Stereotypes Are More Powerful When People Like to Agree with Each Other*

Michael Suk-Young Chwe

Department of Political Science, UCLA

Los Angeles, CA 90095–1472

michael@chwe.net

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Abstract

I find that among 119 academic fields, the more skewed the citation distribution of papers published in the field, the lower the percentage of doctoral recipients who are women. If the citation distribution in a field is more skewed, a smaller percentage of papers receive most of the citations, which indicates a greater preference to agree on which papers should be cited. This empirical result illustrates the argument, which I make in a game-theoretic model, that stereotypes are more powerful when people like to agree with each other.

JEL classification: J16 Economics of Gender, J71 Discrimination, C72 Noncooperative Games

Keywords: stereotypes, coordination, talent

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How do stereotypes influence our opinions? This paper argues that stereotypes are more powerful when people want to express opinions that are close to the opinions of others. Here we consider stereotypes as signals that are publicly shared but have little informational value. For example, it is a stereotype that tall people are better at basketball, and this belief is widely and publicly shared even though being tall is a very weak signal of basketball ability. When people want to express opinions that are similar to those of others, public signals such as stereotypes can influence opinions more than signals that are much more informative but are observed individually (Morris and Shin 2002). I make this argument with a simple game-theoretic model.

I support this argument with evidence from 119 academic fields in the physical, social, and life sciences, engineering, and education, which altogether produce 80 percent of all research doctoral degrees awarded in the United States. I find that the more skewed the distribution of citations of papers published in a field, the lower the percentage of doctoral recipients who are women. If citations are more skewed in a field, a smaller percentage of papers receive most of the citations in the field; for example, if the distribution is maximally skewed, a few papers receive almost all of the citations. The skewness of an academic field thus represents how much people in the field agree on which papers are interesting and important. When people agree more, we understand this as indicating that people have a greater preference to agree. Thus in fields with greater skewness, there is a greater preference to agree with the opinions of others, and thus the public but very uninformative stereotype of women being worse academically than men has a greater effect on people's opinions. In fields with less skewness, people care less about agreeing with the opinions of others, and thus sexist stereotypes are more easily overruled by higher quality information.

I consider competing explanations. For example, there are fewer women in fields in categories such as physical sciences and engineering, which might have more skewed citation distributions because they are more mathematical. But the negative relationship between women's participation in a field and the skewness of the citation distribution in the field holds when controlling for field category and mathematical skill. I also discuss related phenomena, for example how social conventions perpetuate ethnic and gender inequality.

Finally, I compare my result with Leslie, Cimpian, Meyer, and Freedland's (2015) finding that the more that people in a field believe that success in the field requires "inherent talent" or "brilliance" as opposed to hard work or persistence, the lower the percentage of people in the field who are women. I find that their measure of a field's belief in the necessity of inherent talent is positively correlated with the skewness of the citation distribution in the field. In other words, perhaps people in a field believe in the necessity of inherent talent because they want to agree with each other, and "talent" is an explanation, however unrealistic, for success that allows people to coordinate their opinions. Similar examples of success being explained as resulting from an inherent or even physical attribute of a person can be found in political leaders, performing artists, and technology leaders, who face an "audience" in which each person gains by coordinating with others (for example, by all supporting the same leader, enjoying the same singer, and using the same messaging application). I also survey common usage of the term "talented" and find that it most often describes occupations such as musician, artist, and author, that face "audiences," even though of course mechanics and veterinarians can be talented.

Many have studied how stereotypes operate in many different ways. This paper focuses particularly on how stereotypes can be especially powerful when people like to agree with each other. I conclude by suggesting how stereotypes might be most effectively countered.

Argument

Most important decisions, especially in academic life, such as whether to hire a job candidate, fund a grant proposal, or admit graduate students, are made by groups in which people express their opinions. This paper's argument relies on two aspects of group decisions.

First, each person wants to express an opinion that is to some degree similar to others' opinions. Research on this goes back at least to Asch (1956), who asked experimental subjects which of three line segments is the same length as a reference line segment. Subjects answered correctly more than 99 percent of the time when asked alone. However, when subjects were asked after seven to nine other people in a group (confederates of the experimenter) all expressed the same incorrect opinion, subjects were swayed on average 37 percent of the time. Subjects "found it painful to be (as they imagined) the focus of attention, in addition to which they feared exposure of their weakness which they suspected the group would disapprove" (Asch 1956, p. 32). In their meta-analysis of 133 replications of Asch's experiment from 17 countries, Bond and Smith (1996) report that on average a subject was swayed in this manner 29 percent of the time.

