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

ORGANIZATION SCIENCE
Articles in Advance, pp. 1–22
ISSN 1047-7039 (print), ISSN 1526-5455 (online)

Building Status in an Online Community

Inna Smirnova,[a,*] Markus Reitzig,[b] Olav Sorenson[c]

[a] School of Information, University of Michigan, Ann Arbor, Michigan 48109; [b] Department of Accounting, Innovation, and Strategy, University of Vienna, 1090 Vienna, Austria; [c] Anderson School of Management, University of California, Los Angeles, Los Angeles, California 90095
*Corresponding author

Contact: innas@umich.edu, https://orcid.org/0000-0003-2275-1166 (IS); markus.reitzig@univie.ac.at, https://orcid.org/0000-0002-8562-3754 (MR); olav.sorenson@anderson.ucla.edu, https://orcid.org/0000-0002-0599-6738 (OS)

Received: August 11, 2020
Revised: May 7, 2021; September 23, 2021
Accepted: October 27, 2021
Published Online in Articles in Advance: February 11, 2022

https://doi.org/10.1287/orsc.2021.1559

Abstract. We argue that the actions for which actors receive recognition vary as they move up the hierarchy. When actors first enter a community, the community rewards them for their easier-to-evaluate contributions to the community. Eventually, however, as these actors rise in status, further increases in stature come increasingly from engaging in actions that are more difficult to evaluate or even impossible to judge. These dynamics produce a positive feedback loop, in which those who have already been accorded some stature garner even greater status through quality-ambiguous actions. We present evidence from Stack Overflow, an online community, and from two online experiments consistent with these expected patterns.

Funding: All authors would like to acknowledge funding from the Austrian Science Fund [Grant P 25768-G16].

Supplemental Material: The online appendix is available at https://doi.org/10.1287/orsc.2021.1559.

Keywords: status attainment • action ambiguity • online communities • stack overflow • experiment

Introduction

Those held in high esteem enjoy numerous advantages. High-status individuals attract more attention (Simcoe and Waguespack 2011, Bowers and Prato 2018, Reschke et al. 2018), receive outsized credit for their contributions (Kim and King 2014, Waguespack and Salomon 2015), and can more readily access a variety of resources (Merton 1968, Bol et al. 2018). High-status firms can negotiate better terms from buyers and suppliers (Benjamin and Podolny 1999, Hsu 2004, Nanda et al. 2020), receive favorable treatment from authorities (McDonnell and King 2018), and can hire more able employees without offering higher salaries (Bidwell et al. 2015, Tan and Rider 2017).

How do firms and individuals come to hold high status? The most common claim has been that communities award status to those who have provided the most value to them, both through commitment to the community and through high-quality contributions (e.g., Ridgeway 1981, Podolny and Phillips 1996, Sauder et al. 2012, Hahl and Zuckerman 2014). Differences in the value of these contributions nevertheless become amplified because, in assessing quality, audiences rely not just on their own prior experiences but also on the judgments of others (e.g., Gould 2002, Lynn et al. 2009), a process that Correll et al. (2017) have labelled as socially endogenous inference. Scientists, for example, assess contributions not only by reading articles and attending seminars but also by paying attention to who else has cited researchers, giving deference to them. In evaluating the quality of a wine, consumers incorporate both their own opinions about whether the wine tasted good and their beliefs about what others thought (Roberts et al. 2011).

But this explanation for status attainment also poses a puzzle. Status hierarchies often appear steepest and the benefits of status most pronounced in settings in which consumers cannot even determine ex post—after they have consumed the goods—whether what they received had been of high quality (Sauder et al. 2012, Sorenson 2014, Ertug et al. 2016). Consider management consulting or investment banking. Even after receiving a recommendation, clients have little basis for assessing whether BCG or Goldman Sachs provided better advice than they might have received from some less-celebrated firm. Given that these settings offer little in the way of actual, verifiable information on past performance, it would seem that socially endogenous inference has nothing to amplify. How then do status differences arise in these settings?

One possibility is that initial differences in quality or perceived quality emerge entirely by chance (Gould 2002, Lynn et al. 2009). In venture capital, for example, Nanda et al. (2020) demonstrate that early performance differences emerge from investing in the right place at the right time, something that appears almost entirely random. These early successes nevertheless allow these investors to become central players in the community, as entrepreneurs and other investors interpret these random successes as signals of quality.

Another possibility, on which we elaborate here, is that the actions for which actors receive status shift as they move up the hierarchy. Both individual and organizational actors engage in a range of activities that vary in the ease with which others can assess their value. Some actions are objectively better or worse. Others involve a mix of objective elements and those open to debate. At the extreme, ambiguous actions elude any objective evaluation. A management consultant, for example, could provide benchmarking information or he or she might proscribe a particular strategy. With a little research, clients could verify the former. But, for the latter, they have little hope of determining whether another course of action would have been better.

People pay attention to different types of actions and evaluate those actions differently depending on the status of the actor performing them. When actors first enter a community, we argue that community members attend primarily to easier-to-assess actions, awarding status to those who exhibit commitment to the community and competence and quality on relatively objective criteria (Ridgeway 1981, Hahl and Zuckerman 2014). However, for actors who have already attained some status, people increasingly pay attention to their harder-to-assess actions, where value judgments also become more subjective. Because members of the community perceive these middle- to high-status actors as being competent and producing high-quality outputs, they interpret these quality-ambiguous actions as being valuable. These harder-to-assess actions therefore contribute increasingly to the attainment of further status as actors move up the hierarchy.

A statistician beginning his or her career might first gain status by providing accurate answers to objective questions; but as he or she gained standing, audiences would increasingly pay attention to and accord further status to him or her for weighing in on matters open to debate, such as the right approach to research or the significance of open problems. Early on, judges and audiences similarly accord status to artists and musicians in terms of their technical abilities (McCall 1975). For those performers who have already reached a moderate level of status, however, the receipt of additional status depends on more subjective criteria, such as artistic expression (McCall 1975, Sgourev and Althuizen 2014). These dynamics produce a positive feedback loop, in which those who have already received some recognition become further distanced from the rest.

We explore this question empirically using data from Stack Overflow (SO), an online community for seeking and providing coding advice. Online communities have become increasingly important settings for the exchange of information (Hwang et al. 2015, Botelho 2018)—book reviews on Goodreads, travel advice on TripAdvisor, and product reviews on Amazon, to name a few. These communities, moreover, usually incorporate an evaluation system—upvoting, likes, useful votes—as a means of motivating people to provide reviews and of allowing users to sort through the information (Constant et al. 1996, Lakhani and von Hippel 2003, Wasko and Faraj 2005). These systems create status hierarchies, helping to determine who becomes most influential to a wide variety of purchasing and consumption activities (Bianchi et al. 2012). Understanding the dynamics of status attainment on these systems represents an important question in its own right.

But SO also offers some notable advantages for understanding the origins of status more broadly: We can observe community members from the day that they enter the community, before they have been accorded any status. By contrast, interactions in person almost always occur under the shadow of preexisting status. Even when actors first enter communities, they usually arrive with signals of status from their affiliations, their ascriptive characteristics, or their strategic choices (e.g., Ridgeway 1991, Stuart et al. 1999, Phillips et al. 2013, Askin and Bothner 2016).

Community members engage in three main activities on SO: asking questions, answering them, and commenting on questions and answers. We find that when individuals first enter, asking questions most strongly predicts their initial movement up the status hierarchy. As they gain stature, however, further movement up the ladder depends primarily on answering questions and on commenting. Much of the rise from the top 10% to the elite of the elite, the top 5% and higher, appears to depend on commenting. To the extent that these activities range from the value of questions being easier to evaluate to that of answers and comments being harder to evaluate, these results are consistent with our expectations.

Although our use of individual-level fixed effects in our analysis of the SO data allows us to reject many alternative interpretations for these patterns, we cannot rule out within-person increases in objective quality over time, learning, as an alternative explanation. Although the observational data do not allow for an easy resolution to this potential confound, we also ran two online experiments in which we exogenously assigned the status of a contributor to each action (a question, an answer, or a comment). Those experiments produced qualitatively consistent results: the status of the questioner did not influence the status gains associated with questions, but higher status did lead to more positive perceptions of answers and comments. Status also appeared somewhat more important to the evaluation of comments than it did to that of answers. We discuss the implications of our results both for online communities, such as SO, and for the emergence and consequences of status hierarchies in offline communities.

Status Attainment

Actors do not claim status. People bestow status on individuals and on organizations. They have been thought to do so on the basis of the value that they perceive that a particular actor has provided to the community (e.g., Ridgeway 1981, Podolny and Phillips 1996, Hahl and Zuckerman 2014). But actors can influence these conferrals of status through their actions. These perceptions of value presumably come from a combination of the effort or commitment that the actor has demonstrated to the community and the competence or quality of their actions. Because status stems in part from these quality perceptions, it simultaneously serves as a signal of quality (Berger et al. 1972, Podolny 1993, Podolny and Phillips 1996, Cao and Smith 2021).

When actors first enter relationships, groups, and communities, they begin those interactions without status. Being without status does not mean being low status. Low status would imply that others believed the actor incompetent or of poor quality. Being without status instead means that alters simply do not have any beliefs about what value the actor might provide.

People attend to a wide variety of queues as they attempt to situate people in the status hierarchy. Many of these signals provide only diffuse information. They may, for example, infer the status of an individual based on the average status of others with the same ascriptive characteristics, such as gender (e.g., Ridgeway 1991). Or they might observe which other actors in the community interact and affiliate with the entrant, updating their beliefs based on the status of those alters (e.g., Podolny 1993, Stuart et al. 1999, Jensen 2006). Symbolic actions might also provide signals of status (e.g., Askin and Bothner 2016).

But community members also begin to form direct judgments of commitment, competence, and quality and to accord status to entrants to the community on the basis of the actions of those newcomers (Berger et al. 1972, Ridgeway 1981, Henrich and Gil-White 2001, Bendersky and Shah 2012). Although these assessments seem unsurprising in settings where people can easily assess the value added by community members, status orderings curiously emerge even in settings—such as management consulting and investment banking—where it would seem that people have little or no objective basis for evaluating quality (e.g., Podolny 1993, Ertug et al. 2016). In fact, these settings appear to produce some of the steepest and most resilient status hierarchies (Sorenson 2014).

We can reconcile this apparent puzzle and more broadly understand status attainment processes by recognizing that actors engage in a variety of actions, some of which allow for relatively easy and objective valuation, others of which do not. Some actions are easy to evaluate as objectively useful or not. Others mix elements that are easy to evaluate with others that are open to interpretation. Yet others, ambiguous actions, may elude any objective evaluation. Academics, for example, inform each other on a range of issues, from the factual to the speculative. Investment bankers similarly advise their clients on many decisions, from the quickly verified pricing of public securities to the harder-to-assess identification and valuation of private firms to acquire.

In updating their beliefs about the competence or quality of actors, we expect that people will attend to different types of actions, or to different dimensions of those actions, depending on the status of the actors performing them.

Easy-to-Assess Actions

Easy-to-assess actions, by definition, do not require much time, effort, or expertise to evaluate. This fact also means that they should generally involve evaluation on objective criteria.

Even complex and seemingly ambiguous actions often have such easy-to-evaluate components. In many settings, for example, simply expending time or effort on a community may serve as one of the easiest actions to evaluate. Time and effort signal commitment to the community. Numerous experiments have therefore found that groups and communities bestow status on those who expend effort on their behalf, particularly when that effort appears altruistic (e.g., Ridgeway 1981, Willer 2009, Hahl and Zuckerman 2014).

Beyond simply the time involved, many actions have other easy-to-evaluate components. Clients of management consultants and investment bankers, for example, can assess the accuracy of the factual information and calculations reported in a proposal or presentation. They can also easily evaluate their quality on more superficial features, such as the absence of misspellings and grammatical errors.

