What Makes Geeks Tick?
A Study of Stack Overflow Careers

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Abstract

The success of a platform depends crucially on a thorough understanding of the motivations behind user participation. However, identifying incentives behind voluntary contribution has always been a challenging task. In this paper, we use a revealed preference approach to show that career concerns play an important role in user contributions on Stack Overflow, the largest online Q&A community. Using a difference-in-differences (DD) approach, we show that the event of finding a new job implies a reduction of 25% in reputation-generating activity, but only a reduction of 8% in non-reputation-generating activity. We provide direct evidence against alternative explanations such as integer constraints, skills mismatch, and selection into treatment (Ashenfelter's Dip). Our findings suggest that, beyond altruism, career concerns play an important role in explaining voluntary contributions to Stack Overflow.

Keywords: career concerns, signaling, voluntary contributions, online reputation, intrinsic and extrinsic motivation, platform design, public goods.

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1 Introduction

The Internet has revolutionized the world in many ways. Of particular interest is the phenomenon of private contributions to collective projects such as Wikipedia, bulletin boards, and open source software. As Lerner and Tirole (2002) put it: is it a case of altruism, or are there ulterior motives behind private contributions to a public good?

With the prevalence of online platforms, the answer to this research question has become increasingly important. Many businesses tried but failed to launch a successful platform, mostly due to insufficient user participation from one or multiple sides (Edelman (2015)). Due to network effects, platforms suffer from the classic chicken and egg problem that a user won't participate without others' participation. Therefore, in order to build a successful platform that attracts user participation, decision makers need to have a solid and thorough understanding of the motivations behind user participation.[1]

Evaluating the motivations behind user participation is not an easy task, especially for platforms that rely on voluntary contributions through user-generated content, i.e. crowdsourcing. The motivations behind the seemingly altruistic activities can vary dramatically by platform and audience.[2] A well-designed incentive structure can encourage more user participation, thus leading to a successful platform.

Our paper addresses this research question using data from Stack Overflow, the largest online 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.

Affiliated to Stack Overflow (SO), the Stack Overflow Careers (SOC) site hosts job listings and contributors' CVs so as to match employers and employees. The information regarding each job candidate includes their employment history as well as various summary statistics regarding their contribution to SO. A tantalizing possibility — the hypothesis we propose to test — is that contributing to SO is a way of signaling one's ability and thus find a better job.

[1] Users here can be both firms and individuals.

[2] Social interaction and ego gratification are two of the most important factors on Facebook and Twitter, while contributions to Wikipedia are more due to altruism and social interactions.

We construct complete histories of each individual's online trajectory. This includes their contributions to SO as well as individual characteristics and employment histories. We test the career-concerns hypothesis by identifying shifts in behavior following career-relevant shifts, namely employment changes.

We find that before changing to a new job, a contributor gives more and better Answers but asks fewer questions. However, right after the job change, there is a significant drop in Answers both in terms of quality and quantity. We use a difference-in-differences (DD) approach by comparing reputation-generating to non-reputation-generating activities from the same sample of job changers before and after a job change. We conclude that contribution levels decrease by 26.5% right after a job change, of which 13–17% are due to (the removal of) career concerns. We provide direct evidence against alternative explanations such as integer constraints, skills mismatch, and selection into treatment (Ashenfelter's Dip).

To the best of our knowledge, ours is the first paper that empirically identify and estimates the relation between changes in career status and voluntary contributions to online communities as an indirect measure of career concerns. We believe our methodology can be helpful in other contexts; and we believe our empirical results are important, considering the increasing prevalence of user-generated content in a variety of platform settings (Wikipedia, Stack Overflow, GitHub, YouTube, etc).

Related literature. There is a large body of literature on the theory of career concerns, starting with Holmström (1999). However, empirical work has been limited. Chevalier and Ellison (1999) examine the role of career concerns in investment strategies adopted by mutual fund managers. Kolstad (2013) isolates the role of intrinsic and extrinsic incentives in surgeon responses by examining the effects of the exogenous introduction of physician report cards.

Most of the theoretical and empirical literature on voluntary contributions and career concerns addresses the issue of Open Source Software (OSS). In many ways, the OSS phenomenon is very similar to contributions to sites such as SO or Wikipedia, so a review of this literature is warranted.[3] At a conceptual level, Lerner and Tirole (2001, 2002, 2005),

[3]von Krogh and von Hippel (2006); von Krogh et al. (2012) present an excellent survey of this literature. Spiegel (2009) highlights the theoretical difference between free contributions to OSS and to Stack Overflow

Blatter and Niedermayer (2008) and Mehra, Dewan, and Freimer (2011) show how contributors to OSS projects improve their career prospects. At an empirical level, Bitzer and Geishecker (2010) show that the propensity to work on OSS projects is higher among university dropouts, a pattern which they interpret as evidence of career-oriented motivations. Roberts, Hann, and Slaughter (2006) and Hann, Roberts, and Slaughter (2013) find evidence of subsequent returns from participation in OSS projects.

Career concerns is by no means the only motivation behind voluntary contributions. Conceptually, von Krogh et al. (2012) distinguish three types of motivation: intrinsic (e.g., altruism, ideology, fun, kinship); internalized extrinsic (e.g., reputation, learning, reciprocity, own-use); and extrinsic (e.g., career concerns, pay). Emprically, Zhang and Zhu (2011) examine social effects on Wikipedia; Lakhani and von Hippel (2003) study learning motivation on Apache field support system; Dobrescu, Luca, and Motta (2013) characterize social connections in book reviews; Luca and Zervas (2015) investigate economic incentives to commit review fraud on Yelp.

Roadmap. The article is structured as follows: Section 2 introduces a simple dynamic model of user contributions. It develops the idea of career concerns we have in mind and clarifies the assumptions needed for identification. Section 3 describes the data for our analysis. Section 4 discusses how we use various activities to identify the effect of career concerns. It also addresses concerns for alternative explanations. Section 5 estimates the effect of career concerns using various approaches. Section 6 examines the major assumption needed in order for the career concerns to be valid. Section 7 discusses other issues related to our question. Section 8 concludes.

2 A Theoretical Model of User Contribution

We propose a simple dynamic model of user contribution. 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 $s \in \{0, 1\}$,

(whereas the former might succeed or fail, users always benefit from higher contribution levels in the latter).

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 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:

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

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

$$w_t + e_t + a_t = T$$

Consistently with the structure of SO, we assume that 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.[4]

We assume each agent's utility each period is additively separable in each of the three tasks:

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

where $f(\cdot)$ and $g(\cdot)$ are twice differentiable functions such that $f', g' > 0$ and $f'', g'' < 0$. Notice 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 $g_1(w) > g_0(w)$.

Agents are forward looking: in each period, they choose w_t, e_t, a_t so as to maximize value

[4]In addition to Answers, Questions are also a vote-generating activity. For simplicity, we limit our theoretical analysis to the case of one vote-generating activity. In the empirical part of the paper we also consider Questions as part of an agent's optimization process.

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

$$V_0 = g_0(w) + f(e) + f(a) + \delta\, p(a)\, V_1 + \delta\, (1 - p(a))\, V_0$$
$$V_1 = g_1(w) + f(e) + f(a) + \delta\, V_1$$

Finally, we assume reputation at time t is given by the cumulative number of Answers in $t-1$:[5]

$$r_t = A_{t-1}$$

where

$$A_t = A_{t-1} + a_t$$

Our main theoretical result is that a change in state (getting a "better" job) implies an absolute decline in the number of Answers as well as a decline in the ratio Answers / Edits. Moreover, the latter takes place if and only if career concerns matter:

Proposition 1. *Suppose that* $g_0(w) < g_1(w)$. *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 Appendix.

Proposition 1 establishes two effects of a job change: a decline in the time spent on Answers; and a decline in the relative time spent on Answers vis-à-vis Edits. The first effect (decline of Answers) can be decomposed into two effects: an increase in the marginal utility

[5] In the empirical part of the paper we consider various other possibilities. The qualitative nature of our theoretical results remains valid if we assume more complicated reputation functions.

of time spend at work; and a decline in the utility of Answers derived from career concerns. Since there are two effects, 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 provides, therefore, a sharper test of our central hypothesis.

One advantage of a theoretical model is that it helps clarify the assumptions underlying an empirical identification strategy. The assumption that the Edits and the Answers components in the utility function share the same functional form $f(\cdot)$ plays an important role. It can be shown that the results go through if these components are the same up to a linear transformation. This is an important point because, if taken literally, our model implies that $e_t = a_t$ while in state $s = 1$, a very strong restriction. Allowing for the Edits and Answers components in the utility function to vary gives an extra degree of freedom regarding levels while maintaining the result regarding the relative values of e and a. For example, one possible functional form would be

$$u_t = \alpha \, w_t^{\beta_s} \, e_t^{\gamma} \, a_t^{\eta}$$

Taking logarithms (a monotonic transformation of the utility function, which therefore does not change change optimal choices), we get an expression similar to (1) except that the coefficients γ and η appear in front of $f(\cdot)$, which in the present case is given by $f(\cdot) = \ln(\cdot)$.

3 Data

Our dataset is derived from the Stack Overflow (SO) and Stack Overflow Careers (SOC) sites. SO is the largest online Q&A site where programmers ask and answer programming-related questions (figures 1 and 2). It provides for Wikipedia-style editing (figure 3); and it includes a system of Votes, badges and user reputation that ensures high-quality, peer-reviewed Answers. SO is widely used by both programmers and programming-related companies. Founded in 2008 by Joel Spolsky and Jeff Atwood, it currently comprises 4.7 million users. Some summary statistics regarding the site's activity: 6.9 million visits/day; 7.6 thousand questions/day; 10 million cumulative questions, 17 million cumulative Answers.

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

SOC is a related job matching website that hosts programming-related job listings as well as candidate resumes. For contributors, creating a resume on the website (figure 4) is free of charge but by invitation only; and the invitation is based on the contributors' recent activity to the site as well as their field of expertise.[6] On the resume, contributors can easily provide a link to their SO profile (figure 5), 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.

SOC helps employers by reducing hiring search costs (although access to SOC is paid). 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. Finally, employers who access SOC may post their openings as well as search candidates by location, skills, and so on.

Measures of user activity. There are four major activities by users on SO:

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.

Answers — Any registered user can provide Answers to existing Questions.[7] A Question can have multiple Answers and the latter are ranked by total Votes.

[6]The exact criteria is not disclosed by SO. An alternative path to an invitation is to request it on the website.

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

Edits Registered users can also make or suggest minor changes to questions and Answers: Edits.[8] Edits help make the questions and Answers more readable and understandable to future viewers.

Votes Finally, registered users can give upVotes or downVotes to Questions and Answers *but not to Edits*. Votes contribute to the post owner's reputation: upVotes on a Question give the asker 5 points, whereas upVotes on an Answer are worth 10 points.[9]

Data selection. We focus on a set of users that satisfy a series of criteria required by our empirical test:

- Located in the U.S. and Canada: this ensures a more homogenous sample.[10]
- Job changers: the change in the level of career concerns comes from a job change; we select users who experienced a job change from November 2008 until November 2014, the month when we stopped collecting data.
- Job switchers: Employment status (employed vs. unemployed) introduces unnecessary noise; we select users who *switch* from one job to another (with a gap less than or equal to one month between two jobs).[11]
- Active users: for many users, we do not observe any activity on SO during periods of job change; for more accurate estimation, we focus on active users, defined as having at least one answer and at least one edit within the four-month period before or after the month of a job change. (in other words, we exclude inactive SO users).
- Multiple job switches: Some users experienced more than one switch; we exclude such switches if they are less than 8 months apart.

