb{1}(P_{it} = \tau) + \lambda_t + X_{it}\,\theta + \epsilon_{it} \tag{6}$$

$$y_{ijt} = \alpha_{ij} + \sum_{\tau=-20}^{20} \big(\beta_\tau \, \mathbb{1}(P_{it} = \tau) + \gamma_\tau J_j \, \mathbb{1}(P_{it} = \tau)\big) + \lambda_{jt} + X_{ijt}\,\theta + \epsilon_{ijt}. \tag{7}$$

Regression (6) measures how each activity varies over time relative to baseline period −2, which is denoted by β_τ. Regression (7) estimates the differential changes between a VGA (i.e., Answers) and non-VGA (i.e., Edits) between the baseline period −2 and all other periods, and the DD coefficient is denoted by γ_τ.

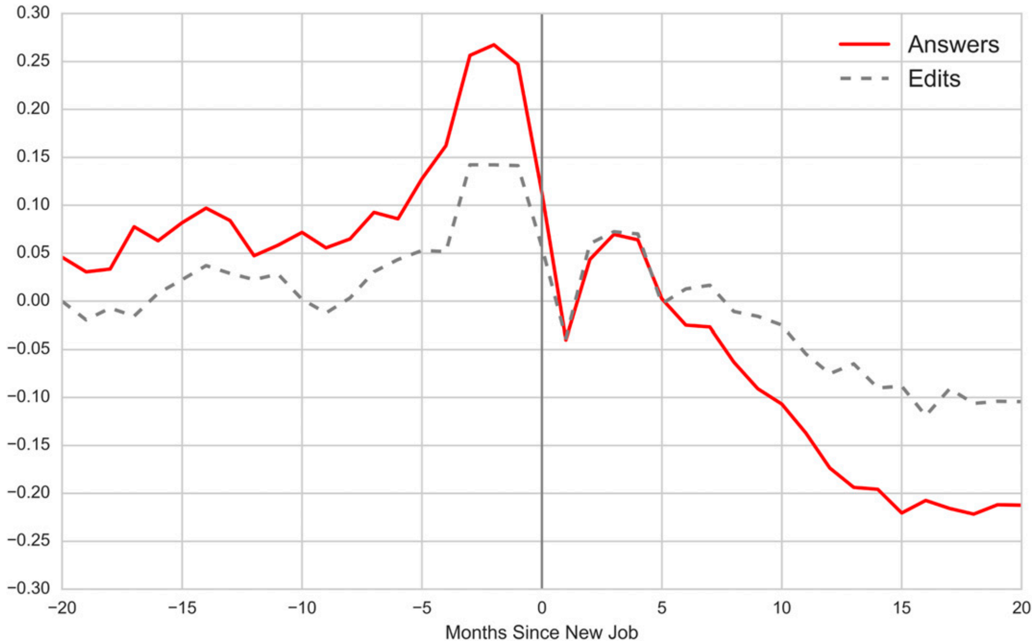
λ_{jt} and X_{ijt} control for seasonal and duration effects for each type of activity. P_{it} represents the number of months after a job change, and $\mathbb{1}(P_{it} = \tau)$ is a dummy variable equal to 1 if the month t for user i corresponds to τ months after a job change.

Figure 5 plots the demeaned values of the estimates of β_τ for Answers and Edits activity.[19] It is essentially Figure 4 with seasonality and duration effects removed. Answers and Edits activity remain relatively stable from 20 to 5 months before the event of a job change. During the 5-month period before a job change, both Answers and Edits activity experience a rapid increase, with Answers growing more than Edits.[20] Then, a rapid drop occurs in both Answers and Edits activity starting from 1 month before a job change, with Answers decreasing significantly more than Edits, and both continue to decrease over time.

Figure 6 shows the differential changes in Answers and Edits activity over time by plotting the DD estimates γ_τ for $\tau \in [-20, 20]$, as well as the 95% confidence interval. Before switching to a new job, all the DD estimates are negative but not significantly different from zero. Following the job-change event, all the DD estimates are significantly negative, with Answers decreasing significantly more than Edits.

Both figures illustrate that the Answers activity continues to drop over time after a job change. This decline may be explained in several ways. First, the first few months are often considered probationary periods during which both employers and employees can freely terminate contracts. Thus, career concerns

Figure 5. (Color online) Activity Trends (After Controlling for Seasonality and Duration Effects)



Notes. This figure plots the demeaned values of β_τ, estimated using regression Equation (6). Compared with Figure 4, this figure removes the seasonality and duration effects.

drop significantly but do not completely disappear as both parties need time to determine the match quality. If career concerns persist, the effects using regressions (6) and (7) are underestimated. Second, job seekers may form the habit of contributing to SO as they improve their online reputation, which can have long-term effects on contribution activities. Without taking into account habit formation, our DD estimates provide a lower bound of the true effect of career concerns.

6.4. Signaling Game: Quality vs. Quantity

The classic career-concerns hypothesis in Holmström (1999) shows that job seekers exert effort to signal their unobserved ability. Questions to ask are (a) what are job seekers signaling through SO, and (b) what information do employers obtain from the online activity of a job candidate?

Figure 7(a) plots the trend of Votes and Answers over time. The correlation between the two measures is remarkably high. The fact that the average quality of Answers remains constant seems to contradict the basic intuition of the career-concerns story.[21] However, one cannot conclude that career concerns have no effects on the quality of Answers.