When actors enter a community, community members first attend to these easy-to-evaluate actions and components of actions when assessing and conferring status on the actors. They reward those who spend time in and on the community. They also hold in higher regard those who perform well on easy-to-evaluate objective criteria, such as being accurate or technically able.

Even if the perceived quality of these easy-to-evaluate elements does not depend on the status of the actor producing them, the extent to which they contribute to conferrals of status will. Before people have strong priors about an actor, observations of effort and high quality on these easy-to-evaluate dimensions will lead alters to update their beliefs about the competence or quality of the actor to regard them as higher status.

Given this line of reasoning, we expect the following:

Hypothesis 1. *At low levels of status, actions that are easier to assess contribute to increases in status.*

Even though these easy-to-evaluate elements often represent but some of the actions or some of the components of the actions in which actors engage, the evaluation of them influences beliefs about the general quality of the actor for at least two reasons. On the one hand, much as people use "test" features when assigning category membership (Hannan et al. 2007), people may infer that quality on one type of action should correlate positively with quality on other sorts of actions. If the analysis in a research paper appears solid in technical terms, the reader might place more faith even in the paper's review of the literature. If a lawyer's brief gets all of its facts right, then readers might give greater credence to any leaps of legal argumentation.

On the other hand, such spillovers in beliefs also stem from automatic psychological processes. People encode their perceptions of quality as moods or emotions (e.g., Swinyard 1993, Danner et al. 2016). But once encoded as a feeling, people can no longer connect that feeling to a specific component of the product or the service or the producer. The positive effect created by these perceptions therefore creates a general mood that leads alters both to recall their past experiences with actors more positively and to overestimate the probability of having good experiences with them in the future (Bower 1981, Johnson and Tversky 1983, Wright and Bower 1992).

The reverse also holds true. The negative effect associated with undesirable experiences can create a pall over the actors responsible and everything that they do (Johnson and Tversky 1983, Wright and Bower 1992). When flights have been delayed, for example, passengers perceive the plane as less clean, the seats as less comfortable, and the food as lower quality (Anderson et al. 2009).

As actors climb the status hierarchy, those interacting with them then have higher expectations about their commitment, competence, and the quality of all of their actions. These expectations rise regardless of whether alters have observed the actors themselves or whether they have simply inferred the status of those actors based on affiliations or patterns of deference.

As the expectations of community members rise, it becomes increasingly difficult for actors to exceed these expectations on easy-to-evaluate actions. They have already demonstrated commitment. Their accuracy cannot exceed 100%. Easy-to-evaluate actions therefore eventually become self-limiting in terms of their further contributions to standing in the community. At some point, the expectations of others for commitment and competence, based on the actor's status, match the actor's observed easy-to-evaluate performances.

We therefore expect the following:

Hypothesis 2. *As status increases, actions that are easier to assess contribute less and less to further increases in status.*

Difficult-to-Assess Actions

As actors rise in the status hierarchy, community members increasingly pay attention to more-difficult-to-assess actions or components of actions. Similar to Phillips and Zuckerman's (2001) argument that actors often require sufficient status to enter the consideration set, community members will only exert the effort necessary to assess the quality of these actions if they believe the actor performing them of sufficient ability or quality to justify their time. People therefore allocate more attention to the ideas and outputs of higher-status actors (Merton 1968, Simcoe and Waguespack 2011). Consistent with the idea that this stems from expectations regarding the quality of their outputs, Cao and Smith (2021) demonstrate that people only differentially attend to those of higher status when they believe status serves as a meaningful signal of quality.

At the extreme, the hardest-to-assess actions, ambiguous actions or components of actions, defy any objective evaluation. Ambiguity does not imply that people vary in their preferences, in what they would regard as high value. Almost everyone would agree that high-quality management consulting should improve the performance of the firm receiving the advice. Similarly, most would concede that a highly competent investment banker should accurately predict the price that investors would pay for a company in an initial public offering or acquisition (Podolny 1993).

The ambiguity rather resides in the near impossibility of assessing whether these objectives have been met. Consider, for example, career advice. Although the person receiving any such advice might perceive it as useful at the time, any objective evaluation of its quality can only be made far in the future, after the recipient has had the opportunity to act on it. Even then, evaluation would prove difficult. To assess its quality, two types of counterfactuals are needed. First, what would have happened to the individual in the absence of the advice, if they had followed a different path? Second, what career advice might another person have given at the time? Without solid evidence of both counterfactuals, any evaluation of the quality of the advice becomes largely subjective.

Such fundamental ambiguity in evaluation exists for actions in many settings. Consider a management consulting firm giving strategy advice. What recommendations would another consulting firm have given? For an investment bank underwriting a public offering, would another bank have proposed a more accurate initial price? With sufficient time and information, some of these actions might be open to objective evaluation. Someone could, for example, examine the average level of underpricing across many public offerings or the average performance of client firms many years down the road. But, in any individual instance and at the time the actions have been performed, the quality of these actions remains ambiguous.

In the face of this ambiguity, we argue that the perceived quality of these actions will depend on the status of the actor performing them. People will find it near impossible to judge the ambiguous actions of those without status, those about whom they have no priors of competence or quality. People may even treat ambiguous actions from low-status actors as confirming evidence of incompetence or of low-quality performance (Riecken 1958).

But as status rises, the fact that the actor has status positively influences the audience's interpretation of the ambiguous action (Merton 1968, Correll et al. 2017). Sgourev and Althuizen (2014), for example, vividly recount how the same style inconsistency that critics denigrated early in Picasso's career (before he had status) became seen as evidence of his genius after he had attained prominence.

Importantly, in contrast to easy-to-evaluate dimensions on which expectations of quality based on status will eventually match observed quality, in the absence of objective evaluation, perceptions rule unconstrained. Advice from a Goldman Sachs or a Nobel Prize winner almost automatically becomes seen as important and insightful, as high quality. When a high-status actor weighs in on some topic, audiences perceive those opinions as further evidence of the individual's brilliance.

In part, this effect probably stems from confirmation bias. When presented with conflicting evidence, people tend to pay attention to the information that would support their existing opinions and to ignore that which would contradict them (Wason 1960, Klayman and Ha 1987). For firms and individuals held in high regard then, audiences may selectively attend to information, even noise, that affirms their opinions.

But this effect probably also stems, in part, from socially endogenous inference. When faced with uncertainty about how to evaluate an action, people rely on the choices and opinions of others—assuming that those individuals have information or insight that they do not—as a means of resolving their uncertainty (Ridgeway and Erickson 2000, Lynn et al. 2009, Correll et al. 2017). Scientists, for example, assess contributions not only by reading articles and attending seminars but also by paying attention to who else has cited these researchers. In evaluating the quality of a song, listeners incorporate both their own opinions and their beliefs about what others thought (Salganik et al. 2006).

However, whereas the existing literature on socially endogenous inference has generally treated the process as a property of the setting (e.g., Podolny 1993, Lynn et al. 2009), we would argue that it only occurs for certain types of actions and, more crucially, that it can only begin *after* actors have been accorded some stature on the basis of easy-to-evaluate actions. The extent to which it operates therefore varies across actors within settings and also over time for any given actor

Although the perceived quality of these ambiguous actions stems from the status of the actors performing them, we believe that they will nevertheless contribute to further gains in the perceived competence or quality of these actors. If people understood that their favorable perceptions of these difficult-to-evaluate activities reflected the status of the actors, then that understanding might inoculate them from using these biased opinions to update their beliefs. However, whether due to confirmation biases or socially endogenous inference, we suspect that people are either not aware of these biases or underestimate the extent to which they operate. Status then increases the perceived quality of difficult-to-evaluate actions, which leads to further increases in status, creating a virtuous cycle of positive feedback.

This line of reasoning leads us to propose the following:

Hypothesis 3. *As status increases, difficult-to-evaluate actions contribute more and more to further increases in status.*

Stack Overflow

We investigate the dynamics of status formation on Stack Overflow. SO provides a forum in which people can find solutions to their programming problems, can help solve others' problems, and can discuss a range of topics related to computer programming and software engineering.

SO provides an amazing resource. It is the most active online exchange for programming-related information, with almost 20 times as many questions and answers as the next most active exchange. Since its inception in 2008, users have posted more than 20 million questions and have received more than 30 million answers to those questions.[1] Most questions receive answers in a matter of minutes (Mamykina et al. 2011). Every month, 50 million unique visitors search the site for programming-related information.

SO also offers an excellent setting for examining the dynamics of status formation. First and foremost, most members of the community interact only through the platform and the platform documents nearly all of their activity. We therefore have a complete archival record of the actions that contribute to status attainment. Second, the fact that few of these individuals have prior experience with each other outside the platform means that members join the community without any preexisting status.

Anyone can join SO. Joining allows a user not just to read the existing discussions but also to contribute content. Members undoubtedly participate for a variety of reasons. Some may derive satisfaction from contributing to the public good; others may enjoy the social exchange or the recognition garnered from their contributions; yet others may see providing advice as a form of generalized reciprocity for the benefits that they themselves have received (Constant et al. 1996, Lakhani and von Hippel 2003, Penoyer et al. 2018, Chen et al. 2019).

We downloaded our data from the archive (https://archive.org/details/stackexchange) that Stack Overview released to the public on March 13, 2017. Our full data set includes information on all activities on the SO platform from its inception, on July 31, 2008, to our download date, of March 13, 2017. Because of the large size of the archive, our analyses focus on a 1% simple random sample of members (30,418 accounts). Each member who had registered on SO before March 13, 2017, had an equal probability of being included in the sample, regardless of their status, their year of registration, and their level of activity. We did, however, exclude elected moderators from this sample as they often appear as outliers in their degree of activity on the platform.

Figure 1 depicts an example of what one would see as a set of actions related to a particular question. Box 1 surrounds the initial question. It includes an explanation of the problem and a snippet of code reporting what the person, "Amit Patil" (see the shaded area just below the box), had tried. Box 2 highlights the best answer given, submitted by "Mark Byers" (again, see the area just below the box). If one scrolled down the screen, one would see the other answers, sequenced in terms of the number of "useful" votes that they had received. The smallest box, box 3, meanwhile, surrounds one of the comments, offered by "Ankur-m" nearly two years after the question had originally been posed.