[8] Most Edits correct grammar or spelling mistakes; clarify the meaning of a post; or add related information.

[9] Older Answers have more cumulative Votes. To control for the comparability among Answers given at different time, we measures the total Votes gained on each answer within 30 days after the answering date.

[10] A large fraction of the jobs posted on SOC are located in the United States and Canada.

[11] We are currently also working on the analysis of contributors who experience a change in employment status, i.e., from unemployed to employed.

- Profile with link to SO: the ability to track users' online activity requires the link to SO.

Applying this series of criteria results in a sample of 1249 users with 1462 job switches.[12] For each user in our sample, we associate their user resumes (which include dates of job changes) to user IDs on SO. With the user IDs at hand, we then collect their activity on SO.

[Table 1 about here.]

Table 1 provides some descriptive statistics of SO activities from the sample of 1249 users. Looking at the user activity, we see that the typical SO user is not active in writing Questions or Answers — or voting, for that matter. The activity distributions are fairly right-skewed, suggesting that a few users are disproportionally responsible for much of the content created on SO. The lower portion of the table suggests that typical users of SO are in their early 30s and have been on SO for 4 years (SO has existed for 7 years).

4 Identification Strategy

Conceptually, our identification strategy is quite straightforward: job seekers are active on SO to signal their ability and thus obtain a better job. If career concerns are important, then we expect a drop in such activity once the goal (a better job) is attained. Since no one expects to remain in the same job for the rest of their lives, career concerns might not entirely disappear; but at least they are diminished following a change in jobs.

In practice, there are various confounding factors that make 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 more generally some time investment so as to be familiarized 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).

[12] Obviously, the sample we use is not representative of the population, so coefficient estimates should be interpreted accordingly. We will return to this issue later.

To account for these effects, we conduct DD regressions using Edits as a control group that proxies for time availability. A crucial difference between Edits and Answers is that the latter give rise to Votes, whereas the former does not. Therefore, we expect the career-concerns effect to act through the Answers channel but not through the Edits channel.[13]

The implicit assumption in our DD approach is that, aside from changes in job status, Edits and Answers follow a parallel path. Essentially, this corresponds to the assumption in Section 2 regarding the utility function functional form. Since this is such a crucial assumption, in Section 6 we provide various pieces of evidence in its support.

[Figure 6 about here.]

Essentially, our DD approach corresponds to the second part of Proposition 1. Figure 6 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 7 about here.]

Figure 7 provides preliminary evidence regarding our hypothesis. It plots the monthly average of the logarithm of user activity in a 20-month window centered around a contributor's job change event. As can be seen, both Answers and Edits activity experience a significant drop when a user starts a new job (month 1); however, the drop in Answers activity is considerably more significant than the drop in Edits activity. This evidence is consistent with the hypothesis that $p'(a_t) > 0$, that is, an increase in Answers increases the probability of a job change.

Naturally, several other alternative hypotheses may explain these dynamics. In Section 6, we present several hypotheses under which the parallel trend assumption could be violated, and evaluate the validity of each hypothesis.

[13] Questions are also reputation generating activities; we will discuss it later in Section 7.3.

5 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 1,249 users who were subject to 1,462 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, define period 1 as the month when a job change takes effect (that is, the month listed on the resume as starting month for the new job). 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 thus exclude months 0 and 1; in this way we get a cleaner perspective on the periods before and after the job change without contaminating the data with noise stemming from the process of job change.

5.1 Basic Difference-in-Differences Results

We use the following regression specifications to estimate the impact of career incentive on voluntary contributions:

$$y_{it} = \alpha_i + \beta\, S_{it} + \epsilon_{it} \tag{3}$$

$$y_{kit} = \alpha_{ki} + \beta\, S_{it} + \gamma\, A_k\, S_{it} + \epsilon_{kit} \tag{4}$$

Equation 3 calculates the first difference of activity levels before and after a job change, whereas equation 4 estimates the additional change in reputation-generating activity over the changes in Edits (that is, 4 corresponds to differences in differences). In these equations, y represents a generic activity, where subscript k denotes Answers (a), Votes gained from Answers (v), or Edits (e). S_{it} is the state dummy variable: $S_{it} = 0$ corresponds to the periods before a job change takes place by user i, whereas $S_{it} = 1$ corresponds to the period after a job change takes place. A_k is a dummy variable that takes on the value 1 if the activity is a vote-generating activity (Answers) and 0 otherwise (Edits). α_{ki} controls for activity type (a, e) interacting with individuals (i) fixed effects. Finally, γ is the DD coefficient.

Equations 3 and 4 essentially correspond to the two parts of Proposition 1. Specifically, we expect the level of SO activity to drop subsequently to a job shift, that is, we expect β

in (3) to be negative. Moreover, we expect the drop in Answers to be greater than that of Edits, so that $\gamma < 0$ in (4), in addition to $\beta < 0$.

[Table 2 about here.]

Table 2 shows the results for our base regressions. There are two pair of regressions, using two measures of reputation-generating activity. For each pair, the first regression is limited to the Answers/Votes activity. We thus have 8,772 observations (1,462 job switches times 6 months: three prior to the job switch, three subsequent to the job switch); the second regression includes both Answers/Votes and Edits, thus doubling the number of observations.

Consider the first pair of regressions (that is, columns 1 and 2), where Answers and Edits are measured in logarithms. One advantage of this approach is that the coefficients can be readily interpreted as percent variations. The first regression has Answers as a dependent variable and S_{it} (job status) as the sole explanatory variable. The coefficient estimate on S_{it} suggests that, upon changing jobs, users decrease their Answers activity by about 24.5%. This is consistent with the first part of Proposition 1. However, as we mentioned earlier, it provides a weak test for our main hypothesis.

Regression 2 has both Answers and Edits as the dependent variable. As independent variables we have S_{it} and S_{it} interacted with A_k, the dummy indicator for Answers activity. Proposition 1 predicts that both coefficients are negative. The results confirm the prediction: a job switch is associated to an 8% decline in activity (both Edits and Answers) and a further 16.5% reduction in Answers; this later variation we attribute to career concerns.

Columns 3 and 4 report the same set of estimates using Votes to measure online activity. Votes is a function of both the number and quality of Answers, and can be a better measure of one's effort to give high-quality Answers. The results using Votes give similar and slightly larger estimates than number of Answers. For the rest of the analysis in this section, we focus on the number of Answers; later we present additional results using Votes.

5.2 Difference-in-Differences with More Controls

The regression estimates from table 2 could be potentially confounded by the effects of seasonal job changes as well as duration effect on SO. In order to control these effects, we

include more data points from the following sources: first, longer periods of the same users used in the regression; second, SO users not in our SOC sample.[14]

$$y_{kit} = \alpha_{ki} + D_{it} * \left(\beta\, S_{it} + \gamma\, A_k\, S_{it}\right) + \lambda_{kt} + X_{kit}\,\theta + \epsilon_{kit} \tag{5}$$

This regression specification builds on the baseline model (regression 4) and adds monthly dummies to control for seasonal effects for both Answers and Edits separately. To control for the SO duration effect, we include dummies for "SO Tenure", which measures the number of months since one's first activity on SO for Answers and Edits. In essence, regression 5) is still the same DD specification as regression 4) using the same sample of job changers, but with more data points to control for seasonal and duration effects.

D_{it} is a dummy variable that indicates the 1,462 job changes and the 6-month period used in previous analysis. α_{ki} includes fixed effects for all individuals and each activity type. λ_{kt} controls for seasonal effects through year and month dummies. X_{kit} includes dummies for the number of months since first activity on SO.

[Table 3 about here.]

Table 3 summarizes the results using different sources of control variable. Panel A uses activities in periods other than $-3, -2, -1, 1, 2, 3$ of the same 1249 users. The DD estimate changes from 16.5% without any control to 10.2% with both seasonality and duration controls. All DD estimates remain statistically significant at similar levels.[15]

However, activity data from the 1249 users might not control the true seasonality and duration effects. For example, if all the 1249 users change jobs in the same month, then the monthly dummies, which are used to control for seasonality, perfectly absorb the activity variation in all periods relative to the job change.[16] Thus DD coefficient would give a zero estimate. In reality, not all job changes occur in the same month; nevertheless the correlation

[14] Although we do not have their CV information and job status, we do observe their online activity over time.

[15] As mentioned before, the extra data points are used to control for seasonal and duration effect, so they do not contribute to the significance of DD coefficient.

[16] Note the differences between two concepts used here: actual month and time periods relative to a job change. Monthly dummies control for seasonality for an actual month, e.g. January, February. Time periods are normalized relative to the time of a job change, with period 1 as the first month after a job change. The DD analysis compares Answers-Edits gap between periods $-3, -2, -1$ and $+2, +3, +4$

between the time of job changes and control variables can leads to a bias in the DD estimate. One way to attenuate this problem is to use a larger dataset to control for seasonality and duration effects. To do that, we collect activity data from a larger pool of SO users not necessarily using SOC. We select all SO users with more than 1000 reputation points and who have at least one answer and one edit activity on SO, which gives around 60k users.

Panel B shows the results with the 60k SO users as control. All the DD estimates give a larger estimate compared to the results in Panel A. That is to say, the problem we discussed previously is a valid concern. With all the controls for seasonality and duration effects, DD coefficient gives an estimate of -14%.

5.3 Month-to-Month Comparison

The analysis in the previous subsections focuses on the 3-month period before and after a job change. In order to show a thorough picture of how activity changes over time, we use all the available activity data from the 1249 users. Then we use period -2 as the baseline period and compare the activity level of all other periods with respect to period -2.[17] We also control for seasonality and duration effects using the sample of 60k SO users mentioned before.

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

$$y_{kit} = \alpha_{ki} + D_i * \Big(\sum_{\tau=-20}^{20} \big(\beta_\tau \, \mathbb{1}(P_{it} = \tau) + \gamma_\tau \, A_k \, \mathbb{1}(P_{it} = \tau) \big) \Big) + \lambda_{kt} + X_{kit}\,\theta + \epsilon_{kit} \tag{7}$$

Regression 6 and 7 calculate the first difference and DD of activities in each period τ against activity in the baseline period -2. D_i is a dummy variable that indicates the 1,462 job changes. λ_{kt} and X_{kit} 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 which equals to 1 if the month t for user i corresponds to τ months after a job change. β_τ in regression 6 measures the differences in activity between period τ and baseline period -2. Moreover, γ_τ in regression 7 is the DD coefficient between period τ and period -2.

[17] Period -2 is used as the baseline since it has the highest average activity level.

[Figure 8 about here.]

[Figure 9 about here.]

The estimates of β_τ from regression 6 and γ_τ from regression 7 are plotted in figure 8 and 9.

Figure 9 is very similar to figure 7, which plots monthly average activities over time, but the estimates plotted in figure 9 removes the seasonality and duration effects. The graph shows that before a job change, both Answers and Edits increases slowly and together over time. Five months before a job change, we observe increases of both Answers and Edits at a faster pace, and Answers increase faster than Edits. Similarly, after a job change, both experience a sudden drop with Answers dropping more than Edits. Both types of activity keep dropping over time.