In academic life, Caplow and McGee (1958, p. 128, emphasis in the original) find that when a department evaluates a job candidate, "there is very little point in trying to determine how good the man really *is*. . . . What is important is what others in the discipline think of him." In other words, most people want to choose a candidate whom other people already like. Merton (1968, p. 57; 1988) mentions how several Nobel laureates interviewed by Zuckerman (1977) say they often receive undeserved credit; in the words of one physicist, "The world is peculiar in this matter of how it gives credit. It tends to give the credit to [already] famous people." It is easier to say a person is excellent if other people say she is excellent. Even if a person does not care to "conform" and agree with others, it can still be quite costly to express a differing opinion. For example, expressing a minority opinion in a tenure case can be very personally costly even when colleagues disagree in good faith.

The second aspect of group decisions is that each person sees public signals and private signals. Public signals are common knowledge: each person knows that everyone sees them, knows that everyone knows that everyone sees them, and so forth. For example, say a group is deciding whether to hire a job candidate who has come for a campus visit. Examples of public signals include the candidate's gender presentation, ethnicity to some degree, physical characteristics such as height, weight, and hair color, and also relatively unspecific descriptors such as the candidate's subfield and home institution.

Private signals are usually much more specific and informational, but each person in a group decision does not know whether other people see them. You get the highest quality information about a job candidate by reading their written work, which is often published and widely available. However, this takes substantial time and effort, and you read a candidate's work with little expectation that anyone else reads it. Even if some of your colleagues do, you know they might judge it quite differently, given their different expertise and tastes.

A person's gender presentation is a very public signal, because people can signal gender in multiple redundant ways, through their physical features, clothing, mannerisms, speech, and name, and also because much of everyday life is organized around gender and thus people can assume that other people find gender distinctions meaningful (Ridgeway 2011). When I perceive a person as male, I am confident that others perceive that person as male also.

There is evidence that stereotypical beliefs based on gender persist. For example, Steinpreis, Anders, and Ritzke (1999) asked 238 academic psychologists to evaluate a job candidate based on the candidate's curriculum vitae, and found that both male and female evaluators were significantly more likely to support hiring a male over a female with identical qualifications. Evidently, the sole fact that a job candidate is a woman is enough for many to switch from supporting to not supporting the candidate.

The informational "power" of this sexist stereotype need not be overwhelming, and indeed might not be easily detectable without making all other aspects of a hiring case identical, as in experimental studies. But even if people think that a stereotype has weak informational value, it can have a large impact because it is public.

The public stereotype that women are academically inferior to men has been created by many years of exclusion and sexist public statements and practices. According to Ridgeway (2011, pp. 62, 170), "basic gender stereotypes appear to be consensual knowledge in the United States in that virtually everyone knows the content of these beliefs and most people presume that 'most others' in society hold these stereotypes. . . . [C]hanges in gender stereotypes have lagged substantially behind changes in material arrangements between men and women." Upson and Friedman (2012), quoted in Meyer, Cimpian, and Leslie (2015), ask readers to name ten female geniuses in history. Even people who personally know many smart women have difficulty doing this because the question refers to public figures, whom everyone is supposed to know (such as Marie Curie), as opposed to geniuses you know but who are not widely known. In other words, the stereotype that a man is more likely to be a genius than a woman is stronger in the public arena than in one's personal lived experience.

So when a job candidate is a woman, her gender itself is a public signal and the stereotype that women are academically inferior is public, even if weak. In comparison, a job candidate's scholarly work is much less public; a person reading it knows most of her colleagues do not.

If a hiring decision is made by a person who cares only about scholarly quality, the superior information provided by a woman's scholarly work can outweigh a stereotypical belief against women. This is the mechanism that some believe will ensure women's proper representation in the academy: over time, true quality will overcome stereotypes.