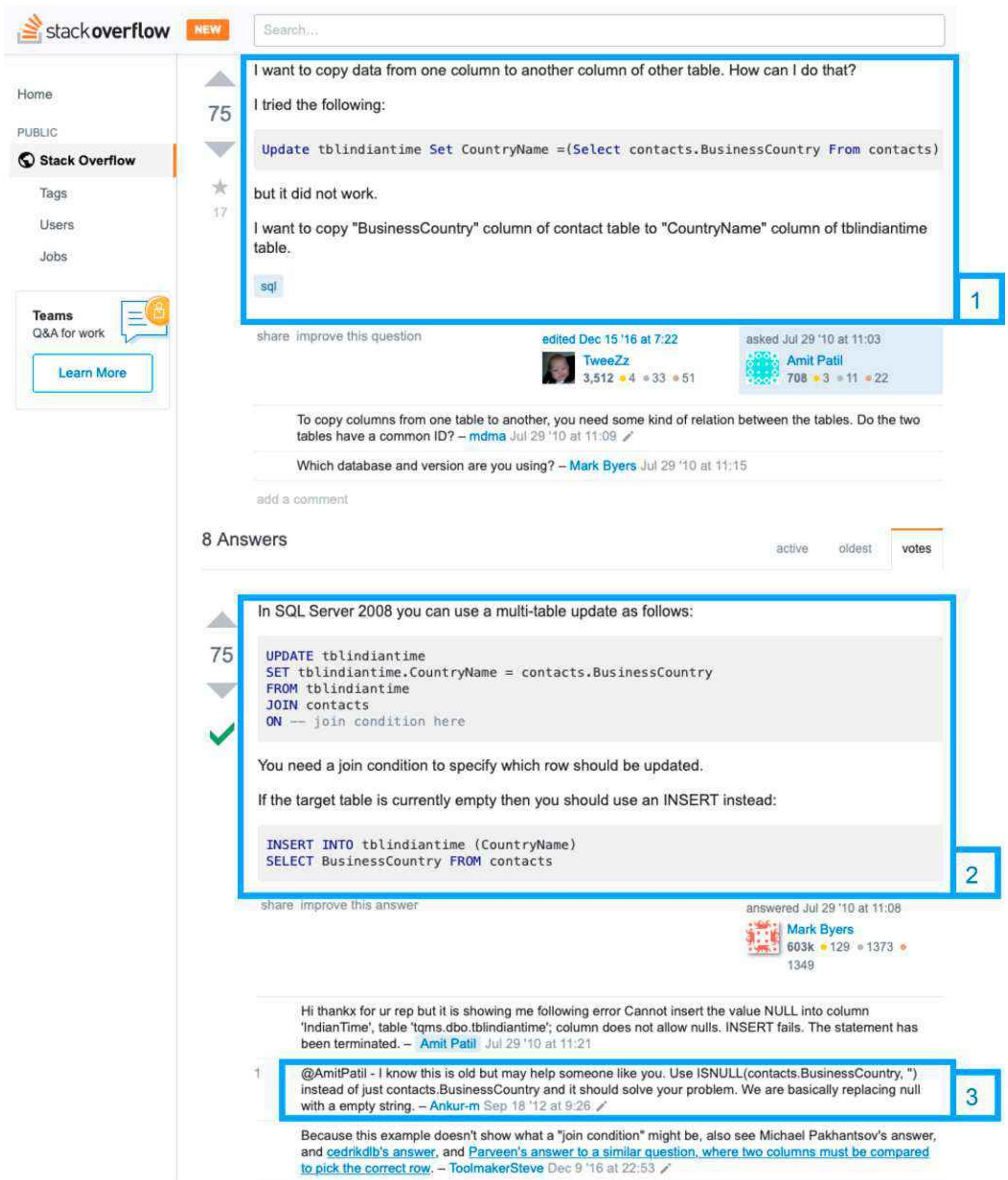
As in many online communities, status plays an important role here. The platform does not moderate participation and questions, answers, and comments vary tremendously in their quality. As in other communities, the solution to this problem involves a type of crowdsourced quality evaluation. Members of the community can upvote (or downvote) questions, evaluating them as clear and useful (or not). In Figure 1, for example, one can see that the question received 75 more upvotes than downvotes (see the number between triangles to the left of box 1). Members can also evaluate answers and comments as useful (or not). The top answer to this question also happened to have received 75 more upvotes than downvotes (see the number between triangles to the left of box 2).

The platform uses community members' reactions to questions and answers to award points and badges to members who provide content. These points and badges both provide rewards for contributing and signals to those consuming the content. SO displays them prominently. Consider Figure 1 again. Look at the line just below the user names for the people asking and answering questions. The first number reports the points that the individual has received; the numbers to the left of the colored dots detail the number of badges that the user has received. "Amit Patil," for example, has 708 points and has earned 3 gold badges, 11 silver badges, and 22 bronze badges.[2]

Users can also find out more about any particular member, in their profile, by clicking on the person's username. Figure 2 provides an example of a profile: "nc3b" has been a member for more than nine years (though one can also see that the user has not been active since 2013), asking 19 questions and posting more than 176 answers. Immediately below the avatar on the left-hand side of the screen, you can see the points (10,879) and the number of badges that nc3b has been awarded. Based on the tag information reported in the middle of the page, this member appears to have expertise primarily in the C programming language. But we have no information about the individual beyond his or her activity on SO. The line—"Apparently, this user prefers to keep an air of mystery about them."—represents generic text that SO displays for all members who have not provided self-descriptions in their profiles.

Although this example does not include any identifying information, some users do provide personal

Figure 1. (Color online) Example of a Stack Overflow Question Page



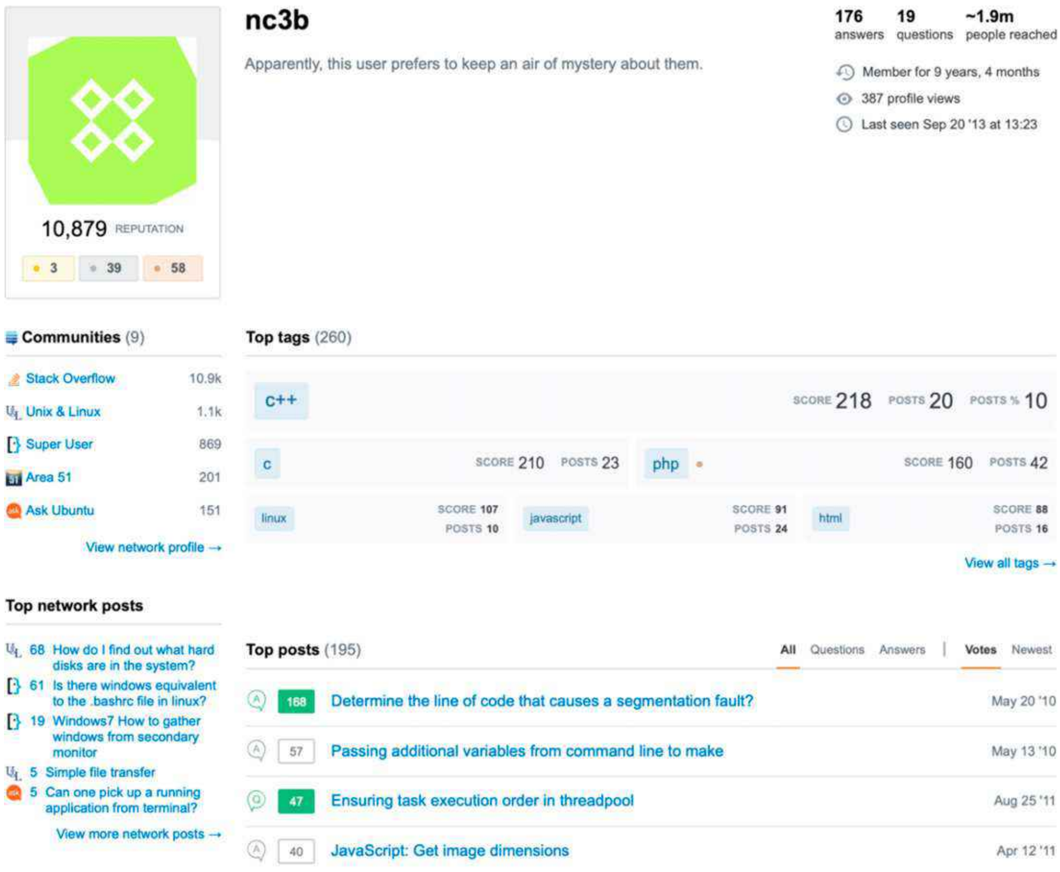
Source. https://stackoverflow.com/questions/3361768/copy-data-from-one-column-to-other-column-which-is-in-a-different-table/13454906#13454906 (accessed April 30, 2019).

information. SO does not maintain official statistics on the proportion of members who have completed their profiles. We therefore examined two subsets of 100 members—one selected at random from our sample and a second set of the 100 users who had accumulated the most points—and hand coded their profiles. Although nothing requires SO members to choose user names that identify them, 46 of 100 individuals in the random sample and 41 of the top 100 scorers chose user names that resembled a combination of a forename and a surname. Of those potentially using real names, fewer than half provided any additional identifying information, such as an employer, in their profile (19 of 46 of the random sample and 20 of the 41 top scorers). For most individuals, therefore, SO users would have little if any information on which to base prior beliefs about their status (cf. Bianchi et al. 2012). High-status members also do not appear to differ from the average community member on this outside information.

Measures

Dependent Variables. Status has usually been measured in one of two ways. The first involves selecting some award, such as the Nobel Prize or an endowed chair (e.g., Merton 1968, Reschke et al. 2018). This approach has the advantage of having a high degree of

Figure 2. (Color online) Example of a Member Profile Page



Source. https://stackoverflow.com/users/226266/nc3b (accessed April 30, 2019).

face validity. Few would argue that the Nobel Prize does not confer prestige on its recipient. But these prizes and positions also reflect status. People win Nobel Prizes and receive chairs because they are already held in high regard. Studies based on this approach therefore compare the pinnacle of the prestige hierarchy to the merely elite (Reschke et al. 2018).

A second approach collects information on patterns of deference (e.g., Podolny 1993). Highly cited scientists, for example, have higher status on average than those receiving less attention. Our own measures follow the logic of this second approach.

We examine two outcomes. Our first measure builds off of the score that SO uses to summarize how other members have evaluated the person's contributions. The second measure captures attention, something strongly correlated with status (Merton 1968, Simcoe and Waguespack 2011).

SO scores its members based on how other members respond to their contributions. Much as publishing a paper does not ensure that anyone cites it, posting a question, an answer, or a comment does not guarantee the poster any points. During the period covered by our data, community members could award or penalize another user in six main ways: (1) Upvoting (downvoting) someone else's question adds 5 points to (subtracts 2 points from) that person's score. (2) Upvoting another member's answer adds 10 points to (subtracts 2 points from) that member's score. (3) When the question asker selects an answer as the best one offered, the person providing that answer receives an additional 15 points. (4) A member can also offer a "bounty" on a question. If they choose to award the bounty to a particular answer, the person awarding the bounty effectively transfers those points from their own score to the person receiving the bounty. (5) If a user proposes an edit to a question, answer, or comment and the original poster accepts that edit, the person proposing the edit receives 2 points. (6) If a person's post receives six flags identifying it as spam or as being offensive, the person loses 100 points. These reactions account for nearly all points awarded to SO members.[3]

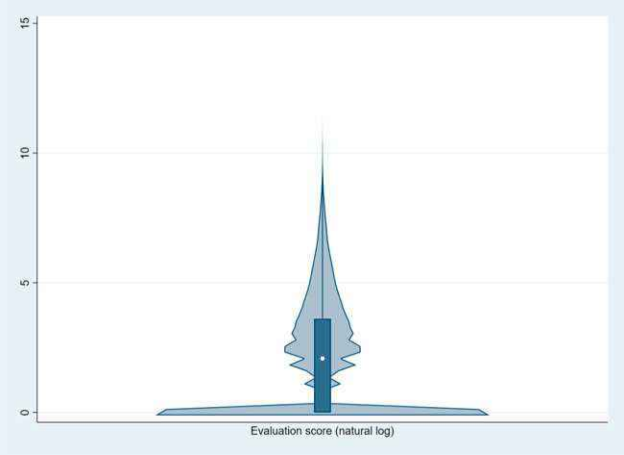
Returning to the example in Figure 1, the asker here received 375 points for this question based on the reactions of other users (= 5 × 75). The person who provided the answer meanwhile received 765 points for the combination of the upvotes plus being accepted as the best answer (= 10 × 75 + 15). But these numbers represent outliers. The modal question and answer receive no reactions—no upvotes or downvotes—and therefore do not result in any points being rewarded to the posters.

The archival data from SO only provided this score at the time of downloading, but SO reports the algorithm that it uses to calculate these scores and our data include nearly all of the relevant information for this calculation. We therefore used the algorithm together with the activity information to create time-varying imputed *evaluation scores*. We computed this variable at the user-month level for the period from SO's inception up until March 2017, giving us a total of 1,420,359 distinct user-period observations. Our manually reconstructed scores for March 2017 correlate to those available from SO at a level of 0.98.[4]

Figure 3 depicts the distribution of these (logged) evaluation scores in our data in a violin plot. The width of the violin at each point depicts the proportion of the mass of the distribution at that point; the dot and boxplot down the center represent the mean and interquartile range, respectively. One can clearly see that a large proportion of members register but then never receive any attention for their activity on the platform. The average individual received 160.6 points over our observation window. But this score has a very long tail, with one person being awarded more than 116,000 points.