Figure 9 plots the Diff-in-Diff estimates γ_τ for $\tau \in [-20, 20]$. DD estimates before period 0 are all negative, but they are not significantly different from zero. However, after a job change, all the estimates are significantly negative.

One phenomenon shown in both figures is that Answers activity keeps dropping over time after a job change. Several possible theories can explain this phenomenon. First, the first few months are often considered as probationary periods where both employers and employees can freely terminate their contracts. Thus career concerns drop significantly but do not completely disappear as both parties gradually discover the true matching quality. If this is the case, then our results from regressions 6 and 7 underestimate the effect of career concerns. A second possibility is that contributors might gradually switch to easier types of activities, i.e. from Answers to Edits activity, since an answer takes significantly more time than an Edit. We have already added controls for duration effects so this is unlikely to be the case. Third, Stack Overflow is a gamification platform that attracts contributors through competition. Through gamification, a contributor develops a habit of contribution that might persist even when the original career incentives are gone. In sum, the changes in online activities over a long term can be attributed to many causes; for this reason, our analysis in Section 5.1, using a relatively short period of time (three-months), has the advantage of providing a cleaner result.

6 Testing Identification Assumptions

Our identification strategy is based on the fundamental assumption that the relative intrinsic utility of Edits and Answers (aside from career concerns) remains constant, which is commonly referred as parallel trend assumption. That is to say, if it weren't for a job shift (thus without changes in career incentives), the relative importance of Edits and Answers would have remained constant. Since this assumption plays a central role in our identification strategy, additional evidence on it is warranted.

6.1 Integer Constraint

A job change brings not only a change in career incentives, but also a change in time availability. The validity of the career-concerns hypothesis relies on the assumption that a sudden change in time availability associated to a busier job affect Answers and Edits in a similar fashion. An alternative interpretations for our result that a_t/e_t drops subsequent to a job change is that users are faced with an "integer constraint:" Answers require a bigger set-up cost than Edits; and when an agent switches jobs, thus becoming busier, there are fewer time windows to justify working on an Answer rather than an Edit. In other words, Edits typically require less time and can thus be fitted into a busy schedule more easily.

The ideal way to test the parallel trend assumption is to check the changes in Answers and Edits activity followed by an *exogenous* job change, namely, an un-anticipated job change.[18] With an *exogenous* job change, contributors experience changes in work responsibility thus changes in time availability, but the level of career concerns stay relatively the same. Unfortunately, such information is rarely available from information on a CV. However, with the whole contribution history and employment history for each user, we can focus on time periods with relatively stable level of career concerns, as well as on activities that take place on the weekends.

Within Job Activity. For each contributor with a profile on SOC, we identify a period of time when no job changes take place, that is, a period of stable employment. It seems

[18] Examples include unexpected promotion, or merger and acquisition.

reasonable to assume that, during these periods, though a contributor's time availability fluctuates, the change in the level of career concerns is small compared to what we observe around the time of a job shift. Thus, consistent with our basic identifying assumption, we expect the ratio a_t/e_t to remain constant.

[Figure 10 about here.]

Figures 10 shows the values of Answers and Edits for months 5 to 42 after an agent's job shift. Consistently with our underlying assumption, the ratio between the two is fairly constant.

Weekdays vs. Weekend. A new job with a busier work schedule should affect time availability mostly during weekdays rather than weekends. Accordingly, we split our sample into weekday and weekend activities and conducted separate DD analyses. The idea is that, to the extent that work hours are more highly concentrated on weekdays, the "integer constraint" hypothesis should imply a bigger effect on a_t/e_t during weekdays.

[Table 4 about here.]

Table 4 shows the results of our basic regressions split into weekday and weekend days (using Answers and Votes as measures of reputation-generating activity). Broadly speaking, the coefficient estimates are similar to those in the base model. The FE regressions show a more negative coefficient for the weekday subsample. This is consistent with the "set-up-cost" alternative hypothesis outlined above. However, the difference is rather small (about 3%).

6.2 Skill Mismatch

An alternative interpretation for the drop in Answers following a job shift is that the new occupation requires skills different from the previous job. For example, a C++ programmer may switch to a job that is based on Java; such SO user would then be spending more time learning Java than answering C++ questions (in fact, such user might spend more time asking questions rather than answering them).

As shown in figure 4, user profiles on SOC provide detailed information regarding work experience as well as user-provided information on the technology associated with each job, in the form of tags. We focus on users who switch to new jobs with similar technology based on tags information. First, we define a measure of skill-similarity between jobs.[19] Then we re-estimate the basic DD regression using users who have switch to jobs with similar technology.

[Table 5 about here.]

Table 5 summarizes the DD estimates using different thresholds job similarity. Column 1 focuses 162 job changers whose new jobs have exactly the same tags as the old ones, and DD coefficient gives an estimate of -20.9%, which is a larger magnitude compared to the estimate of -16.5% from our baseline model. Moving to the right, column 2 to 5 gradually lower the thresholds of job similarity and inlcudes more job changers in the regression. Column 5 includes all the users which is identical to our baseline model.

The results in table 5 show that job changers who switch to positions with similar skill requirement also experience a similar drop in Answers over Edit activity. The magnitudes of the estimates using various thresholds are also comparable to results from the baseline model. Thus we conclude that the DD estimate cannot be explained by the skill mismatch hypothesis.

6.3 Selection into Treatment (Ashenfelter's Dip)

The varitions of activity levels plotted in figure 7 can also be caused due to selection into treatment due to reverse causality, a hypothesis commonly referred to in the labor economics literature as Ashenfelter's Dip (AD).

Suppose that contributors experience random shocks in the number of Answers and Edits in each period. Suppose also that a higher number of Answers helps getting job offers. 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

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

Answers before job changes (as the one in figure 7) is purely caused by the selection into treatment from random activities, not by a change in user behavior in response to incentives.

Through simulation of random activities and given some job changing function, we can easily simulate the problem of AD. Figure 11 plots the simulated activities over time. It shows an increase in Answers activity before a job change, and a reduction afterwards, which resembles figure 7. However, the activity increase is purely due to selecting periods followed by large Answers shock as time of job change, and the reduction is purely due to recovery from the Answers shock.

[Figure 11 about here.]

Undoubtedly, this alternative explanation poses a valid concern to the career-concerns hypothesis. It 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, the dip is assumed to be due to random shocks. Therefore, the correction to the AD concern typically involves removing the random shock by using data from periods away from the treatment period or by matching treatment group with a properly selected control group who also experience a similar shock. However, in our setting of Stack Overflow, the "bump" in the plot, which is like a reversed "dip", is key to our identification strategy. 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.

Identification of AD vs. Career Concerns. In the remaining part of this section, we argue, by means of numerical simulations, that AD does not provide compelling evidence against our career concerns story. We attempt to answer the following questions: If we assume everything is random and the level of Answers activity helps getting a new job, then how large would the DD estimates be? Would the estimates be statistically significantly? Would they allow us 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 activity following a certain distribution and then simulate job change status given a likelihood function of job change. The simulation

is then repeated R times and the DD estimate from each simulation is collected to plot the distribution of the estimates. The comparison between simulated and original DD estimates can show the confidence level with which we can reject the null hypothesis that the "bump" in the number of Answers is explained purely by selection of random shocks instead of behavioral responses.

The simulation requires two main inputs: 1. Random draws of Answers and Edits activity 2. Probability of a job change given Answers activity from the previous period. The simulation parameters can significantly affect the simulation results.

For the first part of the input, we draw Answers and Edits activity from the actual Answers and Edits activity. In order to keep the data as clean as possible —i.e., without potential effect of career incentive — we use activity during a period that is at least five months away from a job change. We draw Answers and Edits both in pairs and separately. The results using the two approaches help us compare the typical DD approach in settings such as AD to the DD approach developed earlier in the paper. As a robustness check, we also conduct simulations drawn from two separate negative binomial distributions fitted to those of actual activities, for cases both with and without correlation between the two distributions.

For the second part of the input, we use parameters from a logistic regression of job change status on lagged Answers activity.[20] There is an endogeneity problem, since job search intensity correlates with both job change status and Answers activity. Unfortunately, we are unable to solve it due to lack of data on both job search intensity and job offers received. However, the estimate from a regression with an endogeneity problem should provide us the upper bound of the true value, which is the worst-case scenario to the career-concerns hypothesis. In other words, by not correcting for endogeniety we are stacking the cards against our preferred hypothesis.

For each simulation method, we simulate the DD results $R = 200$ times. Each simulation includes 1500 job switches which mimics our original DD analysis. Then we plot the estimates using kernel density plot.

[20] We also checked simulation results using alternative specifications, e.g. including or excluding reputation level, lagged Edits, etc. They all produce similar results.

[Figure 12 about here.]

The simulation results are plotted in figure 12. Panel A plots simulated DD estimates using Answers and Edits drawn directly from actual activity data, both in pairs (blue line) and separately (green line). Both simulations have a mean slightly larger than zero at 2-3%, but neither is significantly different from zero. The red line plots the distribution of the actual DD estimate from column 2 of table 2, with a mean of 0.165 and a standard deviation of 0.034. In Panel B, instead of drawing random activity directly from actual activity data, we first fit two negative binomial distributions for Answers and Edits activity using MLE. Then we conduct the same set of simulation and plot the distributions of simulated DD estimates. Panel B gives similar plots to Panel A.

The comparison between the simulation and actual DD estimates shows that the DD estimate of .165 cannot be explained by selection into a job change due to random activities, given reasonable ranges of coefficient values.

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 since both are correlated with the time spent on Stack Overflow.[21] If the two activities are perfectly correlated, then simulated DD always gives zero estimates. However, when drawn independently, Answers and Edits are uncorrelated, thus it's more likely to observe high levels of Answers activity with low Edits activity, which presents a graph similar to ours.

Another main reason that the logic of AD problem doesn't invalidate the career-concerns hypothesis is the small effect of Answers activity on new job offers. Though unable to accurately estimate this effect due to the presence of endogenous variables (as we mentioned above), we can 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 of our conclusion.

Parameter Values Required to Reject Career Concerns. Figure 12 shows a significant gap between simulated and actual DD estimates, which helps us to reject the story

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

of AD in favor of career concerns. However, the simulation crucially depends on the two inputs discussed above. In this subsection, we adjust the second input, the probability of job changes given a certain level of Answers activity, and calibrate the parameters in order to mimic the actual DD estimate.

The job change probability is modeled using the following simple logit model:

$$Pr(JC) = Logit(\alpha + \beta * A) = \frac{exp(\alpha + \beta * A)}{1 + exp(\alpha + \beta * A)} \tag{8}$$

First, we calibrate α while holding $A = 0$ by matching the simulated job length to the distribution of actual job lengths from the data. With the calibrated value $\hat{\alpha} = -3.07$, the unconditional rate of job change is $\frac{exp(\hat{\alpha})}{1+exp(\hat{\alpha})} = 4.43\%$. Then, holding $\alpha = -3.07$, we simulate DD estimates for different values of β. For each β, we run the simulation for $R = 100$ times and plot the average value in figure 13.