However, if a person making a hiring decision wants to express an opinion that is similar to the opinions of others, then the information provided by a woman's scholarly work is disadvantaged because it is effectively private. When people want to express an opinion that is similar to the opinions of others, a public signal, such as from a stereotype, influences expressed opinions much more because people know that if they follow a public signal, they are more likely to express an opinion close to those of others. In contrast, following one's own private signal does not help one choose an opinion close to those of others.

The following model makes this argument precisely. Even when people want to express a correct opinion, if they also want to express an opinion similar to other people's opinions, then public signals such as stereotypes can outweigh private signals that have much greater informational value. The more people care about agreeing with others, the greater the power of stereotypes and the more difficult they are to overcome.

Model

The model is a very simple "discrete" version of the "continuous" model in Morris and Shin (2002). Two people evaluate a candidate, who is either high quality 1 with probability π_1 or low quality 0 with probability π_0, where $\pi_1, \pi_0 \in [0,1]$ and $\pi_1 + \pi_0 = 1$. The two people do not know the candidate's quality, but each person sees an independent private signal about the candidate which is either high (h) or low (l), and correct with probability $p > 1/2$. The two people also see a public signal about the candidate which is either high (H) or low (L), and correct with probability $q > 1/2$. After observing her own private signal and the public signal, each person i chooses an opinion a_i about the candidate, where $a_i \in \Re$. Each person wants to choose an opinion that is close to the candidate's true quality y, but also close to the opinion of the other person. So person 1's utility function u_1 is given by $u_1(a_1, a_2, y) = -(a_1 - y)^2 - r(a_1 - a_2)^2$ and person 2's utility function u_2 is given by $u_2(a_1, a_2, y) = -(a_2 - y)^2 - r(a_2 - a_1)^2$, where $r \geq 0$ is a parameter. The larger r is, the more a person wants to choose an opinion that is close to the other person's.

This is a game of incomplete information with four parameters, which we call $\Gamma(\pi_1, p, q, r)$, and we can make a prediction as follows.

Since the two private signals are either h or l, the public signal is either H or L, and the candidate is either quality 1 or 0, the set of states of the world is $\Omega = \{h,l\} \times \{h,l\} \times \{H,L\} \times \{1,0\}$. Given state $\omega \in \Omega$, person 1's private signal is given by ω_1, person 2's private signal is ω_2, the public signal is ω_3, and the candidate's true quality is ω_4. For example, the state $\omega = (h, l, L, 1)$ is the state in which person 1 gets a high signal, person 2 gets a low signal, the public signal is low, and the candidate is quality 1.

Given the state of the world ω, person 1 sees only his own private signal ω_1 and the public signal ω_3. So a strategy for person 1 is a function $f : \{h,l\} \times \{H,L\} \to \Re$ which we write as $f(\omega_1, \omega_3)$. Similarly, a strategy for person 2 is a function $g : \{h, l\} \times \{H, L\} \to \Re$ which we write as $g(\omega_2, \omega_3)$.

The probability of state ω is given by $P(\omega) = \pi_{\omega_4} e(\omega_4, \omega_1) e(\omega_4, \omega_2) E(\omega_4, \omega_3)$, where e is defined by $e(1, h) = p$, $e(1, l) = 1 - p$, $e(0, h) = 1 - p$, $e(0, l) = p$ and E is defined by $E(1, H) = q$, $E(1, L) = 1 - q$, $E(0, H) = 1 - q$, $E(0, L) = q$. For example, the probability of state $(h, l, L, 1)$ is $P(h, l, L, 1) = \pi_1 p(1 - p)(1 - q)$.

When f is a strategy for person 1 and g is a strategy for person 2, person 1's expected utility is $EU_1(f, g) = \sum_{\omega \in \Omega} P(\omega) u_1(f(\omega_1, \omega_3), g(\omega_2, \omega_3), \omega_4)$ and person 2's expected utility is $EU_2(f, g) = \sum_{\omega \in \Omega} P(\omega) u_2(f(\omega_1, \omega_3), g(\omega_2, \omega_3), \omega_4)$. We say that (f, g) is a Nash equilibrium if $EU_1(f, g) \geq EU_1(f', g)$ for all strategies f' of person 1 and $EU_2(f, g) \geq EU_2(f, g')$ for all strategies g' of person 2.