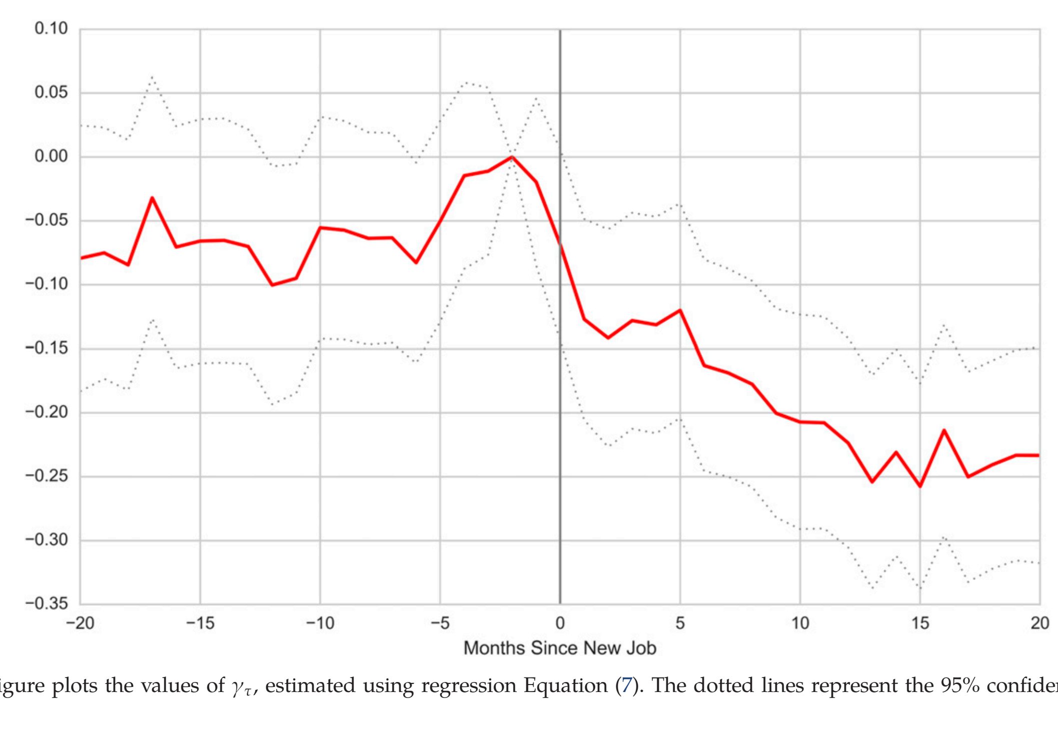
Given a fixed supply of Questions, the additional efforts to answer Questions should lead to (a) better Answers from Questions a contributor would answer regardless of career concerns, and (b) more Answers from Questions a contributor would not answer without career concerns due to low matching qualities. Thus, one should observe that as the time of a job change approaches, a job seeker gives more Answers, and, at the same time, the quality of the Answers is mixed.

To test this hypothesis, we pick the best Answer (measured by Votes) given by a contributor for each month, and Figure 7(b) plots the average Votes from the best Answers over time. It shows that the quality of best Answers follows a similar pattern to the number of Answers. This observation is consistent with the hypothesis that, apart from quantity of Answers, contributors also improve the quality of Answers before a job change. However, caution should be taken regarding the causality, because the result can also be explained by the random distribution of matching quality, with which the largest order statistic (maximum Votes) increases with a larger sample (number of Answers).[22]

6.5. Questions Activity

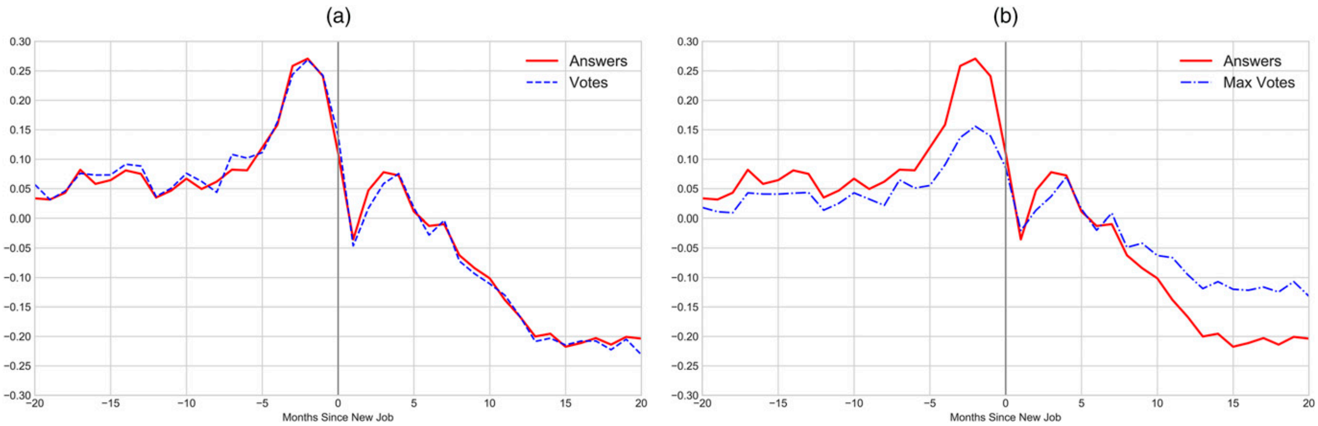
Questions is another important activity on SO, because there are no Answers without Questions. Here, we investigate how Questions activity changes surrounding the event of a job change. The plotting of Questions activity (included in the online appendix) shows little change in the number of Questions over time. Questions activity reduces slightly at the end of a previous job and then increases right after starting a new job. Questions activity is a learning tool, and a shift to a new job creates new learning demands even for new jobs with the same set of technology, an effect that seems to compensate for the higher opportunity cost of time spent on SO as well as the diminished

Figure 6. (Color online) Trends of the Differences Between Answers and Edits



Notes. This figure plots the values of γ_τ, estimated using regression Equation (7). The dotted lines represent the 95% confidence intervals.

Figure 7. (Color online) Quantity and Quality of Answers Activity



incentive to build a reputation. Asking Questions might also be perceived as an inability to solve problems; therefore, job seekers avoid asking Questions.[23]

6.6. Heterogeneous Effects of Career Concerns

The hypothesis of career concerns states that job seekers make efforts to improve the signals to employers that reflect ability. Such signals in the real world can be multidimensional, and Proposition 2 implies heterogeneous responses by job seekers with different backgrounds. This subsection tests the prediction by comparing the reactions of job seekers by reputation and education levels.