Our second dependent variable stems from the fact that with status comes attention. This measure, which we label as *visibility*, counts the cumulative profile views—the page depicted in Figure 2—that a member has received up to a given point of time. SO, again, only provides cross-sectional information on this measure. Because we could not reconstruct it retroactively,

Figure 3. (Color online) Distribution of the Logged Evaluation Scores



we scraped the website for profile views every other week from November 30, 2016, to March 18, 2017 for all SO members, generating eight observations for each member (242,872 user-period records).

Members also vary a great deal in their visibility. The average individual had received 24.7 profile views by March 2017. But the cumulative number of profile views to that point ranged from just 1 to more than 9,000.

Our dependent variables correlate with each other at 0.75. But each measure has its strengths and weaknesses. The primary weakness of the evaluation score is that SO has defined the weights for how particular reactions contribute to status. Visibility, meanwhile, has the advantage of not assuming any weights but has the disadvantage that members may view profiles for reasons not connected to status, introducing noise into that measure. To the extent that both measures reveal similar patterns, however, it should increase our confidence that the results reflect actual status attainment processes.

Independent Variables. Our theory argues that different types of activities contribute to status formation at different points in the process. SO members engage in three main activities: posting questions, answering them, and commenting.[5] Questions seem easiest to evaluate. They demonstrate engagement with the community. Users can understand most aspects of their value simply from reading them.

Consider an example. One new user posted a question, "Combining two vectors element-by-element," with the following text: "I have 2 vectors [examples]. I would like to combine them so that the resulting vector is [example]. I can easily do this with a loop but it is very slow so can anyone provide a fast way to do this?" The title clearly and succinctly describes the issue. Readers can readily assess whether they would value a resolution to it. To date, it has received eight upvotes, adding 40 points to the evaluation score of the asker.

Evaluating answers, by comparison, requires more effort. Simply providing an answer demonstrates commitment to the community. Members devote time to writing them. Answers to questions often run to multiple paragraphs and include lines and lines of code.

In our hand-coded sample, however, upvotes and downvotes came not from length but from whether the solution worked. Determining that demands more effort or expertise. Either the evaluator must have sufficient experience that they had tried the solution before or the person must attempt to implement the advice. Many problems also have multiple solutions. Determining the best approach might require a great deal of expertise and may depend on the situation.

Comments, meanwhile, often seem at least as difficult as answers to evaluate in terms of their value.[6] Understanding the value of these comments often requires reading and understanding the entire thread, not just the original question but also the proposed solutions. Consider some examples. As a response to a proposed answer, the original asker commented: "I don't want R to store 50,000 zeros. Rather, I want some type of sparse storage within each loop." Another user responded to this comment with another comment, "plenty of results here on sparse matrices," with links to two additional SO threads. In another thread, as a comment on a question, one user responded "just count?? the order of the variables is the same as the order of the columns." Effectively, the user offered a solution to the question without posting an official answer.

To the extent that these contributions range from questions being easier to evaluate to answers and comments being more difficult to evaluate, we therefore expect that the SO community will pay more attention to questions for posters at lower levels of status but that they will increasingly attend to answers and comments as posters rise in the status ranks.

Our independent variables measure each of these activities:

Questioning activity counts the (logged) cumulative number of questions (plus one) an individual has posted on the platform up to a given point of time.[7] In our full sample, SO members post three to four questions, on average; but the range runs from 0 to 752.

Answering activity counts the (logged) cumulative number of answers (plus one) an individual has posted on the platform up to a given point of time. In our sample, the median member posted five answers; but the range in answering activity runs from 0 to 1,966 posts.

Commenting activity, meanwhile, counts the (logged) cumulative number of comments (plus one) that a user has submitted.[8] The average member in our sample posted about 13 comments, but some have posted more than 5,000.

Figure 4 depicts the natural logs of the quarterly distributions of activities by status level for all users who eventually reached the 95th percentile of the evaluation score distribution. It therefore provides some sense of how activity on the platform evolves with status, within user. As users rise through the ranks, they become more active on the system. But even those at the lowest levels post comments, and even those at the highest levels still pose questions. The most notable shift in behavior appears to be that users flatten out in their rate of asking questions after reaching the 75th percentile of the evaluation score distribution.

We also included control variables to adjust for a number of user attributes. Because these processes unfold over time, we want to account for any maturation effects, such as learning at the level of the individual. A user tenure variable, therefore, captures the logged number of days since the user joined the platform. All of the models also include a count of the logged number of "favorite" tags that a user has given, for the logged number of times that a user answers his or her own question, and for the logged number of times a user accepts his or her own answer as being the best one, even though these represent rather rare events and even though they have no mechanical relationship to either of our dependent variables. We add one to all of these counts prior to logging to avoid the generation of missing values.

Our models also include a variety of measures of activity and objective quality at the question-answer level. The models include the ratio of questions and answers posted by the individual that include snippets of code. The models also control for the number of bounty points received.

We also included variables to capture the proportion of the users' questions and answers that had been in popular categories. Because these categories have more people posting and reading questions, answers, and comments, activity in these domains may attract more votes and attention. Table 1 reports descriptive statistics for the variables used in our analyses (summary statistics for the control variables appear in Table A1 in the online appendix).

Estimation Strategy. Our theory argues that the actions that the community values and for which it awards status vary as a function of the actor's current status. One obvious approach to exploring this idea would involve regressing the evaluation score in one period on a set of interaction effects between the various

Figure 4. (Color online) Logged Average Number of Posts on Stack Overflow per Quarter per User by Status Level for All Users Who Reached the 95th Percentile of the Evaluation Score Distribution

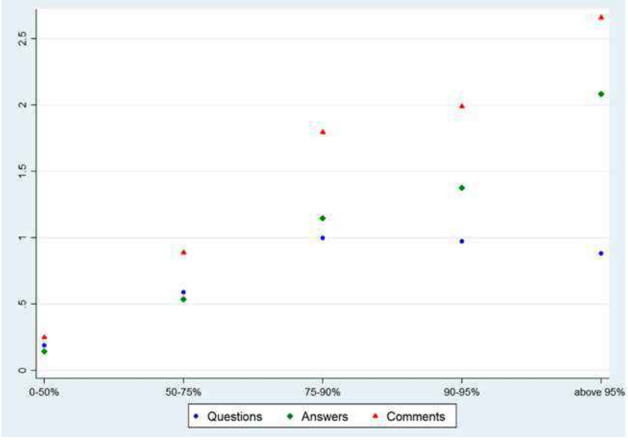


Table 1. Descriptive Statistics for Key Variables

Variables	N	Mean	Std. dev.	Min	Max
Evaluation scores	1,420,359	160.6	1,203.25	1	116,114
Visibility	242,872	24.74	145.05	1	9,037
Questioning activity	1,420,359	3.6	12.95	0	752
Answering activity	1,420,359	5.03	34.08	0	1,966
Commenting activity	1,420,359	12.85	75.57	0	5,027

Note. Std. dev., standard deviation.

actions and the evaluation score in the prior period. But that approach has the disadvantage of imposing a functional form on how attention to types of action change with status.

To allow the relationship between the reactions to actions and status to vary flexibly, we used a modified version of quantile regression. We began by specifying five quantile intervals—0%–50%, 50%–75%, 75%–90%, 90%–95%, and above 95%—for each of our dependent variables. For the evaluation score, the cut points fall at 8, 37, 187, and 506 points; for visibility, the boundaries between the quantile intervals come at 4, 10, 35, and 79 page-views. Although our definition of these boundaries stem from the distributions of these variables at the end of our period, the inclusion of period fixed effects should account for the fact that the underlying distribution evolves over time.[9]

We then estimated coefficients for our independent variables within each of these quantile intervals using a series of models with user-level fixed effects.[10] These fixed effects should capture time-invariant unobserved differences across community members, such as gender, native language, and formal education (as well as ancillary information available on profiles). Our estimates therefore reflect the changing reactions of the SO community to various types of actions within a specific individual within a particular range of the status distribution.

SO user-period provides the unit of analysis in these regressions. Standard errors have been clustered at the user level.[11] We estimate our regression models according to:

$$\begin{aligned}&\textit{Evaluation score}_{i,t} \textit{ or Visibility}_{i,t} = \alpha + \beta_1 \\ &\quad\times \textit{questioning activity}_{i,t} + \beta_2 \times \textit{answering activity}_{i,t} \\ &\quad+ \beta_3 \times \textit{commenting activity}_{i,t} + \gamma_1 \times \textit{user controls}_{i,t} \\ &\quad+ \textit{time dummies}_t + \varepsilon_{i,t}, \qquad (1)\end{aligned}$$

where i refers to the individual user and t to the period (either a month or two-week interval).

Results

Figure 5 plots the coefficient estimates for the relationship between actions and evaluation scores. (Table 2 reports the results in table form). The plots group the coefficients for a particular type of activity across the various quantile ranges, with the lowest status level appearing at the top of each grouping and with status increasing as one moves down.

Consider first the effects of asking questions. At the lowest levels of status, nearly all gains in status appear associated with asking questions (consistent with Hypothesis 1). The coefficient implies that a one-unit increase in questioning activity predicts a 0.57% increase in a person's evaluation score ($p < 0.001$). Asking questions continues to predict gains in status all the way up to the 95th percentile of the evaluation score distribution. The apparent value of asking questions in terms of additional status gains, however, declines rapidly as users move up the distribution of evaluation scores. Based on only questioning activity, an individual entering the platform could move into the top half of the evaluation score distribution by posting 21 questions with average reactions. Moving from the 50th percentile to the 75th percentile would require another 35 average-reaction questions. At the very highest levels, in the top 5%, posting questions actually has a negative association with the evaluation score. At that level, questions disappoint. Consistent with Hypothesis 2, then, the value of easy-to-evaluate activities for status gains exhibits diminishing marginal returns.

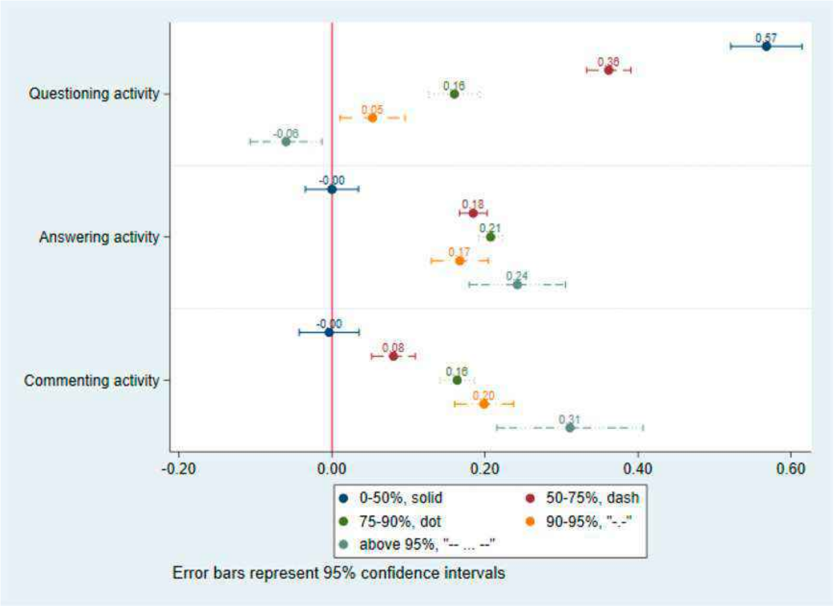
Answering activity, by contrast, does little for status at the very lowest levels (we cannot even reject the null hypothesis that it has no effect). At middle and high levels of status, however, answering questions begins to predict increases in status, consistent with Hypothesis 3.

Commenting activity, perhaps the most difficult to evaluate of the three actions, also has no significant effect on status gains for those in the bottom half of the status distribution. At moderate to high levels of status, posting comments has a more pronounced association with status attainment ($\beta_3 = 0.16$ and 0.20 at the 75th and 90th percentiles, $p < 0.001$). Consistent with Hypothesis 3, the relationship between commenting and status gains becomes ever stronger as individuals climb the status hierarchy.

