ABSTRACT

Title of dissertation: STATUS MOTIVATIONS:
CONSUMER AND SEEKER PERSPECTIVES

Robert Vesco, Doctor of Philosophy, 2017

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My dissertation includes two essays which examine status motivations from different perspectives. In the first essay, I explore the motivations of actors who are seeking to increase their status. In particular, when the competitive signals become opaque, how do their behaviors change? In the second essay I look at status motivations from the perspective of the consumers. In other words, what motivates actors and audiences to reward status? Ultimately, my aim with this dissertation is to extend our understanding of status beyond whether it has an effect and into understanding what is driving those effects. I also seek to highlight the importance of heterogeneity in status motivations since populations of people are unlikely to have homogeneous reasons for pursuing status.

The first essay examines how making the competitive environment opaque changes status-seekers productivity and prosocial behavior. While status competition is generally considered a positive force for increasing productivity, a growing body of research suggests it can have un-

intended consequences. However, the literature on status is largely divided on the motivations behind it. Management scholars tend to see status as an asset to be pursued as a means to an end while economists and psychologists focus on the ego needs associated with it. If these two groups of status-seekers react differently to changing incentives, and ex ante, we cannot identify these groups, then how can we interpret empirical results? To deal with this complexity I leverage an agent-based simulation that explores motive heterogeneity. I then exploit a natural experiment in an online community for technologists where status competition is decreased and then examine how low- versus high-status actors change their helpful behaviors and productivity. I find that productivity decreases with the less competitive (opaque) environment, but that only high-status actors decrease their helpful comments. I argue that the agent-based simulation suggests that this pattern of outcomes is likely due to the community having a heterogenous mixture of status-seekers since a homogenous community of either type of status-seeker would yield different results.

The second essay turns around the motivation lens to the status-consumers rather than to the status-seekers. Why do they value status? This study examines taste-based status motives. That is, motives which are independent of quality considerations. Among this class of status audience, theory suggests that they may either be interested in status intrinsically or that they value status as a form of conspicuous consumption, but few large-scale empirical studies have addressed these different motivations.

To address this challenge, I use a setting where audiences can reward high-status actors either anonymously or publicly. I find high-status actors receive a 60% increase in deference versus their low-status counterparts. However, I find no difference between anonymous or public deference. Thus, while my findings replicate prior work on quality-based status motives, I find no evidence of taste-based status motives. One possibility for this could be that my setting does not contain sizable cohorts of people who have a taste for status. Another possibility could be that a different empirical approach is needed to tease these differing motivations apart from one another.

STATUS MOTIVATIONS:
CONSUMER & SEEKER PERSPECTIVES

by

Robert Vesco

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Acknowledgments

I am frequently asked if I could go back in time, would I choose to do a PhD all over again. Absolutely, I say. The reasons for my response are simple. The pursuit of knowledge is one of the most beautiful, important and rewarding endeavors any human can undertake and a PhD concentrates all of that into a few short years. Few other opportunities in life provide such an experience. But these are not the only reasons why such an endeavor is worthwhile. It's also the people who join you on this journey who matter. Those people who push you to think deeper, explore farther and birth knowledge onto the world. Those people who came before you, who are traveling with you and the ones who will follow you after you are gone.

Because I do things differently, and happily so, I was very lucky to have two dissertation chairs: David Waguespack and Rajshree Agarwal. David was inspirational, not only to me, but also to many other students in the department for his focus on research design. While natural experiments were not a new concept to any student who took microeconomics, within the department, his questions frequently honed in on this topic. In short, he helped make research design "great again" as far as I'm concerned. You can see his influence not just in my work, but in many others who have had the privilege to read his papers and take his research methods class. And while Dave may not be the most talkative of the professors in the M&O department, his relaxed and open approach was always a complementary source of advice and wisdom.

Rajshree is a force of nature. Her infectious conviction of ideas, even if you don't always agree with them, were one of the highlights of my journey. But more importantly, she not only fought for her ideas but for her people. In a day in age where many relationships are transactional, Rajshree always made you feel like family. You weren't a stranger, but someone she cared about and would push to do better. As others have said before me, she would always reciprocate your actions and match your effort. If I left money on the table during my PhD, it would be that I didn't engage her as much as I should have. Anyone who follows in my footsteps should not make the same mistake.

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Introduction

My dissertation examines the motivations of status-seekers, and their audiences, status-consumers, in two essays. In management studies, the focus on status has largely involved treating it as an asset that can yield increased performance and better outcomes for individuals and organizations. On the consumer side of status, it is also generally viewed positively in the sense that status acts as a signal of quality, albeit a potentially biased one. But increasingly a more nuanced story of status is emerging that highlights how it may also result in negative externalities. Additionally, our understanding of why actors pursue status tends to differ greatly between disciplines. Bringing together these different streams of literature and perspectives to create a more complete portrait of status' role and consequences are a main theme of this dissertion.

In my first essay, the phenomena I explore is how a change in the competitive environment impacts prosocial behaviors. But predicting how such a change might impact those outcomes depends on several assumptions. The most important of these assumptions involves the motivations of the status-seekers since those motivations determine their incentive systems. While the vast amount of work in management takes the position that actors are pursuing status for resources, other scholars have argued that some people value status in and of itself. But the assumption that any population is comprised of just one type or another has large implications for what behavioral changes we might expect due to an intervention. My work combines those differing assumptions about status-seeking motives and models how outcomes might differ if we assume a continuum of them in the population.

My second essay tries to understand whether taste-based status motives are driven more by intrinsic value or conspicuous consumption. While some literature has highlighted the causal returns to taste-based status, efforts to distinguish the source of those returns is still nascent. This essay extends prior work by exploiting a situation where affiliations with high-status actors can either be anonymous or public. A preference for one type of affiliation or another would allow us to better understand the status motives of an audience who has taste-based preferences for status.

An inherent challenge in studying status is separating its effects from related constructs and unobserved sources of quality. Recent efforts to tackle these challenges through careful research designs have consistently shown that once these concerns are addressed, the effect size of status is typically not as strong as research has historically suggested. My dissertation attempts to deal with many of the common concerns found in prior work by exploiting exogenous sources of variance when possible. With tight measurement of status effects, we can then more fruitfully impute actor motives.

The theoretical challenge in the first essay involves trying to predict what should happen to prosocial behaviors when the environment for status competition becomes arguably less intense. In this study's setting this means that visibility into how well peers (competitors) are doing becomes obscured. Without the ability to see how well one is doing relative to others has typically shown to reduce competition among actors. Returning to the theory, on the one hand status competition is generally seen as a positive force that can get actors to work harder. However, increasingly research has shown that status competition may also have a dark side as exemplified by actions such as cheating and sabotage. Thus, simplistically, we might assume that a less competitive environment might reduce prosocial behaviors. However, heterogeneity stymies this view in several ways.

First, the motives of why people pursue status may differ in substantial ways. In general, two prominent motives have been identified in the literature. The first motive, as commonly implied in management literature, is the the desire to obtain status in order to gain competitive advantage. In this sense, status becomes a valuable asset like human capital or intellectual property rights. The other main motive described in the literature involves egotistical concerns. That is, some people may value status intrinsically – it is an end in and of itself. With this in mind, we ask again, how might a decrease in status competition affect those two types of actors differently? One might argue that the actors who pursue status for egotistical concerns would be most impacted while those who pursue status for resources will be less fazed. After all, it's not about the glory, it's about getting resources to pursue other goals.

But if actors are expected to react differently depending on their motives for pursuing status, it is also reasonable to ask whether low- versus high-status actors in each category would act differently. For example, if one's goal is to achieve high-status to get resources, what happens when they achieve their goal? Will they continue to be motivated? And will they become more or less prosocial depending on their standing? Take for instance Bill Gates or Michael Bloomberg. Both billionaires have a reputation for being fiercely competitive in their heyday, but today they spend their time supporting social causes and donating millions of dollars to charity. Thus it's reasonable to ask whether changes in the environment matters to people like them in comparison to those who are lower on a status hierarchy.

As detailed in the prior several paragraphs the contingencies mentioned above suggest at least three main concerns: motives, position in status hierachy and whether actors have intrinsically prosocial instincts. I deal with this complexity by utilizing an agent-based model to generate predictions by varying the proportion of certain types of status-seekers. In other words, I go from a population of purely ego-driven status-seekers and then add in resource-driven status-seekers until the population consists entirely of the latter. I draw empirical parameters, such as the number of low- and high-status actors, from the data. What these simulations give me are a set of outcomes that I can use to compare to quasi-experiment.

The quasi-experiment, by itself, asks a simple question: does hiding the public scores of peers (a decrease in status competition) increase or decrease prosocial behavior and does this differ between low- and high-status actors? Assuming my setup reasonably approximates a true experiment, the interpretation is simple. I find that high-status actors decrease their helpful comments but that both low- and high-status actors decrease their not-helpful commments. In total, the productivity of the community goes down as measured in counts of comments. But how should we interpret this finding? We could throw up our hands and say the data just are and not try to interpret the data. Alternatively, we could make the assumption that the population is comprised of homogenous actors with respect to their incentives. My approach is to interpret the results in light of the simulation I described above which derives from theory and the empirical setting. My ultimate conclusion is that the results we see would make sense only if the population consisted of both types of status-seekers.

In addition to the results mentioned above, there are several levels of insights this study contributes to. From a strategy and management perspective, a change to the competitive environment can have both positive and negative effects on productivity but also on the nature of productivity. In my setting, output was decreased as the competitive environment was made more opaque and high-status actors decreased their helpful comments while low-status actors did not. How important is it that we cater to high-status actors? How valuable are their contributions relative to low-status actors? What are the side effects of reduced prosocial behavior? From a theoretical perspective, I combine disparate views of status motivations to illustrate the complexity that can be found in almost all settings involving human beings. Even when we have a priori reasons to believe that heterogeneity of preferences exists in our populations we frequently assume homogenous preferences. This can have significant consequences on both our hypotheses and interpretations of results. Even a perfect experiment cannot save us from drawing the wrong conclusions if we don't specify our assumptions.

The question I examine in my second essay is whether taste-based motives are influenced more by intrinsic needs or conspicuous consumption ones. Since the latter requires third-parties to be present to observe affiliation, then any observed effect size of status will likely be strongly impact by the size and character of these third-parties. But as it stands, prior work has not delineated the broad sources of taste-based status – only that is exists independent from quality-based motives of status consumers.

I examine this question in a setting where status-consumers can affiliate with status-seekers either anonymously or publicly. I also use the fact that occasionally two actors in this community can submit exactly the same output. By fixing the quality of the output and controlling for differences in status and reputation any residual effects of status are more likely to be due to taste and accurately represent status effects.

The results are surprising in one sense. I find no evidence of taste-based status, but rather, evidence that suggests fairly strong status effects more consistent with quality-based status signaling. This is surprising because the setting for the study is well-known for having prominent third-party observers (i.e. journalists and investors) and actors compete for attention from them.

On the other hand, the vast majority of actors in this community may simply be interested in reading news submitted by their peers. If true, then the effect size from the taste-based actors could be too small to pick up.

While this study does not provide any evidence for question I sought to answer, it does replicate existing work in status. I find that status matters most for those members who are likely to have the most uncertainty about them. I draw this conclusion from the fact that when we define high-status at the lowest end of the spectrum, status effects are greatest. However, if we define high-status at an elite level, status effects are insignificant. This largely aligns with results from Azoulay et al (2014) who find status effects of prizes only for scholars at the lower end of the spectrum. High-status actors who receive a prize, actually have negative effects in their case. Likewise, Simcoe and Waguespack (2011) find status effects are greatest when uncertainty is greatest.

In sum, through my essays I sought to understand the motives of status-seekers and status-consumers. I sought to incorporate the heterogeneity and complexity through both empirical methods such as simulations and through theory by combining disparate literature's on status motives. I also attended to many of the methodological challenges in studying status by exploiting opportunities for exogenous variation in key constructs. The results are not novel from traditional standpoints, but their implications point to the great caution our field must take in crafting our data and hypotheses.

"For every complex problem there is an answer that is clear, simple, and wrong."

H. L. Mencken

Status competition and Prosocial Behaviors:

Helpful Comments Among Innovative Peers

INTRODUCTION

How does status competition and status-rank impact prosocial behaviors? In explaining why actors compete for status, prior researched has typically highlighted either prize-like resources (Merton, 1968) or ego concerns (Zuckerman and Sgourev, 2006) as the driving forces. A separate line of work examines the benefits and consequences of particular status positions (Bothner, Kim, and Smith, 2012; Simcoe and Waguespack, 2011a; Stuart, Hoang, and Hybels, 1999a). On average, status competition has been considered a positive force because it increases effort and innovation (Bothner, Podolny, and Smith, 2011; Merton, 1968). But more recently scholars have begun to explore how status competition might induce unproductive efforts like cheating and gaming (Charness, Masclet, and Villeval, 2013; Espeland and Sauder, 2007). However, prior work examining the unproductive effects of status competition has not considered heterogeneity in status-rank and status motives together. Nor has it considered its effects on prosocial behaviors.

This is surprising because we might expect resources associated with high-status to attenuate the effects of status competition. For instance, high-status actors may be able to help others more freely because they have the security and resources to do so. On the other hand, we know that some actors do not compete for resources, but rather, ego. Thus, even with resources, they may not help others if they do not perceive a benefit for doing so. These types of interactions point to the need to consider both status motives and status rank together. However, a key challenge in doing this is the fact that status motives are unobservable.

Scholars who have sought to explain prosocial behaviors have typically not considered status as a prominent predictor, but they have considered the interplay between types of incentives (Ryan and Deci, 2000). One type of incentive is external. For status seekers this means either the expected resources associated with a high-status position or information that allows one to satisfy their ego. Another type of incentive is internal. The implication of these types is that we may observe prosocial actions, but we cannot ascertain to what degree those actions were due to internal versus external incentives. Like status motives, internal incentives for prosocial behaviors are unobservable.

Work on prosocial behaviors has identified another challenge. It involves the fact that external incentives interact with internal ones in a non-linear and complex way. For instance, there is what is known as the "crowding-out" effect (Benabou and Tirole, 2006). This is where external incentives to induce, say prosocial behaviors, crowds-out internal motivations. An example would be paying people to do good deeds when they are already doing good deeds. Paying them may actually cause a decrease in good deeds, which is counter-intuitive, since we might expect an additive effect from external and internal incentives.

While scholars do not fully understand how the crowding-out effect works, there are several conditions under which we are likely to observe this effect[1]. First, an actor must have internal motivations for the prosocial behavior. If not, then there is nothing to crowd-out. Second,

[1] For a review see (Gneezy, Meier, and Rey-Biel, 2011)

external incentives must be relatively weak. Paying people a lot of money can overcome crowding-out effects. Third, within groups, heterogeneity in internal incentives could determine the degree to which this effect is observed.