Part 1 of Proposition 2 shows that because reputation points on SO are cumulative, signals are carried through both existing and new Answers activities. When pursuing new employment opportunities, job seekers with different levels of reputation might have heterogeneous responses to career incentives. For a job seeker who already enjoys an outstanding reputation on SO, the marginal benefit of extra effort to improve that signal should be relatively small. We associate each job switch with the reputation points at the time of the switch and conduct separate analyses by splitting the sample into four equal groups of job switches.[24] Panel A in Table 3 shows that job seekers in the second and third quartiles (columns 2 and 3) respond most to career incentives at 22.8% and 24.2%, respectively. Those with the highest reputations (column 4) show a smaller effect at 13.2%. These results are consistent with the prediction of Proposition 2 and Lerner and Tirole (2002) that the effect of career concerns is larger when effort has a stronger impact on performance, or reputation in our setting.[25] The most striking result comes from job seekers with the lowest SO reputations. The sign of the estimate is opposite that of results from other groups: One possible explanation is that low-reputation users probably do not provide a link to their SO profiles when applying for jobs.[26]

Part 2 of Proposition 2 predicts that job seekers with better offline signals respond less to career concerns through online activities. Similarly, Lerner and Tirole (2002) conjecture that the behavioral responses are most pronounced when performance becomes more informative about talent. We test this possibility by looking at the highest education levels achieved by the job seekers. An individual without postsecondary education should have more incentive to improve the signal through other activities, including online activity; an individual with an advanced degree probably relies less on online activity to signal ability. We extract the highest degree obtained by SOC users and divide the degrees into four groups: High School (HS), Four-Year or Community College (College), Master's, and PhD. Then, we conduct separate analyses for each group. As shown in Panel B in Table 3, the magnitude of the DD estimates is roughly consistent with the hypothesis of career concerns. Those with a high school diploma as their highest education respond to a job change the most (−20.5% in column 1), although the response is insignificant given a very small sample size; on the other hand, those with a PhD show the least response to job switches (−8.8% in column 4).[27] College and Master have similar responses to career concerns (columns 6 and 7), even though the theory predicts otherwise, probably due to other unobserved individual- or group-level characteristics.

Proposition 2 also predicts that those with more work experience might respond more to changes in career incentives.[28] As such, we expect our main result (job change leads to less contribution) to be lower for more experienced agents. We investigate this assumption using age inferred from information on one's CV and find the opposite results, possibly due to a noisy measure of age. More likely, a confounding effect exists: A young worker has more to gain from signaling quality, which would suggest a stronger effect; but for a young worker, a job change is just the

Table 3. Effects of Career Concerns By Education Levels

	Panel A: Reputation quartiles				Panel B: Education level			
Variables	(1) Rep. Q1	(2) Rep. Q2	(3) Rep. Q3	(4) Rep. Q4	(5) HS	(6) College	(7) Masters	(8) PhD
NewJob	0.157***	−0.067*	−0.166***	−0.251***	0.102	−0.084***	−0.045	−0.036
	(0.04)	(0.03)	(0.04)	(0.04)	(0.16)	(0.03)	(0.05)	(0.10)
NewJob × *Answer*	0.102	−0.228***	−0.242***	−0.132*	−0.205	−0.121***	−0.164**	−0.088
	(0.06)	(0.06)	(0.07)	(0.07)	(0.25)	(0.04)	(0.08)	(0.17)
Contributors (DD)	356	350	340	311	12	778	230	51
Contributors (control)	96,422	96,422	96,422	96,422	96,422	96,422	96,422	96,422
N	9,092,012	9,092,002	9,092,012	9,092,000	8,944,282	8,955,016	8,947,346	8,944,870
R^2	0.033	0.033	0.033	0.033	0.033	0.033	0.033	0.033

Notes. Reputation Points: minimum: 0; first quartile (Q1): 770; median: 2,124; third quartile: 5,265; maximum: 132,067. Seasonality and duration dummies are included in all regressions. Robust standard errors are in parentheses, clustered at the individual-activity-type level. Rep., reputation.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

first of many, and the incentives to signal are likely to remain high, which in turn suggests a lower drop in incentives. Another possible explanation is that career incentives play a more important role in driving voluntary contribution for younger users than for the older ones, a pattern consistent with what we usually observe in other types of real-world voluntary activities.

6.7. Economic Significance

The previous analysis shows a statistical significance of career concerns in driving job seekers' contribution behavior. We also attempt to measure the economic significance of career concerns on SO—namely, how much of the Answers activity is driven by career concerns. The answer to this question requires several debatable assumptions. The basic intuition of this counterfactual exercise is to measure the gap between Answers and Edits activities in Figure 6. In the online appendix, we carefully list all the assumptions needed to measure the economic significance and conclude that, given those assumptions, depending on the choices of parameter values, the estimates range from 1.79% to 8.71%—namely, 406,000–1,974,000 out of 22,671,000 Answers on SO are driven by career concerns.

6.8. Job-Search Process

Our finding that online contribution activities start increasing around 3–5 months before moving to a new job (Figure 6) is consistent with some general career guidelines that suggest a best-case scenario of 3-plus months for finding a new job. The time needed to land a new job for SO contributors might be even shorter because the unemployment rate of the technology industry has been consistently lower than the national average (at around half of the national average according to data from the Bureau of Labor Statistics). The common practice of notice of termination, like other industries, is around 2 weeks, which is also consistent with the finding that the contribution activities start dropping in the last month of the previous job. More detailed information on the job-search process can be found in the online appendix.

7. Testing Identification Assumptions

Our identification relies fundamentally on the parallel-trend assumption in Answers and Edits activity. That is, if a job switch did not occur (i.e., without a change in career incentives), the relative ratio of Edits and Answers would have remained constant. Because this assumption plays a central role in our identification strategy, additional evidence on it is warranted. In this section, we first provide some evidence to support this assumption. Then, we will discuss and test for several major challenges to the assumption.