[Figure 13 about here.]

Figure 13 shows that the value of $\beta = 22.76\%$ produces a simulated DD estimate that is closest to our actual DD estimate of 16.5%. $\beta = 22.76\%$ means that one log unit increase of number of Answers increases the likelihood of a job change by 22.76%. One log unit increase is roughly an increase of 170%. For all our 1,249 SOC users used in DD analysis, the average total number of Answers per month is 4.05, thus an increase of 170% means extra $4.05 \times 170\% = 6.88$ Answers per month. That is to say, for an average person who gives 4 Answers per month, simply by answering 6.88 more Answers can increase the likelihood of a job change in the following period by 22.76%, which is extremely high given the small cost of giving Answers. Therefore, we conclude that the causal effect represented by β is over-estimated. That is to say, in order to reject the career-concerns hypothesis, the parameter values needed in the job change function become too large to be reasonable.

7 Extension & Other Results

7.1 Signaling Game: Quality vs Quantity

The classic career-concerns hypothesis in Holmström (1999) shows that job seekers make effort to improve the signals of their unobserved ability. Then the natural questions to ask are (a) what are job seekers signaling through SO, and (b) what information do employers get from the online activity of a job seeker? This is an important research question related to but different from our question. Marlow and Dabbish (2013) interview several contributors and employers on GitHub regarding job searching activities using activities on GitHub.[22] Employers consider the fact of merely having a GitHub profile as a good signal. They also evaluate job applicants' activity, specifically the desire to learn, popularity of a project, and coding style, etc. Job seekers, in turn, expect to show their passion and expertise to employers.

[Figure 14 about here.]

"Popularity" and "expertise" on GitHub are similar to the quality of Answers on Stack Overflow, which can be roughly measured by Votes. In principle, it is possible that the effect of a job shift is also felt in terms of the quality of Answers. Our DD results using number of Answers and Votes from Answers in previous sections give very similar estimates. Figure 14 plots the time evolution of Votes and Answers. 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. 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 *both* better Answers from questions a contributor would answer regardless of career concerns, *and* more Answers from questions a contributor would not answer without career concerns due to low matching quality. Thus one should observe that as the time of a job change approaches, a job seeker

[22] GitHub is a online repository hosting service popular among programmers. It offers services including revision control and source code management. As of 2015, GitHub has over 9 million users and over 21.1 million repositories, making it the largest host of source code in the world.

gives more Answers, and at the same time, the quality of some Answers are higher but others are lower.

[Figure 15 about here.]

To test this hypothesis, we pick the best answer (measured by Votes) given by a contributor for each month, and figure 15 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, indicating that contributors make efforts to give better Answers before a job change, which is consistent to the career-concerns hypothesis.

7.2 Reputation Sizes and Timing of Answers

The career-concerns hypothesis states that job seekers signal their unobserved ability to employers through reputation-generating activity on Stack Overflow, namely Answers. If that is the case, and if employers value the stock of Answers more than the timing of Answers, then career concerns should have heterogeneous effects on job seekers with different levels of reputation. A job seeker with low reputation on Stack Overflow might prefer even not to include his or her SO profile on their resume. By contrast, for a job seeker with outstanding reputation the marginal benefit of extra effort to contribute should be relatively small. To examine the heterogeneous responses to career concerns due to existing reputation points, we associate each job change with the reputation level at the time of job change, and split the sample into four equal groups by reputation points for separate analysis.

[Table 6 about here.]

Table 6 summarizes the DD estimates from four groups of job seekers using number of Answers (panel A) and Votes from Answers (panel B) as measures of reputation-generating activity. Panel A shows that low-reputation users (column 1) do not seem to change their behavior as a result of a job change. By contrast, medium-reputation users (columns 2 and 3) show effects of magnitudes larger than results from our base regressions, and high-reputation users (column 4) very similar to the average. Panel B presents similar result to Panel A.

7.3 Questions Activity to Build Reputation

As mentioned earlier, SO users can build a reputation by answering questions but also by posting questions.

[Figure 16 about here.]

[Table 7 about here.]

Figure 16 shows the rate of questions asked around the time of a job shift. Unlike Answers and Edits, we observe little change in the number of questions. When we redo our basic regressions with questions instead of Answers as a vote-generating activity, we obtain a positive estimate of the $S \times Q$ interaction coefficient, as shown in column 2 of table 7. Moreover, the size of the coefficient is approximately equal, in absolute value, to the coefficient on S. In other words, whereas the number of Edits is reduced following a job shift, the number of questions does not to change significantly, as shown in column 1. One possible explanation is that, more than a reputation-increasing activity, questions are used a learning tool; and a shift to a new job creates new learning demands, an effect that seems to compensate for the higher opportunity cost of time spent on SO as well as the diminished incentive to build a reputation. Another possible explanation is that asking questions might be perceived as inability to solve problems, and thus job seekers avoid asking questions.

8 Discussion and Concluding Remarks

The Internet has created many opportunities for online collaboration and networking. Some platforms have been enormously successful, some less so. Examples of the former include Wikipedia, YouTube, Stack Overflow and Amazon Mechanical Turk; examples of the latter include Yahoo! Answers, Digg. What distinguishes a winner from a loser platform? We suggest that, as often is the case in economics, incentives matter, both intrinsic and extrinsic incentives. In the context of Open Source Software, Lerner and Tirole (2002) emphasize that distinguishing between these two incentive sources would "provide lenses through which the structure of open source projects, the role of contributors, and the movement's ongoing

evolution can be viewed." The same applies, we would argue, to other types of collaboration projects as well.

In this paper, we take one step towards the distinction between intrinsic and extrinsic motivation. We consider the specific case of 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 suggest that achieving the goal of a new job leads users to decrease their contribution to SO; and that a drop of about 16.5% can be assigned to a drop in career concerns. This value is both statistically significant and economically significant.

Regarding our estimate of the size of the job changing effect, some words of caution are in order. First, our sample results from selection according to a series of criteria. For example, it is possible that the users who choose to link their SO record to their resume are more concerned about their careers than those who keep their SO record unlinked. In this sense, our estimate of career concerns may *over-estimate* the population average effect. (Though we are unable to prove that it is a representative sample, we do have some anecdotal evidence from a few programmers that it is a common practice to provide links to online profiles such as GitHub and Stack Overflow when applying for jobs.) Second, the simple theoretical model that forms the basis of our empirical estimation assumes that there are only two states, and that $s = 1$ is an absorbing state. This implies that at $s = 1$ agents have no career concerns at all, which is obviously not very realistic. This in turn suggests that our estimate of career concerns may *under-estimate* the real value.

An alternative strategy for estimating the career-concerns theory of free user contributions is directly to estimate the probability of a job switch as a function of reputation. (We are currently working on this.) Statistically, one problem with this approach is that easily it suffers from unobserved heterogeneity problems: shocks that change a user's level of contribution and also lead the user to change jobs may suggest a causality link that does not exist. In principle, a similar objection might be raised regarding our testing strategy. However, it seems more reasonable to assume the change in the unobservable variable impacts the user's habits at SO before it impacts his or her employment situation.

Appendix

Proof of Proposition 1. Let x_s^* be the optimal value of control variable x ($x = w, e, a$) in state s ($s = 0, 1$). Suppose that $V_1 \leq V_0$. Then by choosing $x_t = x_0^*$ when $s = 1$ a strictly higher value of V_1 and V_0 is obtained. Thus it must be

$$V_1 > V_0 \tag{9}$$

At state s, the agent maximizes V_s subject to $w + e + a = T$ (for simplicity we omit the time subscript). The first-order conditions at $s = 1$ are given by

$$\begin{aligned} \lambda_1 &= g_1'(w_1) \\ \lambda_1 &= f'(e_1) \\ \lambda_1 &= f'(a_1) \end{aligned} \tag{10}$$

where λ_1 is the Lagrange multiplier in state 1. At $s = 0$, we have

$$\begin{aligned} \lambda_0 &= g_0'(w_0) \\ \lambda_0 &= f'(e_0) \\ \lambda_0 &= f'(a_0) + \delta\, p'(A + a_0)\,(V_1 - V_0) \end{aligned} \tag{11}$$

The second and third equations in (10) imply that $e_1^* = a_1^*$. The second and third equations in (11), together with (9), imply that $e_0^* < a_0^*$ if and only if $p'(A + a_0) \geq 0$. Together, these equations imply the second part of the Proposition.

Regarding the first part of the Proposition, it helps to make the comparison in two steps. First consider changing (10) by substituting g_0' for g_1'. Since, $g_1' > g_0'$, this results in a higher value of a (and of e). Second, consider adding the term $\delta\, p'(A + a_0)\,(V_1 - V_0)$. Given (9) and to the extent that $p' \geq 0$, again the value of a increases. ■

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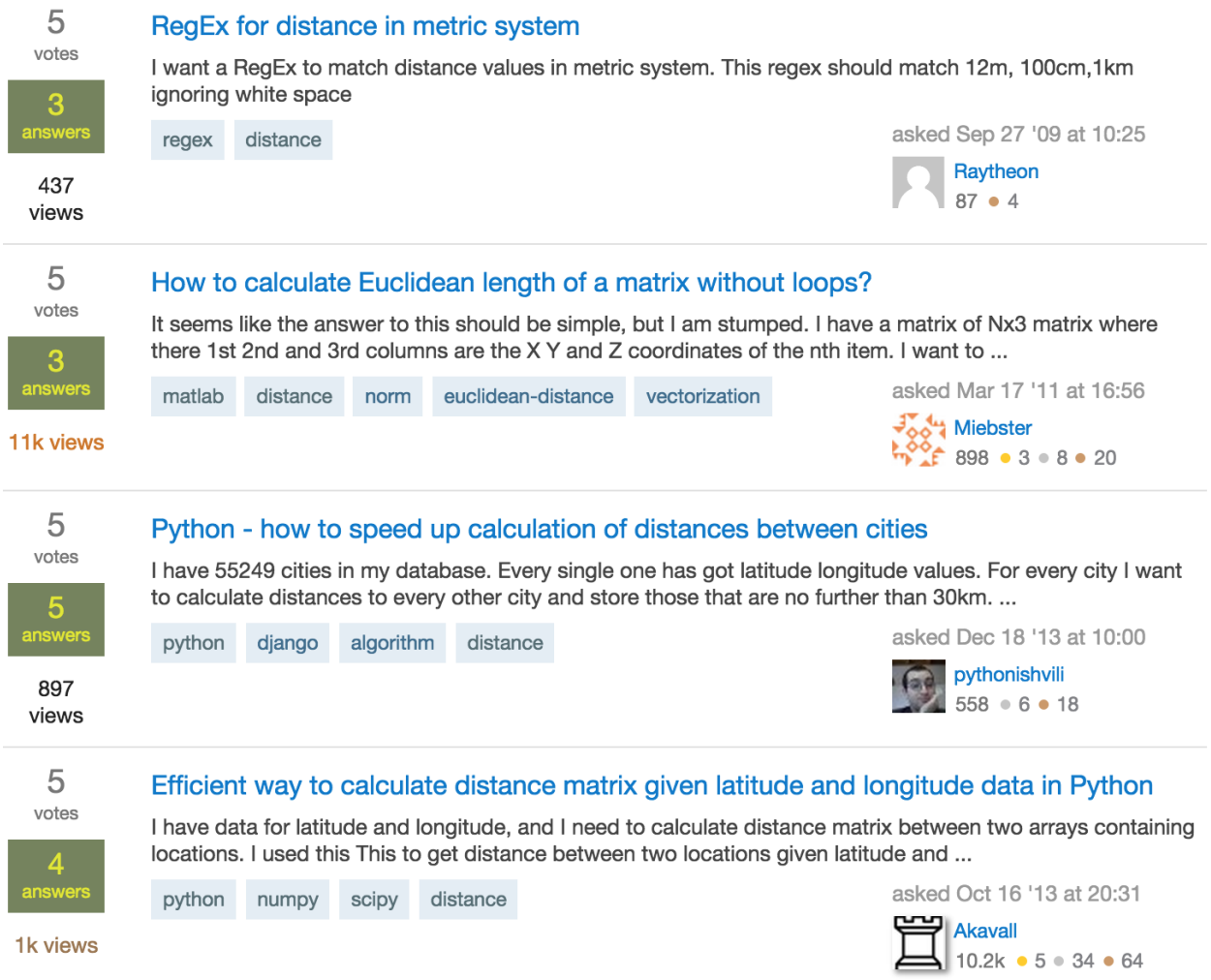

