To rest on one's laurels: Effectiveness and sustainability of status orders

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Abstract

Individuals recognized and celebrated by their peers are generally more productive and cooperative, turning status rewards into critical organizational features to motivate individual behavior and build successful collective enterprises. However, a significant limitation of the studies on this topic is that they fail to show whether status attainment can produce sustainable performance and cooperation as status increases. As individuals climb the status ladder, a high social standing may create opportunities for distraction and complacency, rendering status hierarchies ineffective in producing long-term cooperation. To tackle this puzzle, I compare the cooperative behavior of high-status individuals with similar others who are not high-status (i.e., their counterfactuals). I collect the data from a large Q&A online community comprising 130 million contributions and 235 million status changes from 16 million users. The findings uncover the benefits of status for collective efforts by showing that high status motivates cooperation among the most celebrated. Nonetheless, this effect declines over time, revealing that status orders cannot secure collective outcomes effectively in the long run. More generally, this investigation helps us understand the broader structural consequences of social rewards for cooperative behavior.

Keywords: Status, cooperation, reward systems, public goods, online communities.

INTRODUCTION

Status is the relative standing of an individual in the distribution of honor and prestige (Weber, 1978; Blau, 1964), and differences in status are virtually everywhere in our social life. Individuals rank each other regularly in regard to multiple dimensions: some people are considered more popular, generous, skillful, or helpful than others in almost all social contexts. This type of social ordering is certainly not exclusive to individuals, and it similarly applies to markets and organizations. Some brands have higher prestige than others, and companies try to associate with others considered equals and explicitly avoid others regarded as lesser. These differences in status can then readily turn into tangible and lasting status orders (Podolny, 1993). Most sociological research on status centers on how third parties perceive objective individual differences and the consequences of status beliefs on the social order. Ample evidence shows that status is self-reinforcing because people evaluate these differences based on the perceptions or choices of others (Podolny, 1993; Benjamin and Podolny, 1999; Gould, 2002; Stewart, 2005;

Salganik et al., 2006; Lynn et al., 2009; Simcoe and Waguespack, 2011; Van De Rijt et al., 2014; Azoulay et al., 2014; Manzo and Baldassarri, 2015; Bol et al., 2018). This inference process decouples status from quality and makes third parties distribute social advantages that do not necessarily reflect underlying individual differences (Merton, 1968). Consequently, when status beliefs are spread out and culturally shared by 'most others,' they can give rise to arbitrary status hierarchies that are socially legitimized and remarkably stable (Johnson et al., 2006; Ridgeway and Correll, 2006; Ridgeway, 2014).

We know comparatively far less about the behavioral consequences of status attainment for individuals bestowed with status. An emerging body of evidence shows that status is a critical organizational feature that allows individuals to pursue collective enterprises successfully. It is especially important in public-goods settings that need voluntary contributions and lack other enforcement mechanisms (e.g., monetary rewards or sanctions). For instance, previous research shows that social esteem is a powerful incentive for contributions: individuals motivate themselves to cooperate more towards collective outcomes when they seek the praise of their peers (Milinski et al., 2002; Hardy and Vugt, 2006; Willer, 2009; Simpson et al., 2012). Other research similarly highlights that when individuals are publicly recognized by peers and by receiving awards for their contributions, they are also more enthusiastic, productive, and effortful in collective endeavors (Restivo and Van De Rijt, 2012, 2014; Gallus, 2017; Burtch et al., 2022; Allison and Stewart, 1974; Bol et al., 2018). This virtuous circle between social status and cooperation reveals that status can structure individual behavior towards prosperous group outcomes and guarantee that collective efforts emerge without Leviathans overseeing the social exchange.

Nonetheless, it is unclear whether individuals remain equally motivated in cooperative contexts as they increase their status over time. The previously mentioned studies fail to capture the consequences of *high* status because they focus on the beginning of the status attainment process –e.g., when individuals are new to existing communities. In contrast to the positive findings in this literature, research in non-cooperative contexts shows that high status is detrimental to individual performance and productivity (Malmendier and Tate, 2009; Bothner et al., 2012; Li et al., 2022). The status elite rests on their laurels and decreases their contributions once they attain a high social standing because they become distracted and complacent (Veblen, 1934). While status rewards may initially succeed at incentivizing cooperative behavior, this evidence suggests they may fail to motivate it among the most celebrated individuals, thus threatening the ability of status orders to sustain cooperation in the long run and secure collective outcomes effectively.

This article contributes to our understanding of the effectiveness and sustainability of status orders in cooperative contexts by asking: Does high status increase or decrease cooperation in public-goods settings? To study the role of high status for cooperative behavior, I use data from a large Q&A online community where the relationship between status and cooperation is observed naturally in a non-laboratory environment. Using the website's application programming interface (API), I collected complete timestamped trajectories of status attainment (almost 235 million status changes) and cooperative behavior (nearly 130 million contributions) from 16 million users between 2008 and 2021. These data give us a unique opportunity to study the behavioral consequences of status hierarchies for contributions to collective goods with greater detail than more traditional studies (Lazer et al., 2009; Salganik, 2017).

In the context of this online community, cooperation reflects the number of contributions (more precisely, answers) posted on the site, while social status captures cumulative patterns of social appraisal. Status accrues based on personal gestures of appreciation given by community members through a voting system, so it is plausible to observe variation in status among high-performing contributors. Notably, the granularity with which status is observed enables me to focus on a more natural process of status attainment, which is more general than other forms of status boost (e.g., receiving an award) and hence applies to more people. While awards are clear demarcations of a status change, they fail to include, by their very nature, other equally high-performing individuals who are similarly deserving of awards. Instead, the small tokens of approval in this setting (i.e., the votes) consolidate over time a higher standing among others and hence constitute key determinants of status attainment, a process that often remains unobserved in previous research (Gould, 2002; Ridgeway and Erickson, 2000; Ridgeway et al., 2009).

The research design defines high status using a quantile threshold of the status distribution, namely being in the top 5%.[1] Methodologically, this approach turns a continuous process of status attainment into a binary indicator of high status so that potential outcomes can be more clearly defined in a causal-inference framework (Morgan and Winship, 2014). Substantively, participants in this community are fully aware of their status "score", and hence the high-status

[1]Complementary estimates in the appendix show that findings are robust to the decision of the 95th percentile threshold.

threshold demarks a meaningful boundary for them.[2]

The analysis centers on the effect of crossing this threshold on the number of future contributions to the community. In particular, I use matching to compare individuals above and below the high-status threshold who are almost identical on a battery of different on-site behaviors during a period of time before high-status individuals cross the threshold. The findings show that threshold crossers contribute between 6 and 15 more posts on the week immediately after they cross the top 5% threshold. Results also show that the earlier individuals cross this threshold, the more they contribute to the community, thus highlighting the importance of early recognition for individual contributions. Moreover, the positive direction of this effect remains for at least ten weeks, showing that status orders can incentivize cooperation at the top of the status hierarchy. Nevertheless, results also reveal that status fails to sustain cooperative behavior over the long run as contributions by high-status individuals inevitably decay, regardless of the time at which they become high-status. This gradual decline reveals the limitations of status rewards as motivators and renders status hierarchies ineffective for sustainable cooperation.

This investigation focuses on the inner mechanics of status hierarchies and contributes to a growing line of research that centers on the behavioral impacts of status on collective goods. Although online settings are in some respects unique, the insights from this study carry implications that apply more generally to organizations that need to design reward systems to motivate individual performance and cooperative behavior.

[2]Stack Overflow users know their own status 'score' and everyone else's. They are also aware of their ranking as Stack Overflow displays this information privately to users. Although I cannot guarantee that how I compute the quantile thresholds matches how Stack Overflow does it, the status scores used as thresholds are considered high among Stack Overflow users (see below for more details).

STABILITY AND NEGATIVE SIDE OF STATUS ORDERS

Sociologists have generally studied status hierarchies by focusing on their nature as a social construction that creates and reinforces differences among individuals. This research has consistently shown that *how* status differences are socially constructed can be more consequential than the objective differences they are supposed to be based on (Berger and Luckmann, 1966; Merton, 1948; Zuckerman, 2012). In particular, there is extensive empirical evidence showing that status is self-reinforcing, meaning that initial differences in status become larger over time through a socially endogenous process of inference, whereby underlying quality is inferred from the perceptions or choices of others who have previously revealed their evaluation (Gould, 2002; Stewart, 2005; Salganik et al., 2006; Lynn et al., 2009; Manzo and Baldassarri, 2015; Van De Rijt et al., 2014). Consequently, the inference is based not on a direct assessment of quality but on others' judgments. For instance, Azoulay et al. (2014) compares award-winning and non-winning scientists concerning citation rates of journal articles published before the prize was received. They find that the articles of award recipients published before the award were significantly more cited, showing that the status shock benefits award-winning scientists by altering others' perceptions of quality.

Such status advantages are independent of actual quality, and they benefit high-status individuals by providing significant social rewards, such as being more influential and receiving more resources (Merton, 1968; Podolny, 1993) as well as other psychological benefits like higher self-esteem and self-efficacy (Anderson et al., 2006; Podsakoff and Farh, 1989; Shea and Howell, 2000). More recently, researchers show that these status advantages can even take place in contexts where inferring quality from status is less relevant, such as when individuals use status cues to solve coordination problems (Correll et al., 2017; Henrich, 2017). In these cases, the most central feature of the quality evaluation is not what someone privately thinks about quality but what 'most others' believe, regardless of whether one shares the assessment, so coordination becomes more likely (Ridgeway and Correll, 2006; Ridgeway et al., 2009).

This social process that underlies the formation of status hierarchies is consequential for their durability since status beliefs are collectively validated and reinforced by everyone embedded in the hierarchy, namely those who benefit from high status and those who are at the bottom of the status distribution (Goode, 1978; Ridgeway et al., 2009; Hahl and Zuckerman, 2014). To the extent that differences in status are widely agreed upon and even shared by individuals who are foreigners to a particular status order, status hierarchies are legitimized and can be remarkably resistant to social change (Johnson et al., 2006; Ridgeway, 2014). Part of the reason for this stability is that status rankings change the nature of expectations that people hold: they depart from simple anticipations of what happens regularly to normative expectations of what should occur (Ridgeway and Berger, 1986). The collective reinforcement of these expectations implies that others are likely to treat people in correspondence with status beliefs, which helps further reify the current state of affairs and diffuse status beliefs to multiple social contexts (Webster and Hysom, 1998; Ridgeway et al., 2009). Hence, the legitimacy and durability of status hierarchies hinge upon a widespread consensus about what is socially valuable and what is not; a collective agreement that is essentially sustained by others' perceptions[3].

Given the self-reinforcing character of status dynamics, patterns of deference and influence can create durable status orders that are arbitrary and likely very inefficient as individuals who attain the highest ranks are not necessarily the most qualified or most competent. For instance, research on the status characteristics program has consistently shown that status beliefs are attached to nominal categories like race, gender, and ethnicity that have little to do with individual performance or ability (Ridgeway, 1978, 1987, 1997; Ridgeway et al., 1998; Ridgeway, 2014). And yet, individuals in one category (e.g., whites or males) are systematically considered more worthy and receive more advantages than individuals in other categories (e.g., non-whites or females). This mechanism not only creates cognitive biases through stereotypes that reinforce the arbitrary status order but also gives fewer opportunities to individuals who are overlooked and can potentially make significant contributions.

EFFECTIVENESS OF STATUS ORDERS

While the previously reviewed scholarship has generally stressed the harmful consequences of status differences (such as arbitrary social rankings and undesirable social outcomes like discrimination), an emerging body of research has documented that, under some circumstances, status can create incentives that redirect individual efforts positively towards collective enterprises (Simpson et al., 2012). In the context of scientific endeavors, for instance, previous stud-

[3]Researchers also highlight conditions that make the spread of status beliefs more difficult, such as when status is a weakening signal of quality (Van De Rijt, 2019; Lynn et al., 2016; Simcoe and Waguespack, 2011).

ies have shown that early recognition increases the chances that scientists decide to self-select into further competitions that will likely reinforce status differences among all scientists (Allison and Stewart, 1974; Bol et al., 2018). The study of award-winning early career scientists by Bol et al. (2018) is particularly relevant. They find that a status boost (such as winning an early career grant) activates the socially endogenous inference process described above, whereby scientists who receive awards are evaluated more positively in future grant competitions than non-winning scientists. However, they also show that this status increment simultaneously pushes young scientists to be more effortful and productive.