7.1. Evidence of Parallel Trends: Plotting of Online Activities

Figure 4 plots the average logged activity over time. It provides some evidence on the parallel changes in Answers and Edits over time. Figure 5 further plots the same activities, while removing the potential confounding effects from seasonality and duration. In the periods further away from a job change, the level of career incentives should be relatively stable. Figures 5 and 6 show that in periods before −5 and after 10, although activity levels vary, Answers and Edits move similarly over time. This finding supports for the parallel-trend assumption.

7.2. Evidence of Parallel Trends: Within-Job Activity

The parallel-trend assumption implies that if no changes occurred in career incentives, variations in time availability should have similar effects on Answers and Edits activity. To show cleaner evidence, we identify a period of stable employment for each contributor.[29] We assume that during these periods, although a contributor's availability fluctuates, the change in career concerns is smaller than what we observe leading up to a job change. Consistent with our basic identifying assumption, we expect the differences between a_t and e_t to remain constant.

Figure 8 plots the demeaned value of Answers and Edits for 5–42 months after a job change. Consistent with our underlying assumption, the differences between the two are fairly constant.[30] As a robustness test, regressing the logarithm of Answers on Edits activity gives a coefficient of 0.844–0.958, which is reasonably close to a coefficient of 1, which is consistent with homotheticity.[31]

7.3. Integer Constraints

The validity of the career-concerns hypothesis relies on the assumption that changes in time availability due to a busier work schedule affect Answers and Edits activity similarly. However, an alternative interpretation that can explain our previous result that a_t/e_t drops subsequent to a job change is that users are faced with an "integer constraint:"[32] Answers activity requires higher set-up costs than Edits. When job changes reduce availability, contributors have less time to allocate to Answers; Edits typically require less time and are easier to fit into a busy schedule.

The rich data set of SO user activity, along with employment history of SOC users, allows us to test whether the integer-constraint problem exists in our study and to what extent (i.e., whether we can reject the hypothesis of career concerns).

7.3.1. Weekdays vs. Weekend Activities. Following the start of a new job, a full schedule should reduce user availability predominantly during weekdays rather than weekends. Accordingly, we split our sample into weekday and weekend activities and conducted separate DD analyses. To the extent that work hours are more concentrated on weekdays, the integer-constraint hypothesis should have a more significant effect on a_t/e_t during weekdays.

Table 4 shows the results of the DD regressions split into weekdays and weekends. Panels A and B use Answers and Votes as measures of reputation-generating activities. If no integer constraints existed and all users contributed to Answers and Edits activity on both weekdays and weekends, then we would find no differences between the DD estimates from weekday and weekend activities.[33] Broadly speaking, the coefficient estimates are similar to those in the base model, and the difference between the estimates using weekday and weekend activities is relatively small.

The difference between the DD estimates from weekday and weekend activities implies that, although the integer-constraints problem might exist for certain users, it does not explain the additional drops in Answers relative to Edits after a job change. It fails to reject the career-concerns hypothesis.

7.3.2. Internal Promotion. Internal promotion is an important case in two ways: First, a promotion often assumes more managerial duties that lead to more significant changes in one's work schedule than lateral moves. In this way, internal promotion is most likely to satisfy the integer-constraint hypothesis. Second, the hypothesis of career concerns states that a job seeker signals to potential employers through online activity due to employers' inability to accurately access job candidates based on limited information. In the case of an internal promotion, such a signaling incentive is unlikely, because past internal performance is transparent to the employer.[34]

Figure 8. (Color online) Within-Job Variations of Answers and Edits Activity

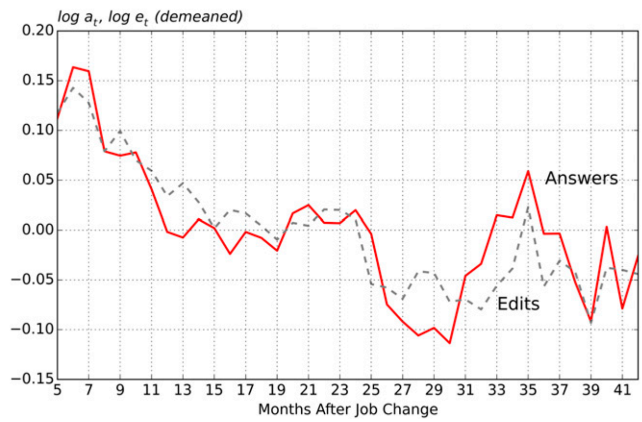


Table 4. Effects of Job Changes on Weekday vs. Weekend Activities

	Panel A: $y \in$ {Answers, Edits}		Panel B: $y \in$ {Votes, Edits}	
Variable	(1) Weekday	(2) Weekend	(3) Weekday	(4) Weekend
NewJob	−0.072***	−0.060**	−0.072***	−0.060**
	(0.02)	(0.02)	(0.02)	(0.02)
NewJob × *Answer/Vote*	−0.122***	−0.103**	−0.135***	−0.124***
	(0.04)	(0.04)	(0.04)	(0.05)
Contributors (DD)	1,159	374	1,159	374
Contributors (control)	96,422	51,296	96,422	51,296
N	7,378,770	2,895,384	7,378,770	2,895,384
R^2	0.031	0.043	0.026	0.031

Notes. Seasonality and duration dummies are included in all regressions. Robust standard errors are in parentheses, clustered at individual-activity-type level.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Our analysis includes both weekday and weekend activities. If an integer-constraint problem exists for job seekers who received internal promotions, then for weekday activities, we expect to observe an additional reduction in Answers relative to Edits. However, an internal promotion should affect the weekday work schedule only, leaving the job seeker similar levels of freedom to organize her schedule on the weekends. Therefore, we expect not to observe a differential effect of an internal promotion on Answers and Edits activities on the weekend.

Table 5 summarizes DD estimates for both internal moves and internal promotions, using weekday and weekend activities separately. Panel A uses all contributors for comparison purposes, which has the same results as Panel A (column 2 and 4) of Table 4. Panel B focuses on internal moves—that is, job changes within the same company. The estimates in Panel B are not vastly different from those in Panel A in magnitude, but both become insignificant (most likely due to a smaller sample size). One potential concern is that many internal moves are lateral and do not necessarily require managerial duties. Panel C focuses on internal promotions using a stricter measure based on job-title information. Column 5 shows that Answers experience an additional drop of 15.6% compared with Edits on weekdays. Although the estimate is insignificant (due to a small sample size), it supports the hypothesis of integer constraints for internally promoted workers. Column 6 shows a negligible DD estimate using weekend activities, which provides additional evidence that only weekday activities are affected by integer constraints.