Figure 1: Sample List of Questions on Stack Overflow

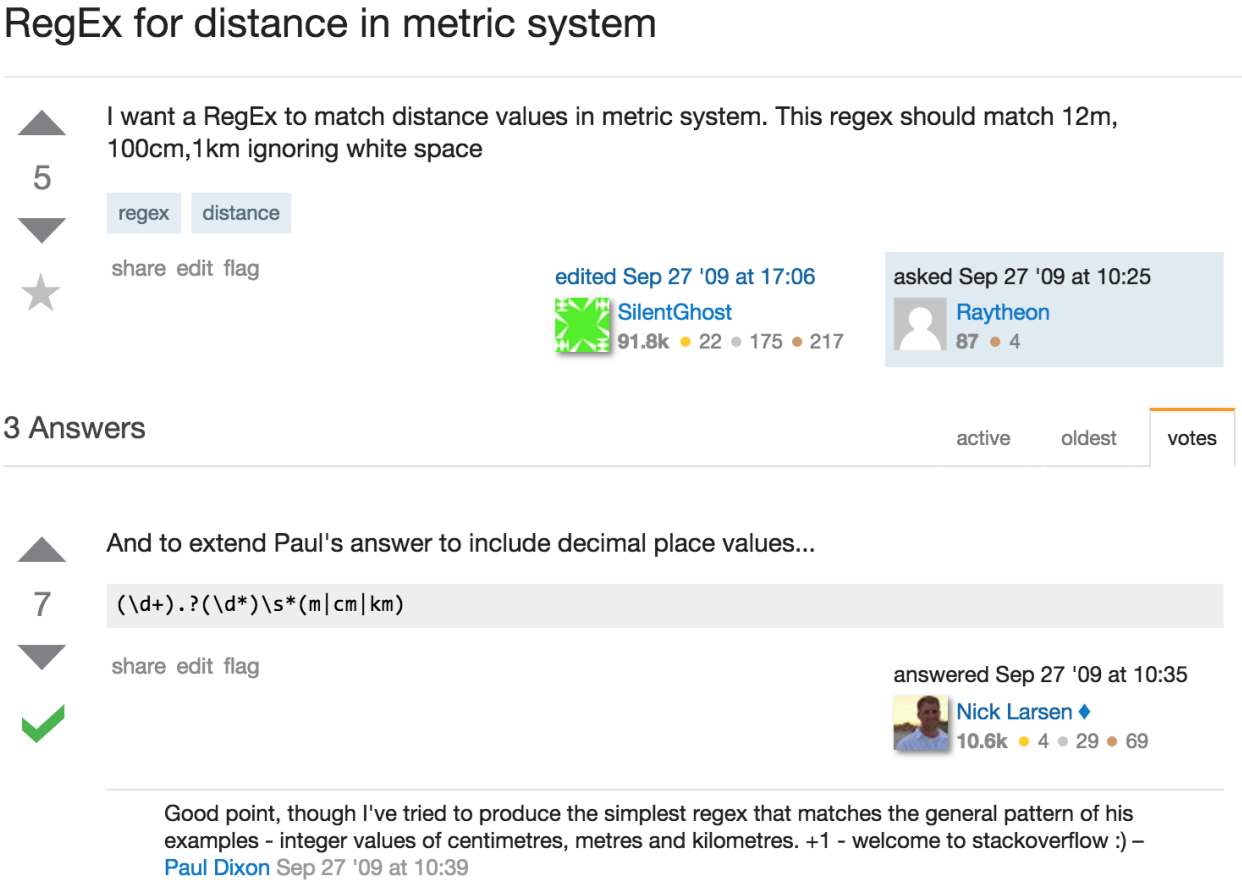

Figure 2: Sample of a Question with its Answers on Stack Overflow

Notes: One question can receive multiple answers which are ranked by Votes by default. Asker of the question can select one answer as the "correct" answer. Users can also comment on questions or answers. Both Questions and Answers receive up-Votes or down-Votes. One up-vote reward to a question rewards the asker 5 points; one up-vote to an answer rewards the answerer 10 points.

Figure 3: Sample of Edits on Stack Overflow

Notes: Majority of Edits on SO are simple corrections to spelling or grammar mistakes. Some also involve more significant changes. Users with reputation under 2000 can suggest edits, which rewards them 2 points if accepted. Users with over 2000 reputation do not get the 2-point reward.

Nicholas Larsen

Norcross, GA, United States
stackoverflow.com
@fody

Last seen 2 days ago

Top 10% for asp.net asp.net-mvc asp.net-mvc-3
Top 20% for c# javascript jquery css algorithm more

Currently **Software Developer** at **Stack Overflow**.

Technologies

Likes: design-patterns algorithm-design artificial-intelligence prototyping database-design

Experience show all

Software Developer, *Stack Overflow* — *January 2011 - Current*
asp.net-mvc c# sql-server performance redis dapper mini-profiler internationalization elasticsearch

Database Programmer, *Credit Union Service Corporation* — *March 2009 - December 2010*
asp.net c# sql-server oracle crystal-reports route-map visual-basic c++ jquery

Education show all

Computer Science - Databases and Knowledge Systems, *Georgia State University* — *2001 - 2008*
java c++ ruby-on-rails databases game-theory algorithms modeling electronics embedded-systems

Stack Exchange show all

Last seen 2 days ago

Accounts

Stack Overflow	**10084** reputation points
Meta Stack Exchange	**7914**

Top Answers

MVC and NOSQL: Saving View Models directly to MongoDB? — *6 votes*
asp.net-mvc mongodb separation-of-concerns