Similarly, status is an incentive for cooperative behavior in collective action problems as individuals strive for the social esteem of their peers. The theory of competitive altruism states that public displays of generosity and cooperation in collective action settings can be costly in the short term but pay off substantially in the long run (Gintis et al., 2001; Milinski et al., 2002; Nowak and Sigmund, 2005). Individuals who make early investments in public goods are likely to obtain non-material gains in the form of higher status and prestige among peers, which can then translate into long-term benefits such as being chosen as a leader and interaction partner more often (Hardy and Vugt, 2006; Ridgeway, 1987). Willer (2009) proposes a more comprehensive theory of status as a selective incentive by inverting the causal arrow between cooperation and social status and arguing that attaining a higher-status position can also become a key driver for further cooperation.

A similar positive effect is documented for awards, which are public acknowledgments of performance (Goode, 1978). However, awards differ from status attainment processes in that they are more visible, involve formal committees, and often have public ceremonies (Goode, 1978). This research shows that awards can be powerful incentives for cooperation as individuals perceive that their contributions are valued by their peers and their communities more generally. For instance, Gallus (2017) conducts a field experiment where a group of established editors in Wikipedia institutionalize a new award to honor editors. This study compares two groups of new shortlisted editors, one of which receives the award at random. The findings show that award-recipient editors are more likely to stay active in Wikipedia and perform more tedious activities to benefit the community.

Furthermore, even when awards do not involve a formal arbiter and more closely resemble the positive feedback a peer gives, researchers find that "peer awards" also incentivize cooperation among new members of communities. This motivation occurs even when these awards are less impactful as signs of acknowledgment since they lack the involvement of the whole community. For example, Burtch et al. (2022) recently find that peer awards incentivize content production among new members of Reddit communities, and Restivo and Van De Rijt (2012) similarly show that receiving peer recognition in Wikipedia increases contributions among productive users, an effect that lasted for at least three months after the award was received. A follow-up study shows, however, that this effect only applies to Wikipedia users who are already sufficiently involved in the community (Restivo and Van De Rijt, 2014), suggesting that social recognition is a motivator among members who are adequately familiar with their community.

It is unclear, however, whether status can remain an incentive for cooperative behavior as individuals move up the status ladder. If status cannot incentivize cooperation among the elite, status orders will prove to be limited for status-based organizations that need to organize voluntary contributions to public goods. Even if high status can bring benefits at the individual level, the structural consequences risk an organization's long-term effectiveness and potential stability. Unfortunately, the previous studies focusing on awards cannot help us understand whether high status continues to be an effective motivational device because they focus on individuals who are newcomers and have relatively low standing in their communities. For instance, Gallus (2017) gives awards at random to new editors in Wikipedia, and Restivo and Van De Rijt (2012) give awards to top performers who have never received one before. The natural advantage of this approach is that the effect of awards can be cleanly observed since these individuals are not familiar with receiving awards in the context they are situated (i.e., as members of online communities). But the disadvantage is that it is unclear whether social recognition always works as an incentive for cooperative behavior as individuals obtain a higher status.

It is plausible that high status works against cooperation. One reason is that high-status positions create opportunities for distraction, and individuals in higher social strata may be more likely to experience self-satisfaction with their positions (Veblen, 1934). For instance, higher-status positions that result from competitive interactions (i.e., winning) make individuals more likely to justify their situation (Molina et al., 2019; Feng et al., 2013), which suggests that a sense of complacency may accompany the attainment of high status. Indeed, when researchers specifically focus on receiving prestigious awards that set their recipients far apart from their peers, they find that individual performance decreases. Malmendier and Tate (2009) study managers' performance after winning a prestigious award and observe that CEOs underperform over the three years that follow the award. Their status shifts also negatively affect the behavior of award-winning CEOs, who spend more time in activities of questionable value for their companies, such as writing books or playing golf. Recently, Li et al. (2022) find that CEOs named among the best business leaders by the media are more likely to engage in financial misconduct. The authors show this happens mainly because the award increases a sense of psychological entitlement among award-winning CEOs. In another study, Bothner et al. (2012) document status's positive and negative effects on performance in sports competitions. They document a concave relationship between status and performance where the inflection point occurs when status is high. This finding suggests that performance decreases only at the top when high status is more likely to induce distraction or complacency.

This study provides novel insights into the effectiveness and sustainability of status hierarchies by asking the following research question: Does high social status increase or decrease cooperative behavior in public-goods settings? In focusing on whether high status can further incentivize cooperation, this article centers on the adaptive behavior of individuals who react to attaining high status. Hence, the critical mechanism that relates to the effectiveness and stability of status is not based on the social perceptions or choices of others that contribute to the legitimacy of status orders (Johnson et al., 2006; Ridgeway, 2014). Instead, it hinges on whether status can successfully motivate individuals already embedded in the status hierarchy to increase their cooperation. My analysis then gives us a lens through the internal mechanics of status orders and their ability to provide social rewards for sustainable public goods.

DATA AND METHODS

The data come from Stack Overflow, a large Q&A online community. The website was created in 2008 and serves as a platform for users of open-source programming languages to discuss broad topics on computing and programming. Each question generates a thread that can contain multiple answers and comments about the question and its answers. The quality of the posts is determined by a voting system where users vote up or down questions and answers based on their assessment of the post. Post owners obtain points from these votes that build up a public profile on Stack Overflow. One "up-vote" gives five points for a question and ten points for an answer, while one "down-vote" subtracts two points, regardless of whether it was a question or an answer.

Stack Overflow also incentivizes different site activities by awarding users bronze, silver, and gold badges. These badges do not necessarily impact the profile score, and the number and types of badges earned are displayed next to this score on the profile. Badges, however, are different from votes in that users are not responsible for awarding them. Instead, Stack Overflow engineers them to steer online behavior towards a more diverse type of involvement on the site. Previous research finds that these badges are successful at this task (Anderson et al., 2013), even when the activities they intend to motivate do not contribute points to a profile score –as with editing or commenting.

Unfortunately, Stack Overflow does not provide public access to timestamps for when users obtain these badges. But to the extent that badges depend on traceable activity on the site, we can minimize their influence on posting by indirectly measuring the actions that lead to them. For instance, some badges are awarded based on activities related to answers ("Answer Badges"). In some of these cases, users receive badges based on the number of answers (or accepted answers) or the points obtained by their answers. While I cannot compare individuals using the information on badges, I can compare users based on the number of answers and points since two users who are comparable in their traceable activity are likely to have similar badges. Below, I explain the traceable information used for the analysis. Also, posts' ownership and accomplishments (points and badges) are visible to all Stack Overflow visitors.

Everyone with access to the Internet can see the content on Stack Overflow, but more involved activity (e.g., commenting or voting) requires a free membership and a minimum amount of points. Users also unlock privileges for different types of participation as they increase their profile scores. For instance, voting up posts by other users requires at least twenty-five points, and voting them down requires one-hundred-twenty-five points. As explained below, I only focus on users with all these permissions.

Using Stack Overflow's application programming interface (API), I collect publicly available data between August 2008 and August 2021, resulting in about 22 million threads and 16 million users. When users join the community, they are assigned a profile with a score equal to one. However, only a fraction of these users ever increase this score by posting on the site (about 25%). For this subset of users, I obtain complete timestamped trajectories of status attainment (nearly 230 million status updates) along with all contributions to the site, including 32 million answers and 80 million comments. To ensure that I can analyze the relationship between status and cooperation, I select users who have at least six months of weekly activity on the site in the form of posting activity (questions or answers) or receiving status points, which results in $608,942$ users. This weekly activity used for user selection is not necessarily consecutive at this stage.

Users become active in the community when they write their first post, not necessarily when they create their account on Stack Overflow. The time when this happens becomes “week zero” for counting contributions and status changes. However, posts can sometimes be removed (e.g., due to "reasons of moderation" or even voluntarily), and votes earned due to this posting activity are retroactively discounted from a user’s profile. All these status updates remain part of the user history, which means that status sometimes cannot be mapped to specific contributions. In a few instances, the first status change occurs many weeks before “week zero”. To deal with this issue, I identify all users for whom status changes exist before the official first contribution to the site and keep only those with less than 30 points earned due to untraceable previous activity. I then reassign these points to week zero, meaning some users start their activity with a minor boost of points in their profile.

I study the relationship between social status and cooperation within the first six months of activity. This is because active users unlock different privileges as they increase their profile score, as mentioned earlier, and these privileges can often correlate with taking different roles on the site, such as editing or moderating other users’ posts. This role shift is standard in many organizations, such as academic settings, where departmental roles often switch with seniority. While young tenure-track scholars are sometimes freed from some service and professional tasks, more senior scholars take over these responsibilities. Similarly, suppose more senior users on Stack Overflow contribute less answers because they take on other roles in the community but still collect upvotes from previous posts. In that case, there will be a negative correlation between contributions and status points. My focus on the first six months of activity is intended to minimize these potential role shifts.

Lastly, I divide these six months into two parts: the first 12 weeks will observe users who attain high status by crossing the high-status threshold, and the remaining weeks will be used to measure the effect of high status on contributions. To capture enough pre-treatment information for threshold crossers, I discard all users who attain high status before week 5. This gives me at least one month of activity that I can use to match threshold crossers with other users who are nearly identical in all observed attributes except for their status during the month before crossing the threshold. Hence, my analytical focus is centered on users crossing the top 5% status threshold every week between weeks 5 and 12.

Measures

The status measure is based on the points received by other users in the form of up-votes and down-votes that users earn for their activity on the site (mainly related to asking and answering questions). In addition to these votes, users also receive a score when they accept an answer to their questions as the official answer and when chosen answers become the officially accepted answer to a question. These answers receive the "accepted answer" flag, which appears as a green check mark next to the answer and is visible to everyone.

However, there are other forms of scoring in which Stack Overflow users can receive points. Figure 1 plots the proportion of points for all types of labels reported on the site that contribute status points to an average user. It displays information coming from all users who have ever received any status update in their profile ($N = 4,043,929$)[4]. The figure shows four salient sources of status points: up-votes, down-votes, accepting an answer, and receiving an accepted answer. This is still the case when we consider users in the top 25% of posting activity, showing that this pattern is not driven by less active users who are less likely to be exposed to other sources of status attainment (not shown here). Overall, this indicates that status changes are driven to a large extent by posting answers and questions on Stack Overflow, and it then supports the decision to measure status attainment mainly using the voting system on Stack Overflow[5].

Crucially, status does not necessarily translate into quality on Stack Overflow since status changes occur based on what other users believe to be good or bad posts. Furthermore, multiple answers respond to the same question, and it is often the case that several are highly up-voted. The "accepted answer" flag could potentially work as a more objective measure of quality as it directly addresses the concern of the user asking the question. But accepted answers are not always the most voted and hence do not necessarily guarantee that they are the highest-quality answers. Notably, the scores in the user profiles most directly show to what extent others in the community *believe* that their contributions are valuable. Since voting summarizes patterns of deference in the community, profile scores are a clear form of social status (Sorenson, 2014).

[4]The proportions displayed in figure 1 do not add up to one because not everyone receives all forms of status changes.

[5]Comments receive "useful comment" votes, but they do not build up a user profile's score.