The prior paragraphs have outlined a number of unobservable and complex interactions based on research in organizational status and prosocial behaviors. One approach that scholars might take to this complexity is to simply assume a particular status motive and declare that all observed prosocial behaviors are due to external incentives. Indeed some early theoretical and lab work did just that (Lerner and Tirole, 2002; Willer, 2009). But again, there is a lot of work, across disciplines, that suggests that prosocial behaviors are at least partially influenced by internal motives.

Another approach might be to select homogenous settings where all status competitors are likely to be driven by similar motives or design careful lab experiments. These approaches are very fruitful (Charness, Masclet, and Villeval, 2013; Kuhnen and Tymula, 2012). However, this approach would leave out many important settings where heterogenous motives are likely the norm such as academia, R&D labs, and open-source communities. In addition, in such settings high-status actors likely have resources that cannot be easily replicated in the lab. Resources that could impact their choices to engage in prosocial behaviors. In this paper, I develop an agent-based simulation that incorporates the complexity mentioned above along with features of my empirical setting.

I test the predictions of the simulations in a prominent community for high-technology entrepreneurs. In particular, in this community, entrepreneurs have the opportunity to provide helpful or non-helpful[2] comments on their peer's early-stage ideas. I conceive of these helpful

[2] Helpful comments contain specific, actionable information that can help move a project forward, such as identifying

comments as a form of prosocial behavior. These comments are themselves evaluated by peers. Good comments can be voted up and bad comments can be voted down. Over time, recognition from one's peers contributes to their status in the community which is a publicly visible score. This study exploits a quasi-experiment where in one period peer recognition for comments is publicly visible, but in the next, it is not. Importantly, recognition is still received, but it is only privately visible to the peer who receives it. Status visibility remains unchanged in both periods. Here, I define peer recognition as the flows of deference to status (stock of deference) (Podolny and Phillips, 1996).

Building on the premises and empirical context above, my simulation model assumes two worlds. One that is dominated by ego-based status-seekers and another that is dominated by resource-based status seekers whom I call *Egoists* and *Pragmatists* for simplicity. The key premises for *Egoists* are (a) they value peer recognition independent of resources, and (b) they are purely motivated by external incentives. In contrast, for *Pragmatists* the key premises are (a) they value peer recognition less as their status increases, and (b) they also have internal motivations to provide helpful comments. The key prediction for *Egoists* is that a shock to the *visibility* of peer recognition reduces their propensity to give any kind of comment, helpful or not. In contrast, *Pragmatists* differ depending on their status-rank. Low-status *Pragmatists* care about the shock more than high-status ones so the crowding-out effect due to peer recognition *visibility* is much greater. Thus, we observe a greater increase in helpful comments.

Empirical findings suggest that low-status peers reduce their non-helpful comments, but increase their helpful comments. In contrast, high-status peers reduce both types of comments.

a problem and/or solution. I use the term non-helpful comments to suggest that the alternative set of comments are not just "unhelpful", but may also include innocuous comments that are not counter-productive per se.

Thus, if the goal is to get high-status peers to provide helpful comments, more information will do so, but this will come at the cost of also increasing non-helpful comments. In contrast, if the goal is to get low-status actors to provide more helpful comments, then less status information will do so with the added benefit of decreasing noisy, non-helpful comments. However, when compared with the simulation predictions, these results are not consistent with a community consisting of just *Egoists* or just *Pragmatists*. Instead, the results appears more consistent with a mixed community.

I believe this contributes to the existing status literature in two ways. First, I examine prosocial behaviors as an outcome of status competition and find differences in how low versus high-status actors react to changes in peer recognition. Prior work had not addressed this outcome before. Second, I model how different types of status seekers might react to status competition. This allows for more nuanced predictions and assessment of the underlying heterogeneity.

The rest of the paper proceeds in the following way. First, the community and the experiment that occurred therein is described. Then, a model is developed based on both the description of the community as well as the key assumptions in the literature with respect to recognition and status. Following that, a description of the data and results are detailed. Lastly, it closes with a discussion and conclusion.

SETTING & EXPERIMENT

Social and Economic Relevance of Setting

Hacker News (HN) is formally an online community designed to allow hackers to share interesting news with fellow hackers or more broadly "anything that gratifies one's intellectual curiosity." Most of these "hackers", however, are either internet entrepreneurs or engineers for major Silicon

Valley companies such as Google and Facebook. But members also include a much broader group who are interested in technology such as academics, investors and media outlets. Today, Hacker News is the most prominent and influential technology community for internet entrepreneurs.

Hacker News was formed in 2005 and has risen to prominence for a number of reasons. First, it was founded by Paul Graham who also founded Y Combinator around the same time. Y Combinator is the most prominent and successful startup incubator in existence today. As of 2012, the combined value of its startups reached nearly $8 billion with notable alumni including AirBnB, DropBox, and Reddit. Most new accelerators and incubators started today are modeled on or inspired by Y Combinator (Miller, 2007a). Thus, Hacker News has benefitted from some of the "reflected glory" of its sister organization Y Combinator. Second, Hacker News has become a valuable source of information and innovation in its own right.

Early in its development Hacker News became a community to both learn from others and showcase early stage work. For instance, companies such as Dropbox first gained traction by previewing their work to their peers. They obtained valuable feedback while also gaining legitimacy and notoriety. Over time, major technology media outlets such as TechCrunch and venture capitalists began to follow and read Hacker News to find new talent and to stay on top of trends (Arrington, 2008a; Jeffries, 2011a; Wilson, 2009b). This made Hacker News not only a valuable source of information sharing, but also an important place to seek out funding and media attention.

Hacker News, despite is name, is not just a place to share news. It is also a place where technology entrepreneurs and innovators can present their early-stage projects in return for feedback from the community.

How Hacker News Works

Hacker News (HN) provides two main avenues by which members contribute. The first is through the submission of web links and questions. The second is through commenting on what others have submitted. And similar to how the academic community works, the quality of the materials submitted contributes to status and prestige of members in the community. This is achieved through a voting process that in some ways emulates citation counts. In addition to these votes contributing to a member's status, called "karma" on HN, it also helps identify high-quality information and filter out bad material and actors. For instance, highly voted submissions reach the front page of HN where the audience is the largest and lowly voted submissions can be obscured or even deleted.

Figure 1.1 illustrates what someone is first likely to see when he or she visits Hacker News. It is a simple list of links and titles along with information on who submitted it, the net number of votes it has received and the number of people that have commented on it. Figure 1.2 provides an example of what you would see if you click on "comments" under any of the links shown in Figure 1.1. This is where the discussion and intellectual debates happen. It is the equivalent of an academic seminar where any member is free to comment on the original material or the comments of others.

The first step in participating in Hacker News, beyond registering, is to submit a link or question. Figure 1.3 shows the options available to members at this step. The title, as for academic journal articles, is an important signal. The wrong titles can get you banned or ignored per the rules of Hacker News. But beyond that, the title allows a member to signal what they want from the community. For instance, an entrepreneur that wants to get feedback from the community on their idea should append "Show HN" to their title. It is important to note that even though HN actively moderates for tabloid-esque titles, it still provides for numerous opportunities to signal quality and there are important strategic considerations that can help entrepreneurs gain status within the community. Lastly, after the material is submitted, it is queued to the "new page" which looks exactly like the "front page" from Figure 1.1. This new page can be thought of as a kind of peer review process except that it is open to all members and it is always one link click away. Submissions that get a sufficient number of votes within a certain time period are promoted to the "front page". This is important because the front page provides the most visibility. Beyond submitting external web links to HN, commenting is the second way to contribute. Just like submissions, comments can be voted up and can contribute to one's status.

Over time, members contributing to HN via submissions and comments will see their status, or "karma", grow. Karma is approximately the sum of those two items. Figure 1.4 shows a user's profile page, which contains their karma score along with several other important items including their average karma score, when they created their account and their username. Moreover, there is an optional "about" section where members may include links to their businesses or personal websites.

The Experiment

The experiment involves an unexpected and unannounced change in the information available to members. Specifically, after April 20th 2011 members could no longer see how many votes fellow members received for their comments. Using the Internet Archive, `http://archive.org`, Figure 1.6 shows what comments looked like before and after the change. On the left hand side, panel (a), the recognition received is visible as a numerical score. However, on the right-hand side, panel (b), the same comment, but after treatment, the numerical score is no longer visible. It is important to note that members still receive information on how many people rated their comments[3]. However, this information is now private and this change in information is the treatment.

The assumption that this treatment was exogenous is important to be able to make any causal interpretations. There are two main facts that support this assumption. First, unlike many other changes made to Hacker News, this one was unannounced. Hacker News maintains an up-to-date page on major site changes but this major change is not listed[4]. Only existing members would have recognized that a change was made although the manager does make an informal post after the change is implemented. Figure 1.5 shows that pre-treatment period is relatively stable with respect to overall commenting, but post-treatment shows a slight and steady decline. If this were not exogenous we might not expect the decline to begin after the treatment.

The second fact that suggests that this was exogenous was that this was tried once before. The motivation of the experiment – from perspective of Hacker News' manager – was to see how this change in information would change member's behavior. A long time problem for HN and similar internet forums is the decorum of the conversation. In particular, the manager wanted to see if this experiment would make members less rude and aggressive. It is important to note that in 2009, the manager attempted a similar experiment , but it only lasted for a couple days because members voiced their displeasure at the removal of the information. However, in 2011, the manager implemented the experiment again and it remains in effect until this day. The important point here is that the implementation of the policy was not made in reaction to any emergent development on the website.

[3] While they know how much recognition they received, they do not know who gave them this recognition

[4] `https://news.ycombinator.com/newsnews.html`

While the motivation for the policy change, from the perspective of HN's manager, was to make members less aggressive, the purpose of this paper is to see how this change impacts the behavior of peers who give feedback to entrepreneurs and innovators. While the majority of submissions on HN involve the sharing of news, a subset of those submissions comes from early-stage startups and projects. These special posts are tagged with "Show HN" letting the community know that it is new. The norm and expectation is that members will give the submitter feedback on their idea or project. Figure 1.2 shows an example of "Show HN" submission. Note that an entrepreneur is showing off their new product, and in this case explicitly asking for feedback.

RESEARCH DESIGN

An ideal experiment would be for some members of the Hacker News community to lose visibility of peer recognition, but for other to keep it. A canonical difference-in-difference estimation technique could then be used to look at the impact of visibility on outcomes. However, in this setting I do not have a control group. A second best alternative would be to identify a plausible synthetic control group. A prominent candidate would have been Reddit's startup subreddit [5]. However, at the time of the intervention, April 2011, this particular community was too small and just starting off.

As such the research design for this paper is pre/post with individual level fixed effects. The exogeneity and undisclosed nature of the intervention means that selection into the community in anticipation of the treatment is likely to be low, but selection in and out post-treatment would be hard to account for. As such, this study focuses on individuals who were in both the pre- and post-

[5] Reddit is one of the world's most trafficked websites. The startup section `http://www.reddit.com/r/startups` is similar in nature to Hacker News.

treatment sampling periods. The exogeneity of the event also means it's unlikely to be correlated with most alternative explanations (i.e. reciprocity).

Another, challenge with the design is since there is no control group, maturational effects and other external shocks to the community could be a problem. Per Shadish, Cook, and Campbell, (2002) the approach I take is to limit the window around the intervention to 30 days +/-. This minimizes maturational effects (i.e. changes in culture, learning) and the possibility that other events would change the behavior of members. I also manually checked to make sure no other interventions occurred during this time period.

THEORY & MODEL

The purpose of this study is to understand how an exogenous change in the visibility of peer recognition impacts helpful commenting behaviors. In the empirical context of this study this means observing how the number of helpful versus non-helpful comments to innovative ideas change. In this section I develop a simulation model that approximates my research design and setting. I use this to generate predictions of effects caused by the change in visibility. To build out the logic of my model, I first describe the main theoretical assumptions. I then proceed through the steps of the model. I close with describing predictions that could be generated from making different assumptions about motivations of actors.

Assumptions and Model

Key Assumptions and Definitions

1. Extrinsic and Intrinsic Motivations; Altruism and Selfishness

Intrinsic motives are internal to actors and reflect the fact some activities provide inherent enjoyment without the need for external compensation (Ryan and Deci, 2000). With respect to helpful behaviors the argument is that individuals either perceive external incentives for being helpful or they are intrinsically motivated via altruistic preferences[6]. A well documented fact is that under certain circumstances, external incentives can "crowd-out" internal motivations such as helpfulness (Deci, Koestner, and Ryan, 1999; Gneezy, Meier, and Rey-Biel, 2011). However, this effect is conditional. One condition concerns the heterogeneity of individuals with respect to their motivations (Andreoni and Miller, 2002) both within and between them. For instance, if individuals are pursuing an action entirely for external incentives, then adding additional extrinsic incentives will not crowd out intrinsic motivations because none exist. Beyond heterogeneity that may exist within people, groups may consist of people who are more or less altruistic. The implication of this is that incentives may have different average effects depending on the types of individual who have selected into a group (Meier, 2007).

Assumption 1. *Conditional on existing intrinsic motivations for an action, extrinsic incentives can crowd-out intrinsic motivation*

I argue that given the diversity of reasons and people who participate in Hacker News (see prior section), the following is also likely to hold

Assumption 2. *The empirical setting consists of peers with heterogenous motives for participating and helping*

[6] In this paper, I focus on "impure" altruism. This means the helpful person enjoys it regardless of whether it is perceived helpful by the recipient

2. Ability, Peer Recognition and Status

In many setting, status is often conceived as one's position (rank) in a hierarchy that comes from accumulated deference (Goode, 1978; Sorenson, 2013a). Status is important in many settings because it has the ability to influence judgments about the quality of products and actions independent of a product's actual quality (Simcoe and Waguespack, 2011a; Stuart, Hoang, and Hybels, 1999a). But in addition to biasing perceptions (or reducing uncertainty), high-status members of communities may gain disportionate deference and access to resources known as cumulative advantage (Merton, 1968).

Given the importance of status in obtaining resources and changing quality perceptions, scholars have sought to understand its underlying mechanisms and true effects. Status effects are most likely to occur when there is uncertainty regarding actors/products (Podolny, 1993a) or taste-based concerns (Malter, 2014a). The reason for this is due to an endogenous process that develops where quality assessments depend on status, but status is a function of quality assessments (Podolny and Phillips, 1996). However, this relationship is further complicated by the fact that high ability actors are likely to both be perceived as higher quality but also able to produce higher quality goods. Recently, a number of scholars have exploited a series of natural experiments to determine the true effect of status. Their finding suggests that indeed status effects exist but that they are likely less significant than most scholars believe (Azoulay, Stuart, and Wang, 2012a; Malter, 2014a; Simcoe and Waguespack, 2011a).