LINQ union with optional null second parameter — ✔ *6 votes*
c# linq union

Figure 4: Sample of User Profile on Stack Overflow Careers

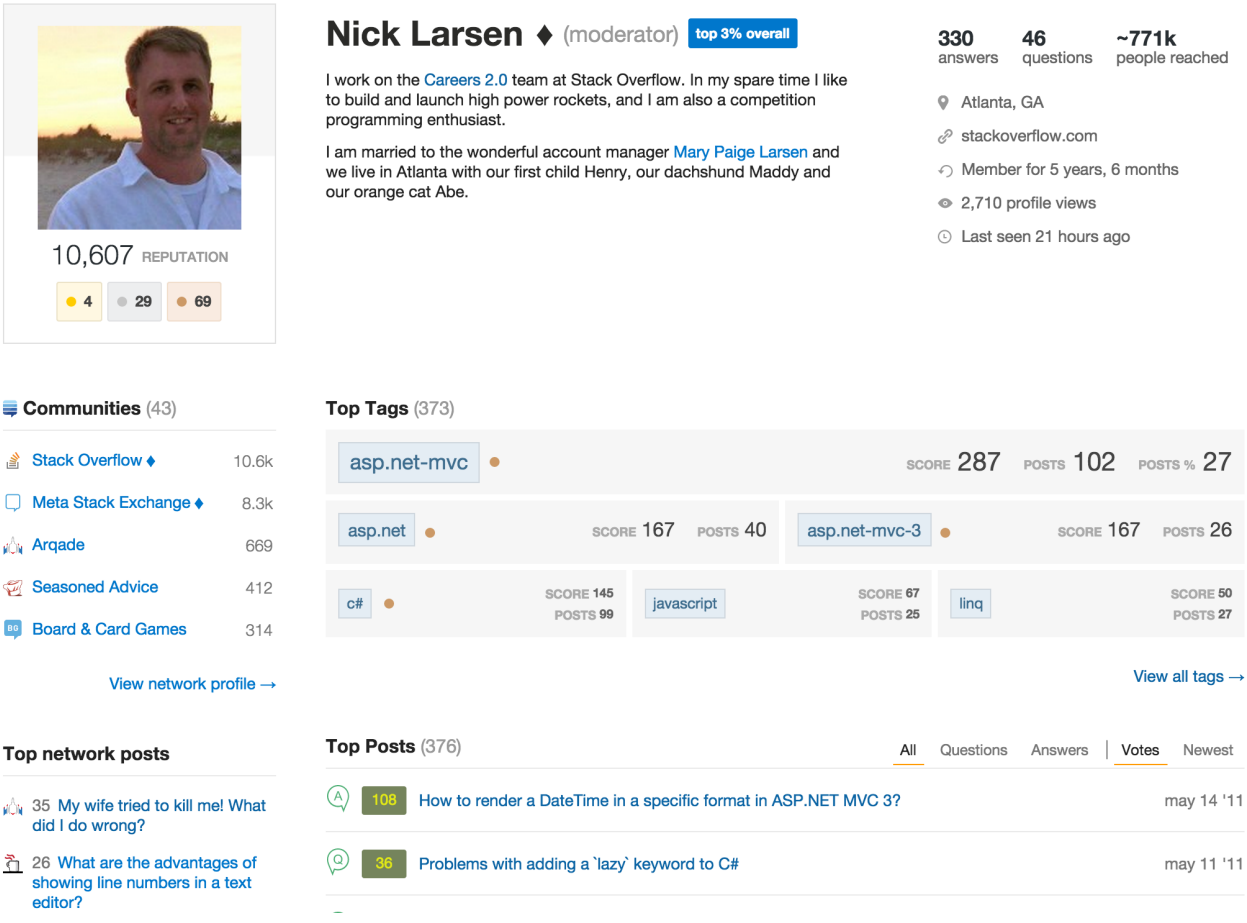

Figure 5: Sample of User Profile on Stack Overflow

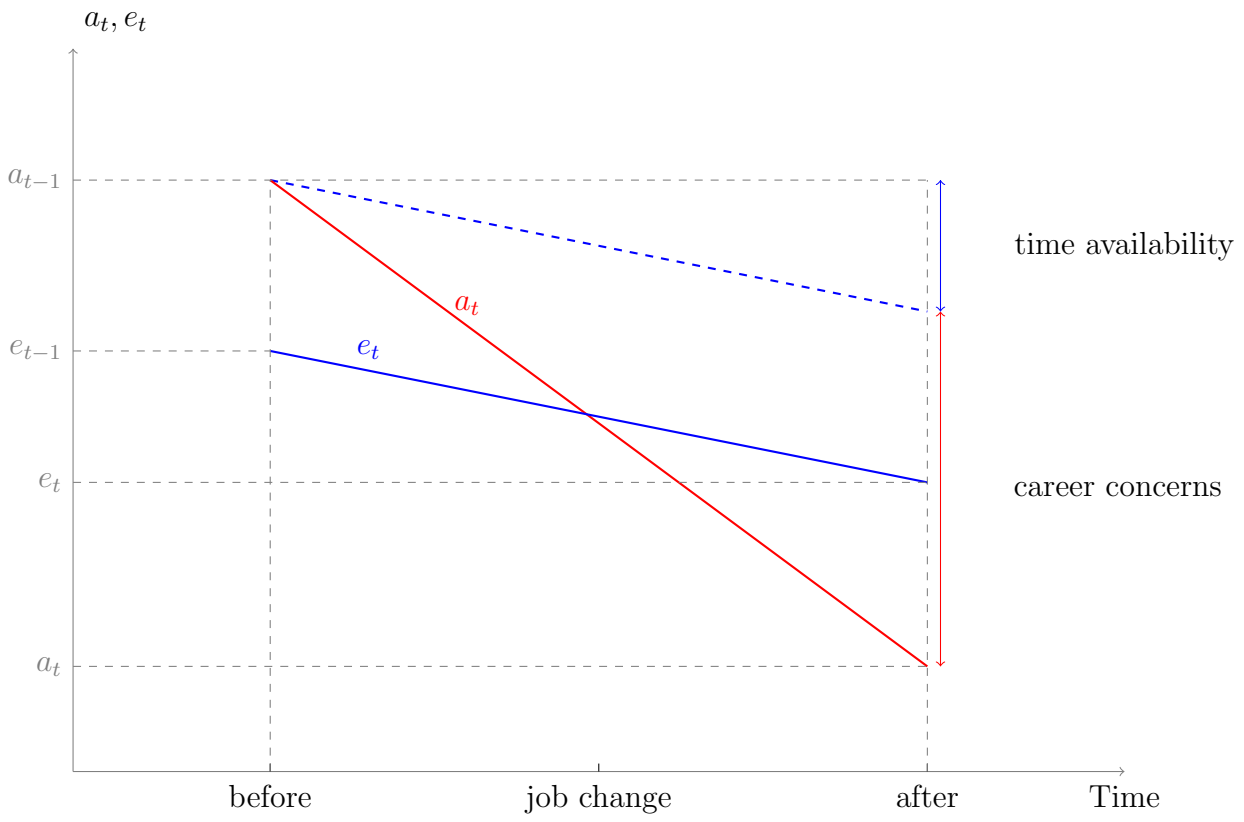

Figure 6: Graphical Illustration of Identification Strategy: Difference-in-Differences

Notes: Treatment group: Answers activity (a); Control group: Edits activity (e). All activity data comes 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 Answers-Edits gap before and after a job change.

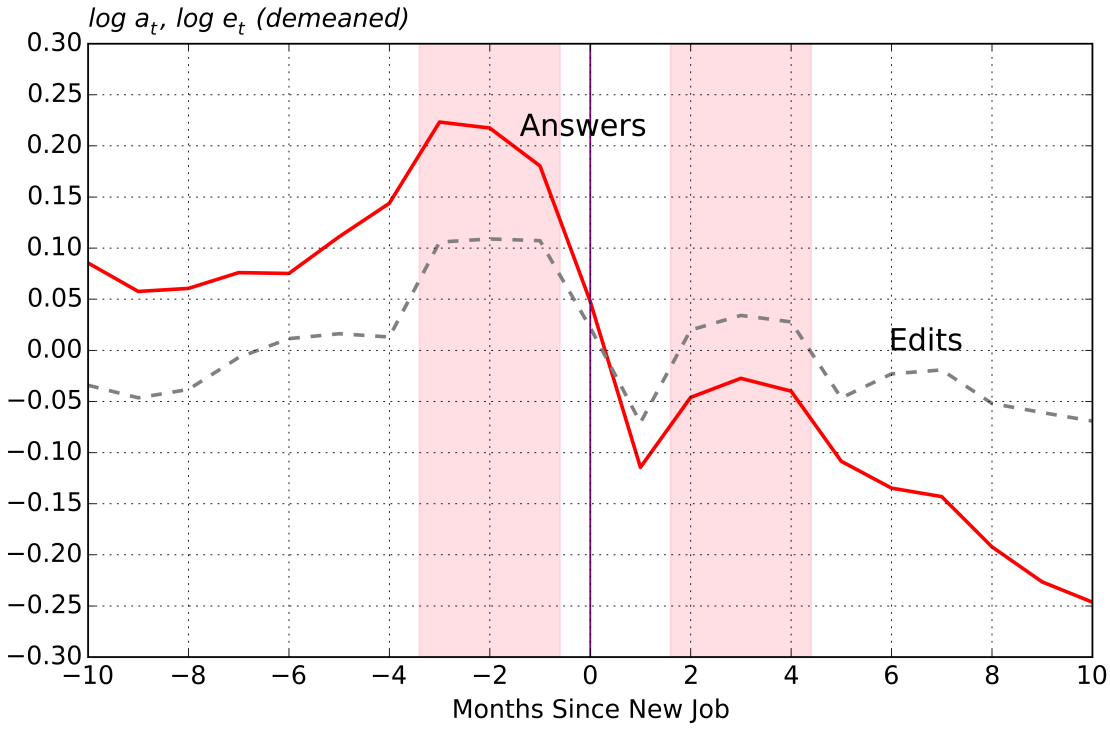

Figure 7: Average Monthly Activity on Stack Overflow (Answers and Edits)

Notes: This figure plots average monthly activity of Answers and Edits. Answers and Edits activity are demeaned log(1+activity count). 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. The initial set of DD regressions focuses on the 3-month before and after the job change, represented as activities in the pink area.

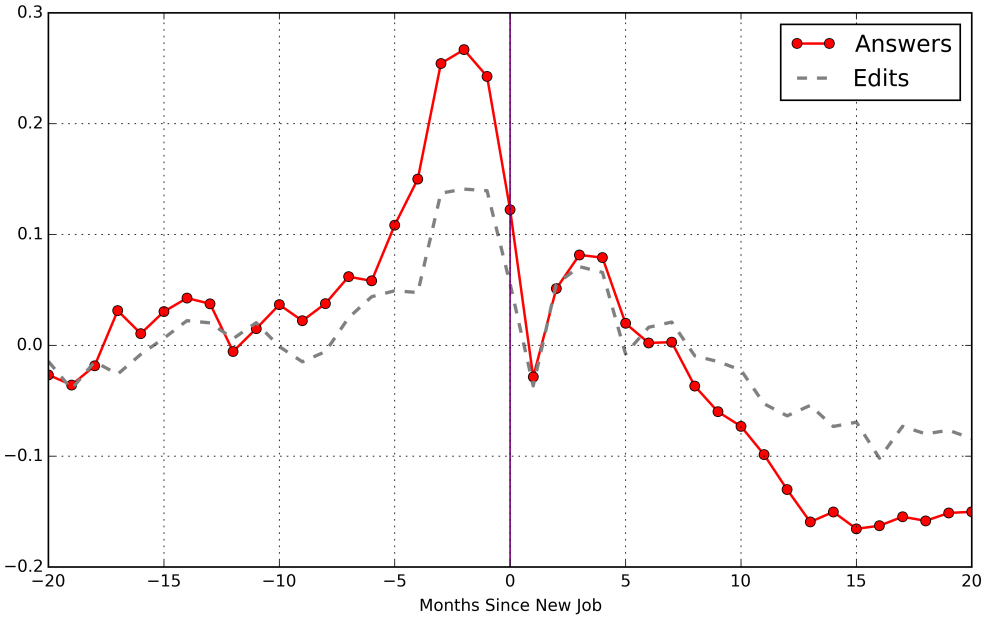

Figure 8: Coefficients Of Periods Relative To Time Of Job Change

Notes: This figure plots values of β_τ in regression 6. Essentially, it is an extended version of figure 7, while controling for seasonality and duration effects.

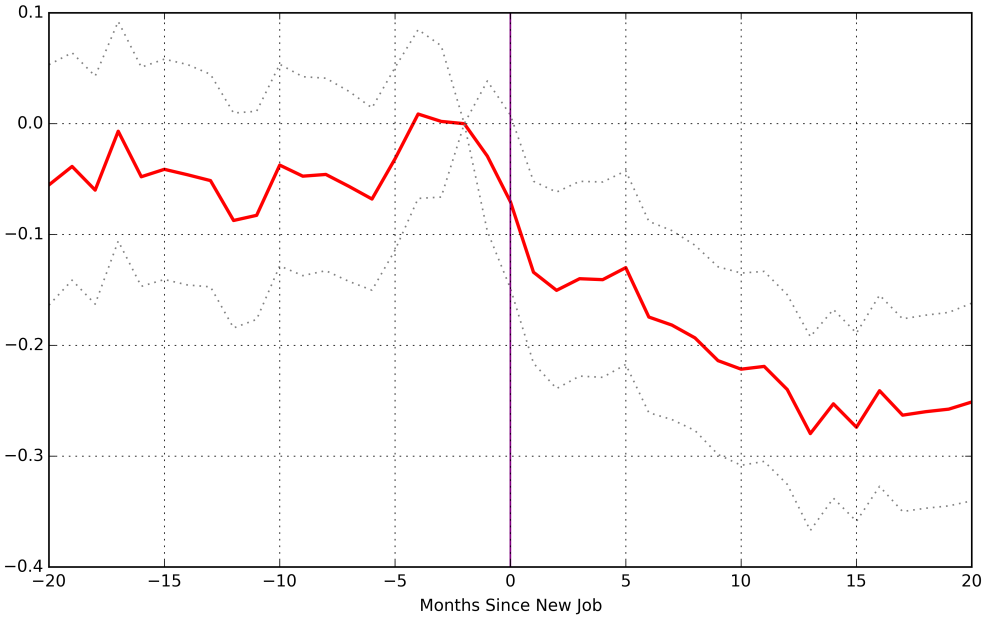

Figure 9: Difference-in-Differences With 95-Percent Confidence Interval

Notes: This figure plots values of γ_τ in regression 7. It uses period -2 as baseline period, and estimates DD coefficients using each of all other periods against the baseline period. It controls for seasonality and duration effects for answers and edits separately.