To summarize, Panel C of Table 5 shows the likely presence of the integer-constraint problem in our DD analysis. Although this problem does not disprove the career-concerns hypothesis, it provides certain explanations regarding the different DD estimates from weekday and weekend activities in Table 4.

7.4. Skills Mismatch

Another interpretation for the decrease in Answers following a job shift is that the new position requires different skills. For example, a C++ programmer may switch to a job that requires knowledge in Java; this SO user spends more time learning Java instead of answering C++ questions.

User profiles on SOC provide detailed information regarding work experience as well as information on the technology associated with each job, in the form of tags.[35] To test whether our estimates are driven by skills mismatch, we focus on users who switch to new jobs with similar sets of technologies based on the tags. First, we define a measure of skill similarity between jobs.[36] Then, we reestimate the DD regressions separately based on the skill-similarity measures. We find that those users who switch to new jobs with similar technology also experience a significant drop in Answers over Edits activity. For robustness checks, alternative measures of job similarity also give similar results.[37]

We also compare the job titles of the old and new jobs. New jobs with the same job title as the old ones are associated with similar responsibilities and availability. These job changes are least likely to be affected by the integer-constraint problem. The DD estimates using this sample are consistent with the baseline results using the full sample. That is, the finding is consistent with the career-concerns hypothesis.

7.5. Dynamic Selection Effects (Ashenfelter's Dip)

The variations in Figure 4 can also be explained by dynamic selection effects, which state that the sample of job switchers are selected due to a special event prior to the job change that only affects the treatment group, but not the control group. This hypothesis is commonly referred to in labor economics literature as Ashenfelter's Dip (AD).[38]

Suppose contributors experience random shocks in the number of Answers and Edits in each period, and

Table 5. Effects of Job Changes for Internal Promotions

	Panel A: All		Panel B: Same company		Panel C: Promotion	
Variable	(1) Weekday	(2) Weekend	(3) Weekday	(4) Weekend	(5) Weekday	(6) Weekend
NewJob	−0.072***	−0.060**	−0.070	−0.039	−0.151**	−0.157
	(0.02)	(0.02)	(0.05)	(0.08)	(0.06)	(0.10)
NewJob × *Answer*	−0.122***	−0.103**	−0.090	−0.119	−0.156	−0.008
	(0.04)	(0.04)	(0.09)	(0.13)	(0.11)	(0.19)
Contributors (DD)	1,159	374	142	41	80	21
Contributors (control)	96,422	51,296	96,422	51,296	96,422	51,296
N	7,378,770	2,895,384	7,364,466	2,890,896	7,363,686	2,890,644
R^2	0.031	0.043	0.031	0.043	0.031	0.043

Notes. Seasonality and duration dummies are included in all regressions. Robust standard errors are in parentheses, clustered at individual-activity-type level.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

suppose a higher number of Answers can significantly improve the chance of getting job offers (i.e., $p'(r_t)$ is large enough). Then, the sample of job shifters tends to include those who experience a large Answers shock in periods immediately preceding a job change. In that case, the "bump" in the number of Answers before job changes (as the one in Figure 4) is purely caused by the selection into treatment from random activities, not by changes in user behavior in response to incentives.

This alternative hypothesis also touches on the issue of reverse causality or selection into treatment in which A_{t-1} causes $NewJob_t$. In the classical AD problem in Ashenfelter (1978), the dip is assumed to be due to random shocks. Therefore, the problem can be solved by using periods further away from the time of treatment or by matching treatment group with a properly selected control group who also experience a similar shock. However, in our analysis, the bump (or the "reversed" dip) in Figure 4 is central to the career-concerns hypothesis. In essence, we are estimating the size of the bump and interpret it as a behavioral response by contributors due to career concerns, rather than a design problem with selection into treatment from random shocks.

7.5.1. Identification of AD vs. Career Concerns. We argue, by means of numerical simulations, that AD does not provide compelling evidence against the career-concerns story. Would the estimates be large enough to reject the career-concerns hypothesis? If not, under what conditions would we be able to do so?

First, we draw random Answers and Edits activities following a certain distribution (as well as bootstrapping from the actual activities) and then simulate job-change status given a likelihood function of job changes. The simulation is then repeated R times, and the DD estimates are calculated and plotted. The comparison between simulated estimates and the actual DD estimate can help us examine whether the career-concerns hypothesis can be rejected in favor of the AD hypothesis.[39] With each simulation, we conduct the DD analysis and plot all the estimates using a kernel density plot.

The simulation results are plotted in Figure 9. Figure 9(a) plots simulated DD estimates using bootstrapped Answers and Edits (i.e., drawn directly from the actual activity), both in pairs (blue line) and separately (green line). The red line plots the distribution of the actual DD estimate from column 1 of Table 2, with a mean of 0.1627 and a standard deviation of 0.033. In Figure 9(b), instead of drawing random activity directly from the actual activity, we first fit two negative binomial distributions for Answers and Edits activities. Neither simulated estimate is significantly far from zero; that is, the DD estimate of 0.1627 cannot be explained by selection into a job change due to random activities.

Simulations using Answers and Edits drawn separately give a wider range of DD estimates than those using data drawn in pairs. In reality, the number of Answers and Edits given in a month by a contributor is always correlated because both correlate with the time spent on SO.[40] If the two activities are perfectly correlated, simulated DD always gives zero estimates. However, Answers and Edits are uncorrelated when drawn independently; thus, we are more likely to observe high levels of Answers activity with low Edits activity.

Another reason the AD problem doesn't invalidate the career-concerns hypothesis is the small effect of Answers activity on new job offers. Although unable to accurately estimate this effect due to the presence of endogenous variables, we obtain an upper bound of the true value. The fact that we cannot reject the career-concerns hypothesis using the upper-bound estimate gives us even more confidence in our conclusion.