I argue that the Hacker News setting has features that are likely to engender the endogenous process mentioned above. First, actors (peers) in this community are writing comments that are difficult to assess objectively (i.e. what is a good comment?). Second, actors are often unknown and they must develop their identity through the comments and submissions they make. Thus, in order to improve their status in the community they need to write comments that their peers will hopefully like. However, their peers are likely to be influenced by the focal actor's status (because comment quality is hard to assess). Lastly, status in the community, as measured by the publicly visible karma score of each actor, is essentially a cumulative function of peer recognition. This means it maps closely to the notion that status is a stock of deference flows. Thus, considering these factors I believe the setting is such that

Assumption 3. *Ability is correlated with comment quality and status*

Assumption 4. *Higher status results in greater peer recognition for a given quality level*

Assumption 5. *High-status actors have greater resources than low-status ones*

3. Motivations for Status

The explanations for why actors pursue status generating activities generally falls into two categories. The first states that rewards associated with high-status motivates efforts (Bothner, Podolny, and Smith, 2011; Merton, 1968). Thus, in contexts like Hacker News and other innovative communities, actors may pursue peer recognition because they believe that obtaining status in the community is valuable. For instance, it may allow them to gain attention and notoriety which they can leverage for their future projects. In contrast to resource pursuit, the second reason actors may pursue peer recognition and status is that they value those items as an end in and of themselves (Kuhnen and Tymula, 2012; Zuckerman and Sgourev, 2006). For simplicity, I will refer to those who pursue status for its potential resources, and as a means to an end, as *Pragmatists* and those who pursue it because they value it as and end *Egoists* [7].

Existing research has tended to focus on one of these two motivations for status seeking, but rarely have they been considered together. This seems odd given that heterogeneity of motives and preferences is likely to be the rule rather than the exception in most contexts. And if indeed actors are pursuing status for different reasons, than per Assumption 1, we can expect changes in the incentive structure to impact *Pragmatists* differently than *Egoists* since one pursues status for intrinsic reasons and the other for extrinsic ones. I argue that the context of study is likely to have both types of status seekers since not all members of Hacker News are trying to start their own startups.

Assumption 6. *Pragmatists seek status for its potential rewards. To them, status is a means to an end. Egoists seek status because they value the deference of peers. For them, status is the end.*

Since *Pragmatists* seek status for its potential rewards, the value of peer recognition is a function of those rewards. In particular, if we believe that high-status comes with rewards and access to resources, then for at least some subset of *Pragmatists* they may no longer need to court the affections of their peers. Peer recognition is an extrinsic motivator whose value decreases as resources to the focal actor increases. Thus,

Assumption 7. *Once a certain level of status is reached, say high-status,* Pragmatists *will place less value on peer recognition*

In contrast, *Egoists*, value peer recognition and status because those items reflect how peers

[7] The term egoist is often used to describe actors who care about their self-esteem. And in particular, the relative deference and standing they receive from their peers.

feel about them. Thus, the resources associated with high status do not change the value *Egoists* place on either.

Assumption 8. Egoists *value peer recognition and status independent of status rank and resources*

4. Visibility of Peer Recognition

Organizations and third-parties certifiers have long sought to measure the performance and rank of its target actors. Accountability and learning are the typical motives involved with these measurement activities. More recently researchers have sought to understand how varying the information available to measured actors changes their behavior (Chatterji and Toffel, 2010; Sauder and Espeland, 2009). For instance, does giving actors their rank and performance information privately affect them differently than if the information is publicly available to all? How do relative vs absolute measures affect behavior differently? The general finding from experimental and field studies is that performance information increases effort and particularly among those at the top of a performance hierarchy [8]. Importantly, this behavior holds even for fixed-wage environments where actors get no additional pecuniary rewards for increased effort (Kuhnen and Tymula, 2012).

In addition to increasing effort, a few studies have documented side effects associated with introducing information. In some studies, actors may engage in sabotage or efforts to "game" the system (Charness, Masclet, and Villeval, 2013; Espeland and Sauder, 2007). In other words, rather than improving performance through expected means, actor switch their actions to alternative behaviors which may provide them with cheaper ways to improve their

[8] For an exception see (Barankay, 2012)

performance and rank.

In this study I conceive of the peer recognition that members get as a type of performance. As mentioned previously, the manager of Hacker News explicitly setup a system so as to track the performance of members and to generate a publicly available status measure. Moreover, in April 2011, the manager changed the visibility of the comment scores from public to private. I argue that without this publicly available information members will be less competitive. By competitive I mean they will try to outperform their peers with respect to attaining peer recognition.

Assumption 9. *The public visibility of peer recognition (performance) information increases competitive preferences.*

Additionally, I assume that in the public information regime, peers will observe each other and choose actions that allow them to most easily match their peers.

Assumption 10. *Increasing competition for relative performance increases a switch to actions that have higher likelihood of increasing performance*

Lastly, because the effort being expended is a function of an external incentive

Assumption 11. *Public peer recognition is an extrinsic motivator distinct from private peer recognition*

5. Helpful Comments vs Non-helpful Comments

   The main outcome in this study involves a change in helpful and non-helpful comments. Helpful comments are defined as comments that contain specific and actionable information that can be used by innovators[9, 10] (Nelson and Schunn, 2009). For instance, comments that identify problems with the idea and/or provide solutions and suggestions are considered helpful. In contrast, comments that merely say things such as “great job” or that are attempts to show off are considered non-helpful. To be clear, these definitions are descriptive, not normative. Thus, a comment that is helpful may not be right or useful. It is up to the innovator to decide whether the suggestion makes sense.

The position this paper takes is that the supply of comments is constrained by ability, fit, and knowledge. Assuming peers lack knowledge in every domain that their feedbacks-seeking peers are working in, the ability to provide helpful comments is constrained by the fit between the idea’s knowledge space and the commenter’s. For instance, a peer who has deep knowledge of music will be less able, on average, to provide a helpful comment about web design than a peer who has extensive experience about web design. However, since non-helpful comments can be about any topic, there is less constraint on them being made. Table 1.3 shows both the high points helpful comments receive as well as the fact that there are fewer of them, than non-helpful comments. Moreover, while helpful comments may be costlier to write in terms of length, see Figure 1.7, we might expect that, conditional on having knowledge about the domain, it is easier to write high-quality, helpful comments than non-helpful ones.

Assumption 12. *Conditional on having fit with the feedback seekers knowledge domain, helpful comments are easier to write and get recognition for.*

Lastly, I assume *Pragmatists* have some degree of intrinsic interest in both helpful and non-

[9] There are other dimensions of "helpfulness" not explored in this study such as motivation and reinforcement
[10] The organizational behavior literature calls this "advice-seeking"

helpful comments that is independent of their need to acquire status. Further, I take *Pragmatists* to have intrinsic helpfulness greater than intrinsic non-helpfulness. To the degree that members of the community chose to read about their peers' ideas when they could have been commenting about other types of submissions, this seems reasonable. In contrast, *Egoists*, choose to make helpful or non-helpful comments to the degree that they believe one or another will maximize the recognition they will receive from peers.

Assumption 13. *Pragmatists have intrinsic interest in making helpful comments and non-helpful ones. Their intrinsic interest in helpful comments is greater than for non-helpful ones.*

Assumption 14. *Egoists have no intrinsic interest in either helpful or non-helpful comments.*

Model

The goal of the model is to approximate the setting in a way that is consistent with the pre-treatment period in order to make predictions about how the actors will change their behavior post-treatment. First, I describe the key components of the model, then I describe steps. After that, I detail what is happening in each step and the main assumptions used in each one.

I assume there are T time periods where, for simplicity, one idea is introduced with each $t \in T$. The number of peers evaluating each idea is N. They enter each idea in a random order o. That is, peer i may be the first observer in one period but the last in another. The simulation begins at $T_s - T/2$ where T_s is the time of the treament/shock and proceeds until T. Lastly, there are two peer types $q \in \{\text{pragmatist}, \text{egoist}\}$.

Step 0 Peers "agents" are given characteristics

Step 1 A round t begins with an innovator seeking feedback on their idea

Step 2 Peer i, from a set of N, arrives at idea at order o

Step 3 Peer i makes a prediction of how much recognition he could get for each comment type

Step 4 Based on expected benefits, peer i chooses to give a helpful, unhelpful or no comment

Step 5 This process repeats until all peers have made a decision about how to respond

Step 6 Peers update their information; A round completes

Step 7 After half the rounds have completed, the treatment is introduced

Step 8 Process repeats until the remaining rounds have completed

1. Step 0

   Prior to the simulation beginning, peers need to be given properties, such as ability and status. The goal for this simulation was to use theory and actual data to populate agent histories as much as possible. So for instance, I assume a normal distribution of ability that is then mapped to status, following Assumption 3, so that it approximates the status distribution in the community (see Figure 7). A detailed discussion of these choices and parameter settings are in the appendix.

2. Steps 1 and 2

   I presume that new ideas are entering the system at random with some normal distribution of quality. I presume the treatment has no impact on the decision to submit ideas and that they are equal, on average, pre- and post-treament. Empirical evidence from Hacker News suggests no change in the rate at which ideas are introduced.

Once an idea is submitted, n peers visit the idea in random order o for each round in T [11].

3. Step 3

Once peer i arrives to an idea t at order o, they need to make a decision about whether to make comment type $k \in \{\text{non-helpful(NH), helpful(H)}\}$. I presume they first make a judgment about how much peer recognition they might get for each comment type as described by

$$P_{k,i,t} = (\bar{P}_{k,i,t} + \epsilon_{k,i,t}) S_{\Delta,i,t} \beta(\epsilon_{H,i,t}) \tag{1.1}$$

The primary component of the term above suggests that judgments about potential peer recognition are a function of average performance, $\bar{P}_{k,i,t}$, plus some random fit, $\epsilon_{k,i,t}$. This baseline assessment assumes peers expect to get something similar to their past performance (Greve, 2002) with some adjustment for the particular idea at hand. On top of this, the assessment is weighted by the increase in relative status of the peer per Assumption 4. Another weight, β, involves the order that a peer enters the idea. On Hacker News, ideas are only discussed for a short period of time before they are eclipsed by other more popular ideas and submissions. Those peers who arrive late will receive fewer votes because most of the other peers have already moved on. Lastly, per Assumption 12, the potential for helpful comments is constrained by the knowledge of the peer. $\epsilon_{H,i,t}$ represents a Bernoulli distribution where there exists some probability that a peer can provide a helpful comment based on distance in knowledge space. This is equal to 1 when the peer has the potential to provide a helpful comment and 0 otherwise. This constraint does not exist for non helpful comments.

For the status weight, $S_{\Delta,i,t}$, I implement Assumption 4 so that peer i adjusts his expected

[11] In reality, there may exist strategic actors, but for simplicity, I do not model this behavior.

peer recognition by the change in the status level between periods scaled by the max status in the community at time t.

$$S_{\Delta,i,t} = 1 + \theta \frac{S_t - S_{t-1}}{S_{max,t}} \tag{1.2}$$

Here, θ represents the max premium "cumulative advantage" that high status actors could receive where $\theta \in [0, 1)$.

Lastly, I conceive of the β weight in the following way.

$$\beta = \frac{n - m_o}{n} \tag{1.3}$$

Peers who enter the round late will have a smaller audience available to view their comments, and moreover, their comments may be redundant as many other peers may have made the same comments. Here m_o means the number of comments that came before peer i, and n is the total possible number of comments in a round.

Lastly, per Assumptions 9 and 11, I argue that when peer recognition is visible, $T_t < T_s$, peer i makes an additional effort to compete with peers[12] that is described by this equation.

$$P_{\Delta k,i,t} = (A_{k,i}\rho_k)(\beta)(\epsilon_{H,i,t})V_{t<s} \tag{1.4}$$

$A_{k,i} \in [0, 1)$ represents an ability parameter, drawn from a normal distribution, weighted by a point factor. ρ_k is the maximum points that can be reached for a particular kind of

[12] An alternative specification would be to consider "reference points" where if projections fell below a certain aspiration level, efforts would increase. For simplicity, I assume all agents increase effort relative to their abilities

comment. I assume $\rho_H < \rho_{NH}$, so this implies high ability, say $A_{H,i} = 1$ can only achieve a max point increase above the base estimation of ρ_H. Thus, ability limits the competitive capabilities of peers which is further limited by the type of comment. $V_{t<s}$ is an indicator variable that is equal to 1 when peer recognition is visible. The remaining terms are defined as before.

4. Step 4

After peer i has determined what it is likely to receive for each comment type, it makes an assessment of the benefits that each choice brings. The choice that brings the most benefits is chosen. The following equation represents the benefits function.

$$B_{i,t} = \begin{cases} \xi & \text{if no comment,} \\ \\ Pwt_{k,i,t} + Pwt_{\Delta k,i,t}V_{t<s} + Iwt_{q,k,i,t} & \text{if comment} \end{cases} \tag{1.5}$$

$Pwt_{k,i,t}$ is equivalent to $P_{k,i,t} - P_{k,i,t}S_{B,i,t}$ which represents the estimated points for a comment type minus those same points weighted by an increasing function in status $S_{B,q,i,t}$. For q = pragmatists, this status function increases, after a threshhold of “high status” is reached. At the very highest levels of status, this implies *Pragmatists* no longer value peer recognition. Per Assumption 8, *Egoists* experience no decrease in the value of peer recognition, so $S_B = 0$. The same idea holds for $Pwt_{\Delta k,i,t}$ which are the points motivated by peer recognition visibility.

$Iwt_{q,k,i,t}$ is the intrinsic/extrinsic crowd-out/crowd-in term. It will increase the value of intrinsic interest for a comment type as extrinsic interests decrease. Per Assumption 14, *Egoists* only have extrinsic interest in peer recognition and status, so there is nothing to crowd out for them. However, for *Pragmatists* $I_H > I_{NH}$ and I comes from a non-negative, truncated normal distribution. The full term is described with this equation.

$$Iwt_{q,k,i,t} = I_{q,k,i,t}S_{B,q,i,t} + I_{q,k,i,t}(1 - S_{B,q,i,t})(1 - V_{s<t}) \tag{1.6}$$

I assume the value from not making a comment, ξ, is small with a truncated, non-negative, normal distribution. This could be considered the utility peers receive for simply reading comments.

5. Steps 5 and 6

   After all peers have made their choices for round T. They update their information such as average performance, status and so on. For simplicity, I assume peers are more or less right in their assessments with some random error.

6. Steps 7 and 8

   At this point $V_{t=s}$ from equation (5) in Step 4 switches from 1 to 0. This essentially turns off the competitive behavior of the actors since they can no longer compare their scores with those of their peers. The rounds continue until t reaches T.

Predictions

Status Seeking for Resources (Pragmatists)

Pragmatists seek peer recognition because they believe high status will get them resources that they otherwise may not have access to. The main way I operationalize this type of actor is by assuming that as their status reaches a certain threshold, the value they receive from peer recognition decreases, but the value from their intrisic motivations increase. Thus, once they have achieved their status "goal" their reasons for participating will be based solely on their intrinsic interests in providing helpful comments [13]. Additionally, I assume that when peer recognition is public, these actors are motivated to compete and will exert more effort to signal to others their competence. However, as their status increases, the value from competing also decreases.