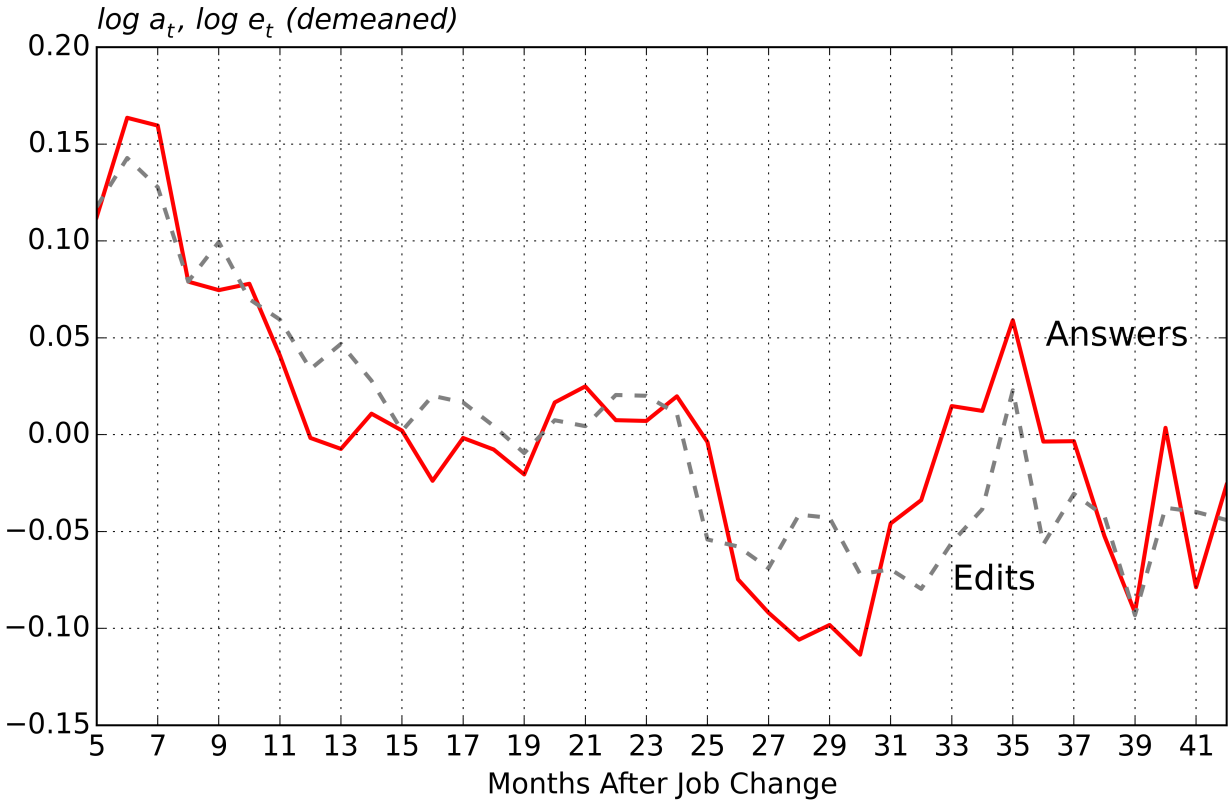

Figure 10: Within-Job Variation of Activities

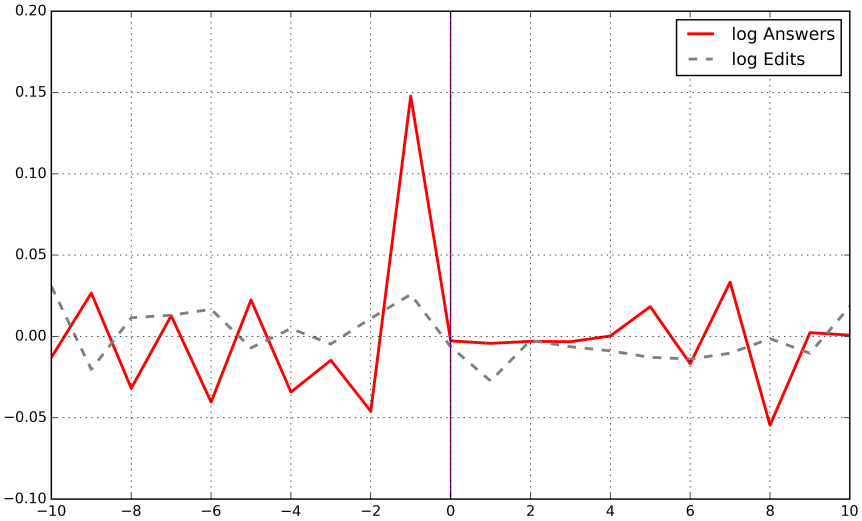

Figure 11: Simulation of AD Problem

Notes: Given random shocks of Answers and Edits activity, and given a job changing function that increases in lagged Answers activity with certain parameter value, one can simulate job changes and plot a graph similar to what we observed using actual SO activity data.

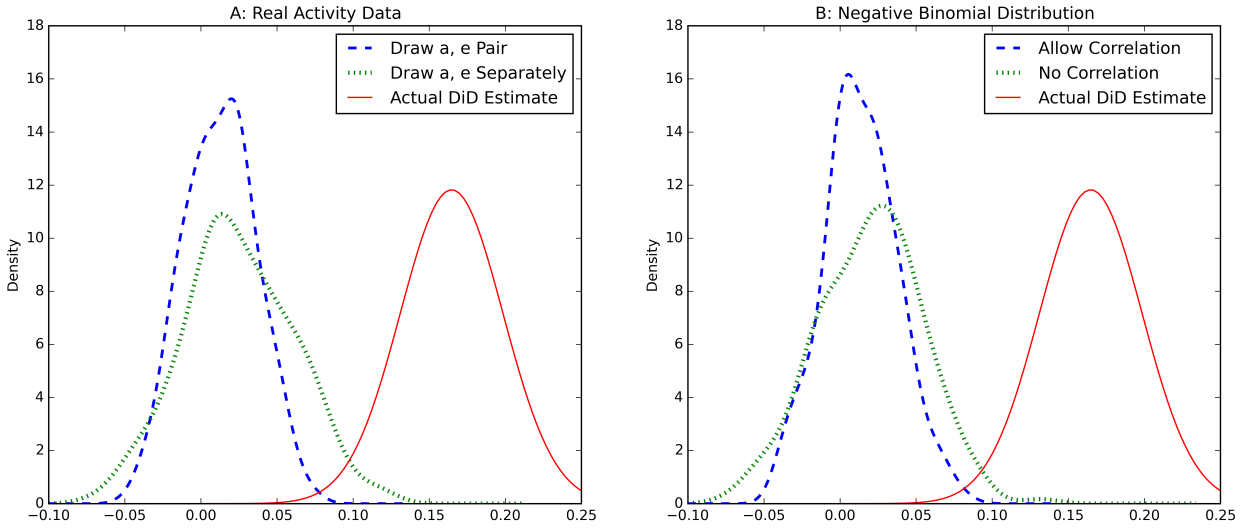

Figure 12: Density Plot of Simulated DD Estimates

Notes: Panel A draws data directly from actual activity data; Panel B draws data from negative binomial distributions fitted from Answers and Edits data. Blue lines allows for correlation between Answers and Edits; Green lines draws Answers and Edits independently. Red lines plot the distribution of the actual DD estimate with mean of 0.165 and standard deviation of 0.034.

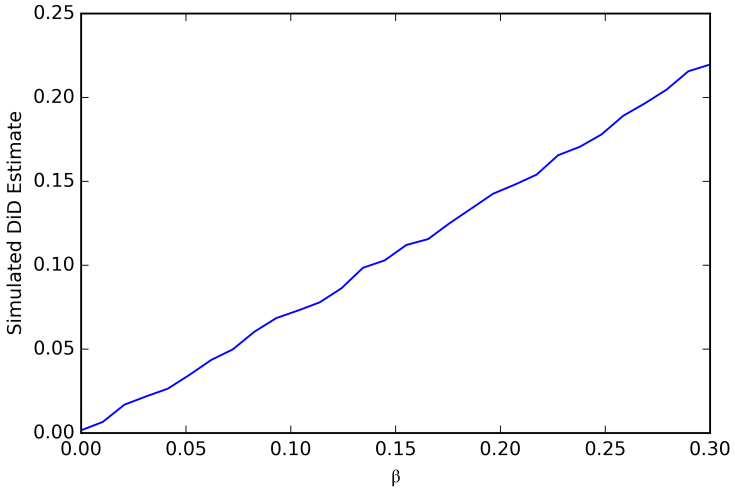

Figure 13: Average Simulated DD Estimates Given Values of β

Notes: The figure plots average simulate DD esimates by using different values of β.

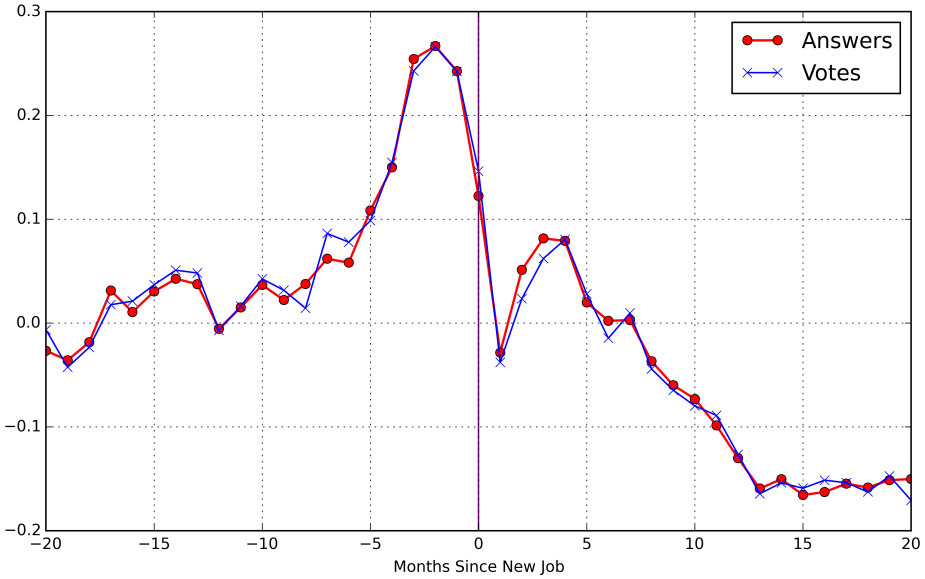

Figure 14: Different Measure of Answers Activity (Number of Answers vs. Votes from Answers)

Notes: This figure presents alternative measurement of Answers activity: Votes from Answers up to 30 days after an answer is given. It takes into consideration of both quality and quantity of Answers. Both measures give almost identical graph shows that the average quality of Answers does not change.

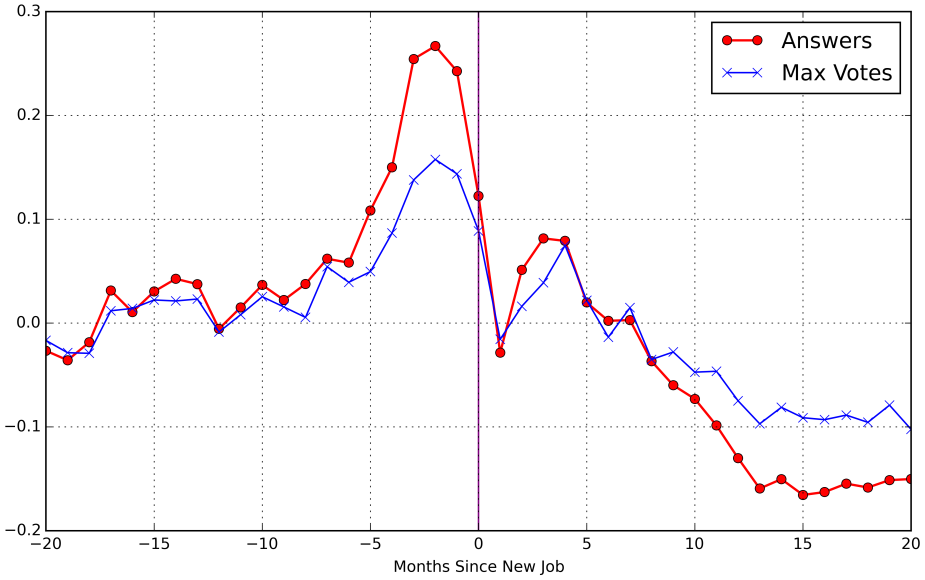

Figure 15: Answer Quality Variation Over Time

Notes: This figure decomposes total Votes from Answers. It shows that even though average quality does not change, the quality of best Answers in a given month indeed goes up before a job change, which indicates increased efforts to give better answers.