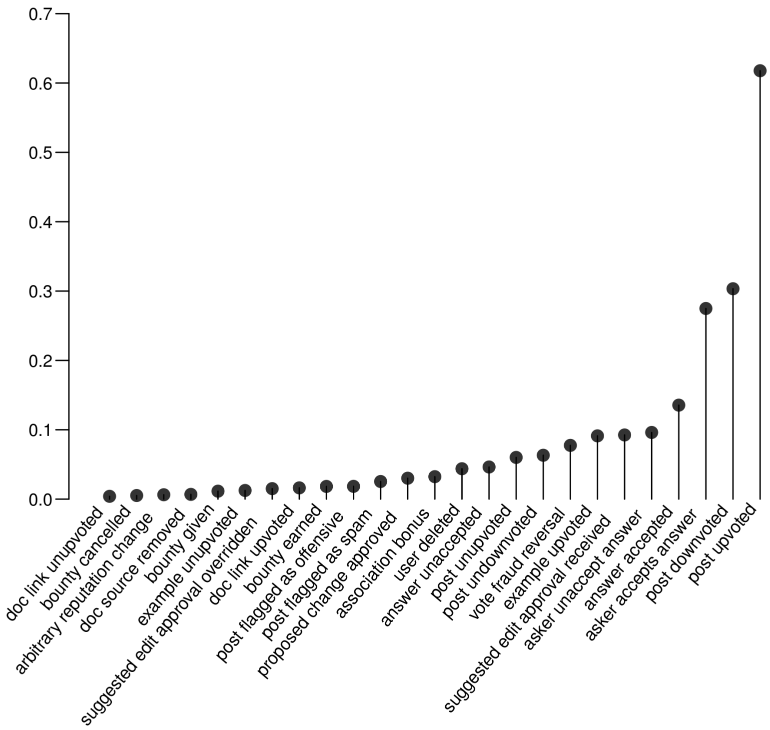

Figure 1: Proportion of points contributed by all status labels for the score profile of an average user ($N = 4,043,929$).

For the analysis below, I define a threshold of being in the top 5% of the status distribution to measure when users become high status in the Stack Overflow community. As users move up the status ladder, they notice their status increasing relative to others as they post on threads where other users also participate. Moreover, Stackoverflow provides the quantile ranking for a score profile privately to high-performing users. Nonetheless, the top 5% cut point arbitrarily turns the continuous process of status attainment into a binary process (the appendix contains results using a 10% threshold, showing that findings are robust to the threshold decision). Moreover, since quantile thresholds are relative to other users, they are subject to changes in the community composition and activity over time. If more users join Stackoverflow or some decide to become more active at any given time, the status threshold will likely be affected as well. Community growth and competition will then change what being at the top means. Therefore, I construct status thresholds every six months between December 2008 and December 2020, considering the status attained by all users up to the time point under consideration. For example, the status threshold by December 2012 uses the status distribution for all users with any status updates up to December 31, 2012.

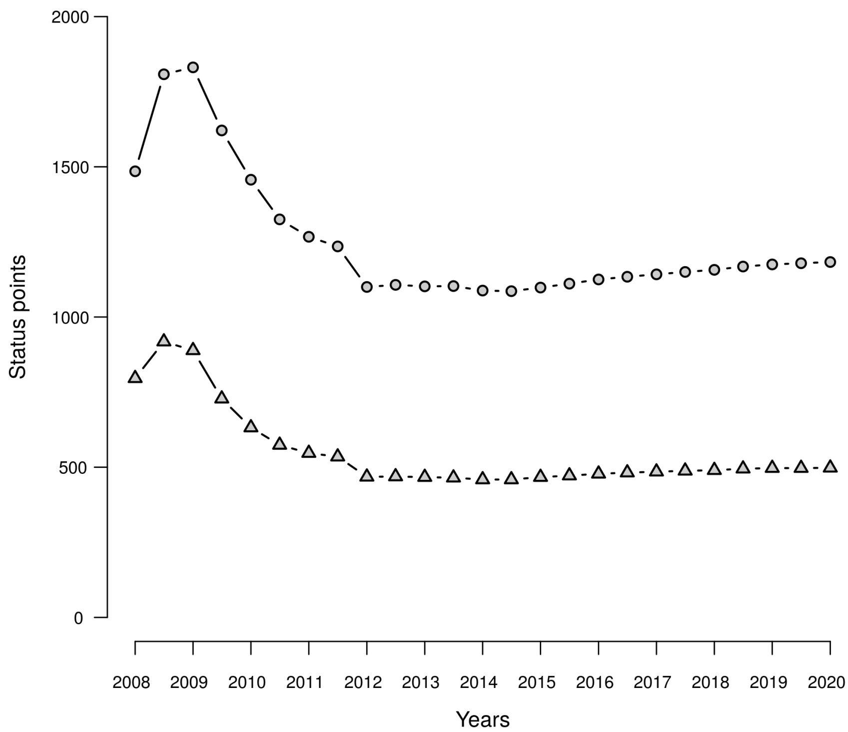

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Figure 2: Distribution of status thresholds that determine being part of the top 5% and top 10% of users between 2008 and 2020. Thresholds were computed using all users who ever received a status update up to the semester of consideration.

Figure 2 shows how status thresholds change over time. We observe that the top 5% (circles) and 10% (triangles) cut points change more drastically during the first four years of the community's existence, after which all status thresholds become more stable –likely due to an increase in the number of users over time. The figure shows that in 2009 users crossed the top 5% status threshold when they obtained around 1,800 points. But in 2013, users were in the top 5% of the status distribution when they received approximately 1,100 points. Furthermore, these community changes can also affect differently how many users cross the top 5% status thresholds between 2009 and 2020. For instance, cohorts of users exposed to changes in the technology industry are likely to have different engagements with the Stack Overflow community. For example, technological companies routinely post job ads on Stack Overflow to recruit personnel. If the use of specific programming languages in demand by the technology industry changes over time, this will likely affect how users engage with the platform.

The top panel in figure 3 shows that the average number of top 5% users increases up to 2013, decreasing monotonically after that. This decline likely happens because many users join Stack Overflow and remain low status over time. In 2020, there were only 200 users who crossed the top 5% threshold, almost four times less than the number of users who crossed the threshold in 2013. More generally, these figures show that it is essential to account for community-level and temporal changes when considering the status distribution so that the high-status threshold is meaningful to users in different cohorts.

Moreover, high-status users within the same cohort may change their status threshold at different weeks from when they start posting on the community. For instance, some users may quickly cross the top 5% threshold relative to their initial activity on the site, while others may take slightly longer to cross their thresholds. The bottom panel of figure 3 breaks down the total

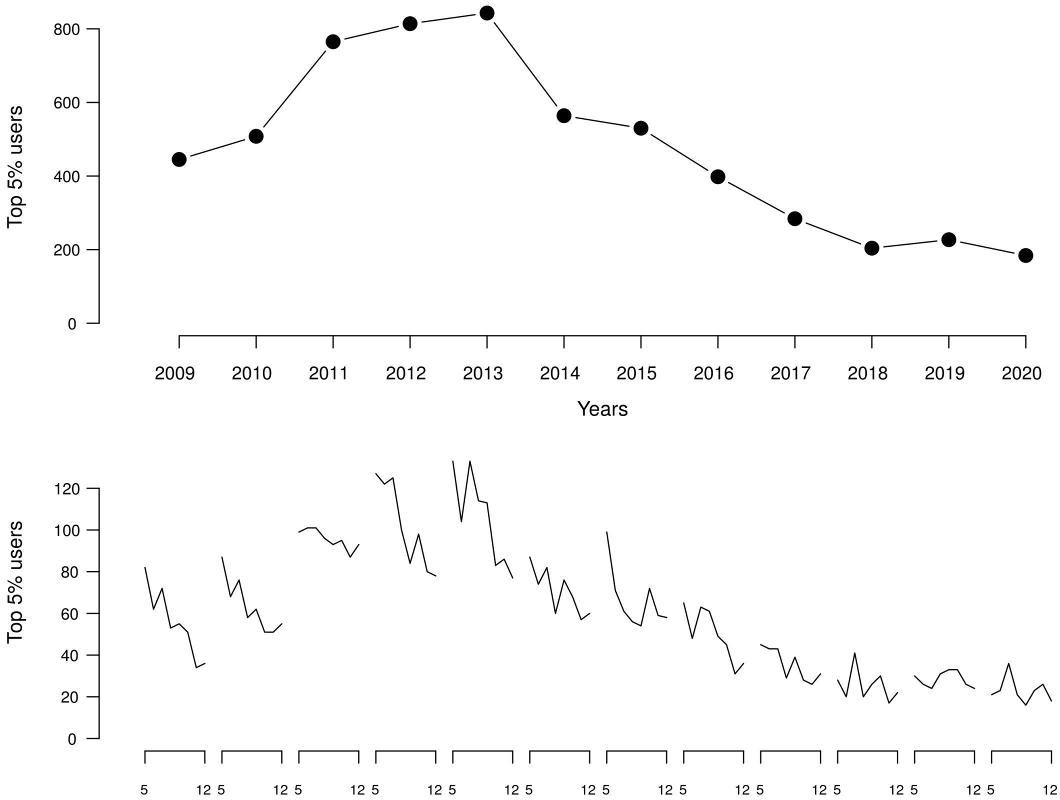

Figure 3: Distribution of top 5% users between 2009 and 2020. The top panel shows the average number of top 5% users between weeks 5 and 12, and the bottom panel shows the number of users that cross the top 5% threshold between weeks 5 and 12 for each year between 2009 and 2020.

number of high-status users crossing the top 5% threshold between weeks 5 and 12. It shows precisely that more users in 2010 crossed their status threshold by week five than users in 2020 did. By 2020, almost an equal number of users crossed the top 5% threshold between weeks 5 and 12. This within-cohort variation in how users attain high status can have very different consequences for high status as a motivator. For instance, the longer users take to become high-status, the more likely they are to get accustomed to their status positions. For this reason, my analysis separately focuses on the top 5% crossers between weeks 5 and 12 to document whether high status works differently as a motivational driver depending on how quickly users attain high status.

My measure of cooperation uses the number of answers Stack Overflow users post on the site. Answers are arguably the most valuable contribution to the site. First, answers represent about 25% of all posts on Stackoverflow, while questions add up to 15%. Second, there is an internal division of labor between question and answer writers: the correlation between the average number of answers and the average number of questions contributed to the site is -0.06. This weak (negative) correlation occurs mainly because active users, on average, write about ten times more answers than questions. And third, voting is the main form of status attainment on the site, and answers are the type of posts getting more voting and can receive the "accepted answer" flag (see figure 1). These three reasons provide a compelling argument to focus on answers as a critical source of cooperation in the Stack Overflow community.

One disadvantage of working with data from online communities is that sociodemographic information is challenging to obtain. To address this concern, I construct a rich and detailed set of control variables based on weekly on-site behavior on Stack Overflow. The most crucial control variable is the lagged number of answers contributed before users cross the top 5% threshold, a significant predictor of the number of answers that users will contribute after attaining high status. Other measures include the number of accepted answers contributed before becoming high status, the median time users take to write answers to questions (in days), and the number of replies (answers and comments) within a day. I also include measures for the number of questions and comments on the site.

Furthermore, I add a measure for how many threads users visit weekly to account for the exploration users do on the website, particularly considering that users may comment on threads to which they have not contributed answers. I also measure the number of posts contributing to status attainment to distinguish between users receiving status from multiple posts and users receiving status from a smaller subset of posts. Finally, I include indicator variables for the year users initiate their activity on Stack Overflow.

Methodological Strategy

Ideally, we want to compare the levels of cooperation of a user who crosses the top 5% threshold with the levels of cooperation of the same user had this individual remained below the threshold. But in the absence of an experimental approach where we can manipulate high status exogenously, we need to find a reliable empirical proxy for the unobserved counterfactual. Comparing the levels of cooperation of a high-status individual with the levels of cooperation of all individuals remaining below the threshold is not the right approach because status is obtained *thanks to* the cooperative efforts that collectively benefit other individuals in the community. Hence, since high status is rarely, if ever, exogenously assigned to individuals in natural settings, it is almost certain that high-status individuals will be more cooperative than most users because high status will act as a byproduct of individual contributions. We would be comparing high contributors to low contributors, and high status would be merely a proxy for high contributors. Instead, we need an empirical proxy for the counterfactual of a high-status individual that accounts for this endogeneity problem.