It is easy to show that a unique Nash equilibrium of $\Gamma(\pi_1, p, q, r)$ exists (proofs are in the appendix) and is symmetric: each person plays the same strategy f.

Fact 1. The unique Nash equilibrium of $\Gamma(\pi_1, p, q, r)$ is (f, f), where f is given by

$$f(h, H) = \frac{\pi_1 pq[\pi_1(1 - p)q + \pi_0 p(1 - q) + r(1 - p)(\pi_1 q + \pi_0(1 - q))]}{p(1 - p)(\pi_1 q - \pi_0(1 - q))^2 + \pi_1 \pi_0 q(1 - q) + rp(1 - p)(\pi_1 q + \pi_0(1 - q))^2}$$

$$f(l, H) = \frac{\pi_1(1 - p)q[\pi_1 pq + \pi_0(1 - p)(1 - q) + rp(\pi_1 q + \pi_0(1 - q))]}{p(1 - p)(\pi_1 q - \pi_0(1 - q))^2 + \pi_1 \pi_0 q(1 - q) + rp(1 - p)(\pi_1 q + \pi_0(1 - q))^2}$$

$$f(h, L) = \frac{\pi_1 p(1 - q)[\pi_1(1 - p)(1 - q) + \pi_0 pq + r(1 - p)(\pi_1(1 - q) + \pi_0 q])}{p(1 - p)(\pi_1(1 - q) - \pi_0 q)^2 + \pi_1 \pi_0(1 - q)q + rp(1 - p)(\pi_1(1 - q) + \pi_0 q)^2}$$

$$f(l, L) = \frac{\pi_1(1 - p)(1 - q)[\pi_1 p(1 - q) + \pi_0(1 - p)q + rp(\pi_1(1 - q) + \pi_0 q)]}{p(1 - p)(\pi_1(1 - q) - \pi_0 q)^2 + \pi_1 \pi_0(1 - q)q + rp(1 - p)(\pi_1(1 - q) + \pi_0 q)^2}$$

and $\pi_0 = 1 - \pi_1$.

To understand this result, first note that when $r = 0$, people do not care about having an opinion similar to anyone else's, and a person's opinion is simply her belief that the candidate is quality 1 given her evidence and Bayes' Rule.

Fact 2. When $r = 0$ we have

$$f(h,H) = \frac{\pi_1 pq}{\pi_1 pq + \pi_0(1-p)(1-q)}$$
$$f(h,L) = \frac{\pi_1 p(1-q)}{\pi_1 p(1-q) + \pi_0(1-p)q}$$
$$f(l,H) = \frac{\pi_1 (1-p)q}{\pi_1(1-p)q + \pi_0 p(1-q)}$$
$$f(l,L) = \frac{\pi_1(1-p)(1-q)}{\pi_1(1-p)(1-q) + \pi_0 pq}$$

For example, if a person sees signals h and H, a high private signal and a high public signal, then her belief that the candidate is quality 1 is the probability that the candidate is quality 1 and she sees h and H, which is $\pi_1 pq$, divided by the total probability that she sees h and H, which is $\pi_1 pq + \pi_0(1-p)(1-q)$, the probability the candidate is quality 1 and both signals are correct plus the probability the candidate is quality 0 and both signals are incorrect.

Table 1 shows some examples of how the Nash equilibrium strategy f changes when the parameters π_1, p, q, r change. In Table 1, we have $\pi_1 = 0.5$; each person has an unbiased prior opinion about the candidate's quality. In the first three rows, we have $r = 0$; people do not care about agreeing with others. In the first row, $p = 0.7$ and $q = 0.7$; the private signal and public signal are equally informative. Here, if both private and public signals are high, then a person's opinion is $f(h,H) = 0.845$. If both private and public signals are low, then a person's opinion falls to $f(l,L) = 0.155$. If the private signal is high but the public signal is low, the two signals "cancel each other out" and a person's opinion is $f(h,L) = 0.5$, the same as her prior.