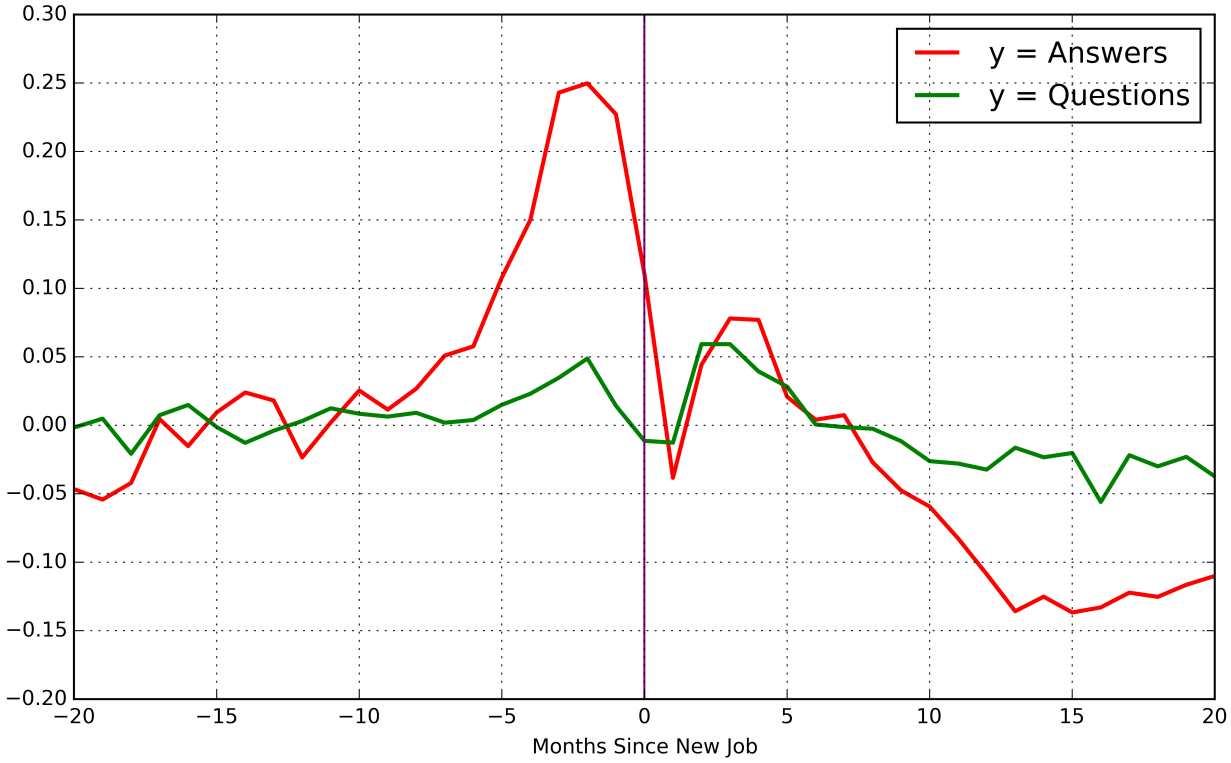

Figure 16: Average Monthly Activity on Stack Overflow (Answers and Questions)

Table 1: Descriptive Statistics of Sample of Users on Stack Overflow

	Mean	Median	Std. Dev.	Min.	Max.
User Activity (Monthly)					
Answers	4.055	0	12.310	0	417
Votes (from Answers)	5.967	0	23.023	0	966
Questions	0.637	0	1.933	0	58
Edits	1.748	0	9.883	0	689
User Characteristics					
Profile Views	359.723	71.5	2170.283	0	112967
Total UpVotes	334.669	82	800.728	0	15143
Reputation Points	1603.965	150	6204.839	-6	132122
Age	33.889	33	7.433	16	95
Time on SO	4.225	4.337	1.503	0.167	6.507

Notes: This table lists the descriptive statistics of lifetime activities of the 1249 contributors used in our DD analysis.

Table 2: Effect of Job Change on Answers Activity

	(1) $y = a$	(2) $y \in \{a, e\}$	(3) $y = v$	(4) $y \in \{v, e\}$
$NewJob\,(S)$	-0.245***	-0.080***	-0.259***	-0.080***
	(0.03)	(0.02)	(0.03)	(0.02)
$NewJob\,(S) \times Answer\,(A)$		-0.165***		-0.179***
		(0.03)		(0.04)
Regression	FE	FE	FE	FE
Contributors	1249	1249	1249	1249
N	8772	17544	8772	17544
R^2	0.021	0.015	0.019	0.014

Notes: FE: OLS Regression with Fixed-Effects. Dependent Variable: y: generic activity, a: Answers, e: Edits, v: Votes from Answers. Independent Variable: $S_{it} = 0$ prior to job switch, $S_{it} = 1$ after job change; $A_k = 1$ if $k = a$, $A_k = 0$ if $k = e$. Time Period: November 2008 - November 2014. Number of Contributors: 1249; Number of job switches: 1462. Robust standard errors in parentheses, clustered at individual-activity type level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Effect of Job Change on Answers Activity (With Control Variables)

	Baseline	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$y \in \{a, e\}$	$y \in \{a, e\}$	$y \in \{a, e\}$	$y \in \{a, e\}$	$y \in \{a, e\}$	$y \in \{a, e\}$	$y \in \{a, e\}$
$NewJob\,(S)$	-0.080***	-0.065***	-0.081***	-0.075***	-0.063***	-0.077***	-0.067***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$NewJob\,(S) \times Answer\,(A)$	-0.165***	-0.104***	-0.101***	-0.102***	-0.153***	-0.129***	-0.134***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Seasonality Dummy	No	Yes	No	Yes	Yes	No	Yes
Duration Dummy	No	No	Yes	Yes	No	Yes	Yes
# Users for Control	-	1249	1249	1249	60k	60k	60k
R^2	0.001	0.070	0.073	0.076	0.011	0.011	0.010

Notes: Panel A uses all activity data of 1249 users as control for seasonality and duration effects; Panel B uses a sample of 60k users from SO to control for the same effects. Dependent Variable: y: generic activity, a: Answers, e: Edits. Independent Variable: $S_{it} = 0$ prior to job switch, $S_{it} = 1$ after job change; $A_k = 1$ if $k = a$, $A_k = 0$ if $k = e$. Number of contributors for DD analysis: 1249; Number of job switches: 1462. Robust standard errors in parentheses, clustered at the level of the individual-activity type level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Effect of Job Change on Weekday vs. Weekend Activity

	Weekday		Weekend	
	(1)	(2)	(3)	(4)
	$y \in \{a, e\}$	$y \in \{v, e\}$	$y \in \{a, e\}$	$y \in \{v, e\}$
$NewJob\,(S)$	-0.070***	-0.070***	-0.061**	-0.061**
	(0.02)	(0.02)	(0.02)	(0.02)
$NewJob\,(S) \times Answer\,(A)$	-0.163***	-0.178***	-0.126***	-0.150***
	(0.04)	(0.04)	(0.04)	(0.05)
Regression	OLS-FE	OLS-FE	OLS-FE	OLS-FE
Contributors	1159	1159	374	374
N	16104	16104	5004	5004
R^2	0.014	0.013	0.016	0.017

Notes: This table summarizes DD estimates using weekday and weekend activity separately. FE: OLS Regression with Fixed-Effects. Dependent Variable: y: generic activity, a: Answers, e: Edits, v: Votes from Answers. Independent Variable: $S_{it} = 0$ prior to job switch, $S_{it} = 1$ after job change; $A_k = 1$ if $k = a$, $A_k = 0$ if $k = e$. Time Period: November 2008 - November 2014. Robust standard errors in parentheses, clustered at individual-activity type level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: DD Estimates For New Jobs With Similar Technology

	(1)	(2)	(3)	(4)	(5)
	$y \in \{a, e\}$	$y \in \{a, e\}$	$y \in \{a, e\}$	$y \in \{a, e\}$	$y \in \{a, e\}$
$NewJob\,(S)$	-0.013	-0.054	-0.071**	-0.075***	-0.080***
	(0.05)	(0.05)	(0.04)	(0.03)	(0.02)
$NewJob\,(S) \times Answer\,(A)$	-0.209**	-0.153*	-0.162***	-0.157***	-0.165***
	(0.09)	(0.08)	(0.06)	(0.04)	(0.03)
Job Similarity (by Tags)	≥100%	≥75%	≥50%	≥25%	≥0%
Contributors	162	240	407	778	1249
N	2064	3000	5184	10272	17544
R^2	0.012	0.011	0.014	0.014	0.015

Notes: Dependent Variable: y: generic activity, a: Answers, e: Edits. Independent Variable: $S_{it} = 0$ prior to job switch, $S_{it} = 1$ after job change; $A_k = 1$ if $k = a$, $A_k = 0$ if $k = e$. Time Period: November 2008 - November 2014. Robust standard errors in parentheses, clustered at individual-activity type level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: DD Estimates by Reputation Points

	Panel A: $y \in \{a, e\}$				Panel B: $y \in \{v, e\}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$NewJob\,(S)$	0.161***	-0.065*	-0.170***	-0.247***	0.161***	-0.065*	-0.170***	-0.247***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
$NewJob\,(S) \times Answer\,(A)$	0.048	-0.254***	-0.282***	-0.171**	0.053	-0.206***	-0.336***	-0.226***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.08)
Reputation	0-25%	25-50%	50-75%	75-100%	0-25%	25-50%	50-75%	75-100%
Contributors	358	354	343	314	358	354	343	314
N	4392	4392	4380	4380	4392	4392	4380	4380
R^2	0.018	0.027	0.053	0.048	0.018	0.018	0.055	0.045

Notes: This table summarizes regression estimates by dividing the job changes into four groups by reputation points at the time of job change. Job seekers with medium-reputation respond most to career concerns, whereas low-reputation job seekers probably do not use SO as a signaling channel. Dependent Variable: y: generic online activity, a: Answers, e: Edits, v: Votes from Answers. Reputation Points: Min: 0; First Quartile: 770; Median: 2,124; Third Quartile: 5,265; Max: 132,067 Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Effect of Job Changes on Questions Activity

	(1)	(2)
	$y = q$	$y \in \{q, e\}$
$NewJob\,(S)$	-0.012	-0.080***
	(0.01)	(0.02)
$NewJob\,(S) \times Questions\,(Q)$		0.068***
		(0.02)
Regression	FE	FE
Contributors	1249	1249
N	8772	17544
R^2	0.000	0.003

Notes: Dependent Variable: y: generic online activity, q: Questions, e: Edits. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$