Figure 1.8 shows how low vs. high-status actors change their commenting behaviors given the mechanisms described. Low-status actors increase both their helpful and non-helpful comments since some of their intrinsic interests are substituted. In contrast, high-status actors change their commenting behaviors very little since they are already following their intrinsic interests.

Status Seeking for Recognition (Egoists)

An alternative view of status motivation is that invividuals are motivated to pursue it because they desire to be well-regarded by their peers and others. Like *Pragmatists*, *Egoists* are more competitive and exert more effort when they can observe the recognition received by others. However,

[13] In reality, we might expect such actors to exit the community. In this model, I assume all actors stay. Moreover, in some communities, actors may require ongoing resources, so as long as they do, they will still have a residual need to appease their peers

unlike *Pragmatists*, I assume that they have no intrinsic motivation for commenting and that their value for peer recognition remains constant with respect to status. Thus, when the visibility regime changes they are less incentivized to pursue all kinds of activities. This holds for both low and high status *Egoists*. This can be observed by Figure 1.9.

Heterogenous Actors - Pragmatists and Egoists

While two common views of status motives are represented by *Pragmatists* and *Egotists*, it is possible that both types of actors are present in a community of peers. If this is true, then the observational patterns we observe should roughly be a function of the two types. [14] Figure 1.10 illustrates what this could look like assuming a continuum between *Egoists* and *Pragmatists*.

DATA

Hacker New Data & Empirical Sample

Individual level data on all participants of Hacker News was collected between 2007 and 2011 using their API (application programming interface). This data includes every comment and submission made by members along with associated time stamps and the points they received. This allows reconstructions of many of the key variables discussed in the context section, such as karma (status). Importantly, private peer recognition scores for comments are available in both the pre- and post-treatment periods even though on the Hacker News website they are obscured in the post-treatment period.

As discussed in the research design section, this study uses a pre- post- design, also

[14] However, there could also be unique interactions between different kinds of actors, but this is not modelled.

called an interrupted time-series approach. While a canonical difference-in-difference methodology would be preferable, this is a second-best approach. As such, I chose a 30 day window around the treatment date (60 days total) from which to sample the data. Since pre-post designs are unable to control for maturational effect or alternative shocks, restricting the sample around the event minimizes the probability of having spurious effects.

Within this +/- 30 day window, a random sample was chosen so that comments could be labelled as either helpful or non-helpful. This was accomplished by randomly selecting a submission id, among the "Show HN" type submissions between the pre- and post-periods. Then all comments associated with that submission were coded using Amazon Turk. This process continued until the money budgeted for coding the comments ran out. This resulted in approximately 80 submissions pre- and post-treatment along with approximately 3000 comments.

Another limitation of the empirical design is that it is difficult to know whether a member of the community selected out or in the post-treatment period due to the treatment. Thus, the ultimate empirical sample is conditional on individuals being in both the pre- and post-treatment periods. This reduces the sample to 128 individuals who commented at least once in each time period. Table 1.1 provides a list of variable definitions and Table 1.2 provides descriptives for the final estimation sample described above.

Measurement

Helpful and non-helpful comments are the main dependent variables of interest in Table 1.2. All Comment Types are total count of comments across the two types. Helpful and non-helpful comments were coded using Amazon Turk where if 3 out of 4 Amazon Turk reviewers graded a comment as Helpful, it was accepted as such. If there was no agreement, then the comment was randomly assigned to being either helpful or non-helpful. The definition of a Helpful comment was one that contained specific and actionable information such as a problem or solution that the innovator could act on. Comments such as "that's great" or "that's bad" were treated as non-helpful comments regardless of their intention or tone.

Peer recognition is the main treatment variable where 0 represents the public, pre-treatment regime and 1 represents the private, post-treatment one. As before, after treatment, peers can no longer see the peer recognition scores for other members, but they can still see the recognition they received from others[15].

High-status 90th and High-status 95th are indicator variables that represent high-status members above the 90th and 95th percentile rank of all karma scores[16] at the time of the intervention. These two percentiles were chosen to show the sensitivity of outcomes to various definitions of "high-status" while also simplifying interpretation. In addition, the rankings were constructed using active members from the prior 3 months. The rationale for this was that most members of Hacker News only comment a few times and have very low-status. To the degree that members generate judgments about other members it is likely to be around those who have been active for some period of time. More concretely, I interpret a member's rank as a function of the karma scores of active members and not all members who may not have stopped participating a long time ago [17].

[15] While they can see the amount of peer recognition they received from others, they cannot see who gave them said recognition. Hence, peer recognition is anonymous.
[16] Karma is the approximately the sum of points across comments and submissions.
[17] One challenge with status rankings in general is how to count inactive or dead members.

Statistical Strategy

The goal of the study to understand the change in commenting behavior for helpful and non-helpful comments with respect to peer recognition visibility and commenter status. More specifically, I wish to examine if high-status actors change their helpfulness differently than low-status ones. Per the section on the experiment and research design, I assume the change in peer recognition visibility is exogenous and uncorrelated with relevant unobservables.

Equation 1.7 is the empirical model used to estimate effects. Since the dependent variables are counts and because I employ individual-level fixed effects, I use a Poisson quasi maximum-likelihood estimator. This estimator is particularly appropriate for count data and has a number of robustness properties. In particular, it is capable of standard errors that are robust to arbitrary serial correlation.

In this model i indexes the individuals and t indexes the public vs private peer recognition regimes. β_1 measures the effect of a change in the peer recognition regime. Specifically, the change in the count of comments once the scores on them become private. Since *High-Status* is an indicator variable and because I am using a fixed effects model, β_2 drops out of the equation for main effects of the interaction model. β_3 represents the effect on counts of comments for high-status actors in the private, post-treatment regime.

$$Y_{i,t} = \exp(\beta_1 \text{PrivateCommentScores}_t + \beta_2 \text{Status}_i + \beta_3 \text{PrivateCommentScores}_t \text{xStatus}_i + \gamma_{it} + \epsilon_{it}) \tag{1.7}$$

RESULTS

Table 1.5 presents the main results. The table is broken into two sets. The first set, Columns (1)-(4), uses a definition of high-status that indicates individuals in the top 5 percentile rank for status whereas for the second set, Columns (5)-(8), represents a broader, top 10 percentile rank cutoff. All models are estimated with a Poisson QML fixed-effects estimators with cluster robust standard errors.

Columns (1) and (2) examine the impact on helpful comments. Column (1) suggests that obscuring peer recognition, by making comment scores private, has no effect on helpful commenting. Column 2 suggests that there is heterogeneity depending on a member's status level. To interpret the interaction Hilbe, (2011), we need to exponeniate *Private Peer Recognition* and the interaction itself, so $\exp(.250 - .647) = .673$. This can be interpretated as among high-status actors, those in private peer recognition regime, they provide helpful comments 33% less often than those in the public peer recognition regime. To understand the impact on low-status actors, we exponeniate the *Private Peer Recognition* coefficient $\exp(.25) = 1.28$. This suggests that low-status members are 28% more likely to provide helpful comments when peer recognition is private. Columns (3) and (4) examine the impact on non-helpful comments. Here column (3) suggests that, overall, members are 35% less likely to provide non-helpful comments in the private regime. However, Column (4) implies that among groups, there is no significant effect. Columns (5)-(8) replicate the first four models, but with a broader definition of high-status. The results are qualitatively the same.

While the main goal of the paper is to understand the impacts on helpful and non-helpful comments, I also include Table 1.4 which looks at the effects on all comments, regardless of type. Column (1) suggests that the change in the visibility of peer recognition has no effect on commenting counts. Column (2) shows that there is a slight decrease in total commenting by high-status peer in comparison to low-status peers. With respect to lab studies testing the visibility of status signals, this replicates the fact that high-status actors are more likely to be motivated by seeing others' peer recognition scores (Charness, Masclet, and Villeval, 2013; Kuhnen and Tymula, 2012), but it does not see an overall change in productivity, unlike some prior lab experiments.

DISCUSSION & CONCLUSION

Understanding how incentives shape, positively or negatively, the disposition of peers to provide helpful comments could have important spillover effects to the innovation process in peer communities. Whereas existing research tends to assume status-seekers have a singular motive, either that they seek resources (*Pragmatists*) or deference (*Egoists*), I argue that considering both motives is important for making behavioral predictions. Through a simulation, I predict what changes to helpful comments are likely to look like assuming groups of homogenous *and* heterogenous peers. Evidence appears more consistent with the assumption that this particular community may be comprised of peers with heterogenous motives (i.e. both *Pragmatists* and *Egoists*).

The study contributes to the literature on status in several ways. First, it considers how status differences are associated with helpful behaviors amongst peers, whereas the typical focus is on direct or team-based performance. Second, it combines different assumptions about status-seeking that are typically not considered together and shows how they can lead to different predictions. While some scholars have emphasized ego-based motives (Goode, 1978; Zuckerman and Sgourev, 2006) for status seeking, others have tended to highlight resource considerations

(Merton, 1968). Third, while lab studies and field studies have examined how status rank visibility impacts behaviors, this study looks at how a shock to peer recognition visibility, an input to status, impacts behaviors.

These results also contribute to a stream of literature on prosocial behaviors where status concerns have not been actively theorized. In particular, how resources associated with status may enable or constrain certain kinds of prosocial behaviors. For instance, one of the puzzles in this literature is why people decrease or increase their prosocial behavior over time. Considering resource constraints imposed by status concerns could be one possible explanation not usually considered.

While the model developed here was particularized, the general concepts are applicable to other knowledge communities where peers compete for recognition and status. Overall, we should expect some subset of the population to change their behavior as resources enable them to pursue their intrinsic motivations with no distractions. Another subset of the population is likely to remain motivated despite their status and resources.

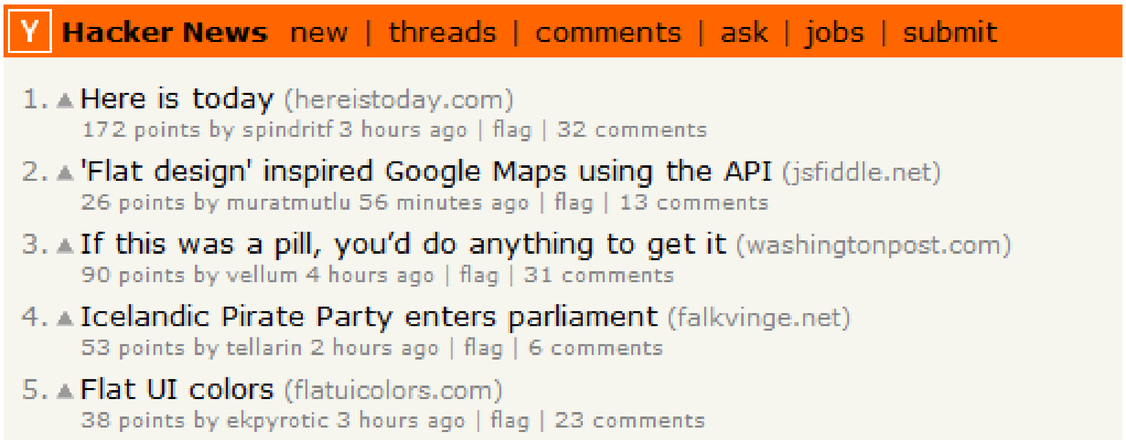
While the exogenous shock to the visibility of peer recognition provides some protections against alternative explanations for changes in helpful behavior, my research design has a number of limitations. First, in some sense these are short-term effects. Given that peers can no longer observe which comments get rewards and which get penalized this could impact norms in the long-run which in turn could impact the relative prices for helpful and non-helpful comments. Second, I am not able to say anything reliable about selection effects which would be interesting. Who chooses to leave the community?

While I have assumed that *Egoists* and *Pragmatists* exist in the community, I cannot identify who those people are *ex ante*. While on the one hand, this would allow a better test of the theory, it would face a number of challenges. For instance, *Egoists* may not admit, or realize, they are driven primarily by desires for peer recognition.

There are a number of useful extensions that could be considered for this model. For example, in a winner-takes-all settings, where failure to gain entry to high-status roles means exiting, we might imagine profound changes to helpfulness and perhaps even malice, around the high-status mark.

FIGURES

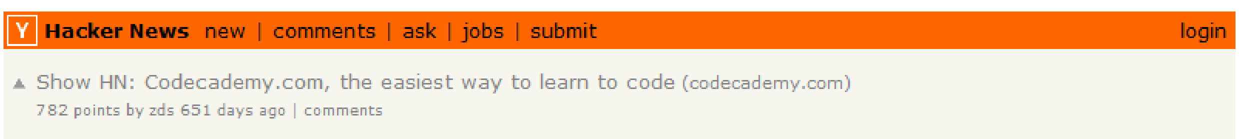
Figure 1.1: Hacker News Front Page



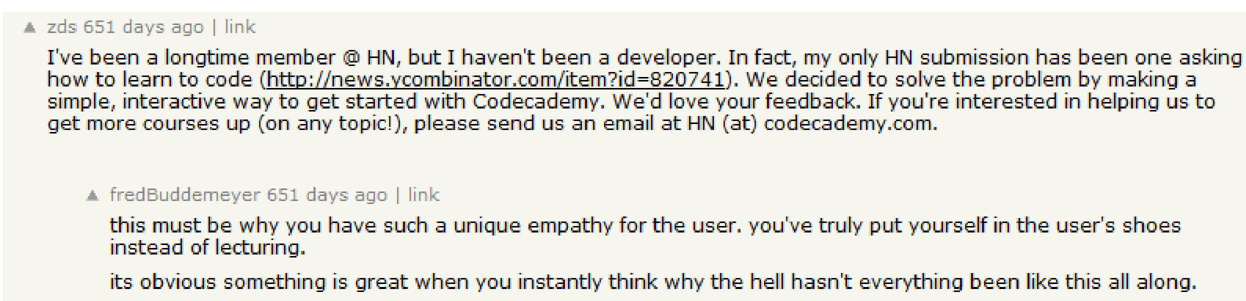
Notes: The front page lists submissions by the number of points they have received roughly weighted by time of submission.