Figure 6 again depicts the main results, this time using visibility as the measure of member status (for the corresponding table, see Table 3). The results largely mirror those in Figure 5. At low levels of status, the community-wide interest correlates primarily with questioning activity, consistent with Hypothesis 1. Over this range of status, a one-unit increase in the number of questions predicts a roughly 0.25% increase in profile views ($p < 0.001$). At these modest levels of status, however, providing answers and comments adds little to visibility within the SO community.

As status increases (75%–90% and 90%–95% quantile intervals), however, more difficult-to-evaluate

Figure 5. (Color online) Within-Quantile Coefficient Estimates for the Relationship Between Various User Actions on Stack Overflow and Their Evaluation Scores



actions become the more powerful predictors of further increases in community-wide attention. Asking questions becomes less important and does not even differ significantly from zero once users pass the 90th percentile threshold ($p > 0.2$). Answering questions also adds little to further increases in visibility at the highest levels of the status distribution ($\beta_2 = 0.04$ at the 95th percentile, $p = 0.027$). Only posting comments continues to correspond to increasing attention at the highest levels. Moving from the 90th percentile to the 95th percentile of visibility would require millions of questions generating average reactions, hundreds of average-reaction answers, or roughly five average-reaction comments.

We estimated a number of additional models to assess the extent to which our results might reflect some sample selection or estimation choice. We first restricted the analysis to those who eventually achieved high status (the 95th percentile). In other words, this regression estimates what accounted for the status gains of the elite users as they moved from having no status to being in the top status category. Figure 7 depicts the coefficient estimates for the same models within this subset of users (Table 4 reports the results in table form). As one can see, the patterns appear the same even among this set of elite users.

We next restricted the analysis to those who joined the platform during its first full year of operations (July 31, 2008 to July 31, 2009). This subset addresses two potential issues. First, it accounts for the fact that the platform and the nature of contributions to it might have evolved over time. Second, it addresses the possibility that the definition of what it means to be elite may have changed over time. Although this smaller subsample produces noisier estimates (see Table A2 in the online appendix), the point estimates follow a similar pattern to that found in the full sample.

Experiments

The individual-level fixed effects allow us to rule out a wide range of alternative interpretations. For example, if members revealed their gender or nationality through their user names or on their profiles and those characteristics led to differences in status, the fixed effects would absorb those effects. But one important potential confound remains. Members might get better at these activities over time, meaning that the quality of their answers and comments might rise in tandem with their score and their visibility. Solving this simultaneity problem would either require exogenous variation in status or accurate measures of the objective components of question, answer, and comment quality. Because neither of these solutions seemed feasible in the archival data, we developed a pair of online experiments as a second test of our predictions.

We had a panel of Python experts create realistic threads of questions, answers, and comments. We assembled these threads using the same formatting as an SO thread, so that they would appear almost as screen shots from the SO website (see Figures A3 and A4 in the online appendix). However, as opposed to an actual thread, the experiment allowed us to assign randomly the status of the users associated with the question, answers, and comments in each thread. We ran two online experiments.[12] The first tested our

Table 2. Within-Quantile OLS User Fixed-Effects Regressions for the Relationship Between Various User Actions on Stack Overflow and Their Evaluation Scores

Variables	(1)	(2)	(3)	(4)	(5)
	0%–50%	50%–75%	75%–90%	90%–95%	Above 95%
log(*Questioning activity* + 1)	0.57***	0.36***	0.16***	0.05*	−0.06*
	(0.024)	(0.015)	(0.017)	(0.022)	(0.024)
log(*Answering activity* + 1)	−0.00	0.18***	0.21***	0.17***	0.24***
	(0.018)	(0.009)	(0.008)	(0.019)	(0.032)
log(*Commenting activity* + 1)	−0.00	0.08***	0.16***	0.20***	0.31***
	(0.020)	(0.014)	(0.012)	(0.020)	(0.049)
log(*User tenure* + 1)	0.07***	0.25***	0.43***	0.29***	0.59***
	(0.011)	(0.016)	(0.040)	(0.080)	(0.122)
log(*Answering activity to own questions* + 1)	−0.03**	−0.01	0.02***	0.01*	0.02***
	(0.011)	(0.004)	(0.004)	(0.004)	(0.005)
log(*Number of "favorite" votes given* + 1)	0.00	0.01**	0.01***	0.01***	0.01***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
log(*Number of "favorite" votes given to self* + 1)	−0.00	−0.00	−0.00	0.00**	0.00*
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
log(*Accepting own answers as best* + 1)	0.00	0.00*	−0.00	−0.01**	−0.01**
	(0.005)	(0.002)	(0.002)	(0.003)	(0.003)
Ratio of posed questions with snippets of code	0.08***	−0.02*	−0.04***	−0.01	0.00
	(0.012)	(0.009)	(0.010)	(0.014)	(0.018)
Ratio of given answers with snippets of code	−0.00	0.01**	0.01	0.00	0.02
	(0.006)	(0.004)	(0.005)	(0.011)	(0.032)
Ratio of posed popular questions	0.00	−0.01†	−0.01	−0.02*	0.01
	(0.009)	(0.007)	(0.009)	(0.011)	(0.014)
Ratio of given answers to popular questions	−0.00	−0.01	−0.01**	0.00	−0.06*
	(0.006)	(0.004)	(0.005)	(0.009)	(0.030)
log(*Number of bounty points received* + 1)	0.01***	0.00**	0.00***	0.00†	0.00**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Time dummies (month)	YES	YES	YES	YES	YES
N	689,765	373,569	214,686	71,306	71,033

Notes. OLS user fixed-effects panel regressions where robust standard errors clustered at the user level are reported in parentheses. All independent variables are normalized. OLS, ordinary least squares.
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests).

arguments for questions and the second our predictions related to answers and comments.

Experiment 1: Methods

Participants. We recruited 90 English-speaking participants, who had prior knowledge of Python, through Amazon's Mechanical Turk (MTurk) online platform.[13] MTurk provides a diverse participant pool for academic research, one demographically similar to the general population (Buhrmester et al. 2011, Chandler and Shapiro 2016). To ensure that our participants had the relevant expertise to evaluate the questions, answers, and comments, we screened potential participants for their prior knowledge of the Python programming language. We embedded this screening question in a set of questions about their experience with several programming languages to reduce the likelihood that participants might not answer truthfully (see Figure A1 in the online appendix).[14]

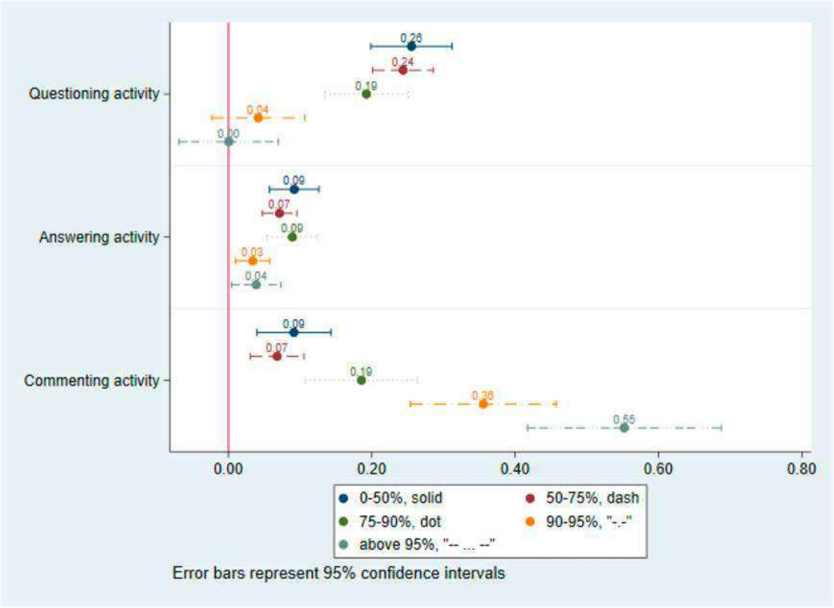
Design. We used a between-subjects design with three different conditions per thread, in which we experimentally manipulated the status level of the question asker to one of three levels: low status (a score of 6 points), medium status (158 points), or high status (1,714 points). We selected these values based on the distribution of the SO scores in our field data, with low status being a below-median value, medium status falling in the 50th-to-75th percentile interval, and high status being in the top 5% of the SO score distribution.

Each participant read six fictitious threads (presented in random order), so each of the 18 experimental conditions of our 6 (six question threads) × 3 (status of the question asker: low, medium, or high) design appears 30 times in our data. Two threads involved simple beginner-level Python questions; two touched on more intermediate issues; and two concerned advanced topics. Out of each pair, one question included a snippet of code and the other did not. Participants then evaluated each of the six questions by giving them a "downvote," a "no vote," or an "upvote," mirroring the SO setting.

Experiment 2: Methods

Participants. For the second experiment, we recruited a second set of English-speaking participants with prior knowledge of Python on the MTurk platform (270

Figure 6. (Color online) Within-Quantile Coefficient Estimates for the Relationship Between Various User Actions on Stack Overflow and Their Visibility



individuals).[15] We screened for Python expertise using the same procedures as in the first experiment.

Design. We again used a between-subjects design. In this experiment, participants read two medium-difficulty threads, one with a code snippet and one without one. One answer in each thread solved the problem; the other did not. Two comments appeared below one of these answers on each thread, one that our expert panel perceived as a stronger comment.

In all of the threads, we kept the status level of the question asker constant at 160 points (medium status), but we randomly assigned the reputation scores associated with those giving answers or comments. We again used three levels: low (6 points), medium (158 points), and high (1,714 points).

We again asked each participant to evaluate these answers and comments with a downvote, no vote, or an upvote.[16] Because each participant viewed two threads, each of which consisted of two answers and two comments, each person evaluated four answers and four comments. We treated these responses as orthogonal. The 18 possible experimental conditions of 2 (two threads) × 3 (status of the first answer/comment poser: low, medium, or high) × 3 (status of the second answer/comment poser: low, medium, or high) appear 30 times in our data.

Results

As a reminder, given our theory, we would expect status to have little or no effect on the evaluation of questions, to have a larger effect on answers, and to have the largest effect on comments.

To analyze the effect of the status of a post author on the rating that their post receives, we ran a series of linear regression models with fixed effects for the specific questions, answers, and comments.[17] The post-level fixed effects account for any differences in the objective quality of the specific post as well as for variation in the expertise required to evaluate a post. Our dependent variable codes a downvote as −1, no vote as 0, and an upvote as +1.

Table 5 summarizes these regression results. The top panel reports the models for the entire sample. Some of the participants rushed through the survey, completing it in such a short time that we did not believe that they could have read the entire thread. We therefore estimated the models also on the subset of participants who took longer than average to complete the survey in the middle panel. To assess whether status might have stronger effects on the evaluations of novice programmers who could not assess the quality of the posts directly, the bottom panel estimates the models on the subset of users who self-reported themselves as having expert or near-expert level proficiency in Python.

The first column reports the results for questions. Both in the full sample and in the two subsets, the small magnitude of the coefficient points to little or no effect of status on question evaluation. Despite having relatively small standard errors, none of the models allows us to reject the null hypothesis that the coefficient for status is zero.