π_1	p	q	r		$f(h,H)$	$f(h,L)$	$f(l,H)$	$f(l,L)$
0.5	0.7	0.7	0	$\Rightarrow$	0.845	0.5	0.5	0.155
0.5	0.8	0.7	0	$\Rightarrow$	0.903	0.632	0.368	0.097
0.5	0.7	0.8	0	$\Rightarrow$	0.903	0.368	0.632	0.097
0.5	0.7	0.7	2	$\Rightarrow$	0.753	0.373	0.627	0.247
0.5	0.8	0.7	2	$\Rightarrow$	0.786	0.441	0.559	0.214
0.5	0.855	0.7	2	$\Rightarrow$	0.812	0.5	0.5	0.188

Table 1. Examples of how the equilibrium
$f(h,H), f(h,L), f(l,H), f(l,L)$
depends on π_1, p, q, r, when $\pi_1 = 0.5$

In the second row, we now have $p = 0.8$ and $q = 0.7$; the private signal is now more informative than the public signal. Now $f(h, L) = 0.632$ is higher than $f(l, H) = 0.368$ because now a private signal is a better signal of quality than a public signal. In the third row, we have $p = 0.7$ and $q = 0.8$, and $f(l, H) = 0.632$ is higher than $f(h, L) = 0.368$. When $r = 0$, all that matters is a signal's informativeness; whether a signal is private or public makes no difference. This is all just Bayesian updating.

Next we have three rows in which $r = 2$; people want to agree with others. In the fourth row, both $p = 0.7$ and $q = 0.7$; private and public signals are equally informative. But now $f(l, H) = 0.627$, which is greater than the prior 0.5. Because people want to agree with each other, a high public signal far outweighs a low private signal, even when the signals are equally informative. Another way to say this is that if the impact of the public signal and the private signal were the same, we would have $f(h, L) = f(l, H)$; however, $f(l, H) = 0.627$ is greater than $f(h, L) = 0.373$ because the public signal influences opinion much more than the private signal.

In the fifth row of Table 1, the private signal is more informative than the public signal: $p = 0.8$ and $q = 0.7$. But still $f(l, H) = 0.559$ is greater than $f(h, L) = 0.441$. Even though the private signal is more informative than the public signal, the public signal still has greater influence on opinion. It turns out that only when $p = 0.855$ does the private signal have the same impact as the public signal; in the sixth row, when $p = 0.855$ and $q = 0.7$, we have $f(h, L) = f(l, H)$. Because people like to agree with each other, a private signal must be correct 85.5 percent of the time to have the same impact as a much less informative public signal that is correct 70 percent of the time.

Figure 1 shows curves that are the set of (p, q) that make the private and public signal influence a person's opinion equally; in other words, the (p, q) that satisfy $f(h, L) = f(l, H)$. Here we have $\pi_1 = 0.5$. When $r = 0$, people don't care about agreeing with each other, and thus there is no difference between public and private, and so we have the line $p = q$: if the public signal is correct with probability 0.7 for example, a private signal has the same impact if it has probability 0.7. When $r = 2$, we have a curve which goes through $(p, q) = (0.855, 0.7)$, our example from Table 1; when the public signal is correct with probability $q = 0.7$, a private signal must be correct with probability $p = 0.855$ to have the same impact. When the public signal is correct with probability $q = 0.8$, a private signal must be correct with a probability a bit more than 0.9 to have the same impact. When $r = 10$ and people care a lot about agreeing with each other, an almost completely uninformative public signal, correct only 60 percent of the time, has the same impact as a private signal correct more than 90 percent of the time.