We also build a simple logit model in which Answers activity leads to job offers. We show that to mimic the estimates of our main result, the effect of Answers activity on job offers would be unreasonably large.[41]

7.6. External Validity

External validity is one of the most common challenges for empirical studies without a randomly selected sample. Our research is no exception. In fact, our sample is not representative of all SO contributors in terms of total online activities. SO, like any platforms that rely on user-generated content, shows a long-tail pattern that the majority of users contribute very little content, and the contributors in our sample are drawn from a much more active population. Without the less-active contributors in our analysis, we believe our results still provide valuable information to platform managers. First, on SO, 10% of the users contribute roughly 90% of all content. These active contributors are the core users that SO cares about most. Our result unravels one of the motivations that drives user activity. Second, we believe platforms can potentially motivate less-active users through career concerns, due to the existing information-asymmetry problem between job seekers and employers.

Another challenge to the external validity touches on the central element that allows us to conduct this research: the links between CV and the online activities. Without this link, online activities and real-life job-switching events cannot be connected, because contributors often adopt pseudonyms. The link is found through SOC profiles. SOC first sends out invitations to active contributors on SO. Then, an invited user chooses whether to accept the invitation as well as provide a link to her SO page on the SOC profile. Therefore, a primary concern is that those users who accept the invitation and provide a link between their SO and SOC profiles are those who are most interested in ability-signaling through SO activities. In other words, our result that SO contributors respond to career concerns might not apply to other active users who chose not to open an SOC profile or provide a link between their SO and SOC profiles.

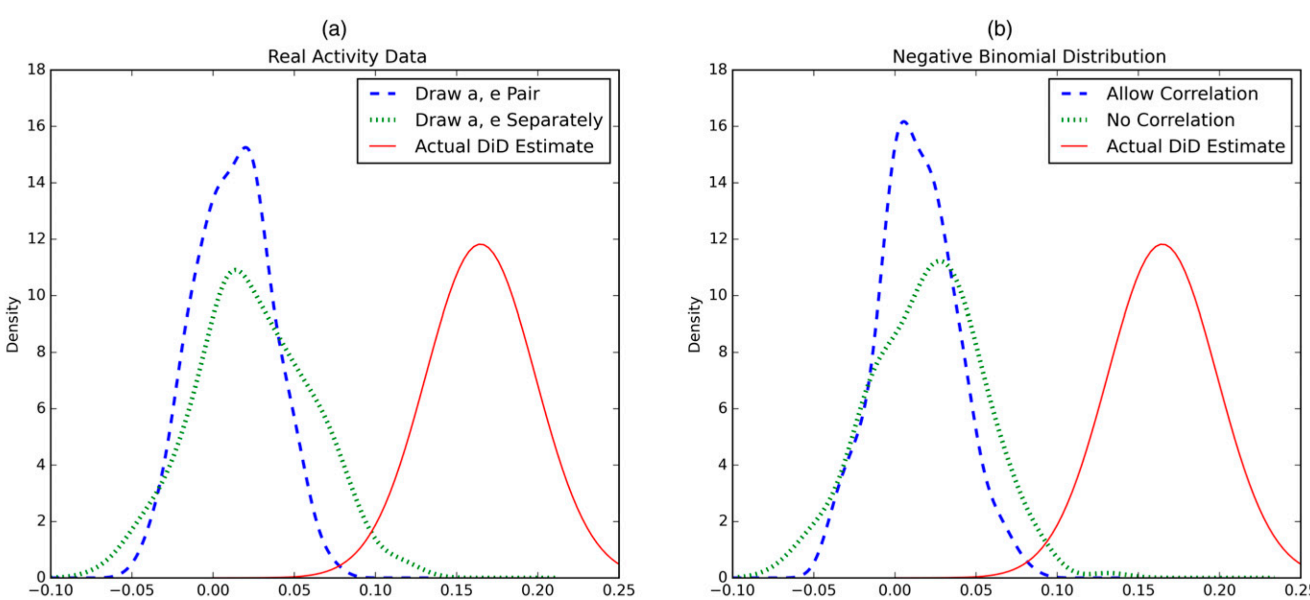
To address this concern, we propose a way to test the external validity: We search for *indirect* links between user CVs and user SO histories. Specifically, we click through on an SO profile until we find a link to the user's LinkedIn page. Once there, we analyze the user's work history from the LinkedIn profile to determine the time of job change.

We explicitly exclude from this sample all users with an SOC profile and those who provide a direct link to LinkedIn. We do so to address the concern that a link to SO may result from an endogenous user choice and bias the sample. This alternative sample may be biased *against* users whose contributions to SO depend on career concerns.

Using the same regression specification as in Section 6, Table 6 shows the result of the DD analysis with data collected by using the indirect-link approach. Column 2 shows a DD estimate of 12.5%, which is slightly smaller than the estimates in our baseline results in Table 2. The estimates are also less statistically significant due to a smaller sample of 197 contributors.

Admittedly, the test of external validity using the indirect-link approach is not without limitations. Many job-application processes are conducted through emails or through internal application systems. Moreover, for many SO contributors, the links between CV and SO profiles do not exist (or we could not find them). Nevertheless, our additional results provide additional

Figure 9. (Color online) Density Plot of Simulated Difference-in-Differences Estimates



Note. DiD, difference-in-differences.

evidence of career concerns that is consistent with our baseline results.

8. Discussion and Concluding Remarks

In this paper, we analyze data from the online Q&A site Stack Overflow and show that career concerns provide a strong incentive for users to contribute—namely, to answer questions posted on the various SO boards. Our strategy for identifying career-concern-based incentives is to estimate the effect of a job change. Our regressions estimates suggest that achieving the goal of switching to a new job leads users to decrease their contribution to SO and that a drop of about 12.5%–16.5% can be assigned to a drop in career concerns. This value is both statistically and economically significant. We discuss and test the validity of the identifying assumption by showing evidence related to our career-concerns hypothesis as well as to alternative explanations.