Figure 1.2: Submissions and Comments

(a) Submission

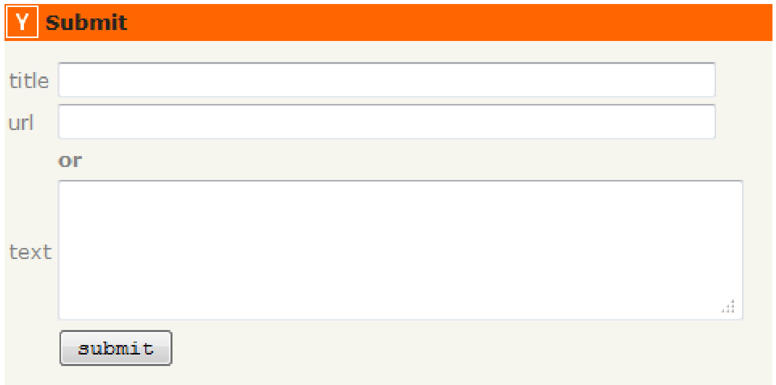


(b) Title



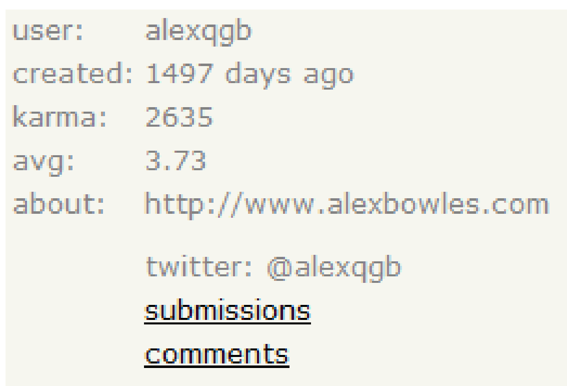
Notes: Figure 2a shows the title of the submission that an actor wishes peers to evaluate. Clicking on the title will take peers to a link where they can evaluate the website. Figure 2b shows the comments made in response to the website.

Figure 1.3: Hacker News Submission Form



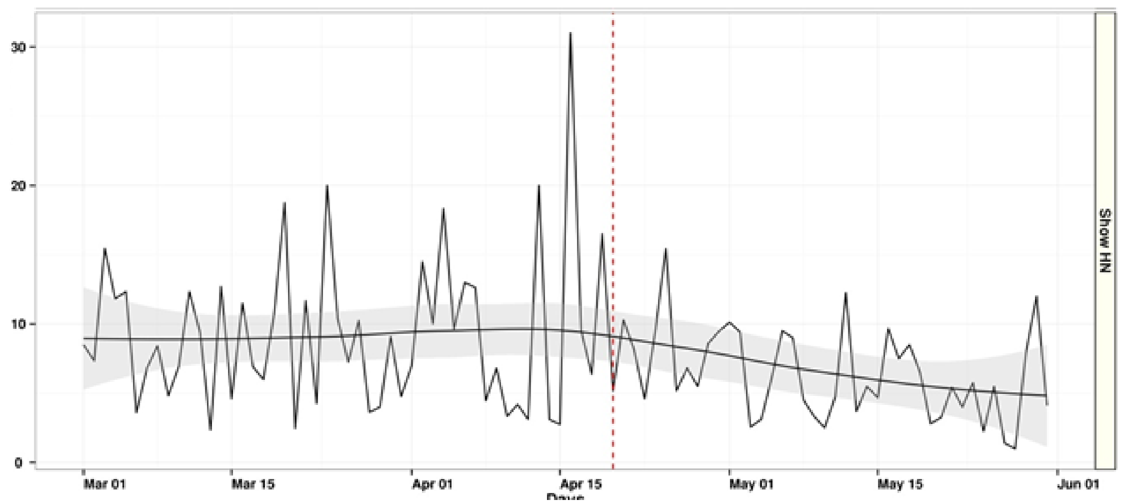
Notes: The submission form is where innovators can put a link to their website and give it a title.

Figure 1.4: Hacker News Profile Page



Notes: Anywhere on the site, peers can click on another member's name and get information about them. In addition to the information shown here, members can peruse their history

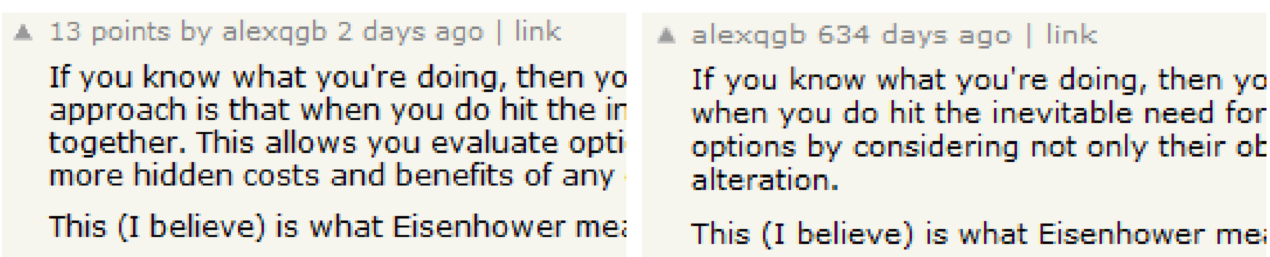
Figure 1.5: Total "Show HN" Comments Pre-Post



Notes: This shows the average number of comments on "Show HN" submissions each day for 3 month pre- and post-treatment. The shock occurred on April 20th, 2011 as represented by the red dotted line. The spike a few days prior to the shock was due to a particularly popular start up idea that received nearly 200 comments.

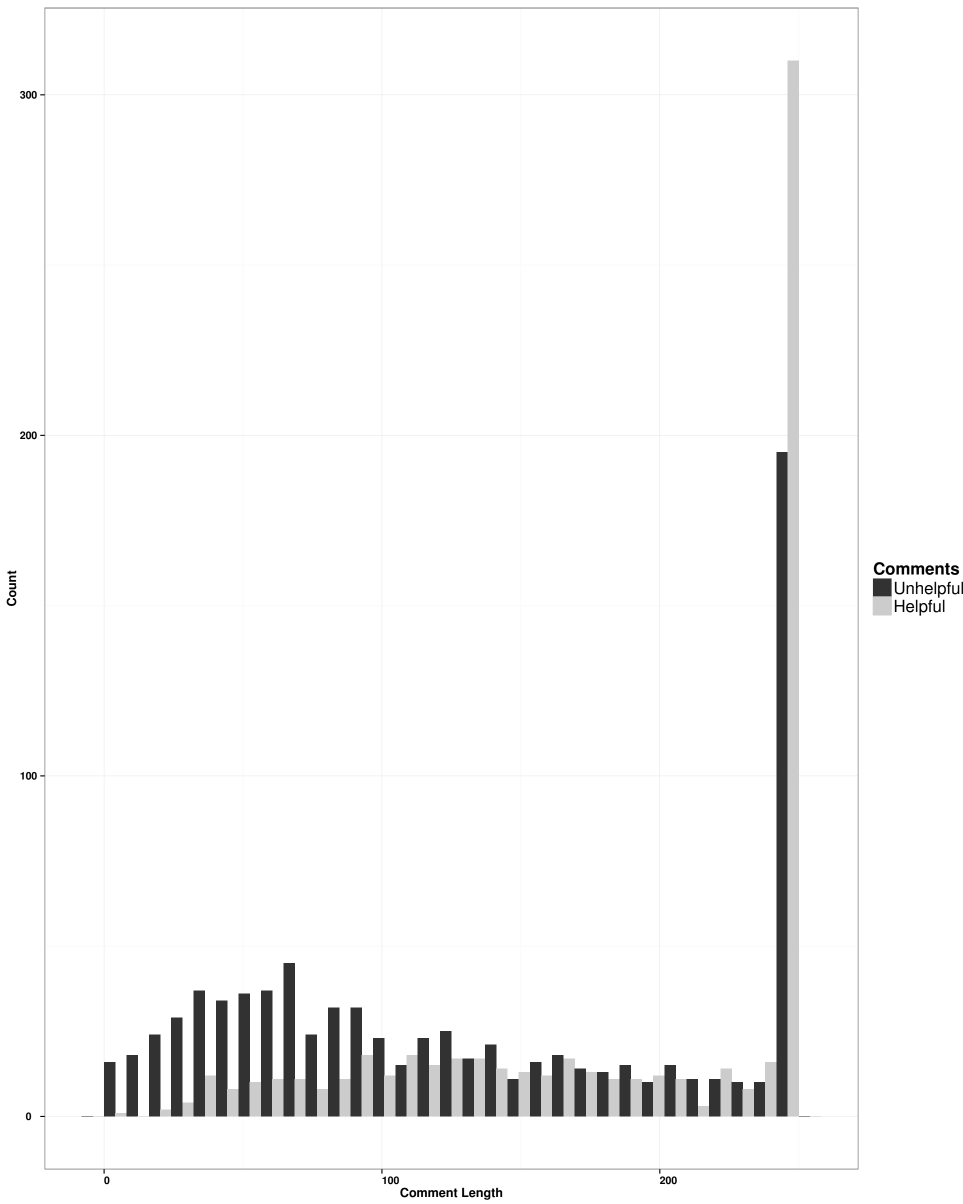
Figure 1.6: Example of Peer Recognition Pre (Public) and Post (Private)

(a) Pre-treatment,Public Recognition **(b)** Post-treatment, Private Recognition



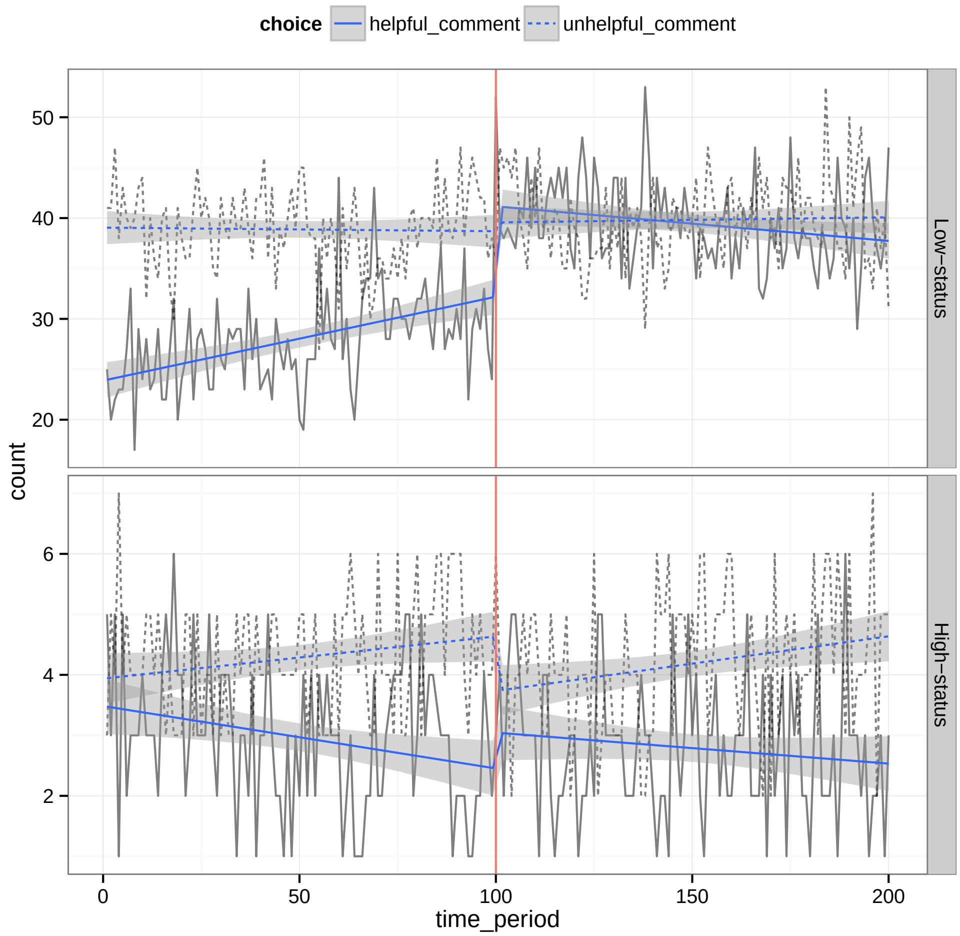
Notes: Both Figure 6a and 6b show the exact same comment. The Internet Archive was used to go back in time to see what the website looked like prior to the policy change. The top left hand corner of Figure 6a show that this comment had received 13 points at the time of the Internet Archive snapshot. Figure 6b shows what the comment looks like after the policy change. Now members of Hacker News can no longer see what their peers received on their comments. However, the one receiving peer recognition can see how much deference they received – but not who – gave them deference.

Figure 1.7: Density of Comment Length



Notes: This figure show the count of non-helpful and helpful comments by length of the comments. Non-helpful comments are more numerous among the shorter comments, but helpful comments are equal or greater than non-helpful comments as the length of the comments increase. The last bar is truncated at 255 characters due to Stata. Nevertheless, it shows that among the "long" comments there are greater counts of helpful comments than non-helpful comments.

Figure 1.8: Simulation: Resource-seeking Status Motivation *Pragmatists*



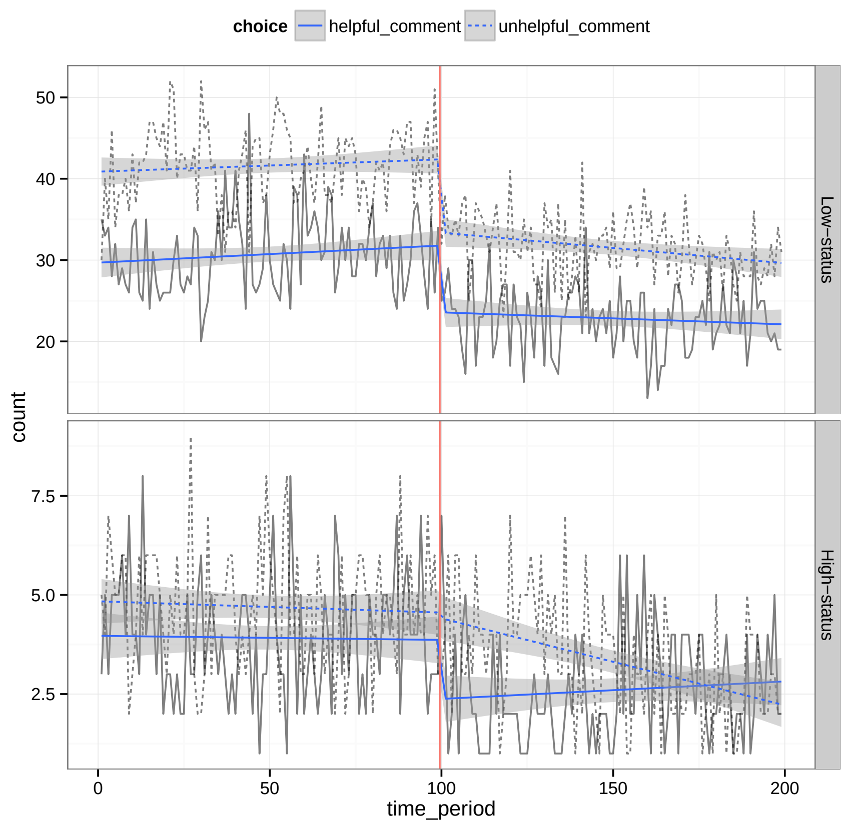
	choice	Pre mean	Pre sd	Post mean	Post sd	percdiff
Low-status	Helpful Comment	25	10	36	25	0.43274
	Non-helpful Comment	35	16	36	21	0.04758
High-status	Helpful Comment	39	17	33	22	−0.14530
	Non-helpful Comment	28	22	30	32	0.07018
	All	30	14	36	23	0.20040

Notes:

This Figure represents the simulated per-round absolute counts of helpful and non-helpful comments by the status level – for *Pragmatists*.