To impute potential outcomes, I take the following steps. First, for each group of users who cross the top 5% status threshold at week w, I define pre-treatment covariates by taking their average between weeks $w-4$ and $w-1$. Second, I find matches using the information on these covariates so that matched users have the same number of active weeks as users crossing the high-status threshold at week w. For instance, a user who becomes high status at $w = 7$ will have a match that has similar average information on the covariates between week 6 and week 3. This approach guarantees that those above and below the threshold are nearly identical before high-status users cross the top 5% threshold. Third, I use nearest-neighbor matching to find reliable proxies for the counterfactual case in each set of high-status users from weeks 5 to 12. This step is essential because a counterfactual case for a high-status user at week $w = 5$ may not serve as a counterfactual for a high-status user at week $w = 12$ since pre-treatment covariates between weeks $w-1$ and $w-4$ are likely to differ over time. Searching for potential outcomes separately for each type of high-status user gives us a more careful strategy to estimate the effect of high status on cooperation. Fourth, to the extent that the unconfoundedness assumption is met[6] and pre-treatment covariates are balanced, the approach mentioned above implies testing the causal relationship between high status and cooperation as many times as samples with unique high-status users. In this case, since we consider high-status individuals between weeks 5 and 12, this relationship will be tested with eight different sets of high-status users.

Fifth, I manually perform matching (with replacement and using up to 4 control units, when

[6]The unconfoundedness assumption in causal inference (or ignorability assumption) would state that crossing the top 5% threshold can be thought as exogenously assigned once we condition on the observed pre-treatment covariates (Morgan and Winship, 2014). This is undoubtedly a non-trivial assumption, and below I provide more details for its plausibility in this context.

possible) repeatedly until covariates between treated and control units are sufficiently balanced. Following a standard measure in causal inference to assess the quality of matches (Imbens and Rubin, 2015), I define covariate balance to be good when most of the standardized mean differences of the covariates between treated and control units are below $|0.1|$ (see the appendix for details). I intentionally avoid using propensity scores for matching, as recommended by King and Nielsen (2019). However, since propensity score matching is widely used, I also show that the results are robust to the use of propensity scores for matching (see the appendix for more details)[7].

Additionally, I use exact matching on cohort years to compare above-threshold users to identical below-threshold users who initiated their activity in the same year. Since the other covariates are continuous and finding matches with the same values in the covariates of treated and control units is almost impossible, I use calipers on all pre-treatment covariates. This approach is flexible in allowing covariates of treated and control units to differ by some amount. For the covariates of lagged outcomes (i.e., number of answers and number of accepted answers), however, I impose very restrictive calipers so that high-status users and their counterfactuals are almost identical on these covariates (the appendix displays quantile-quantile plots for these covariates). I define caliper values by trial and error until covariates are balanced. Note that this is still the design stage, so iteration through matching to find a good covariate balance is accept-

[7]One could argue that the pre-treatment variables do not entail enough information to specify the propensity score function properly. To address this concern, I use a combination of machine learning classifiers to estimate propensity scores–a super learner (Laan et al., 2007; Zivich and Breskin, 2021). This strategy enables me to flexibly include classifiers that test complex interactions among all the pre-treatment variables used for matching (e.g., random forests and gradient boosting classifiers).

able as long as this iterative process does not see the outcome variable (Imbens and Wooldridge, 2009; Ho et al., 2007).

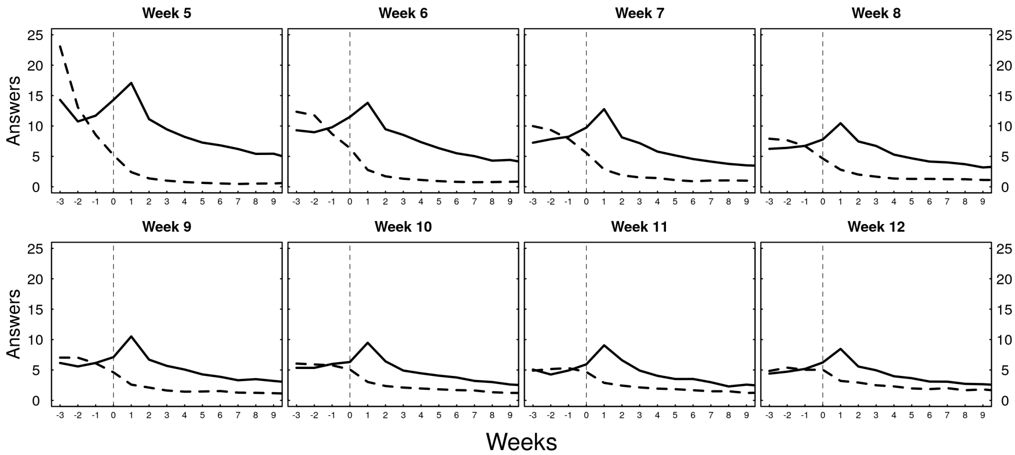

Figure 4: Number of answers contributed by users who cross the top 5% status threshold (solid line) and users who remained below the threshold (dashed line) between weeks 5 and 12. The dotted line at week zero marks the last when high-status users were below the threshold.

One fundamental assumption for the causal identification is that users who remain below the threshold are similar to those who cross the threshold during the four weeks before the 'treatment assignment.' Figure 4 shows the number of answers before and after users cross the top 5% threshold (marked by the vertical dotted line at week 0). The solid line shows the contributions of high-status individuals, and the dashed line shows the counterfactual. We observe that high-status users and their counterfactuals behave very similarly before high-status users cross the status threshold, especially users crossing the threshold between weeks 7 and 12. To further explore the plausibility that the treatment may be thought of as exogenously assigned, I regress the average lagged number of answers (used for matching) on the indicator for being in the top 5% (the 'treatment assignment'). If this indicator variable is not a simple epiphenomenon of high contributors, we should observe that it is not a predictor of the number of answers in the past. The last row of table 1 shows the p-values for this test (Answers | Top 5%) across all groups of high-status users who cross the threshold at different weeks (the next row in table 1 also shows a similar test for the lagged number of accepted answers). We observe that all p-values are non-significant, making it plausible that high-status users are not simply self-selecting into the high-status condition.

Remember that the indicator of being in the top 5% of the status distribution simplifies a continuous status attainment process on Stack Overflow. That is, being a high-status individual in this community does not suddenly happen, and the top 5% users are continuously increasing their status up to when they are assigned to be in the top 5%. For this reason, I intentionally did not include status as a covariate to find matches for high-status individuals. Figure 7 shows the difference in status between above-threshold users (solid line) and below-threshold users (dashed line). We observe that high-status users differ in their status trajectories with their counterfactuals before they crossed the top 5% threshold, even though they are comparable regarding the number of answers contributed before the treatment. This figure shows that status can increase independently of the number of answers posted on the site. To the extent that status is self-reinforcing, as discussed earlier, status can plausibly be considered exogenously assigned once we condition on the number of answers.

Table 1: Linear regression of number of answers on high-status (being in the top 5%).

	Number of answers															
	Week 5		Week 6		Week 7		Week 8		Week 9		Week 10		Week 11		Week 12	
Top 5%	14.67***	15.70***	11.03***	11.50***	9.92***	10.28***	7.64***	7.90***	7.92***	8.16***	6.45***	6.66***	6.17***	6.19***	5.27***	5.46***
	(0.65)	(0.71)	(0.60)	(0.65)	(0.55)	(0.58)	(0.52)	(0.52)	(0.57)	(0.60)	(0.54)	(0.54)	(0.63)	(0.61)	(0.55)	(0.55)
Questions		0.16*		−0.03		−0.004		0.08		0.15**		−0.02		0.01		0.20*
		(0.07)		(0.09)		(0.06)		(0.05)		(0.05)		(0.04)		(0.05)		(0.08)
Answers		0.10*		0.16***		0.15**		0.13**		0.24***		0.23***		0.10		0.13*
		(0.05)		(0.04)		(0.05)		(0.05)		(0.06)		(0.07)		(0.06)		(0.06)
Questions		−0.03		0.03		−0.02		−0.02		0.05		0.03		−0.05		−0.05
		(0.03)		(0.03)		(0.03)		(0.03)		(0.04)		(0.04)		(0.04)		(0.04)
Comments		0.02		0.004		0.01		0.02		−0.01		−0.09*		0.06		0.01
		(0.03)		(0.03)		(0.03)		(0.04)		(0.04)		(0.04)		(0.04)		(0.03)
Threads		−0.22***		−0.10***		−0.06***		−0.07***		−0.07***		−0.06***		−0.03*		−0.08***
		(0.03)		(0.02)		(0.01)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)
Status source		0.04		−0.02		0.01		0.02		−0.06		0.01		0.03		0.04
		(0.03)		(0.03)		(0.03)		(0.03)		(0.03)		(0.04)		(0.04)		(0.04)
Reply within day		−0.07		−0.10*		−0.16***		−0.09		−0.09		−0.04		−0.02		0.06
		(0.05)		(0.05)		(0.05)		(0.05)		(0.05)		(0.07)		(0.07)		(0.07)
Answers accepted		0.03		−0.003		−0.005		0.001		−0.01		0.0001		−0.002		−0.001
		(0.04)		(0.004)		(0.003)		(0.002)		(0.01)		(0.004)		(0.003)		(0.001)
Time diff in answers		0.84		−1.11		−2.89		0.69		−1.15		−0.66		1.47		−1.26
		(1.73)		(1.35)		(1.64)		(1.83)		(1.25)		(1.40)		(0.84)		(1.35)
Constant	2.40***	5.05**	2.77***	2.76*	2.85***	3.74*	2.81***	0.42	2.59***	1.30	3.03***	1.46	2.88***	−1.13*	3.20***	1.43
	(0.15)	(1.77)	(0.13)	(1.33)	(0.13)	(1.60)	(0.15)	(1.77)	(0.15)	(1.22)	(0.17)	(1.21)	(0.15)	(0.49)	(0.17)	(1.27)
N	1,841	1,841	1,766	1,766	2,210	2,210	1,734	1,734	1,746	1,746	1,831	1,831	1,615	1,615	1,546	1,546
Adjusted R^2	0.37	0.41	0.30	0.33	0.26	0.30	0.22	0.27	0.21	0.25	0.15	0.23	0.13	0.24	0.12	0.23
Matched units (%)	0.61		0.64		0.69		0.65		0.64		0.68		0.67		0.65	
Lagged outcome | *Treatment* ($p-$values)																
Answers | Top 5%	0.92		0.65		0.74		0.78		0.76		0.82		0.85		0.78	
Accepted Answers | Top 5%	0.17		0.28		0.07		0.34		0.62		0.41		0.45		0.72	

Notes: Robust standard errors in parentheses. All regression models use weights defined by nearest-neighbor matching. Cohort indicators are included in all models with covariates but omitted on the table. *p<0.05; **p<0.01; ***p<0.001

RESULTS

Table 1 displays results using linear regression to estimate the average causal effect of being in the top 5% of the status distribution on the number of answers that Stack Overflow users contribute to the community. Causal estimates represent the number of answers contributed on the week users cross the top 5% threshold. Columns show estimates for models with and without statistical controls for each group of high-status users (weeks 5 to 12). I include statistical controls to account for potential confounders due to the covariate imbalance that remained after matching (see the appendix for details on the covariate balance). All models include robust standard errors and use weights defined by matching.

Findings show that the top 5% users contribute between 15 and 6 more answers than users who remained below the status threshold, indicating that high status does incentivize cooperation among Stack Overflow users. Causal estimates of the regression models without controls are similar to the causal estimates of the models with controls, showing that these findings are robust to model specification. This consistency across models reveals that matching did an excellent job of finding reliable proxies for the potential outcomes of high-status users. It shows that the remaining covariate imbalance is not severe enough to alter causal estimates dramatically. We also observe that the earlier Stack Overflow users cross the status threshold, the more answers they contribute to the community on the week they become high status. Users crossing the top 5% threshold by week 5 or 6 contribute between 15 and 11 more answers, while users who cross it by week 11 or 12 contribute between 7 and 6 more answers.

Next, I extend these results to show how being a high-status user can translate into more contributions over time. Figure 5 shows the causal effect of being a top 5% user on contributions up to 10 weeks after users cross the status threshold. The number of answers is aggregated biweekly between weeks 1 and 10. All estimates come from linear regression models, including all pre-treatment covariates, robust standard errors, and weights defined by matching (similar to the models with controls in table 1).