Table 3. Within-Quantile OLS User Fixed-Effects Regressions for the Relationship Between Various User Actions on Stack Overflow and Their Visibility

Variables	(1)	(2)	(3)	(4)	(5)
	0%–50%	50%–75%	75%–90%	90%–95%	Above 95%
log(*Questioning activity* + 1)	0.26***	0.24***	0.19***	0.04	0.00
	(0.029)	(0.022)	(0.030)	(0.033)	(0.035)
log(*Answering activity* + 1)	0.09***	0.07***	0.09***	0.03**	0.04*
	(0.018)	(0.012)	(0.018)	(0.012)	(0.018)
log(*Commenting activity* + 1)	0.09***	0.07***	0.19***	0.36***	0.55***
	(0.026)	(0.019)	(0.040)	(0.052)	(0.069)
log(*User tenure* + 1)	0.18***	0.41***	0.88***	1.74***	1.71***
	(0.031)	(0.061)	(0.143)	(0.366)	(0.365)
log(*Answering activity to own questions* + 1)	0.03***	0.02*	0.02**	0.00	0.01†
	(0.010)	(0.008)	(0.005)	(0.004)	(0.005)
log(*Number of "favorite" votes given* + 1)	0.00	0.01	0.01***	0.01***	0.02***
	(0.007)	(0.004)	(0.004)	(0.004)	(0.003)
log(*Number of "favorite" votes given to self* + 1)	−0.00	0.00	−0.00	0.00*	−0.00
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
log(*Accepting own answers as best* + 1)	−0.01	−0.00	−0.00	−0.00	−0.00
	(0.005)	(0.004)	(0.005)	(0.002)	(0.003)
Ratio of posed questions with snippets of code	−0.05***	−0.03*	−0.00	0.01	0.00
	(0.013)	(0.014)	(0.019)	(0.012)	(0.017)
Ratio of given answers with snippets of code	−0.01	−0.01*	0.00	−0.02*	−0.04†
	(0.008)	(0.007)	(0.011)	(0.009)	(0.023)
Ratio of posed popular questions	−0.00	−0.02	−0.03†	−0.00	−0.03
	(0.011)	(0.010)	(0.017)	(0.010)	(0.030)
Ratio of given answers to popular questions	0.01	0.02**	−0.01	0.00	0.03
	(0.009)	(0.009)	(0.010)	(0.009)	(0.017)
log(*Number of bounty points received* + 1)	–	0.00***	0.00†	–	−0.00
		(0.000)	(0.000)		(0.000)
Time dummies (two-week interval)	YES	YES	YES	YES	YES
N	120,075	57,789	40,390	12,411	12,207

Notes. OLS user fixed-effects panel regressions where robust standard errors clustered at the user level are reported in parentheses. All independent variables are normalized. OLS, ordinary least squares.
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests).

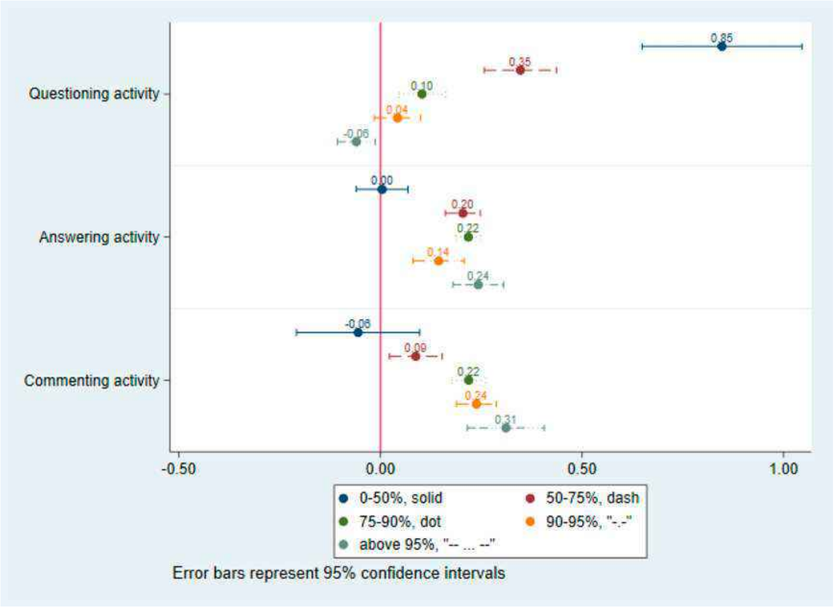
In the second column, the coefficients capture the effects of status on answer evaluation. In the full sample, the status of the answerer increases the perceived value of the answer. Moving from a status of 10 points to one of 100 points, for example, would predict a 0.13-point increase in the average evaluation of the answer. That represents a more than 100% increase over the average. In the subsample of users who spent more time on the survey, status had even larger effects. Moving from 10 points to 100 points in that subsample would increase the expected evaluation by 0.22 points. Status interestingly also had larger effects on the subsample of experts. Expertise did not inoculate participants from being influenced by status; if anything, they appeared more susceptible to it.

The third column reports our results for comments. Once again, the status of the commenter increases the perceived quality of their posts in the full sample. Moving from a status of 10 points to one of 100 points predicts a 0.12-point increase in the average evaluation of a comment. Among those who spent more time on the survey, status once again has much larger effects: moving from 10 points to 100 points corresponds to a 0.27-point increase in comment evaluation. Experts, again, also appeared more influenced by status than the full sample.

As expected, then, status has larger effects on the evaluation of answers and comments than it does on questions. The relative effects of status on answers versus comments in the experiment, however, are less clear. In the full sample, the point estimates of the coefficients for status are nearly equal. However, in the subsamples of experts and of those who spent more time on the survey, status has larger point estimates for its effects on comment evaluation than for its effects on answer evaluation. We also see evidence that the effects of status on comments relative to answers become more pronounced at high levels of status, consistent with the estimates from the archival data. Participants rated comments associated with high-status users significantly higher than they did answers from those users ($t = 2.6$; $p < 0.05$).

However, although the experiments provide causal estimates consistent with our hypotheses, they do not allow us to dismiss the possibility that a portion of our archival estimates may stem from members

Figure 7. (Color online) Within-Quantile Coefficient Estimates for the Relationship Between Various User Actions on Stack Overflow and Their Evaluation Scores (for Users Who Made it to the 95th Percentile)



becoming more adept at answering and commenting, on objective dimensions, over time.

Discussion

How do actors' actions contribute to their accrual of status? We argue that actors engage in a range of actions and that the value of these actions to status attainment changes as actors climb the status ladder. At lower levels of status, actors need to develop a reputation for commitment to the community and for high-quality production through easier-to-evaluate actions. As they move up the status hierarchy and as those with whom they interact come to expect more from them, however, these easy-to-assess activities become less and less valuable for further status attainment.

Moving further up the hierarchy depends increasingly on more-difficult-to-assess actions. At lower levels of status, audiences may not be willing to allocate time and attention to these actions or they may not understand how to interpret them. But as the status of the actor engaging in them rises, audiences increasingly pay attention to difficult-to-assess actions and perceive ambiguous actions as further evidence of the high quality of the actor.

The fact that high-status actors have more opportunities to engage in these activities would come as no surprise. The already famous are asked to participate in and to weigh in on a surprising range of topics. They may even choose to engage in these activities more frequently as they gain confidence from their stature. But the fact that these activities would also serve to cement and elevate their stature has been less appreciated.

These dynamics produce a positive feedback loop, in which those who have already achieved some stature further distance themselves from others through quality-ambiguous actions.

We examined these status attainment dynamics on the Stack Overflow platform, an online community in which people can post questions, answers, and comments regarding programming and software development. When users first enter the community, asking questions appears to contribute most strongly to their early rise in status. Once users reach the middle of the status distribution, however, asking questions does little in terms of moving them higher up the hierarchy. Answering questions, by contrast, contributes little to status attainment at the lowest levels of status but becomes important to further status gains as users acquire status. Answers prove more difficult to assess than questions for two reasons. First, understanding whether an answer will solve the problem requires either prior experience with the solution or implementing it. Second, questions often receive multiple answers that solve the problem in different ways, the relative value of which depends on a number of factors, such as coding efficiency, execution speed, and robustness.

Commenting similarly has little or no value in terms of status gains at low levels of status but becomes increasingly important as users move from being merely well regarded to being the elite of the elite. Comments seem the most difficult-to-assess type of

Table 4. Within-Quantile OLS User Fixed-Effects Regressions for the Relationship Between Various User Actions on Stack Overflow and Their Evaluation Scores (for Users Who Made It to the 95th Percentile)

Variables	(1)	(2)	(3)	(4)	(5)
	0%–50%	50%–75%	75%–90%	90%–95%	Above 95%
log(*Questioning activity* + 1)	0.85***	0.35***	0.10***	0.04	−0.06*
	(0.101)	(0.046)	(0.030)	(0.029)	(0.024)
log(*Answering activity* + 1)	0.00	0.20***	0.22***	0.14***	0.24***
	(0.033)	(0.022)	(0.015)	(0.032)	(0.032)
log(*Commenting activity* + 1)	−0.06	0.09**	0.22***	0.24***	0.31***
	(0.078)	(0.033)	(0.021)	(0.025)	(0.049)
log(*User tenure* + 1)	0.05	0.38***	0.75***	0.46***	0.59***
	(0.043)	(0.092)	(0.159)	(0.117)	(0.122)
log(*Answering activity to own questions* + 1)	−0.16***	−0.02†	−0.00	0.00	0.02***
	(0.031)	(0.014)	(0.008)	(0.008)	(0.005)
log(*Number of "favorite" votes given* + 1)	0.02†	−0.00	−0.00	0.01*	0.01***
	(0.013)	(0.011)	(0.005)	(0.003)	(0.003)
log(*Number of "favorite" votes given to self* + 1)	−0.03†	−0.03*	−0.00	0.00	0.00*
	(0.016)	(0.015)	(0.003)	(0.001)	(0.002)
log(*Accepting own answers as best* + 1)	0.04***	0.01	0.00	−0.00	−0.01**
	(0.013)	(0.005)	(0.004)	(0.004)	(0.003)
Ratio of posed questions with snippets of code	0.06	−0.05†	−0.05*	−0.02	0.00
	(0.050)	(0.027)	(0.024)	(0.013)	(0.018)
Ratio of given answers with snippets of code	−0.00	−0.01	0.02	0.01	0.02
	(0.014)	(0.013)	(0.013)	(0.017)	(0.032)
Ratio of posed popular questions	−0.03	−0.02	−0.02	−0.02	0.01
	(0.039)	(0.026)	(0.018)	(0.011)	(0.014)
Ratio of given answers to popular questions	−0.00	0.00	−0.04**	−0.00	−0.06*
	(0.013)	(0.014)	(0.012)	(0.013)	(0.030)
log(*Number of bounty points received* + 1)	–	0.00***	0.00***	0.00	0.00**
		(0.000)	(0.000)	(0.000)	(0.000)
Time dummies (month)	YES	YES	YES	YES	YES
N	7,179	6,163	13,319	23,583	71,033

Notes. OLS user fixed-effects panel regressions where robust standard errors clustered at the user level are reported in parentheses. All independent variables are normalized. OLS, ordinary least squares.
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests).

action on average. They sometimes try to clarify aspects of the question or argue for the merits of one solution versus another, but they also often simply point readers to other related threads.

Although our analysis of the SO data incorporates individual-level fixed effects—thereby accounting for a wide range of potential confounds—we cannot completely rule out within-person improvements over time in the objective quality of actions as an alternative explanation for the results. We therefore also ran a pair of experiments, in which we could randomly assign the status of members to questions, answers, and comments. Consistent with our arguments, in the experiments, we find no relationship between the status of the asker and question evaluation. But contributor status positively influences answer and comment evaluations.

The changing importance of various types of actions helps to explain why status and reputation seem so inextricably intertwined. Reputation, a concept which emerges from the economics literature, has been seen as something like a trailing average of past performance (Sorenson 2014). At lower levels of status and in settings dominated by actions that can be easily and objectively assessed, status and reputation rise hand in hand. High-status academics must begin their careers exhibiting technical competence. High-status artists often first demonstrate their ability in classical styles. High-status management consultants and investment bankers write reports with accurate information and error-free calculations. Developing a reputation for high quality therefore serves as a necessary condition for attaining high status.

In contexts that involve more ambiguous actions, status increasingly diverges from simply being a trailing average of objective past performance (Sorenson 2014). In these settings, actors increasingly rely on the judgments of others to form their own beliefs, observing the endorsements of others (Stuart et al. 1999) or their acts of deference (Ridgeway and Erickson 2000). Because these processes create positive feedback loops, the perceived status differences across actors increase with the ambiguity surrounding the evaluation of competence and quality.