The Table examines the mean counts of comments by type and status level.

Figure 1.9: Simulation: Deference-seeking Status Motivation (*Egoists*)



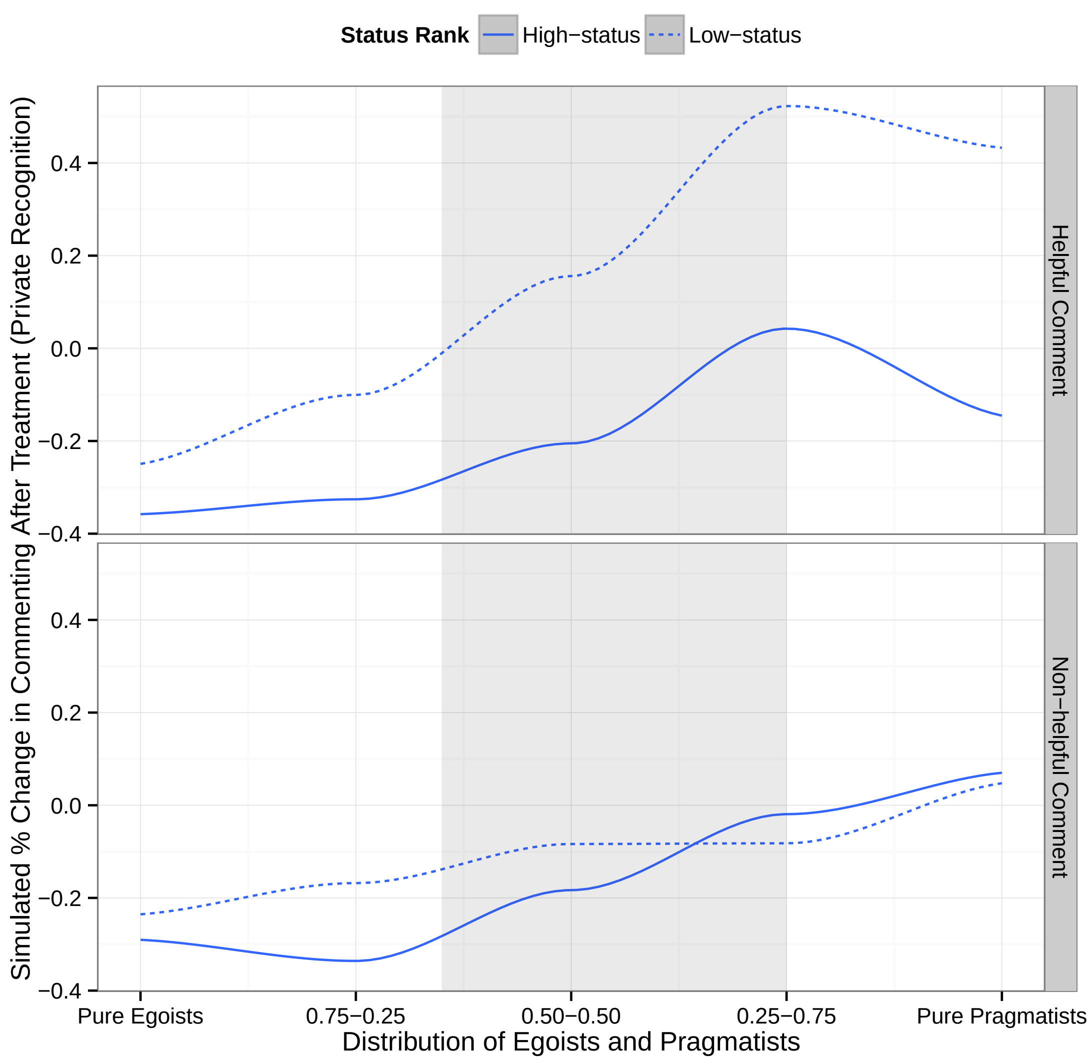
		Pre		Post		
	choice	mean	sd	mean	sd	percdiff
Low-status	Helpful Comment	27.7	8.4	20.8	7.3	−0.2494
	Non-helpful Comment	37.5	13.4	28.6	12.8	−0.2354
High-status	Helpful Comment	29.2	7.3	18.8	7.6	−0.3579
	Non-helpful Comment	35.8	10.8	25.4	10.1	−0.2903
	All	32.6	11.9	24.4	11.0	−0.2497

Notes:

This Figure represents the simulated per-round counts of helpful and non-helpful comments by the status level – for *Egoists*.

The Table examines the mean counts of comments by type and status level.

Figure 1.10: Simulation: Heterogenous Status Motivations



Notes:

This figure examines the impact on commenting assuming a continuum of status seekers ranging from pure *Egoists* to pure *Pragmatists*. The grey bar is where the simulated data overlaps with the empirical data (see Table 4).

TABLES

Table 1.1: Definition of Variables

Variable	Description
DV: Helpful Comments	Comments that contain specific and actionable information
DV: Non-helpful Comments	Comments that do not contain actionable information
High-status	Dummy = 1 if commenter has a rank greater than 90, 95%
Private Recognition	Dummy = 1 if comment scores are only visible to the recipient

Table 1.2: Descriptive Statistics - Individuals in Both Pre- and Post-treatment Periods

	mean	sd	median	min	max	n
Public (Pre)						
Helpful Comments	1.086	1.249	1	0	7	128
Non-helpful Comments	1.414	2.451	1	0	23	128
All Comment Types	2.500	3.035	1	1	27	128
High-status 95th	0.281	0.451	0	0	1	128
High-status 90th	0.375	0.486	0	0	1	128
Private (Post)						
Helpful Comments	1.117	0.977	1	0	5	128
Non-helpful Comments	0.945	1.652	0	0	12	128
All Comment Types	2.062	2.095	1	1	15	128
High-status 95th	0.281	0.451	0	0	1	128
High-status 90th	0.375	0.486	0	0	1	128
Total						
Helpful Comments	1.102	1.119	1	0	7	256
Non-helpful Comments	1.180	2.099	1	0	23	256
All Comment Types	2.281	2.612	1	1	27	256
High-status 95th	0.281	0.450	0	0	1	256
High-status 90th	0.375	0.485	0	0	1	256

Table 1.3: Descriptives - Mean Comment Points - Full Sample

	Low-status		High-status	
Treatment Period	Non-Helpful	Helpful	Non-Helpful	Helpful
Public (Pre)	1.37	1.89	1.72	2.02
	1.07	1.66	1.86	1.82
	370	146	325	153
Private (Post)	1.71	2.00	1.76	2.88
	1.47	1.78	1.67	3.73
	272	112	346	117

Notes:
The purpose of this table to provide reasonable starting conditions for the simulation. It shows that (a) helpful comments generally receive higher recognition from peers than non-helpful ones, (b) that helpful comments are less numerous than non-helpful ones, and (c) high-status peers receive higher recognition than their low status peers. This last point could be due, entirely or partly, to ability being correlated with status.

Table 1.4: Counts of Total Comments

	High Status in Top 5		High Status in Top 10	
	(1) Comments	(2) Comments	(3) Comments	(4) Comments
Private Recognition	−0.192	−0.016	−0.192	−0.000
	(0.132)	(0.134)	(0.132)	(0.146)
Private Recognition X High-status		−0.497*		−0.434*
		(0.285)		(0.259)
LogLike	−184.4	−180.4	−184.4	−181.1
Groups	128	128	128	128
N	256	256	256	256
Individual FE	yes	yes	yes	yes

Data:
Observations are the $peer_i - period_t$ level.
Sample is conditional on peers being both in the pre- and post-treatment regimes. *Comments* are the total counts of comments consisting of both helpful and non-helpful comments.Columns (1)-(2) use a definition of high-status of being ranked greater than the 95th percentile. Columns (3)-(4) use a broader definition of 90th percentile.
Interpretation:
Column (1) suggests that mean count of comments did not change after visibility of peer recognition became private. However, the significance of the interaction in Column (2) suggests that high-status peers reduce their commenting by about 40 percent, $\exp(-.497 - .016) = .597$ in comparison to public regime. If we use the broader definition, this drops to about 35 percent.
Models:
Regressions use Poisson quasi-maximum likelihood estimators.
Cluster robust standard errors at the individual level in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Counts of Comment Types

	High Status in Top 5				High Status in Top 10			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HELPFUL	HELPFUL	NOT HELPFUL	NOT HELPFUL	HELPFUL	HELPFUL	NOT HELPFUL	NOT HELPFUL
Private Recognition	0.028	0.250*	−0.403**	−0.278	0.028	0.343**	−0.403**	−0.334
	(0.125)	(0.128)	(0.200)	(0.239)	(0.125)	(0.140)	(0.200)	(0.267)
Private Recognition X High Status		−0.647**		−0.337		−0.721***		−0.150
		(0.294)		(0.394)		(0.258)		(0.392)
LogLike	−119.8	−116.5	−133.5	−132.5	−119.8	−115.3	−133.5	−133.3
Groups	117	117	106	106	117	117	106	106
N	234	234	212	212	234	234	212	212
Individual FE	yes	yes	yes	yes	yes	yes	yes	yes

Data:
Observations are the $peer_i - period_t$ level.
Sample is conditional on peers being both in the pre- and post-treatment regimes. Columns (1)-(2) use a definition of high-status of being ranked greater than the 95th percentile. Columns (3)-(4) use a broader definition of 90th percentile.
Interpretation:
Column (1) suggests that count of helpful comments did not change after visibility of peer recognition became private. However, the significance of the interaction in Column (2) suggests that among high-status peers those in the private regime reduce their commenting by about 33 percent, $\exp(-.647 - .250) = .672$, in comparison to those in the public regime. However, among low-status peers, we observe a 28 percent increase in helpful commenting between regimes. Column (3) suggests a 32 percent drop in non-helpful comments and Column (4) suggests no interaction. Results are qualitatively similar for Columns (5)-(8).
Models:
Regressions use Poisson quasi-maximum likelihood estimators.
Cluster robust standard errors at the individual level in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Conspicuous Consumption or Eating Alone?:

Understanding the Motives of Taste-based Status

INTRODUCTION

An ample body of evidence has been brought to bear showing that status, an actor's position relative to competitors, matters for a variety of performance concerns (Podolny, 1993b; Stuart, Hoang, and Hybels, 1999b). Underlying most of the studies on status is the assumption that audiences are motivated to find signals of quality that help guide their choices when true quality information is costly or unavailable (Azoulay, Stuart, and Wang, 2012b; Simcoe and Waguespack, 2011b). While some scholars have recognized that audiences may have motives independent of quality, such as conspicuous consumption (Veblen, 1994), few have sought to delineate between quality and taste motives (Benjamin and Podolny, 1999). However, in advancing this line of inquiry, Malter, (2014b) examined a period of the wine industry when uncertainty about wine quality was declining, due the rise of the internet, but where status effects were increasing, in contrast to the predictions of extant theory. This suggests that, at least in some contexts, audiences may not consider status solely a signal of quality.

In this paper, I seek to extend the study of taste-based status motives by testing whether they are driven by practical concerns such as conspicuous consumption or internal ones. The main idea is to find a situation where high-status actors are being rewarded by audiences independent of quality, but where the audiences have a choice in giving their deference either anonymously or publicly. Thus, if we observe audiences rewarding high-status actors more publicly than anonymously, then we might have some evidence to suggest audiences prefer status for reasons of conspicuous consumption. In contrast, if we observe audiences giving more deference anonymously, then this might suggest that actors have more of an intrinsic taste for status since they are receiving no benefits from third parties.

To explore the taste-based motives of audiences, I use data from an online, semi-anonymous community devoted to technology startups and news. Members of the community submit news and comments that their peers vote on. These votes accumulate points which grow their publicly displayed reputation and status scores, but other aspects of their identities like gender and race remain unknown. And while members are free to submit whatever news they wish, no two members are supposed to be able to submit the same news item. However, the system designed to filter duplicate submissions is imperfect and so sometimes duplicates get distributed on the website. This provides a unique opportunity to examine how audiences treat two individuals who submitted the exact same article, but differ on observable reputation and status. Lastly, while who comments on submissions is public, who votes is completely anonymous. I use this fact to explore if high-status actors are rewarded more due to a taste for status, which we would see as an increase in anonymous votes, or more due to a need to engage in conspicious consumption which we would see as a relative increase in publicly visible commenting.

Using a sample of nearly 9000 "twin" submissions compiled over 2009-2011, I examine whether high-status members receive relative more points (anonymous) or comments (public). Surprisingly, while high-status actors receive a premium in terms of points on their submissions and the number of comments they receive, I do not find that a significant difference in the premium between them. This suggests that taste-based status motives may not play a role in this setting. However, the results do replicate prior studies in two ways. First, it confirms that status has effects. Second, it shows those effects are most beneficial for relative lower status actors, as opposed to elite ones, where this is likely too little uncertainty about their quality.

THEORY

Efforts to explain the motives of audiences who reward high-status actors have taken three positions. The first position assumes that audiences are seeking quality and that status is a useful signal of it when more direct measures are not present (Podolny, 1993b). While some argue that high-status actors are unduly privileged by their positions (Kim and King, 2014; Merton, 1968), this is not the same as status having value independent of quality, but is rather a bias. The second position suggests that status holds value independent of quality because audiences can leverage status to gain indirect value. This argument often takes the form of conspicious consumption where audiences pay more for a good than what they value for it personally. In this case, the consumption of High-status goods or affiliations are a signal of status to third-parties. The last position suggests that audiences simply have an intrinsic taste for status which is also independent of quality. Some scholars suggest that such status motives may be due to a need to affirm insecurity in status position and ego (Sivanathan and Petit, 2010). The last two motives are generally considered taste-based since the choice to pursue status is not based on seeking quality.

While compelling causal evidence has emerged to show that audiences have both quality and taste reasons for rewarding high-status actors, there have been fewer efforts to understand what drives taste-based status consumption. Part of the challenge in advancing our understanding of these motives are the complicated causal mechanisms involved in the status process. To ensure that status effects are not simply due to omitted or correlated signals of quality requires isolating and delineating them effectively. In addition, it requires a priori judgment about whether taste-based status preferences are likely to play a significant role in the decision-making process of audiences. For example, if conspicuous consumption requires third-party observation, then in settings where there are no third-parties, we would not expect to see any effects from it. Likewise, if audiences do not personally have a vested interest in their status position vis-a-vis the target actor, they may not care about associating with that actor.