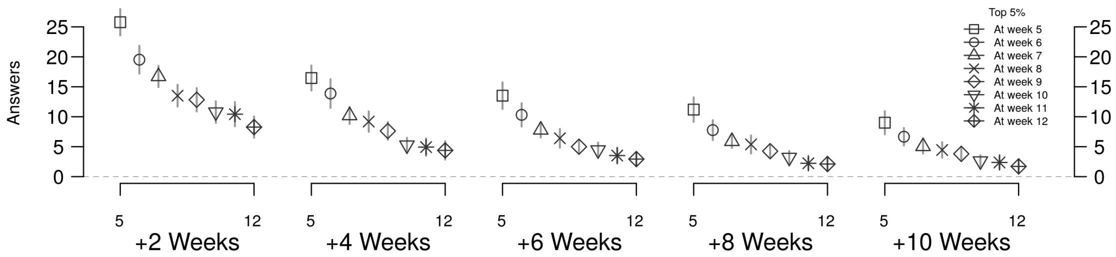

Figure 5: Treatment effect of high status on the total number of answers for users who cross the top 5% threshold between weeks 5 and 12. The effect is displayed by adding up biweekly answers contributed until ten weeks after users become high-status. Results come from linear regressions with robust standard errors and weights defined by nearest-neighbor matching. Vertical bars represent 95% confidence intervals.

Each sub-panel in figure 5 shows the average causal effect for users who cross the top 5% status threshold at different weeks. For instance, the first sub-panel (to the left of figure 5) shows that contributions in the next two weeks after being in the top 5% are higher for all types of high-status users. But the number of answers decreases as users cross the top 5% threshold in later weeks. This is the same decreasing pattern we observed in table 1, but non-overlapping confidence intervals now reveal that these differences are statistically significant. High status works more strongly as a motivational driver for users who become high status earlier in their trajectory of contributions. As we move to the right of figure 5, we observe that the decreasing pattern in contributions among users who cross the status threshold at different weeks is consistent within each sub-panel, and it even remains after ten weeks.

Moreover, we observe that the number of answers contributed by each type of high-status user also decreases over time, showing that the motivation for further contributions triggered by being in the top 5% decays, regardless of the week when users cross the top 5% threshold. For instance, high-status users at week 5 contribute 25 more answers two weeks after crossing the status threshold than users below the threshold. However, this boost in contributions for these high-status users decreases over time and goes down to almost 10 answers more than below-threshold users. This is still a substantial number of additional answers in response to being a renowned user in the community, but the causal estimate remarkably decreased by 60%. A similar phenomenon is observed across all groups of top 5% users, suggesting that the motivation of high status for more cooperation weakens as time goes by.

Together, these results reveal three main takeaways. First, high status generally incentivizes contributing more answers to Stack Overflow, a positive trend that remains for almost three months. Second, the time at which users are part of the top 5% affects the strength of the incentive for more contributions: the earlier users attain high status, the more answers users post on Stackoverflow. This finding suggests that acknowledging contributions early matters in cooperative settings. And third, the passage of time works against high status as a motivational device regardless of the week at which users attain high status, indicating that status orders have limitations in organizing sustainable reward systems.

Alternative Explanations

One possibility to explain why high-status users contribute more than comparable users who remain below the top 5% is that they trade quality for quantity. The argument would be that high-status users can post a higher number of answers because they post qualitatively worse answers. If this happens, it would mean that high status works as a perverse incentive for cooperation because it stimulates users to contribute more by damaging the quality of those additional cooperative efforts. This potential trade-off that high status may incentivize can be particularly deleterious for the community if its elite contributes poor-quality resources. Indeed, while the community's resources increase, the overall quality decreases, thus damaging its long-term ability to attract and recruit new members.

To evaluate this possibility, I examine if high-status users contribute more answers that will be chosen as official answers in the future by receiving the 'accepted answer' flag. As I mentioned, this flag is given by the person who posts the question to which the answer is responding; hence, it is not a purely objective measure of quality. Nonetheless, accepted answers are probably the best way to capture some more objective quality than counting the number of answers as they directly solve the problem described in the question. Moreover, the person who finds them useful often has to choose among several alternative options and can even revert the choice, if necessary.

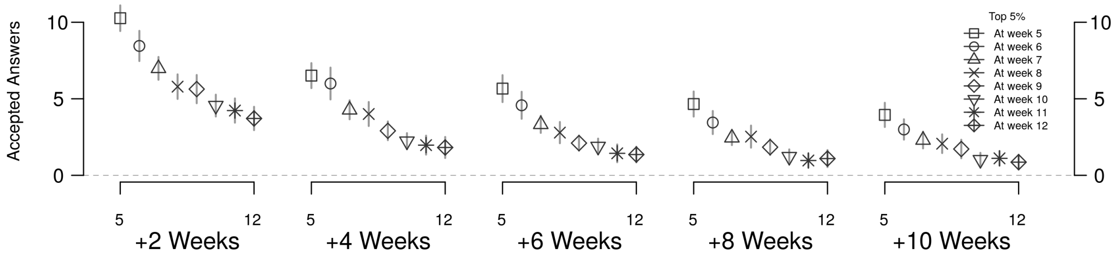

Figure 6: Treatment effect of high status on the total number of accepted answers for users who cross the top 5% threshold between week and week 12. The effect is displayed by adding up all answers contributed biweekly until 10 weeks after users become high-status. Results come from linear regressions with robust standard errors and weights defined by the nearest-neighbor matching. Vertical bars represent 95% confidence intervals.

Figure 6 shows the number of accepted answers as a function of becoming a top 5% user in the status distribution on Stack Overflow. Accepted answers are aggregated biweekly between weeks 1 and 10. As with findings from figure 5, all estimates come from linear regression models with all pre-treatment covariates, robust standard errors, and weights defined by matching. Findings reveal that early status crossers (by week 5 or 6) contribute between 8 and 10 accepted answers after two weeks of attaining high status and between 4 and 5 accepted answers after ten weeks. We also observe that the later users cross the top 5% high-status threshold, the lower the number of accepted answers they contribute. For users who cross the status threshold by weeks 9 and 12, contributions are around five after two weeks of attaining high status but around one after ten weeks. Similarly to what we observed in figure 5, top 5% users generally contribute less over time regardless of the week at which they crossed the threshold. These results rule out the possibility that high-status write more answers because they sacrifice the quality of their contributions.

Another possibility to explain why users decrease their contributions over time is that their status is also reducing so that they leave their high-status positions. The argument implies that high status is always a positive incentive for cooperative behavior, and a gradual loss of status must consequently explain a decreasing pattern of contributions. In other words, if high status is a strong motivational instrument for cooperation, it may also be a strong disincentive in the presence of downward status mobility.

To evaluate this, I descriptively examine the complete status trajectories of high-status users and their counterfactuals for the period under study. Figure 7 shows how status evolves for both above-threshold and below-threshold users (solid and dotted lines, respectively) since the time users posted for the first time on Stackoverflow. The starting point varies across panels depending on the week at which high-status users cross the status threshold. The vertical dotted line at week 0 marks the last week at which high-status users remain below the top 5%

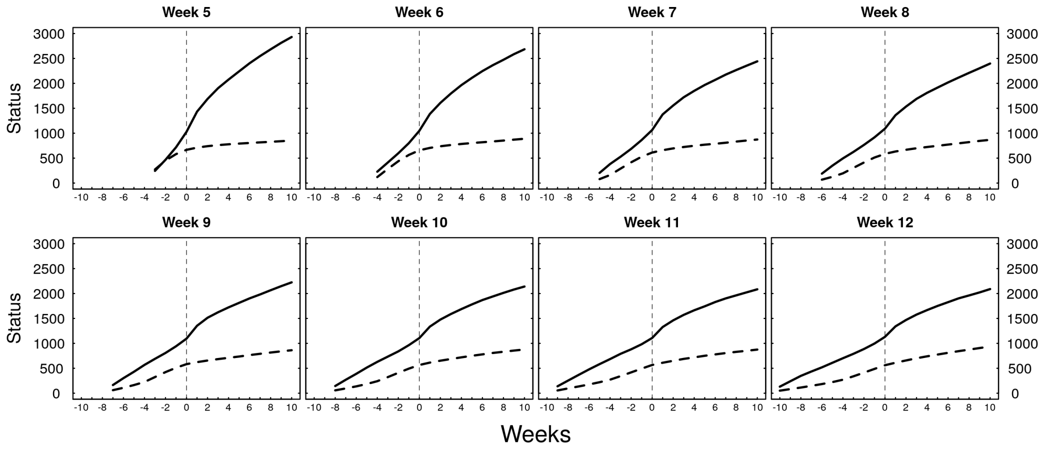

Figure 7: Cumulative status for users who cross the top 5% status threshold (solid line) and users who remained below the threshold (dashed line) between weeks 5 and 12. The dotted line at week zero represents the last week where high-status users were below the top 5% threshold.

threshold. We observe that status is constantly increasing for high-status users and their counterfactuals[8], but it rises more steeply among top 5% users in all panels of figure 7, showing that a decline in status does not drive a decrease in contributions among top 5% users over time.

DISCUSSION

Status boosts can be powerful organizational instruments to incentivize cooperation, especially in public-goods settings where voluntary contributions are the cornerstone of collective efforts. We know that higher status increases cooperative behavior and identification with the community, making higher-status individuals important members willing to perform crucial activities for the group (Willer, 2009; Restivo and Van De Rijt, 2014; Gallus, 2017). However,

[8]It is not very surprising that status never decreases among these users because Stack Overflow makes it easier for status to increase by design, given that up-votes count more than down-votes.

being at the top of the status hierarchy may create opportunities for distraction and induce complacency and unproductiveness, casting doubt on whether high status can encourage individuals to keep producing critical resources for their communities. So is high status strong enough to sustain cooperation in public-goods settings? The answer to this question carries broad implications for the long-term effectiveness of status orders. If high status fails to motivate sustained cooperation among the most celebrated, status orders will be ineffective at securing sustainable collective goods.

This article studies the efficacy and sustainability of status hierarchies in cooperative contexts, moving away from previous studies that highlight the consequences of high status due to shifting the audiences that pay attention to high-status recipients and modifying their evaluation criteria (Kovács and Sharkey, 2014; Hahl and Zuckerman, 2014). It centers on the behavioral consequences of high status for cooperation and uses data on millions of timestamped contributions and status changes from Stackoverflow–an online community that discusses programming and computing topics. The findings show that high status, measured via cumulative patterns of deference, has a substantial positive effect on the number of answers contributed to the community. This effect is tested with eight samples of individuals who become high-status at varying moments relative to their initial activity. This approach reveals that the earlier a user becomes high-status, the more answers they contribute to the community, showing that recognizing contributions early matters for cooperative behavior. Moreover, the increase in cooperation motivated by high status does not sacrifice quality for quantity, confirming that high-status individuals provide valuable resources for the community. These results show that high status can be a powerful driver of cooperation even among the elite and demonstrate that the virtuous circle between status and cooperation persists as individuals climb the status ladder.

Nevertheless, the results also show that high status becomes a weaker incentive for cooperation over time. This behavior applies to all high-status users, regardless of whether they cross the high-status threshold earlier or later relative to when they start contributing to the community. To the extent that high status decreases its influence on cooperative behavior over time, the elite that once contributed more than others will not be able to continue producing the resources their organizations need in the future.

This result has significant theoretical consequences for understanding the organizational efficacy of status orders. One possibility is that status is simply not enough to sustain cooperation in the long run, although it can effectively motivate individuals to start cooperating. In this situation, there may exist an optimal high-status position so communities can praise some individuals highly for their contributions without disincentivizing their future cooperative behavior. If organizations can discover this optimum, they can anticipate that a higher status beyond this point will be ineffective in motivating more cooperation, a piece of knowledge they can use to inform the design of new organizational strategies to the community's benefit. For example, communities can redirect resources previously used to incentivize cooperation among high-status members and refocus them on recruiting new members of the community that can be motivated by higher status early on.

Moreover, the alternative explanations section discards that cooperation declines because status also decreases. This fact reveals a peculiar way in which Stack Overflow structures status differences because it allows individuals to accumulate status unlimitedly from previous contributions. Status is then decoupled from contributions by design. Although this form of organizational structure is unique to Stack Overflow and other online communities, understanding the status attainment process more generally in these settings can help us design reward systems that are also useful to other types of organizations. One potential implementation is to make the loss of status more salient to incentivize further cooperative behavior among the elite. For instance, one could include in someone's profile both the overall cumulative status and a more current status 'score' (e.g., over the last year) that informs more accurately about the status positions based on recent contributions. This configuration would be similar to how some systems (e.g., Google Scholar) reveal information about scientists' influential work by exposing both all their citations and citations in the last five years only. Future research can explore whether these system designs can successfully counteract or at least partially offset the declining effect of high status on cooperative behavior.