Although our results pertain to a particular reputation mechanism on a particular online platform, we believe they may have wider application, including application to other Q&A platforms that are in some way connected to job placement. For example, one problem that online education platforms such as HBX need to solve is scalability—specifically, answering student questions when the number of students increases by one or two orders of magnitude with respect to typical brick-and-mortar class sizes. One possible solution is to resort to artificial intelligence systems (witness, e.g., the 2016 Watson-based experiment in Georgia Tech's Computer Science class). An alternative solution is to rely more heavily on crowdsourcing from users themselves (e.g., encourage students to answer each others' questions or to grade each others' quizzes).

Suppose the platform creates an SO-like reputation system to measure each student's contribution. To the extent that potential employers have access to reputation scores, our paper's results suggest that students' incentives to contribute (help each other) will be considerably enhanced. In fact, the better the student's contribution to the platform, the better impression potential employers will have about the student's abilities. In this sense, the value created by a reputation mechanism is two-fold: It increases the quality of services provided by the platform to students, and it increases the quality of services provided to employers.[42]

In a broader (and looser) sense, our paper also contributes to a central issue in organizational behavior: assessing the importance of intrinsic and extrinsic motivation.

Many successful corporations rely on user-contribution platforms as a source of value. For example, Amazon reviews provide value to Amazon shoppers; Apple's technical-help Q&A boards add value to Apple products; and Yelp's restaurant reviews provide value to restaurant goers. These platforms are rather different from SO and SOC. In particular, career concerns do not play an important role for Amazon or Yelp reviewers. That said, an important question in these platforms is how to provide incentives for extensive and high-quality user reviews. What leads users to contribute? What makes them tick? Our paper suggests that extrinsic motivation (in the form of reputation scores observable by potential employers) plays an important role. What the equivalent mechanism might be on Amazon or Yelp is unclear. One possibility is free goods or services offered to high-reputation users. Our point is that a well-designed reputation mechanism might be an important component of an effective rewards program, which in turn will contribute to a quality review system. However, one concern that platforms should consider is the potential crowd-out effects of extrinsic over intrinsic motivation. The literature has shown mixed results in different settings (Bénabou and Tirole 2003, 2006; Roberts et al. 2006; Mellström and Johannesson 2008; Ariely et al. 2009), and further research is needed in such a potential effect in the design of online platforms.

Even more broadly, our paper contributes to understanding the increasingly important phenomenon of crowdsourcing. Crowdsourcing is broadly understood as the acquisition of information or services from customers, users, or other unspecified third parties at low or zero economic cost. Media sites such as CNN or *the New York Times* make frequent and increasing use of this type of source. As competing content aggregators fight for this rich supply of original content, some form of compensation provided to contributors may be necessary. But lest the media site be inundated by

Table 6. Effects of Career Concerns: Data from LinkedIn Profiles

Variables	(1) $y = a$	(2) $y \in \{a, e\}$	(3) $y = v$	(4) $y \in \{v, e\}$
NewJob (S)	−0.165***	−0.040	−0.185***	−0.040
	(0.06)	(0.04)	(0.07)	(0.04)
NewJob (S) × *Answer* (A)		−0.125*		−0.146*
		(0.07)		(0.08)
Contributors	197	197	197	197
N	1,396	2,792	1,396	2,792
R^2	0.012	0.008	0.011	0.008

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

low-quality or irrelevant material, rewards must be given to the better content pieces. In this context, a reputation system such as SO's may be what the media platform needs to maintain an effective incentive system.

Finally, as mentioned earlier, the issue of career concerns is central to the discussion of the viability of open-source software. Understanding motivation, as Lerner and Tirole (2002) aptly put it, will "provide lenses through which the structure of open source projects, the role of contributors, and the movement's ongoing evolution can be viewed." Is there any hope for quality code to be written by someone who is not being paid? To the extent that peer recognition may lead to employer recognition, the answer may be yes. Although our paper does not deal with open-source software directly, our results suggest that thoughtfully designed reputation mechanisms may enhance the link between effort and employer recognition in ways that informal peer recognition may not achieve.

Endnotes

[1] In Holmström's (1999) classic theory of career concerns, performance in the current job serves as a signal of one's ability to future employers. A job seeker makes effort to improve current performance in order to signal a higher ability, thus earning a higher salary from the new job. In this paper, we use "career incentive" and "career concern" interchangeably to denote any career-related incentives, such as salary increases and more job offers. In Section 6, we provide an in-depth discussion of the information being signaled through online activity.

[2] Only active SO contributors are invited to list a CV on SOC. Thus, our analysis is based on a more active sample of SO users. In additional to the typical information on a CV such as education and work experience, CVs on SOC also include summary statistics and top contributions on SO.

[3] The vast majority of users have a low level of activity. Our research focuses on the select sample of active contributors. See Section 4 for more details.

[4] In brief, by integer constraints, we mean the situation whereby a busier work schedule does not leave enough free time to write Answers, because Answers take more time than Edits; skills mismatch corresponds to the situation in which a new job requires a different set of skills, and a contributor is unable to write Answers related to the new required skills; and the dynamic selection effect (known as Ashenfelter's Dip in labor economics literature) refers to the situation in which the sample of job changers only consists of those who happen to contribute many Answers, and thus the drop in Answers activity is nothing more than a reversion-to-the-mean effect.

[5] In addition to providing independent evidence of career-concerns effects, our LinkedIn-based alternative data set addresses potential selection concerns from using SOC pages, given that inclusion in SOC is limited to a set of invited contributors who choose to link their CV to their SO activity page.

[6] See von Krogh and von Hippel (2006) and Osterloh and Rota (2007) for detailed surveys of this literature.

[7] Founded in 2008, it currently comprises 4.8 million users. Some summary statistics regarding the site's activity follow: 7.7 million visits/day, 7.9 thousand Questions/day, 10 million cumulative Questions, and 17 million cumulative Answers.