STATUS AS A SIGNAL OF QUALITY

Status is a position in a ranking or hierarchy that gives audiences a relative sense of quality of one actor over another (Sorenson, 2013b). How status is formed depends largely on the context. Informally, an actor's status may be defined by the participants in a market and the deference they give one another (Podolny, 1993b) or, more formally, it can be constructed through careful measurements as seen in university or olympic rankings (Sauder and Espeland, 2007). Regardless of the formality of status, it is linked to an actor's historical performance. But whereas an actor's reputation may represent a weighted average of historical quality on some dimension, status may broadly represent accumulations of quality such that distinct differences, or positions, between actors can be obtained. Consider two athletes who have both won every competition they have competed in, but who have competed a different number of times. We would expect the athlete that has competed in more competitions to be higher ranked than the one who has competed in fewer even though they both have the same perfect average score.

The most common management theory that seeks to explain why audiences care about status considers it a signal of quality. It assumes that audiences are most interested in pursuing quality when making decisions of affiliation, consumption or investment, but that costly or unavailable information about quality forces them to rely on a variety of alternative measures. While somes measures are thought to be discriminatory in that they are not correlated with quality, others such as status and reputation, are thought to be useful given that they are functions of past quality. How valuable status is thought to be as a signal of quality depends on the availability of other quality information. So if audiences can easily determine quality and can confidently determine the quality of the output they are interested in, then status is thought to be less valuable. In other settings, status may be the only signal that is available so in such cases status should be a more important signal.

The idea that status is one of several possible signals had long motivated scholars to include as many factors as possible in their models, but this approach was problematic for a variety of reasons. First, complex settings meant that key indicators such as an actor's reputation or output quality were often missing. Azoulay et al (2014) and Malter (2015) both showed that not including alternative signals of quality often inflated the importance of status. However, more problematic than omitted variables is the challenge of dealing with correlated measures such as product quality, reputation and status. Since they are jointly determined by historical quality, and hence correlated, they can result in biased estimates even if they are all controlled for in typical regression models.

One way to deal with the complexities of measuring the impact of status is to randomize the status of actors, or more conveniently, signals of status. For instance, Simcoe & Waguespack (2011) examined how a quirk in the publication process at a standards-setting organization impacted publication rates. The quirk involved randomly obscuring author names with the "et al" designation. When the authors were high-status, the "et al" designation reduced the audiences' receptiveness to the papers in question. While this kind of approach can reveal the effects of status, it alone, cannot tell us if status is a signal of quality since the motivations for status could be a result of pursuing quality or they could be motivated by other concerns. Thus, to provide evidence that observed status effects are indeed due to status being a signal of quality, scholars have sought to find ways to compare settings and outputs that vary in the amount or cost of quality information. For instance, Azoulay et al (2014) compare how a change in status amoung authors causes different citation rates depending on how well-known they are prior to the status change. They found that the more uncertainty existed about a publication or author, the larger the status effect was observed. This kind of test supports the notion that status is functioning as a signal of quality.

TASTE-BASED (NON-QUALITY) STATUS MOTIVES

An alternative view of status is that it has value independent of quality. Scholars who take this view usually argue that some audiences have a taste for status, that is, they derive intrinsic value from associating with it, or they argue, status is a fungible asset that can be used to achieve other ends. A classic example of this is conspicuous consumption. This type of consumption occurs when audiences consume goods to signal to third-parties something about their own status. The actual quality of the good is not the point, only what that good represents. Alternatively, some audiences may have a taste for status simply because they like or need it. In this case, some psychologists have argued that consuming status goods help audiences build or repair their egos and identities (Sivanathan and Petit, 2010).

While scholars in management have acknowledged the possibility that audiences may have motives independent of quality, relatively fewer scholars have sought to discern those motives much less to distinguish their causes. From a management perspective, this has implications for attributing the performance effects of status. For instance, the prevalence of third-party signaling opportunities could be a crucial component in understanding the observed effect of status rather than the prevalance of quality information. However, part of the challenge of studing status motives is that ex-ante it's not clear which settings might be more or less conducive to different kinds of motives.

But even if one is able to show that non-quality, taste-based status effects exist, disambiguating whether those are due third-party signaling opportunities or whether they are driven by some internal need presents an additional challenge. To do so, we must consider who can benefit from status exchanges. For instance, if an audience member rewards a high-status actor even when their quality does not merit it, they may value that exchange because they value status intrinsically or they may be wishing to use that affiliation in some other way. In contrast, if the status exchange is anonymous, that is, neither the high-status producer nor any third-party observes who initiated the transaction, then this could provide some evidence that status is driven independent of quality for intrinsic reasons. In the following sections I describe an approach that may provide an opportunity to test the source of taste based motives.

SETTING

Hacker News is an online community designed to allow hackers to share interesting news with fellow hackers or more broadly "anything that gratifies one's intellectual curiosity". Most of these "hackers", however, are either internet entrepreneurs or engineers for major Silicon Valley companies such as Google and Facebook. But members also include a much broader group who are interested in technology such as academics, investors and media outlets. Hacker News was formed in 2005 and has risen to prominence for a number of reasons. First, it was founded by Paul Graham who also founded Y Combinator around the same time. Y Combinator is the most prominent and successful startup incubator in existence today. As of 2012, the combined value of its startups reached nearly $8 billion with notable alumni including AirBnB, DropBox, and Reddit. Most new accelerators and incubators started today are modeled on or inspired by Y Combinator (Miller, 2007b). Thus, Hacker News has benefitted from some of the "reflected glory" of its sister organization Y Combinator. Second, Hacker News has become a valuable source of information and innovation in its own right.

One key way that Hacker News succeeds in surfacing valuable information and promising ideas is through it voting and publication system. This system relies on quantifying members' contribution of submission and comments by the points they receive from peers. Members who write contribute high-quality comments and submissions can see their status and reputations improve. With increasing status in the community their submissions and comments are taken more seriously and key rights, such as the ability to flag spam or downvote their peers becomes available to them. Lastly, if a member decides to show off their side-project or startup having prominence in the community enhances their ability to get feedback and resources. For instance, Drew Houston, the founder of Dropbox, an early and prominent member, leveraged his recognition on Hacker News to display an early prototype of Dropbox. He credits this experience with much of the positive attention and customers he received early on.

Hacker News provides two main avenues by which members contribute and build up their social capital. The first is through the submission of web links and questions. The second is through commenting on what others have submitted. And similar to how the academic community works, the quality of the materials submitted contributes to the status and prestige of members in the community. This is achieved through a voting process that in some ways emulates citation counts. These votes contribute to two metrics measured in points. The first is called âĂIJkarmaâĂİ and it reflects the sum of cumulative deference, or status. Higher status actors are afforded special rights. The second is called “avg” and reflects an actor’s historical quality or reputation. Both reputation and status are visible to all visitors of the site by clicking on any member’s name. An example of what members can see can be found in Figure 2.2 [1].

As a data source Hacker News provides a unique setting to study the impact of status. First, it provides detailed and publicly available scores for each member’s reputation and status. Through their API, or application programming interface, the microlevel data underlying the website can be obtained rather than having just a “snapshot” of reputation and status. Therefore, detailed histories for nearly all points in time can be obtained [2]. Second, achieving status in the community is a valuable activity since it allows members special rights and improves their visibility. Third, because it is online and shows no pictures of the users, other human attributes such as gender, race and educational pedigree play less of a role allowing the publicly visible scores of reputation and status to take a primary role, and thus minimizing typical biases. Lastly, a quasi-experiment, in the form of identical news submissions, allows the unobserved quality of the submissions to be controlled for. This is akin to two scholars submitting the same manuscript but

[1] During the time period of this study both the average score and karma were visible. However, in 2015 they removed avg score and only karma is now seen.

[2] A limitation to this would be if people continued to vote up comments long after they were made. This is a fairly rare occurence since new stories only stay on the front page of the website for usually only a few hours and are quickly replaced with more up-to-date, cutting edge news

with the scholars' reputations and status being the only key differentiators.

Empirical Strategy

When members submit an article, it gets posted to a "new" page where if it receives a significant number of points, it gets upgraded to the "front" page. In addition to submitting a link to an external website, members must also decide on the title they wish users to see. In general, most members simply repeat the title of the article verbatim. And while there are checks that are supposed to ensure that duplicate submissions do not get through, they occasionally do. The result is that two members, who differ in terms of their reputation and status, may end up submitting the exact same article and title. Figure 2.1 demonstrates an example of this phenomena.

The empirical strategy of this paper is to use this quirk in the publication process as quasi-experiment. For example, under ideal experimental settings we might show the same resume, or output more generally, but vary just elements that reveal the identity. While this setting approximates this ideal, it differs in a number of ways. First, while the submissions are identical they are not released simulateously. On average, there is a 2-3 week lag. This means that whichever twin submits the article first will receive some first-mover advantages because news gains its value from being new. In other words, the second twin will always have, on average, fewer points since it is the second time this news item was submitted to the community. Second, because there is a lag in submissions, it means the second twin will have a chance to accumulate more status even if the status of both twins were the same at time t=0. This would create a bias because the second twins would, on average, have more status but fewer points. Lastly, in the example of the resume experiment above all information about the author is contained in the resume. Thus, there is no opportunity for omitted variable bias. In contrast, while my setting is very strong in terms of only a few variables being publicly visible like reputation, status and tenure, there might be identity leakage not accounted for.

To address some of the concerns raised above, I do the following. First, I control for time between submissions. This should control for most of the first-mover advantages. Second, I normalize status so that we have the counter-factual status of the second twin match the first twin. What I mean by that is that I adjust the status of the second twin so that we have what it would have been at the time of first submission. This puts both twins on a more equal footing. Lastly, with respect to identity leakage this is a difficult problem which is likely to be more problematic for high-status members since they have time to become structually embedded in the community - a key issue I do not control for in this study.

While the quasi-experiment and related controls mentioned help ensure we are capturing status effects relatively cleanly, there is the challenge of determining which status motives are most salient. I attempt to do this in several ways. First, I test for quality based status motives, I examine status effects at different cutoffs. The marginal effect of status should be most salient for relatively lower status actors and those with less tenure. Second, I test for taste-based status by examining the effects between two different outcomes one which is anonymous and another which is public. While direct comparison of coefficients between models is challenging we can make some broad-based inferences. For example, if status is significant for one model but not the other this might tell us some useful information.

METHODS

Sample

Individual-level data on all participants of Hacker News (HN) was collected between 2007 and 2011 using the Hacker News API (application programming interface) [3]. This data includes every comment and submission made by members along with associated time stamps and the points they received. This allows reconstruction of the variables that are observable on the website such as status and reputation [4] for any point in time.

From this full sample, I identified duplicate submissions by members of HN. While HN tries to block duplicate submissions a fair number succeed in getting through due to idiosyncrasies in the submission process [5]. I identify these duplicate submissions by truncating URLs to their domain names and matching on the titles. This creates 8595 identical, twin submissions [6] which are exactly the same except for the identity of the submitters and the time between which they were submitted.

Measurement

Table 2.1 provides an overview of the variable definitions. Table 2.2 show descriptive statistics for both twins as well as the those across the entire sample.

[3] This data comes from the old API. HN recently updated their API in 2014. Moreover, after 2015 they no longer display "avg". This is an opportunity for another natural experiment.

[4] The API does not provide aggregate statistics such as status or reputation. Such statistics must be reconstructed from individual-level data

[5] In particular, HN tries to block duplicate URLs. However, some URLs may have additional symbols or characters which make them difficult to identify as duplicates. In 2015, Sam Altman, the new CEO of Y Combinator changed the policy so that duplicate submissions could be allowed under certain conditions

[6] The vast majority of duplicates are twins, but there are also triplets and quadruplets which I do not include in my sample

Dependent Variables

To measure the impact of status this study focuses on two outcomes: *Points* and *Comments*. Status consumers, or the audience, can give *Points* to submissions they wish to see rewarded through a voting process. The final number of points a submission receives is the net of both positive and negative votes.[7] These votes are anonymous to both the public and the recipient. The audience can also *Comment* on a submission. In contrast to *Points*, *Comments* are public and the identity of the author can be observed by everyone. The average number of comments is about 6.5 per submission while the average number of points is 15.5. Notably, the median count for both is zero.

Independent Variables

The main independent variables are *Reputation* and *Status*. Reputation is what the Hacker News site calls "avg" which roughly corresponds to the historical average of past points on submissions and comments for each member of Hacker News. Status on Hacker News is called "karma" and it reflects the cumulative sum of points over time. The average reputation of both the first and second twin is about 7 points, but the second twin has about 150 higher status points than the first one. This reflects the fact that the second twin has time to accumulate more points.

In terms of measures of *Reputation* and *Status* "avg" and "karma" have a number of advantages and disadvantages. First, they are main public measures available for each user. Any other user of Hacker News can click on a member's name and see their reputation and status scores. While other factors may also influence how members are viewed like gender or origin, those types of factors are not disclosed or easily known. Figure 2.2 provides an example of how prominent

[7] One limitation of the API is that each comment and submissions has the latest number of point it has received.

these measures are relatively to any alternatives. In terms of disadvantages *Status* reflects a cumulative sum of deference from peers, but it is a continuous measure and thus delineations between high and low status members is largely imputed by the members themselves with some exceptions.

As mentioned in the empirical strategy section, in order to make *Status* more comparable between twins, I adjust *Status* to be what it would be had both twins submitted it at the same time. I call this variable *Status-Tenure-Adjusted*. I use a simple linear approximation that uses the time between submissions and the *Tenure* of the second twin to achieve this. Table 2.2 shows the impact of this transformation that makes the average *Status* between twins more comparable. Likewise, I also create a new *Tenure-Adjusted* variable which makes the second twins *Tenure* be equivalent to the first twin's *Tenure* had they submitted their articles at the same time.

Control Variables

The two main control variables are *Tenure* and *Time Since First Twin*. *Tenure* is measured as the length of time, in months, since a member registered with Hacker News. While registering is not required to view submissions, it is required if one wants to submit stories or write comments. *Time Since First Twin* is measured in days and it reflect the time since the first twin submission was posted. The average *Tenure* of the first twin is about 19.5 months and the second twin has about two months more *Tenure*. The adjusted version of *Tenure* makes the average between the twins nearly the same. The median number of days the second twin posts a submission is about 18 days.

STATISTICAL STRATEGY

The main statistical strategy I employ in this study is to leverage fixed-effect Poisson. The fixed effect captures the unobserved quality of the submission, but unfortunately not of the twin submitters. Since both *Points* and *Comments* are counts the Poisson model is the most appropriate. Additionally, I employ cluster-robust standard errors at the twin level.