Although these processes can explain initial differences and their amplification, they cannot completely

Table 5. Effects of Status on the Evaluation of Various Actions in the Online Experiments

	OLS regressions		
	(1) DV: Question vote Question FE model	(2) DV: Answer vote Answer FE model	(3) DV: Comment vote Comment FE model
Full sample			
ln(Status of a question poser)	0.008		
	(0.016)		
ln(Status of an answer poser)		0.057**	
		(0.008)	
ln(Status of a comment poser)			0.051*
			(0.011)
Thread-level controls	YES	YES	YES
N	540	1,080	1,080
Subsample of users who spent longer time to complete the survey			
ln(Status of a question poser)	0.011		
	(0.036)		
ln(Status of an answer poser)		0.098**	
		(0.014)	
ln(Status of a comment poser)			0.117*
			(0.021)
Thread-level controls	YES	YES	YES
N	186	356	356
Subsample of users proficient with Python			
ln(Status of a question poser)	0.018		
	(0.039)		
ln(Status of an answer poser)		0.073*	
		(0.013)	
ln(Status of a comment poser)			0.087**
			(0.014)
Thread-level controls	YES	YES	YES
N	282	544	544

Notes. OLS post-level fixed-effects regressions where robust standard errors clustered at the post level are reported in parentheses. DV, dependent variable; OLS, ordinary least squares; FE, fixed effects.
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (two-tailed tests).

explain the emergent differences. Why, for example, do status levels diverge among the competent, among those who have exhibited high quality on easy-to-evaluate dimensions?

We see at least four possibilities. First, random success on noisy but objective outcomes may differentiate actors. In many settings, audiences cannot readily distinguish luck from skill. Did a song become a hit because of the songwriter or the artist? Did an entrepreneur succeed because he or she managed a startup well or because he or she had been in the right place at the right time? When audiences see positive outcomes, they tend to interpret them as evidence of the ability of the actor (Kahneman and Tversky 1973, Einhorn and Hogarth 1978, Denrell et al. 2019). To the extent that these beliefs provide performance advantages, they can then become self-confirming (Merton 1968, Podolny 1993). Nanda et al. (2020), for example, demonstrate that status in the venture capital industry appears to emerge from happening to invest early in a hot industry or region. Despite being due to chance, that status leads to long-run differences in returns because it provides better access to future deal flow.

Second, actors may vary in their opportunities and propensities to engage in more ambiguous actions (Phillips and Zuckerman 2001, Anderson and Kilduff 2009). Not all academics are asked to expound on issues far beyond their expertise. Not all of those asked feel comfortable doing so. At the individual level, overconfidence and personality differences may then contribute to stratification at the highest levels of status hierarchies. High-status individuals often seem supremely confident. The assumption has usually been that status leads to confidence, but confidence might also accelerate status attainment (Anderson and Kilduff 2009).

Third, individuals may also differ in their ability to benefit from ambiguous actions. Here, the social psychological literature on status characteristics comes to mind. Nominal characteristics, such as race and gender, often become status signals (Berger et al. 1972, Ridgeway 1991). To the extent that these characteristics shape audience expectations of quality, they may limit the ability of those from lower-status groups to gain stature from ambiguous actions. Higher-status women, for example, may gain little from general pronouncements. In fact, these actions might even hurt them. Ambiguity becomes a double-edged sword in which audiences skeptical of the quality of the actor can interpret them as evidence that the person is only a pretender to the throne.

Finally, time probably also plays a role. To the extent that audiences accord more status to difficult-to-evaluate actions from already high-status actors, those who have achieved status earlier always have an advantage. One would therefore expect to see a strong positive correlation between the tenure of an actor in a community and the actor's status, particularly in the tail of the status distribution. Harvard, the highest-status university in the United States, is also the oldest. Goldman Sachs can trace its history to the mid-nineteenth century. McKinsey similarly is one of the oldest management consulting firms. Recent research from the science of science suggests that progress only occurs with the retirements of the stars of an earlier generation (Azoulay et al. 2019). All of these factors represent potentially fruitful paths for future research.

In addition to forwarding our understanding of status attainment processes, our research also advances research on online communities in multiple ways. As noted above, these digital platforms have become increasingly important forums for the exchange of information (Hwang et al. 2015, Botelho 2018). To the extent that they guide choices, such as what to buy and where to eat, they will increasingly influence the distribution of rewards in society. Firms have even begun to see these platforms as sources of useful ideas and information (Constant et al. 1996, Lakhani and von Hippel 2003, Wasko and Faraj 2005, Botelho 2018). Research on the dynamics of these platforms nevertheless remains at an early stage.

With respect to these dynamics, our results reveal, perhaps surprisingly, that questions play an important early role in differentiating contributors to the platform. This process may even prove quite functional at the platform level. Focusing first on the easier-to-evaluate actions spares the scarce attention of the audience. But it provides a path for new members to demonstrate their competence and commitment to the community (Ridgeway 1981, Willer 2009).

But our results also point to potential maladies in these systems. Why individuals contribute to (open) collectives has been a topic of much research (Lakhani and von Hippel 2003, Lakhani and Wolf 2005, Jeppesen and Frederiksen 2006). To the extent that recognition and status serve as motivating factors but that the actions that contribute to such gains also depend on current status, individuals may "game" the system in a way that reduces the value of their contributions to these communities and that may even add noise to the system.

Interview and survey evidence suggests that recognition and status do play important roles in getting users to contribute to these communities (Nam et al. 2009, Mamykina et al. 2011, Tausczik and Pennebaker 2012, Penoyer et al. 2018). So far, these studies have found little evidence that users try to game the system. However, as users become more aware of status dynamics on these online communities and as participation on them becomes more important to careers (e.g., Capiluppi et al. 2013, Xu et al. 2020), users could become more strategic in their behavior.[18] The opportunities for such manipulation may also rise with the scope of the ideas being exchanged (because broader scope generates more ambiguity in the evaluation of actions).

Such gaming behavior, if it emerged, could also raise questions about the governance of these (open) collectives. Contrary to public perception, open innovation communities often resort to an authoritarian structure in their organizational designs—particularly in terms of exception management (Puranam et al. 2014). The legitimacy of this authoritarian structure, however, stems primarily from perceived competence rather than formal position, as one would find in most traditional organizations (Fleming and Waguespack 2007, O'Mahony and Ferraro 2007, Dahlander and O'Mahony 2011, Klapper and Reitzig 2018). If individuals can manipulate the systems for establishing perceived competence, the legitimacy of the system itself may come into question.

Acknowledgments
Corrine Bendersky, Tristan Botelho, Anne Bowers, Dave Waguespack, and four anonymous reviewers provided helpful comments on earlier versions of this paper. Special thanks goes to Menaka Sattmann for her support in creating the database.

Endnotes

[1] This is according to the statistics posted at https://stackexchange.com/sites?view=list#questions (accessed April 26, 2021).

[2] The badges depend on the same underlying information as the reputation score.

[3] Upvotes and edits are subject to a 200 point-per-day limit; edits are also subject to a 1,000-point lifetime limit. Users also receive two points when they accept an answer (except their own) and lose one point when they downvote an answer. Total scores, however, can never fall below one.

[4] We dropped 59 of the 30,418 SO users in our sample because our manually computed scores for March 2017 differed substantially from those downloaded.

[5] To understand better what drives reactions to questions and answers, we followed all 6,470 questions posed and 9,259 answers provided on February 21, 2019 and used voting patterns over the

subsequent year to select the 100 highest- and 100 lowest-rated questions and answers. We hand coded each of these latter 200 questions and answers, respectively, on 10 and 15 different dimensions, capturing aspects of quality (e.g., spelling errors) and adherence to community norms (e.g., did it include tags).

[6] Although community members do not upvote and downvote comments in the same way that they do questions and answers, comments can nevertheless contribute to the evaluation scores of those posting them by clarifying questions, arguing for one answer over another, or directing users to other posts that the commenter had made. In trying to classify comments by purpose, Zhang et al. (2019) argue that 45% fall in the first category and 31% in the second. Roughly 6% of comments link to other threads (Sengupta and Haythornthwaite 2020).

[7] All independent variables have been scaled to a base equal to the average level of that activity, meaning that the coefficients correspond to power functions of the average activity levels.

[8] Until they reach an SO score of 50 points (roughly the 80th percentile of the evaluation score distribution), users can only post comments related to their own questions and answers. Practically, this restriction rarely ends up being a constraint. More than three-quarters of comments in a thread come either from the person who asked the question or from someone who already provided an answer, and more than 60% come from users with fewer than 50 reputation points (Zhang et al. 2019). We also found no evidence that the rate of commenting increased after members pass the 50-point threshold.

[9] Defining the cut points instead based on the distribution for each period could result in individuals losing status simply because of an increase in the denominator (i.e., because others gained more points than they did).

[10] We also estimated traditional jump quantile regressions. That approach should and does yield parallel results.

[11] We also estimated the models using bootstrapped standard errors. The results remain unchanged.

[12] Although we originally planned a single experiment, our pretest suggested that evaluating questions, answers, and comments required too much time. We therefore split it into two experiments.

[13] We determined the sample size in advance based on wanting a balanced design and to have 90% power to detect a 20% effect size (Cohen's d) in moving from a lower status level to a higher one. In our pretesting, participants needed an average of 10 minutes to complete the task. We therefore paid them a fixed fee of $2 to ensure an average wage of $12/hour.

[14] As a secondary check, participants had to answer a simple programming question (see Figure A2 in the online appendix) in a limited period of time. Most participants who claimed expertise in Python provided an adequate solution to this question.

[15] We again determined the sample size in advance based on a balanced design that should provide at least 90% power to detect a 20% effect size (Cohen's d) in moving from a lower status level to a higher one. In our pretesting, participants needed an average of seven minutes to complete the task. We therefore paid them a fixed fee of $1.40 for an average wage of $12/hour.

[16] On the SO platform, users can only evaluate comments as "useful" or not. We nevertheless decided to use the same evaluation schema for answers and comments to avoid confusion.

[17] Ordered logit models produce equivalent results.

[18] See https://softwareengineering.stackexchange.com/questions/20407/will-high-reputation-in-stack-overflow-help-to-get-a-good-job for related debates among community members.

References

Anderson C, Kilduff GJ (2009) The pursuit of status in social groups. *Current Directions Psych. Sci.* 18(5):295–298.

Anderson SW, Baggett LS, Widener SK (2009) The impact of service operations on customer satisfaction: Evidence on how failures and their source affect what matters to customers. *Manufacturing Service Oper. Management* 11(1):52–69.

Askin N, Bothner MS (2016) Status-aspirational pricing: The "Chivas Regal" strategy in US higher education, 2006-2012. *Admin. Sci. Quart.* 61(2):217–253.

Azoulay P, Fons-Rosen C, Graff-Ziven JS (2019) Does science advance one funeral at a time? *Amer. Econom. Rev.* 109(8):2889–2920.

Bendersky C, Shah NP (2012) The cost of status enhancement: Performance effects of individuals' status mobility in task groups. *Organ. Sci.* 23(2):308–322.

Benjamin BA, Podolny JM (1999) Status, quality, and social order in the California wine industry. *Admin. Sci. Quart.* 44(3):563–589.

Berger J, Cohen BP, Zelditch M Jr (1972) Status characteristics and social interaction. *Amer. Sociol. Rev.* 37(3):241–255.

Bianchi AJ, Kang SM, Stewart D (2012) The organizational selection of status characteristics: Status evaluations in an open source community. *Organ. Sci.* 23(2):341–354.

Bidwell M, Won S, Barbulescu R, Mollick E (2015) I used to work at Goldman Sachs! How firms benefit from organizational status in the market for human capital. *Strategic Management J.* 36(8):1164–1173.