Although high status is detrimental to cooperative behavior among the most recognized community members over the long run, the public display of these reputable individuals may be functional to the community and serve as an example for lower-status groups. Recent research shows that high-status individuals change their behavior as they increase their status and engage in more difficult-to-evaluate actions (Smirnova et al., 2022), which also allows them to reach broader audiences where their expertise is less recognizable. Having these celebrated community heroes participate more broadly in their communities may also encourage others to engage and contribute resources to the community. Future work can investigate whether increasing the presence of high-status individuals in broader contexts, where their expertise is not immediately apparent and lower-status individuals are the majority, can provide further incentives for others to cooperate more.

Additionally, this study does not address why high-status individuals might cooperate less over time. One alternative is that identification with their communities deteriorates, and consequently, their motivation to cooperate is less group-oriented over time (Willer, 2009). Another possibility is that high-status individuals have different locations in a community's network structure, so their contributions receive feedback and engagement from others at different rates. This different network location can potentially reinforce a weakening identification with the community if the contributions of some high-status individuals do not attract much attention from others. This can provide a fruitful research avenue to explore network mechanisms that mediate cooperative behavior.

This study has several limitations. First, it defines high status using a binary indicator when the status attainment process occurs continuously. Although this strategy facilitates the definition of potential outcomes, a binary indicator is a crude approximation of an incremental awareness of becoming high status. Future research should investigate the continuous effect of high-status attainment on cooperative behavior and compare it with the consequences of receiving visible signs of high status (such as prestigious awards). Second, even though the previous analysis uses rich information on individual behavior throughout the site to find close matches of high-status users, it does not include sociodemographic characteristics. This is an important consideration because sociodemographic information is unobserved and may induce bias in the causal estimates, despite including detailed behavioral information on the site. One potential solution would be to use the names of Stack Overflow users to infer their gender, ethnicity, and race using natural language processing techniques. And third, while the findings document that high status can motivate cooperative behavior in the short term, it remains unclear whether these contributions to the community are of high quality. The use of 'accepted answers' to approximate objective quality (see figure 6) is somewhat problematic because the 'accepted answer' flag is based on the assessment of an unqualified person (i.e., the user who asks the question) and it does not guarantee that the answer is the best out of all possible answers that responded to the question. Future research should explore more clearly whether high status specifically incentivizes high-quality contributions.

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APPENDIX

Top 10% Status Threshold

Below, I present results using the top 10% of the status distribution as the high-status threshold. Table 2 displays results using linear regression to estimate the average causal effect of being in the top 10% of the status distribution on the number of answers that Stack Overflow users contribute to the community. As in table 1, all models include robust standard errors and use weights defined by nearest-neighbor matching. Also, as before, regressing the number of lagged answers (and lagged accepted answers) on the treatment indicator (crossing the top 10% threshold) renders p-values that are above the traditional cutoffs of statistical significance, making it plausible that status is exogenous conditional on the pre-treatment observed covariates.

Results show that users cross who cross the top 10% status threshold contribute between 9 and 4 more answers than similar users who remain below the threshold. In all cases, causal estimates from models without controls are similar to models with controls, showing that results are robust to model specification. This reveals that matching did a good job at balancing pre-treatment covariates between treated and control cases.

Additionally, figure 8 shows causal estimates of crossing the top 10% threshold over time. As in figure 5, the number of answers is aggregated biweekly between weeks 1 and 10 and all estimates come from linear regression models including all pre-treatment covariates, robust standard errors, and weights defined by nearest-neighbor matching. Each sub-panel also shows the average causal effect for users who cross the top 10% status threshold at different weeks.

Table 2: Linear regression of number of answers on high-status (being in the top 10%).

	Number of answers															
	Week 5		Week 6		Week 7		Week 8		Week 9		Week 10		Week 11		Week 12	
Top 10%	9.13***	9.54***	7.49***	7.69***	6.09***	6.25***	5.78***	5.91***	6.47***	6.59***	5.12***	5.19***	4.95***	4.99***	4.03***	4.07***
	(0.29)	(0.31)	(0.30)	(0.30)	(0.29)	(0.29)	(0.29)	(0.29)	(0.36)	(0.37)	(0.30)	(0.30)	(0.30)	(0.30)	(0.25)	(0.25)
Questions		0.10*		0.20***		0.12**		0.12***		0.17***		0.01		0.03		0.05
		(0.04)		(0.04)		(0.04)		(0.03)		(0.04)		(0.04)		(0.05)		(0.03)
Answers		0.14***		0.18***		0.20***		0.24***		0.28***		0.20**		0.15*		0.20***
		(0.04)		(0.04)		(0.05)		(0.05)		(0.06)		(0.06)		(0.06)		(0.05)
Questions		−0.002		−0.01		−0.04		−0.002		−0.04		−0.03		−0.02		−0.06
		(0.02)		(0.03)		(0.03)		(0.03)		(0.04)		(0.04)		(0.04)		(0.03)
Comments		−0.02		−0.04		−0.03		−0.04		−0.09*		0.01		0.04		−0.02
		(0.03)		(0.02)		(0.03)		(0.03)		(0.04)		(0.04)		(0.05)		(0.04)
Threads		−0.20***		−0.18***		−0.13***		−0.11***		−0.14***		−0.07**		−0.07**		−0.05***
		(0.03)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.03)		(0.01)
Status source		0.01		0.04		0.04		0.003		0.07*		0.02		−0.002		0.06
		(0.02)		(0.03)		(0.03)		(0.03)		(0.03)		(0.03)		(0.04)		(0.03)
Reply within day		−0.17***		−0.10**		−0.12*		−0.14**		−0.10		−0.14*		0.001		−0.02
		(0.04)		(0.04)		(0.05)		(0.05)		(0.07)		(0.06)		(0.06)		(0.07)
Answers accepted		0.002		0.01		−0.001		−0.001		−0.0002		0.0001		−0.001		−0.001*
		(0.002)		(0.01)		(0.002)		(0.001)		(0.001)		(0.001)		(0.0004)		(0.0003)
Time diff in answers		1.30		−0.39		−0.10		−0.45		0.30		−1.06		−0.71		−2.18
		(1.18)		(1.07)		(0.59)		(0.65)		(0.72)		(0.68)		(0.82)		(1.32)
Constant	0.85***	2.54*	1.05***	2.19*	1.13***	0.81	0.99***	1.65**	0.97***	0.36	1.04***	1.13	0.97***	1.19	1.13***	2.01
	(0.04)	(1.06)	(0.04)	(1.02)	(0.05)	(0.48)	(0.05)	(0.58)	(0.05)	(0.66)	(0.05)	(0.64)	(0.06)	(0.70)	(0.06)	(1.29)
N	5,522	5,522	4,620	4,620	4,003	4,003	3,837	3,837	3,538	3,538	3,561	3,561	3,467	3,467	3,218	3,218
Adjusted R^2	0.31	0.34	0.26	0.29	0.23	0.27	0.22	0.26	0.20	0.24	0.19	0.22	0.18	0.22	0.16	0.25
Matched units (%)	0.61		0.57		0.55		0.57		0.56		0.60		0.62		0.59	
Lagged outcome | *Treatment* ($p-$values)																
Answers | Top 5%	0.82		0.79		0.84		0.72		0.70		0.72		0.76		0.73	
Accepted Answers | Top 5%	0.17		0.18		0.14		0.27		0.37		0.28		0.31		0.38	

Notes: Robust standard errors in parentheses. All regression models use weights defined by nearest-neighbor matching. Cohort indicators are included in all models with covariates but omitted on the table.

*p<0.05; **p<0.01; ***p<0.001

Overall, findings are similar to results in figure 5. Within each sub-panel, we observe that high-status crossers contribute more answers the earlier they cross the top 10% threshold. Nonetheless, we also observe across sub-panels that the number of answers contributed by each type of high-status user decreases over time, reinforcing the idea that high-status is a motivational driver that weakens with time.

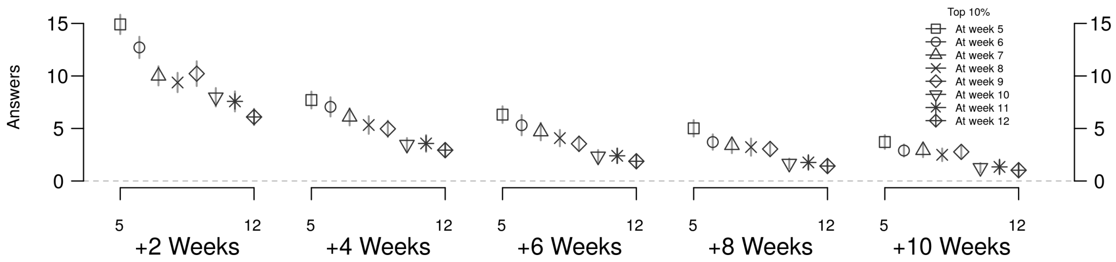

Figure 8: Treatment effect of high status on the total number of answers for users who cross the top 10% threshold between week and week 12. The effect is displayed by adding up biweekly answers contributed until 10 weeks after users become high-status. Results come from linear regressions with robust standard errors and weights defined by nearest-neighbor matching. Vertical vars represent 95% confidence intervals.

Covariate Balance

Figure 9 displays standardized mean differences before and after matching (empty and filled circles, respectively) on all pre-treatment variables for each group of high-status users between weeks 5 and 12. As observed, covariate balance is significantly improved after matching in all cases and, as intended, normalized differences for the lagged number of answers and the lagged number of accepted answers are generally below the $|0.1|$ cut point (i.e., most of the solid points are between the two lines around zero). However, in some cases, normalized differences were slightly above this point, which may raise concerns for raw comparisons between treated and untreated units. In this case, researchers suggest presenting causal estimates using pre-treatment covariates as statistical controls to account for potential differences that were not resolved by matching (Imbens and Wooldridge, 2009; Ho et al., 2007).

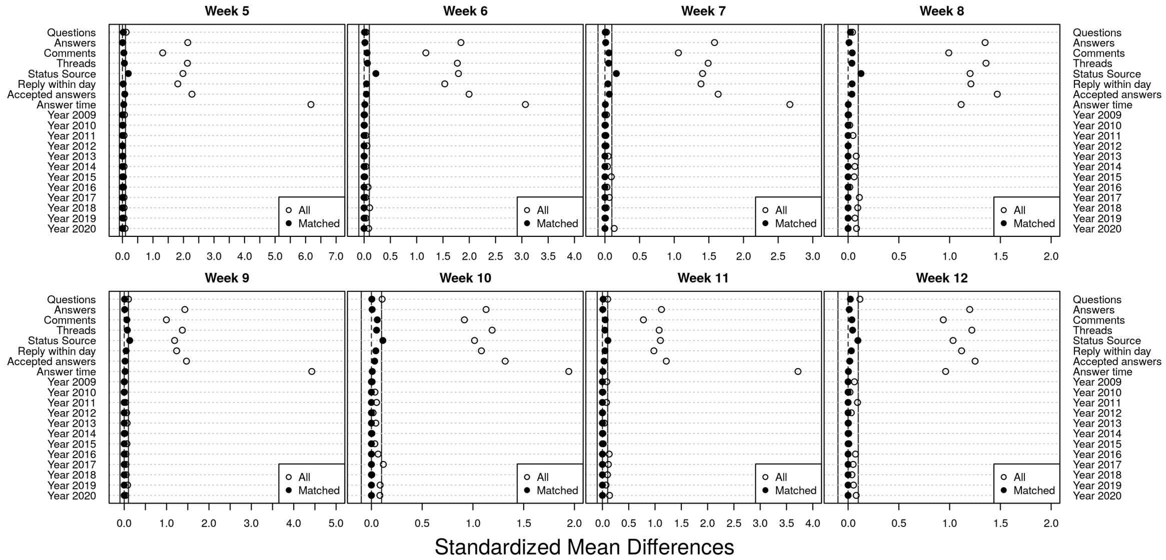

Figure 9: Covariate balance before (empty circles) and after matching (filled circles) for users who cross the top 5% threshold between weeks 5 and 12. Values are standardized mean differences in absolute value.