In order to make the regression coefficients between *Points* and *Comments* more interpretable and comparable I define two-cutoffs for *High Status*. The first cutoff defines *High Status* where *Status* > 500 and the second cutoff defines it where *Status* > 10000. The rationale for the first cutoff is that above 500 points members receive special privileges such as the ability to downvote their peers and flag submissions. The rationale for the second cutoff is that in 2011, above 10000 points got members on the leaderboard. This leaderboard show the top 100 members ranked by *Status*.

In addition to defining status cutoffs in an absolute sense, I also consider them in a relative sense. By this, I mean each twin is compared to the other. For the first cutoff, if the difference in status of one twin to another is greater than zero, then I define that twin as the *High Status* one. I also use a cutoff of greater than 1000 points.

RESULTS

Table 2.3 shows the main results and Table 2.4 shows whether *High Status* is significantly different between the models compared in 2.3.

Table 2.3 suggests that *High Status* matters for both *Points* and *Comments*. However, at least qualitatively, the difference in the effect sizes *High Status* between the dependent variables does not seem to be significant. Moreover, the effect of *High Status* appears to be conditional on magnitude of the status differences between the twin submitters.

The columns in Table 2.3 are broken into pairs of models representing the dependent variables *Points* and *Comments*. Each pair highlights a different definition for *High Status*. The first two columns in the table focus on an absolute definition of *High Status* where it is cutoff at 500 points. Again, the rationale for this is that above 500 points members receive special privileges such as the ability to downvote other members and flag stories. Model (1) examines *Points* and shows that *High Status* members have 60% more points than their low status counterparts. Model (2) examines *Comments* and finds a similar effect only slightly lower. These effect sizes are quite substantial when compared to *Reputation* which is a little over 9%. However, the fact that effect sizes are so close in range suggests that taste-based status motives may not be the cause since we might expect *Comments*, which are public, to vary in some way from *Points* which are completely anonymous.

Models (3)-(4) change the threshold of *High Status* to 10,000 points. In 2011 this was approximately the cutoff needed for a member to get on the leaderboard. The leaderboard shows the top 100 members of Hacker News ranked by status. Consequently the sample size for these models decreases as there are fewer twins where one member meets this status threshold. Suprisingly, the effect of *High Status* is not significant for either dependent variable. Again, if taste-based status motives were at play we might expect the very highest status member of the community to gain outsized benefits.

Models (5)-(8) examine relative, rather than absolute, status differences. If taste follows the magnitude of status, then higher status members, regardless of their true standing should experience some benefits. Model (5)-(6) define *High Status* as any member whose status is larger than their twin. Defined on these terms, *High Status* members see about a 20% increase in *Points* and *Comments* with the latter being slightly higher. But as with Model (1)-(2) the differences appear non-significant. Models (7)-(8) define *High Status* as one twin having status that is at least 1000 points higher. Under this sample neither *Points* or *Comments* are significant.

While qualitatively models (1-2) and (5-6) do not appear to have significantly different effect sizes for *High Status*, table 2.4 provides some statistical support that this is the case. Here *Comments Dataset* is a dummy variable indicating the observations with the *Comments* dependent variable. The interaction effect between *Comments Dataset* and *High Status* is insignificant for all models. It should be noted that the guidance on cross-model hypotheses is an area of much confusion and active research.

DISCUSSION & CONCLUSION

The purpose of this paper was to explore the motives behind a taste for status. In particular the study focused on two alternatives, the first which relates to "conspicuous consumption" where status consumers gain value depending on the presence of third-party observers. The second alternative focuses on whether actors desire status inately and independent of any external benefits. I investigated this question in a online community known as Hacker News which is frequented by technology focused start-ups, engineers and investors. As such, it's a setting where the demand for status affiliations are likely to be based on taste as much as quality (Stuart, Hoang, and Hybels, 1999b). I exploit a feature of the setting where two members can submit the exact same news article for evaluation by peers. Since the quality of the article is fixed, any observed difference in evaluation between the "twins" is more likely to be due to the member's publicly visible attributes. Moreover, because quality at both the article and member level are tighly controlled, any residual effect of status is more likely to be based on taste rather than quality assuming taste-based status motives are present in the setting. To distinguish between the taste motives I use the fact that members can choose to affiliate with high status peers either through anonymous rewards of points or through public commenting.

Despite a plausible setting for seeing taste-based status motives and tight controls, the evidence suggests the residual effect of status is not due to taste, but rather, remains a signal of quality. High status actors, regardless of whether rewards are anonymous or public, receive a significant increase in both *Points* (anonymous) and *Comments* (public) that are not significantly different from one another. Had Points received a significantly higher benefit from status than comments or if comments had not been significant, we might have had some evidence that actors had an intrinsic taste for status. While it is possible that the population is equally divided between people who have an intrinsic taste for status and desire conspicuous consumption, this seems unlikely and is not a testable assumption with the data.

While no evidence is provided to delineate taste-based motives, the paper does reinforce several elements of existing research on status. I find that status is a stronger signal of quality when comparing low to high status actors rather than medium to high status actors. This is likely due to the fact that there is less uncertainty about an actor's quality at the higher ends of status. This is in line with prior work from Simcoe and Waguespack, (2011b) and Azoulay, Stuart, and Wang, (2012b) which find status effects are strongest when uncertainty is higher. Interestingly, I find that reputation effects for this group are smaller, but more consistent and reliable despite any status differences.

While this study attempted to isolate taste-based status effects and found none, a number of lessons could be gleaned for future research in this area. First, I examined all cases where two members of Hackers submitted the same article, but I did not examine different kinds of articles. For example, some articles may be experience goods in the sense that once they are read, their quality can be ascertained. In contrast, credence goods defy easy categorization and are much more subjective. It could be that taste-based status motives are more prevalent in the latter than in the former. Second, in this paper, I did not explore the interactions between reputation, status and tenure. In particular, a member's tenure show significance when status differences are greatest. This might mean tenure is a proxy for friendship or structurally embedded exchange. This relationship might overwhelm status concerns. Prior research such as Malter, (2014b) found taste-based status motives, but these were in a setting where wine producers are not friends with the people who are judging them.

Exploring and confirming taste-based status motives is important because it can help us understand conditions under which status may result in superior outcomes. And even if we can measure the effect of status perfectly that does not tell us the foundation of those effects. It may also help us understand why high status actors receive benefits in excess of their true quality. However, isolating the effects of taste from signaling is challenging because they are both likely to exist and ex ante it is not clear which settings are most likely to show taste-based effects. While this paper was not able to delineate with the theorized motives behind taste based status, it did build on and reinforce existing research by broadly replicating the prior causal findings on status signaling – namely that status benefits appear to benefit those with greater uncertainty surrounding their true quality.

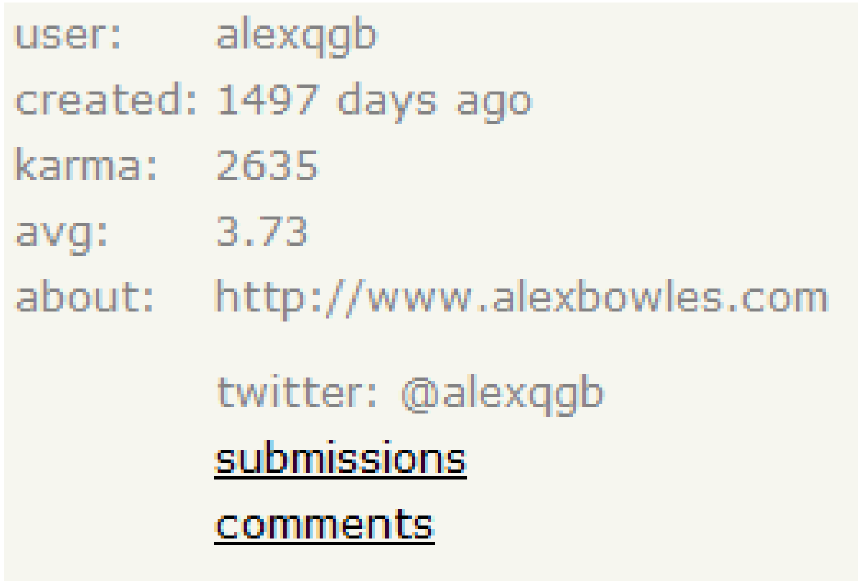
Figure 2.1: Example of Twin Producers

(a) Twin A

(b) Twin B

Notes: This figure provides an example of two producers, "Twins", who submitted the exact same product. In this example, Twin A submitted a product for evaluation before Twin B and received more attention and positive evaluations. However, in many cases, this situation is reversed.

Figure 2.2: Example of Submitter Profiles



Notes: This figure shows the status (karma) and reputation (avg) scores for each user.

TABLES

Table 2.1: Definition of Variables

Type	Variable	Description
Dependent Vars	Comments	The number of comments that a submission received
	Points	The number of points a submission received
Indepent Vars	Reputation	The average number of points for prior comments
	Status	The cumulative number of points received by twin
	Status-Tenure-Adjusted	Adjusted for time between submissions
	High Status	=1 for High Status. Based on adjusted status
Controls	Tenure	Time since membership (in days)
	Tenure-Adjusted	Tenure adjusted for time in between submissions
	Time Since First Twin	The time (in days) between twin submissions
	Twin Order	Dummy var qual to 1 for twin submission that came first

Table 2.2: Descriptive Statistics

	mean	sd	median	min	max	n
First Twin						
Comments	7.9	25.1	0.0	0.0	330.0	7409
Points	18.9	55.7	3.0	0.0	1638.0	7409
Reputation	6.9	6.2	6.0	0.0	178.0	7409
Status	4043.0	7099.7	1069.0	1.0	99843.0	7409
Status-Tenure-Adjusted	4043.0	7099.7	1069.0	1.0	99843.0	7409
HigherStatus	0.5	0.5	0.0	0.0	1.0	7409
Tenure (Mo)	19.5	14.3	17.0	0.0	67.0	7409
Tenure-Adjusted	19.5	14.3	17.0	0.0	67.0	7409
Time Since First Twin	0.0	0.0	0.0	0.0	0.0	7409
Second Twin						
Comments	5.2	19.5	0.0	0.0	320.0	7409
Points	12.1	38.1	2.0	0.0	896.0	7409
Reputation	6.5	5.3	5.0	0.0	117.0	7409
Status	4735.7	8020.0	1402.0	−1.0	117932.0	7409
Status-Tenure-Adjusted	4100.6	7242.3	1150.2	0.0	113685.7	7409
HigherStatus	0.5	0.5	1.0	0.0	1.0	7409
Tenure (Mo)	22.3	14.9	20.0	1.0	68.0	7409
Tenure-Adjusted	19.4	14.4	16.3	0.0	66.9	7409
Time Since First Twin	89.0	180.9	13.9	1.0	1918.6	7409
Total						
Comments	6.5	22.5	0.0	0.0	330.0	14818
Points	15.5	47.9	2.0	0.0	1638.0	14818
Reputation	6.7	5.8	5.0	0.0	178.0	14818
Status	4389.4	7581.5	1227.5	−1.0	117932.0	14818
Status-Tenure-Adjusted	4071.8	7171.2	1109.8	0.0	113685.7	14818
HigherStatus	0.5	0.5	0.5	0.0	1.0	14818
Tenure (Mo)	20.9	14.6	18.0	0.0	68.0	14818
Tenure-Adjusted	19.4	14.4	16.7	0.0	67.0	14818
Time Since First Twin	44.5	135.5	0.5	0.0	1918.6	14818

Table 2.3: Counts of Points and Comments

	Absolute Status: > 500		Absolute Status: > 10000		Relative Status: > 0		Relative Status: > 1000	
	(1) Points	(2) Comments	(3) Points	(4) Comments	(5) Points	(6) Comments	(7) Points	(8) Comments
High Status	1.638***	1.590***	0.929	0.837	1.180***	1.195***	1.123	1.125
	(0.149)	(0.167)	(0.143)	(0.125)	(0.073)	(0.076)	(0.095)	(0.098)
Reputation	1.091***	1.094***	1.110***	1.132***	1.072***	1.061***	1.075***	1.053*
	(0.019)	(0.019)	(0.021)	(0.023)	(0.014)	(0.022)	(0.021)	(0.031)
Time Between Twins	1.000	1.000	0.999*	1.000	0.999***	0.999***	0.999***	0.999**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	1.000	0.997	1.017***	1.014**	1.008**	1.003	1.011***	1.006
	(0.004)	(0.005)	(0.006)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
Groups	1772	1772	800	800	4096	4096	2664	2664
N	3544	3544	1600	1600	8192	8192	5328	5328
FE	yes	yes	yes	yes	yes	yes	yes	yes

Data:
Observations are at the $member_i - twin_j$ level where twin refers to an identical story submitted by two different members of Hacker News. The dependent variables *Points* and *Comments* are both counts. *High Status* is equal to 1 for the member with higher status. *Reputation* is the average points across all past submissions and comments. *Time Between Twins* is the time, in days, between the first and second twin submissions. *Tenure* is the length of time, in months, the member has been registered with Hacker News.
Models:
All Models use Poisson QML regression with fixed effects and cluster-robust standard errors at the twin level.
High Status is defined two ways: Absolute and Relative. Absolute Status uses two definitions for hierarchy. The first, for models (1)-(2), a threshold of > 500 is used because above that number a member receives special privileges. The second, for models (3)-(4), a threshold of > 10000 is used because that got members on the leaderboard in 2011. This leaderboard displayed the top 100 members ranked by their status. Relative Status means one members has greater status than the other independent of where they fall on the Absolute Status hierarchy. Models (5)-(6) use a theshold of > 0 status points between twin members. Models (7)-(8) examine a subsample where the difference is > 1000 status points.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: Test if High Status differs between Points and Comments

	Absolute Status: > 500	Absolute Status: > 10000	Relative Status: > 0	Relative Status: > 1000
	(1)	(2)	(3)	(4)
	PointsComments	PointsComments	PointsComments	PointsComments
High Status	1.664***	0.923	1.187***	1.125
	(0.151)	(0.140)	(0.073)	(0.095)
Comments Dataset	0.498***	0.481***	0.458***	0.448***
	(0.019)	(0.025)	(0.012)	(0.015)
Comments X High Status	0.925	0.917	0.993	0.994
	(0.045)	(0.064)	(0.034)	(0.044)
Reputation	1.092***	1.116***	1.068***	1.068***
	(0.019)	(0.021)	(0.016)	(0.025)
Time Between Twins	1.000	0.999	0.999***	0.999***
	(0.000)	(0.001)	(0.000)	(0.000)
Tenure	0.999	1.016**	1.006**	1.009**
	(0.004)	(0.006)	(0.003)	(0.004)
Groups	1772	800	4096	2664
N	7088	3200	16384	10656
FE	yes	yes	yes	yes

Data:
Similar to Table 4 but Point and Comment models are stacked to test if *High Status* is significantly different between them.
Models:
All Models use Poisson QML regression with fixed effects and cluster-robust standard errors at the twin level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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