Bol T, de Vaan M, van de Rijt A (2018) The Matthew effect in funding. *Proc. Natl. Acad. Sci. USA* 115(19):4887–4890.

Botelho T (2018) Here's an opportunity: Knowledge sharing among competitors as a response to buy-in uncertainty. *Organ. Sci.* 29(6):1033–1055.

Bower GH (1981) Mood and memory. *Amer. Psych.* 36(2):129–148.

Bowers A, Prato M (2018) The structural origins of unearned status: How arbitrary chances in categories affect status position and market impact. *Admin. Sci. Quart.* 63(3):668–699.

Buhrmester M, Kwang T, Gosling SD (2011) Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspect. Psych. Sci.* 6(1):3–5.

Cao J, Smith EB (2021) Why do high-status people have larger social networks? Belief in status-quality coupling as a driver of network-broadening behavior and social network size. *Organ. Sci.* 32(1):111–132.

Capiluppi A, Serebrenik A, Singer L (2013) Assessing technical candidates on the social web. *IEEE Software* 30(1):45–51.

Chandler J, Shapiro D (2016) Conducting clinical research using crowdsourced convenience samples. *Annual Rev. Clinical Psych.* 12:53–81.

Chen L, Baird A, Straub D (2019) Why do participants continue to contribute? Evaluation of usefulness voting and commenting motivational affordances within an online knowledge community. *Decision Support Systems* 118:21–32.

Constant D, Sproull L, Kiesler S (1996) The kindness of strangers: The usefulness of electronic weak ties for technical advice. *Organ. Sci.* 7(2):119–135.

Correll SJ, Ridgeway C, Zuckerman EW, Jank S, Jordan-Bloch S, Nakagawa S (2017) It's the conventional thought that counts: How third-order inference produces status advantage. *Amer. Sociol. Rev.* 82(2):297–327.

Dahlander L, O'Mahony S (2011) Progressing to the center: Coordinating project work. *Organ. Sci.* 22(4):961–979.

Danner L, Ristic R, Johnson TE, Meiselman HL, Hoek AC, Jeffery DW, Bastian SEP (2016) Context and wine quality effects on consumers' mood, emotions, liking and willingness to pay for Australian Shiraz wines. *Food Res. Internat.* 89(1):254–265.

Denrell J, Fang C, Liu C (2019) In search of behavioral opportunities from misattributions of luck. *Acad. Management Rev.* 44(4): 896–915.

Einhorn EJ, Hogarth RM (1978) Confidence in judgment: Persistence of the illusion of validity. *Psych. Rev.* 85(5):395–416.

Ertug G, Yogev T, Lee YG, Hedstrom P (2016) The art of representation: How audience-specific reputations affect success in the contemporary art field. *Acad. Management J.* 59(1):113–134.

Fleming L, Waguespack DM (2007) Brokerage, boundary spanning, and leadership in open innovation communities. *Organ. Sci.* 18(2):165–180.

Gould RV (2002) The origins of status hierarchies: A formal theory and empirical test. *Amer. J. Sociol.* 107(5):1143–1178.

Hahl O, Zuckerman EW (2014) The denigration of heroes? How the status attainment process shapes attributions of considerateness and authenticity. *Amer. J. Sociol.* 120(2):504–554.

Hannan MT, Polos L, Carroll GR (2007) *Logics of Organization Theory: Audiences, Codes, and Ecologies* (Princeton University Press, Princeton, NJ).

Henrich J, Gil-White FJ (2001) The evolution of prestige: Freely conferred deference as a mechanism for enhancing the benefits of cultural transmission. *Evolution Human Behav.* 22(3):165–196.

Hsu DH (2004) What do entrepreneurs pay for venture capital affiliation? *J. Finance* 59(4):1805–1844.

Hwang EH, Singh PV, Argote L (2015) Knowledge sharing in online communities: Learning to cross geographic and hierarchical boundaries. *Organ. Sci.* 26(6):1593–1611.

Jensen M (2006) Should we stay or should we go? Accountability, status anxiety, and client defections. *Admin. Sci. Quart.* 51(1): 97–128.

Jeppesen LB, Frederiksen L (2006) Why do users contribute to firm-hosted user communities? The case of computer-controlled music instruments. *Organ. Sci.* 17(1):45–63.

Johnson EJ, Tversky A (1983) Affect generalization and the perception of risk. *J. Personality Soc. Psych.* 45(1):20–31.

Kahneman D, Tversky A (1973) On the psychology of prediction. *Psych. Rev.* 80(4):237–251.

Kim JW, King BG (2014) Seeing stars: Matthew effects and status bias in Major League Baseball umpiring. *Management Sci.* 60(11):2619–2644.

Klapper H, Reitzig M (2018) On the effects of authority on peer motivation: Learning from Wikipedia. *Strategic Management J.* 39(8):2178–2203.

Klayman J, Ha YW (1987) Confirmation, disconfirmation, and information in hypothesis testing. *Psych. Rev.* 94(2):211–228.

Lakhani KR, von Hippel E (2003) How open source software works: 'Free' user-to-user assistance. *Res. Policy* 32(6):923–943.

Lakhani KR, Wolf RG (2005) Why hackers do what they do: Understanding motivation and effort in free/open source software projects. Feller J, Fitzgerald B, Hissam S, Lakhani K, et al. *Perspectives on Free and Open Source Software* (MIT Press, Cambridge, MA), 3–21.

Lynn FB, Podolny JM, Tao L (2009) A sociological (de)construction of the relationship between status and quality. *Amer. J. Sociol.* 115(3):755–804.

Mamykina L, Manoim B, Mittal M, Hripcsak G, Hartmann B (2011) Design lessons from the fastest Q&A site in the west. *Proc. SIGCHI Conf. Human Factors Comput. Systems* (ACM, New York), 2857–2866.

McCall MM (1975) The sociology of female artists: A study of female painters, sculptors, and printmakers in St. Louis. Doctoral thesis, University of Illinois at Urbana-Champaign, Champaign.

McDonnell MH, King BG (2018) Order in the court: How firm status and reputation shape the outcomes of employment discrimination suits. *Amer. Sociol. Rev.* 83(1):61–87.

Merton RK (1968) The Matthew effect in science: The reward and communication systems of science are considered. *Science* 159(3810):56–63.

Nam KK, Ackerman MS, Adamic LA (2009) Questions in, knowledge in? A study of Naver's question answering community. *Proc. SIGCHI Conf. Human Factors Comput. Systems* (ACM, New York), 779–788.

Nanda R, Samila S, Sorenson O (2020) The persistent effect of initial success: Evidence from venture capital. *J. Financial Econom.* 137(1):231–248.

O'Mahony S, Ferraro F (2007) The emergence of governance in an open source community. *Acad. Management J.* 50(5):1079–1106.

Penoyer S, Reynolds B, Marshall B, Cardon PW (2018) Impact of users' motivation on gamified crowdsourcing systems: A case of StackOverflow. *Issues Inform. Systems* 19(2):33–40.

Phillips DJ, Zuckerman EW (2001) Middle-status conformity: Theoretical restatement and empirical demonstration in two markets. *Amer. J. Sociol.* 107(2):379–429.

Phillips DJ, Turco CJ, Zuckerman EW (2013) Betrayal as a market barrier: Identity-based limits to diversification among high-status corporate law firms. *Amer. J. Sociol.* 118(4):1023–1054.

Podolny JM (1993) A status-based model of market competition. *Amer. J. Sociol.* 98(4):829–872.

Podolny JM, Phillips DJ (1996) The dynamics of organizational status. *Indust. Corporate Change* 5(2):453–471.

Puranam P, Alexy O, Reitzig M (2014) What's 'new' about new forms of organizing? *Acad. Management Rev.* 39(2):162–180.

Reschke BP, Azoulay P, Stuart TE (2018) Status spillovers: The effect of status-conferring prizes on the allocation of attention. *Admin. Sci. Quart.* 63(4):819–847.

Ridgeway C (1981) Nonconformity, competence, and influence in groups: A test of two theories. *Amer. Sociol. Rev.* 46(3):333–347.

Ridgeway C (1991) The social construction of status value: Gender and other nominal characteristics. *Soc. Forces* 70(2):367–386.

Ridgeway C, Erickson KG (2000) Creating and spreading status beliefs. *Amer. J. Sociol.* 106(3):579–615.

Riecken HW (1958) The effect of talkativeness on ability to influence group solutions of problems. *Sociometry* 21(4):309–321.

Roberts PW, Khaire M, Rider CI (2011) Isolating the symbolic implications of employee mobility: Price increases after hiring winemakers from prominent wineries. *Amer. Econom. Rev.* 101(3): 147–151.

Salganik MJ, Dodds PS, Watts DJ (2006) Experimental study of inequality and unpredictability in an artificial cultural market. *Sci.* 311(5762):854–856.

Sauder M, Lynn F, Podolny JM (2012) Status: Insights from organizational sociology. *Annual Rev. Sociol.* 38:267–283.

Sengupta S, Haythornthwaite C (2020) Learning with comments: An analysis of comments and community on stack overflow. *Proc. 53rd Hawaii Internat. Conf. System Sci.* (HICSS, Maui, HI), 2898–2907.

Sgourev SV, Althuizen N (2014) "Notable" or "not able": When are acts of inconsistency rewarded? *Amer. Sociol. Rev.* 79(2):282–302.

Simcoe TS, Waguespack DM (2011) Status, quality, and attention: What's in a (missing) name? *Management Sci.* 57(2):274–290.

Sorenson O (2014) Status and reputation: Synonyms or separate concepts? *Strategic Organ.* 12(1):62–69.

Stuart TE, Hoang H, Hybels RC (1999) Interorganizational endorsements and the performance of entrepreneurial ventures. *Admin. Sci. Quart.* 44(2):315–349.

Swinyard WR (1993) The effects of mood, involvement, and quality of store experience on shopping intentions. *J. Consumer Res.* 20(2):271–280.

Tan D, Rider CI (2017) Let them go? How losing employees to competitors can enhance firm status. *Strategic Management J.* 38(9): 1848–1874.

Tausczik YR, Pennebaker JW (2012) Participation in an online mathematics community: Differentiating motivations to add. *Proc. ACM 2012 Conf. Comput. Supported Cooperative Work* (ACM, New York), 207–216.

Waguespack DM, Salomon R (2015) Quality, subjectivity, and sustained superior performance at the Olympic Games. *Management Sci.* 62(1):286–300.

Wasko M, Faraj S (2005) Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quart.* 29(1):35–57.

Wason PC (1960) On the failure to eliminate hypotheses in a conceptual task. *Quart. J. Experiment. Psych.* 12(3):129–140.

Willer R (2009) Groups reward individual sacrifice: The status solution to the collective action problem. *Amer. Sociol. Rev.* 74(1): 23–43.

Wright WF, Bower GH (1992) Mood effects on subjective probability assessment. *Organ. Behav. Human Decision Processes* 52(2): 276–291.

Xu L, Nian T, Cabral L (2020) What makes geeks tick? A study of stack overflow careers. *Management Sci.* 66(2):587–604.

Zhang H, Wang S, Tse-Hsun PC, Hassan AE (2019) Reading answers on stack overflow: Not enough! *IEEE Trans. Software Engrg.* 47:1–15.

Inna Smirnova is the postdoctoral research fellow at the School of Information at the University of Michigan. She received her PhD in strategic management from the University of Vienna, Austria. Her research interests include innovation, online communities, organization design and the division of labor, and nonfinancial incentives.

Markus Reitzig is the Endowed Chaired Professor of Strategic Management at the University of Vienna. His group is dedicated to studying how firms can structure work to better motivate employees and increase performance.

Olav Sorenson is the Joseph Jacobs Chair in Entrepreneurship Studies, professor of strategy, and professor of sociology, at the University of California, Los Angeles. He received his PhD from Stanford University. He studies a broad range of topics, including economic geography, entrepreneurship, social networks, venture capital, and the evolution of organizations and industries.