Additionally, figures 10 - 17 display empirical quantile-quantile plots for key covariates that can potentially induce endogeneity (e.g., number of answers and number of accepted answers) for users who cross the high-status threshold between weeks 5 and 12. Results from these QQ-plots provide further evidence that the covariate balance is excellent for these three variables (right column in figures 10 - 17).

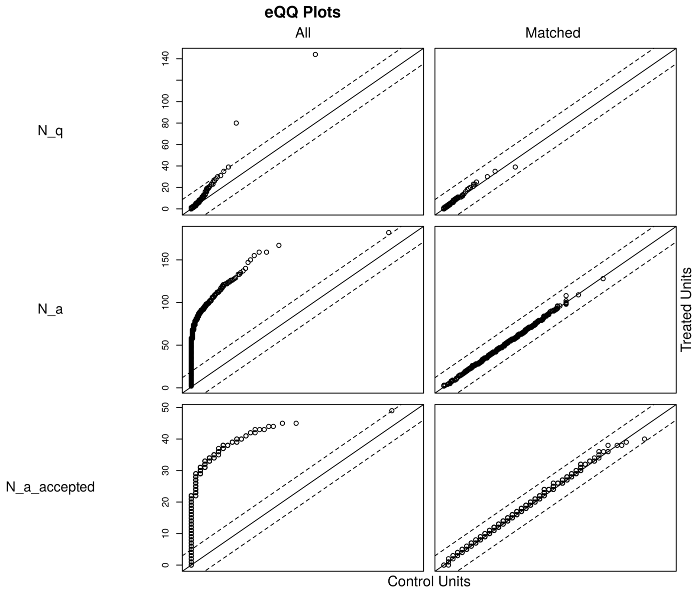

Figure 10: Empirical quantile-quantile plots comparing number of questions, number of answers, and number of accepted between treated and control cases after matching for high-status crossers at week 5.

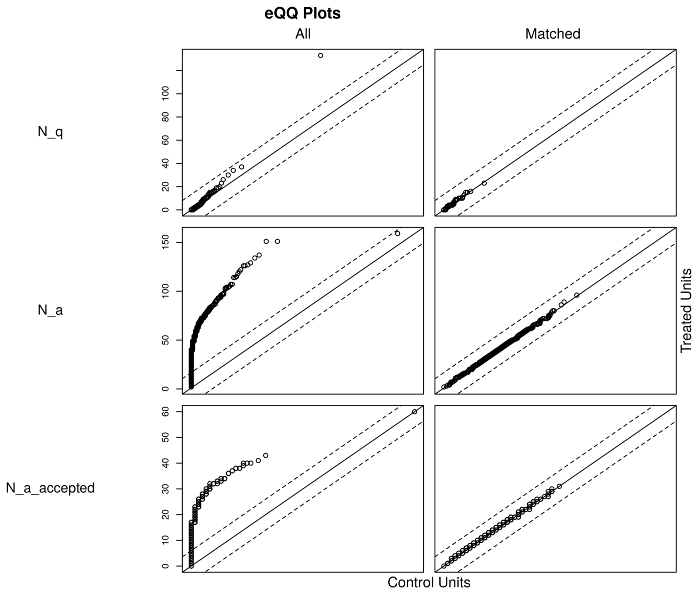

Figure 11: Empirical quantile-quantile plots comparing number of questions, number of answers, and number of accepted between treated and control cases after matching for high-status crossers at week 6.

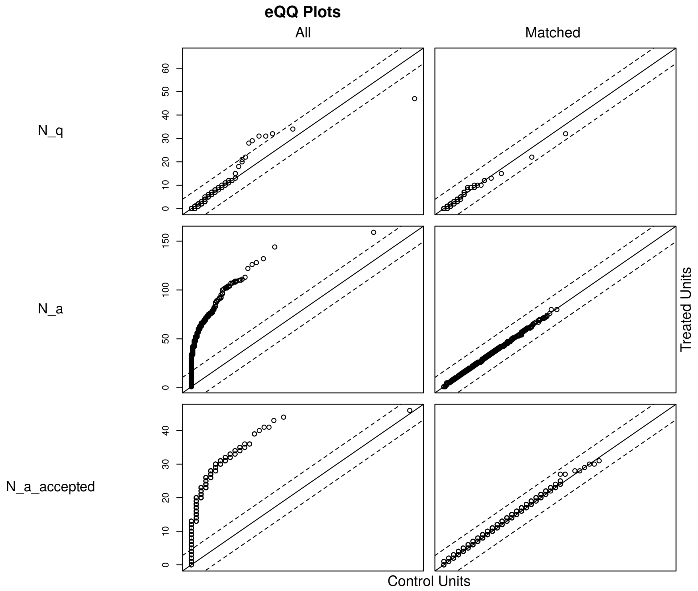

Figure 12: Empirical quantile-quantile plots comparing number of questions, number of answers, and number of accepted between treated and control cases after matching for high-status crossers at week 7.

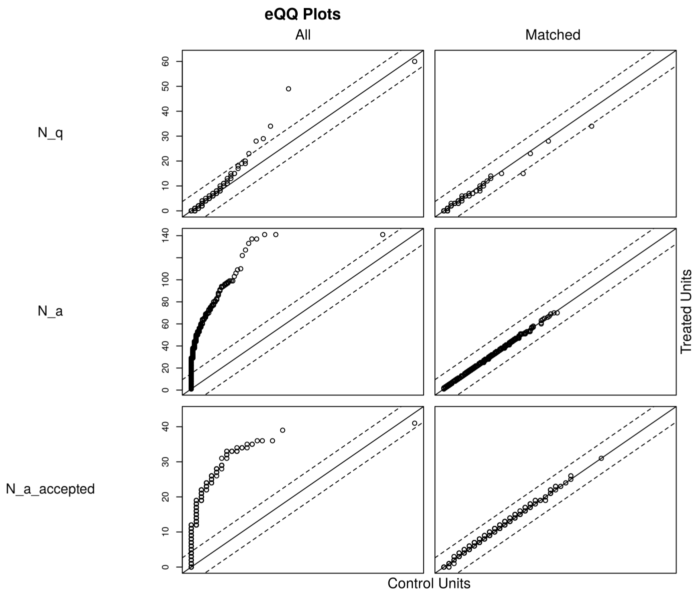

Figure 13: Empirical quantile-quantile plots comparing number of questions, number of answers, and number of accepted between treated and control cases after matching for high-status crossers at week 8.

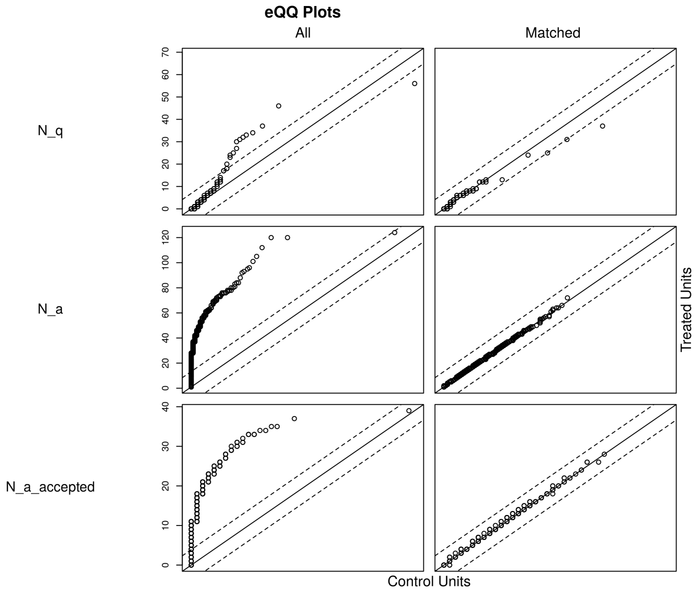

Figure 14: Empirical quantile-quantile plots comparing number of questions, number of answers, and number of accepted between treated and control cases after matching for high-status crossers at week 9.

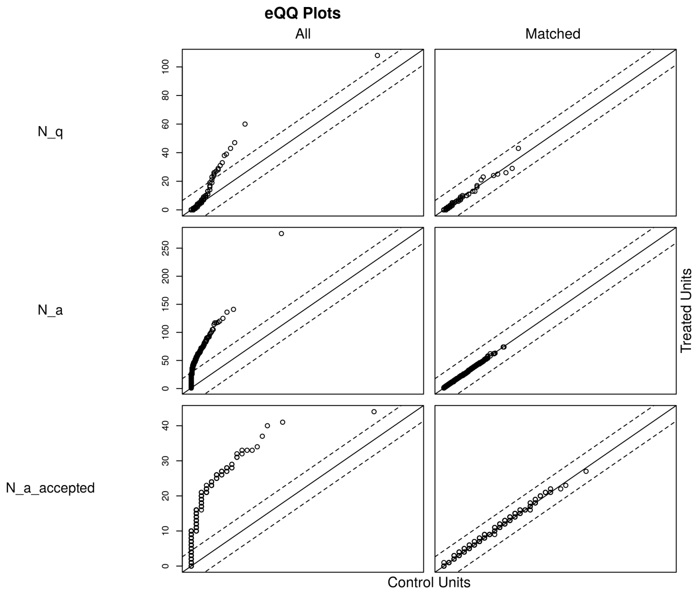

Figure 15: Empirical quantile-quantile plots comparing number of questions, number of answers, and number of accepted between treated and control cases after matching for high-status crossers at week 10.

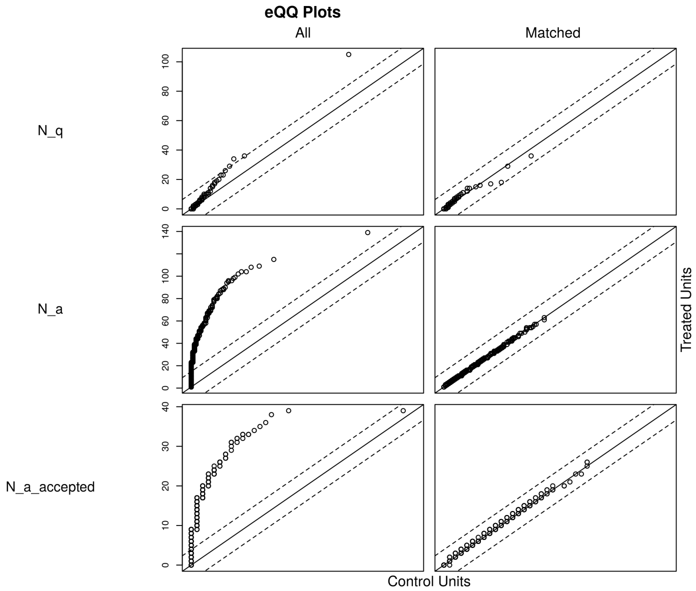

Figure 16: Empirical quantile-quantile plots comparing number of questions, number of answers, and number of accepted between treated and control cases after matching for high-status crossers at week 11.

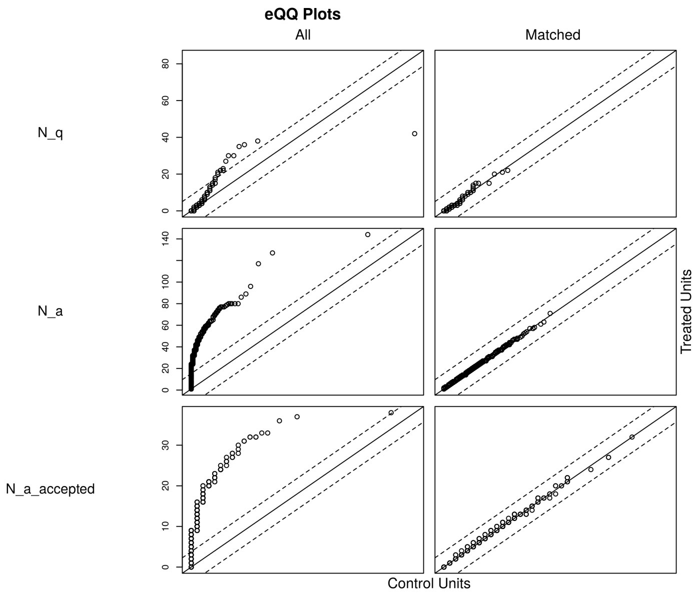

Figure 17: Empirical quantile-quantile plots comparing number of questions, number of answers, and number of accepted between treated and control cases after matching for high-status crossers at week 12.