[8] Stack Overflow is the earliest website of Stack Exchange, which has a network of 150-plus Q&A communities that cover both programming- and nonprogramming-related sites. Our research focuses on Stack Overflow, which is the most active community, and it holds 67% of Q&As and 52% of daily visits of the whole Stack Exchange Network as of 2016. Please check http://stackexchange.com/sites for more details.

[9] Our analysis focuses mostly on Answers activity instead of Questions activity for two main reasons: First, ability-signaling is more likely to be done through Answers rather than Questions activity; second, the incentive structures between Questions and Answers/Edits are very different in that the former is done to seek help, whereas the latter is to offer help (private contribution to online public goods). For more discussion, please refer to Section 6.5.

[10] A user can also answer his or her own question, but to avoid gaming the system, no reputation points are earned.

[11] Older Answers have more cumulative Votes. To control for the comparability among Answers given at different time, we measure the total Votes gained on each Answer within 30 days after an Answer was given.

[12] Sample screenshots of SO and SOC profiles can be found in the online appendix.

[13] The exact criteria are not disclosed by SO. Requesting an invitation on the website is also possible.

[14] As of October 24, 2015, the SOC site lists 1,283 jobs, with 893 jobs located in the United States and Canada. The number is quite small compared with jobs on other major employment websites such as Monster.com and Indeed.com, where employers can post jobs free of charge.

[15] In addition to Answers, Questions can also attract votes (thus reputation points). However, most Questions are asked to solve work-related problems, and we consider them as part of w. Please refer to Section 6.5 for more discussion on Questions activity.

[16] A more detailed account of the selection procedure can be found in the online appendix. It also includes a more detailed comparison and discussion on differences between SO users, SOC users, and our selected sample.

[17] Although without information on CV and job status, we observe their online activity over time. The additional data are used to control for seasonality and duration effects only.

[18] Period −2 is used as the baseline period because it has the highest average Answers activity level.

[19] The detailed estimates of β_τ from regression (6) and γ_τ from regression (7) can be found in the online appendix.

[20] Huang and Zhang (2016) also show a positive association between increasing open-source software (OSS) activities with a higher likelihood of job changes.

[21] The measure of average Votes per Answer is typically defined as $v_{i,t}/a_{i,t}$. However, we are unable to draw this line directly, due to the prevalence of $a_{i,t} = 0$.

[22] The validity of the causality depends on the distribution of random matching quality. In Section 4.3 of the online appendix, we propose a parsimonious vote-generating process with random matching quality. Assuming the random matching quality is an independent and identically distributed variable which follows a logistic distribution, the finding of maximum Votes rising before a job change cannot be fully explained by the largest-order statistic.

[23] Please see the online appendix for more analysis related to Questions activity.

[24] We also tried other grouping measures, and all the results are qualitatively similar.

[25] Miklós-Thal and Ullrich (2015) also find a similar heterogeneous effect of career concerns for soccer players. They find that players with intermediate chances of being selected to their national team exert the most effort before the Euro Cup season.

[26] Spiegel (2009) shows that multiple equilibria can exist where separating equilibrium can exist that talented agents exert effort and untalented agents do not. We are reluctant to group contributors with low SO reputations as "untalented agents," because these contributors might have other better ability-signaling channels.

[27] Related to our observation, Bitzer and Geishecker (2010) show that the propensity to work on OSS projects is higher among university dropouts.

[28] Holmström (1999) also predicts that as a career proceeds, the market is better informed about a worker's ability, and the incentives to signal such ability are lower.

[29] To identify the time periods of stable employment, we need to observe the entire duration of a job, and we also require the contributors to have minimal total activities in the periods of stable employment. Figure 8 plots the demeaned logarithm of activities of 1,237 contributors, with around half overlapping with the 1,301 contributors in the main DD analysis.

[30] Using the same set of contributors, we also plotted a graph using periods before the end of the stable employment, which can be found in the online appendix. It shows similar stable variations of differences between a_t and e_t.

[31] The regression can be found in the online appendix.

[32] Integer constraint originally comes from mathematical programming when some choice variables are restricted to integer values. With this constraint, the agent has less freedom to allocate resources.

[33] The majority of contribution activities take place on weekdays rather than on weekends. The selection requirement of having at least one Answers and Edits activity leads to a smaller sample of users for the analysis of weekend activities.

[34] A job seeker might pursue outside opportunities in order to bargain with a current employer (Blatter and Niedermayer 2008). In this case, public signals become valuable for internal promotions. Unfortunately, we do not have data on how promotions occur. However, we do not think most employees being reviewed for promotion use this bargaining tool. Otherwise, firms might establish internal policies that forbid employees from building high-quality public signals, unless such a policy puts a company at a disadvantage in the hiring process.

[35] Users create tags by attaching relevant terminology to each job to convey technological experience. In our sample, the average number of tags for each job is 5.32. Tags are typically organized into three types: programming languages (e.g., Python or Java), packages/libraries/routines (e.g., NumPy or Matplotlib), and functionality (e.g., Data Analysis or Plotting).

[36] Let the set of tags associated with the new job be $S1$ and those with the old job be $S0$. We define JobSimilarity $\equiv \frac{Size(S0 \cap S1)}{(Size(S0)+Size(S1))/2}$.

[37] Detailed regression results can be found in the online appendix.

[38] In a more general econometric setting, AD can be considered a source of endogeneity through reverse causality or selection into treatment. Please refer to Ashenfelter (1978) for a detailed discussion.

[39] Detailed simulation methods can be found in the online appendix.

[40] The actual correlation between Answers and Edits is 0.564.

[41] Details can be found in the online appendix.

[42] An additional managerial implication is that it may be optimal to introduce some form of depreciation in reputation mechanisms such as Stack Overflow's: As Holmström (1999) argues, an agent's incentive to signal quality decreases as their audience becomes better informed about the agent's ability. Introducing a depreciation rate into an agent's reputation score may help in keeping the agent "on his or her toes." The downside is that the discounted value of reputation increases at time t may be lower in the presence of a reputation system with depreciation. Although the behavioral effect of reputation depreciation falls outside of the present paper's scope, we believe it is an interesting research question.

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