Propensity Score Matching

As discussed in the main text (section "Methodological Strategy"), I avoid using propensity score for matching, as King and Nielsen (2019) recommend. One of their reasons is that matching on propensity scores can create a severe imbalance in the pre-treatment variables used to estimate propensity scores. This problem can make causal estimates more sensitive to model specification and lead to some bias. However, since propensity score matching is widely used in the social sciences, I reproduce the main findings with a different identification strategy.

The first step is to define the propensity score function. Rather than using a logistic regression, as is common among social scientists, I use a super learner, which combines different machine-learning classifiers for prediction(Laan et al., 2007).[9] Specifically, I use the following models: a logistic regression with regularizer (lasso), random forests, extreme gradient boosting, and support vector machine. The algorithm produces a propensity score that averages over the outputs of these four classifiers, weighted by their out-of-sample performance using k-fold cross-validation ($k = 3$). The main advantage of using a super learner is that some classifiers (e.g., random forests or extreme gradient boosting) can explore complex partitions of the predictor space, meaning that this approach essentially accounts for complex interactions between the main independent variables. Hence, it partly addresses the problem of having a correct specification of the propensity score function (Zivich and Breskin, 2021)[10].

[9]See Molina and Garip (2019) for an introduction of machine learning to sociological research.

[10]An incorrect specification of the propensity score function may lead to severe bias in causal estimates (Imbens and Rubin, 2015). Since we rarely know its true functional form, misspecification and bias can be a significant problem for causal inference.

Table 3: Linear regression of number of answers on high-status (being in the top 5%).

	Number of answers															
	Week 5		Week 6		Week 7		Week 8		Week 9		Week 10		Week 11		Week 12	
Top 5%	17.26^{***}	13.35^{***}	12.33^{***}	11.27^{***}	11.23^{***}	7.81^{***}	9.26^{***}	8.80^{***}	8.99^{***}	8.43^{**}	6.90^{***}	6.19^{***}	6.03^{***}	7.79^{***}	5.37^{***}	7.90^{*}
	(1.05)	(2.04)	(0.75)	(0.98)	(0.87)	(1.86)	(0.74)	(1.14)	(0.84)	(2.58)	(0.65)	(0.76)	(0.73)	(1.83)	(1.27)	(3.28)
Questions		−0.12		-0.12^{*}		−0.03		0.004		0.40		−0.05		0.02		0.03
		(0.07)		(0.05)		(0.08)		(0.08)		(0.29)		(0.03)		(0.04)		(0.06)
Answers		0.04		0.26^{***}		0.28^{*}		0.15^{*}		0.06		0.17^{*}		0.22		0.22
		(0.13)		(0.07)		(0.12)		(0.06)		(0.14)		(0.08)		(0.11)		(0.14)
Questions		−0.09		0.04		−0.01		−0.02		−0.16		0.02		−0.09		−0.03
		(0.08)		(0.05)		(0.08)		(0.04)		(0.09)		(0.04)		(0.06)		(0.11)
Comments		−0.05		−0.004		−0.04		−0.01		−0.06		−0.01		0.06		0.01
		(0.06)		(0.04)		(0.06)		(0.03)		(0.07)		(0.02)		(0.05)		(0.08)
Threads		−0.03		−0.02		−0.04		−0.01		−0.002		−0.01		0.02		0.02
		(0.03)		(0.02)		(0.03)		(0.01)		(0.03)		(0.01)		(0.02)		(0.03)
Status source		0.12		−0.05		0.02		0.02		0.20^{*}		−0.02		0.05		0.03
		(0.08)		(0.05)		(0.07)		(0.04)		(0.08)		(0.05)		(0.05)		(0.10)
Reply within day		−0.23		-0.35^{**}		-0.46^{*}		−0.11		−0.14		−0.11		−0.20		−0.24
		(0.15)		(0.13)		(0.21)		(0.12)		(0.19)		(0.10)		(0.20)		(0.23)
Answers accepted		0.09		−0.003		0.02		0.01^{***}		−0.003		0.01		−0.01		−0.003
		(0.06)		(0.03)		(0.06)		(0.002)		(0.02)		(0.01)		(0.02)		(0.002)
Time diff in answers		6.23		−2.18		−4.11		5.33		2.26		1.33		−4.34		
		(5.78)		(2.91)		(6.50)		(7.10)		(11.36)		(2.10)		(5.89)		
Constant	1.67^{***}	6.45	2.19^{***}	3.31	1.86^{***}	9.61	2.17^{***}	−2.94	1.44^{***}	−0.09	2.13^{***}	−1.21	2.24^{***}	-6.26^{*}	3.57^{***}	−4.05
	(0.39)	(7.35)	(0.26)	(4.07)	(0.31)	(6.47)	(0.28)	(3.53)	(0.31)	(5.85)	(0.24)	(2.31)	(0.35)	(2.52)	(0.90)	(6.49)
N	333	333	669	669	503	503	461	461	374	374	600	600	424	424	144	144
Adjusted R^2	0.30	0.36	0.25	0.29	0.16	0.19	0.19	0.22	0.11	0.14	0.14	0.17	0.09	0.24	0.09	0.29
Matched units (%)	0.25		0.50		0.39		0.41		0.40		0.51		0.49		0.18	
Lagged outcome | *Treatment* ($p-$values)																
Answers | Top 5%	0.23		0.16		0.16		0.35		0.37		0.27		0.59		0.70	
Accepted Answers | Top 5%	0.11		0.01		0.25		0.04		0.05		0.28		0.12		0.72	

Notes: Robust standard errors in parentheses. All regression models use weights defined by nearest-neighbor matching. Cohort indicators are included in all models with covariates but omitted on the table.

*p<0.05; **p<0.01; ***p<0.001

Once propensity scores are computed for each type of high-status crosser on Stack Overflow, I use nearest-neighbor matching (with replacement and up to 4 neighbors, when available), using the distance of propensity scores as guidance to find the nearest neighbors. Similarly to the main text, I include calipers for propensity scores, the lagged number of answers, and the lagged number of accepted answers, and I exact match on users' cohort years. I do not include calipers on the other pre-treatment variables to avoid reducing the sample size further (see table 3).

The findings confirm the main results from table 1 in the main text: crossing the top5% status threshold leads to more community contributions. This result holds across all users who cross the high-status threshold at different weeks. Nonetheless, we also observe some differences concerning table 1. First, causal estimates fluctuate more when the linear model includes statistical controls. For instance, users who cross the top 5% threshold at week 5 contribute 17 more answers than users who remain below the threshold when the model has no controls. This effect drops to 13 when the model adds all controls (the coefficient for these users reported in table 1 is 15). Instead, users who cross the high-status threshold at week 12 contribute 5 more answers according to the model without controls. When controls are included, the estimate increases to 8 more answers. This variation in the estimates likely occurs due to the imbalance produced by matching on the propensity score. Indeed, figure 18 shows that, while balance on the propensity score is significantly improved after matching in all cases, balance on other pre-treatment covariates does not improve as much and, in some cases, worsens. In any case, although coefficients for the treatment effect sometimes increase or decrease in table 3, the direction of the estimates always remains positive.

Second, we also observe that statistical significance suffers from propensity score match-

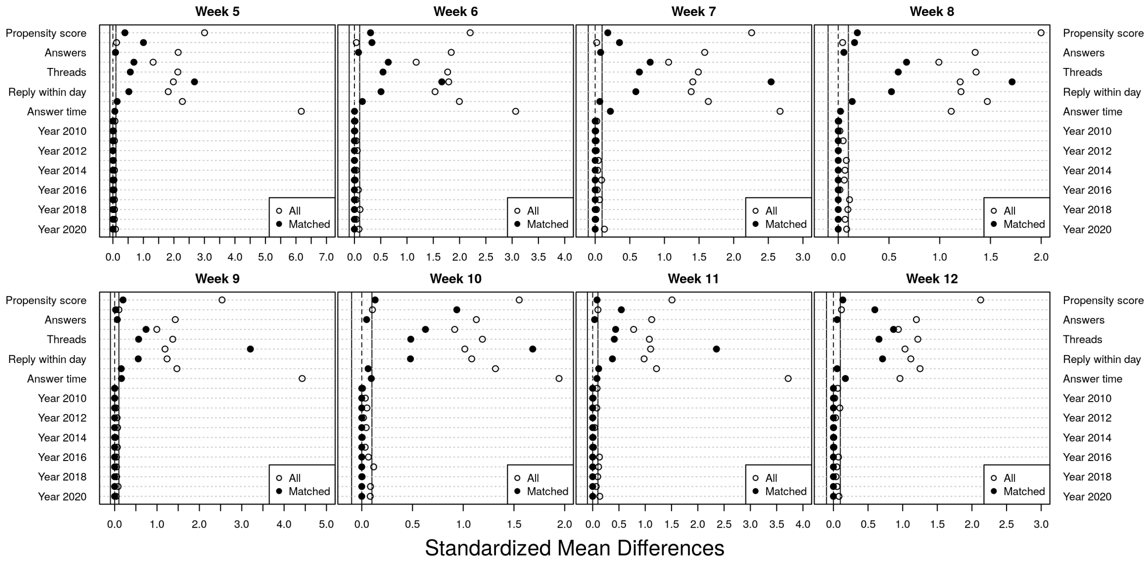

Figure 18: Covariate balance before (empty circles) and after matching (filled circles) for users who cross the top 5% threshold between weeks 5 and 12. Values are standardized mean differences in absolute value.

ing. The increment in the size of standard errors happens because the sample size is significantly reduced, meaning that most users who cross the top 5% threshold are now discarded. As revealed in table 3, matched units range between 18% and 50%. The fact that these results are similar to the results in the main text gives more credibility to the causal estimates in table 1 because this identification strategy was able to reproduce them with a sample of users with more internal validity.

This issue of statistical significance becomes more apparent in figure 19, which plots the effect of crossing the top 5% status threshold on cooperation over time. Confidence intervals are larger due to the reduced sample size for matches–this is especially salient among users who cross the high-status threshold at weeks 5 and 12, where the sample size after matching was the lowest. Again, findings are similar to those observed in figure 6, and the overall trend replicates in two ways. First, the earlier users cross the top 5% threshold, the more they contribute answers, as shown within each sub-panel of figure 19. Second, cooperation decays over time, indicating that high status cannot produce cooperative behavior that is sustained in the long run.

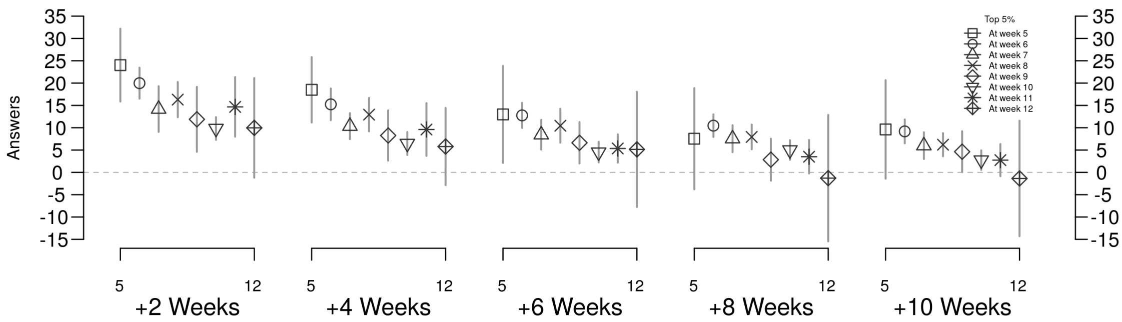

Figure 19: Treatment effect of high status on the total number of answers for users who cross the top 5% threshold between weeks 5 and 12. The effect is displayed by adding up biweekly answers contributed until 10 weeks after users become high-status. Results come from linear regressions with robust standard errors and weights defined by nearest-neighbor matching. Vertical vars represent 95% confidence intervals.