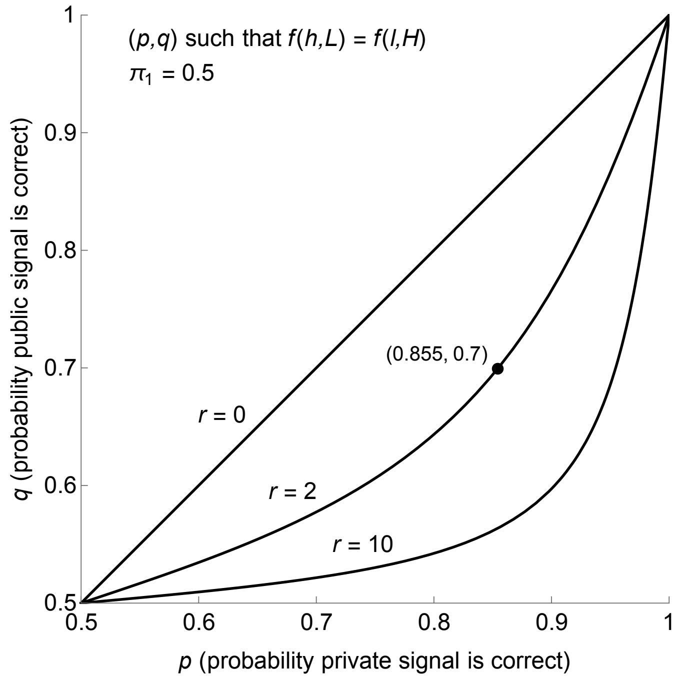

Figure 1. Each curve is the set of (p, q) that make $f(h, L) = f(l, H)$ (the public signal and private signal affect opinions equally), for $r = 0, 2, 10$, when $\pi_1 = 0.5$

When $\pi_1 = 1/2$ and $p = q$, in other words when priors are unbiased and public and private signals are equally informative, we can make a general statement about the impact of the public signal relative to the private signal. The impact of the public signal can be understood as $f(h, H) - f(h, L)$ and the impact of the private signal can be understood as $f(h, H) - f(l, H)$. We can show that the impact of the public signal is $r+1$ times the impact of the private signal. If $r = 0$, the public and private signals have the same impact; as r increases and people have a greater desire to agree with each other, the impact of a public signal relative to a private signal increases. Fact 3 is the analogue of equation (21) in Morris and Shin (2002).

Fact 3. When $\pi_1 = 1/2$ and $p = q$, $(f(h, H) - f(h, L))/(f(h, H) - f(l, H)) = r + 1$.

What happens when prior beliefs differ from $\pi_1 = 1/2$? When a candidate is almost certainly of high quality, perhaps there should be less of a difference between public and private signals (see also Dale and Morgan 2015). However, the difference remains and in relative terms increases. Table 2 shows some examples when $\pi_1 = 0.9$ and $\pi_1 = 0.99$. Signals have a smaller absolute effect than in Table 1 because people already believe that the candidate is almost certainly high quality. However, as one can see from the second and fifth rows, when $r = 2$, the effect of a public signal is still large relative to the effect of a private signal. As shown in the third row, when $\pi_1 = 0.9$, a private signal has to be correct with probability 0.876 to have the same impact as a public signal that is correct with probability 0.7, which is more demanding than when $\pi_1 = 0.5$ in Table 1. As shown in the sixth row, when $\pi_1 = 0.99$, a private signal has to be correct with probability 0.8996 to have the same impact as a public signal which is correct with probability 0.7, which is even more demanding.

π_1	p	q	r		$f(h,H)$	$f(h,L)$	$f(l,H)$	$f(l,L)$
0.9	0.7	0.7	0	$\Rightarrow$	0.980	0.9	0.9	0.623
0.9	0.7	0.7	2	$\Rightarrow$	0.963	0.832	0.936	0.733
0.9	0.876	0.7	2	$\Rightarrow$	0.969	0.876	0.876	0.582
0.99	0.7	0.7	0	$\Rightarrow$	0.9981	0.99	0.99	0.9479
0.99	0.7	0.7	2	$\Rightarrow$	0.9965	0.9814	0.9938	0.9672
0.99	0.8996	0.7	2	$\Rightarrow$	0.9970	0.9845	0.9845	0.9214

Table 2. Examples of how the equilibrium $f(h,H), f(h,L), f(l,H), f(l,L)$ depends on π_1, p, q, r, when $\pi_1 = 0.9, 0.99$

Figure 2 shows curves that are the set of (p,q) that satisfy $f(h,L) = f(l,H)$ when $\pi_1 = 0.9$ and $\pi_1 = 0.99$ (the curves when $\pi_1 = 0.5$, from Figure 1, are shown in gray as a comparison). As π_1 goes from 0.5 to 0.9 to 0.99, the absolute impact of any signal decreases, but the impact of a public signal relative to a private signal increases. In other words, a very senior candidate whom everyone believes is almost certainly high quality is less vulnerable to a public negative signal, because even with a negative signal, a person's opinion that she is high quality declines only slightly in absolute terms. However, her vulnerability to a public signal relative to a private signal is even greater than for a candidate who is not well known.

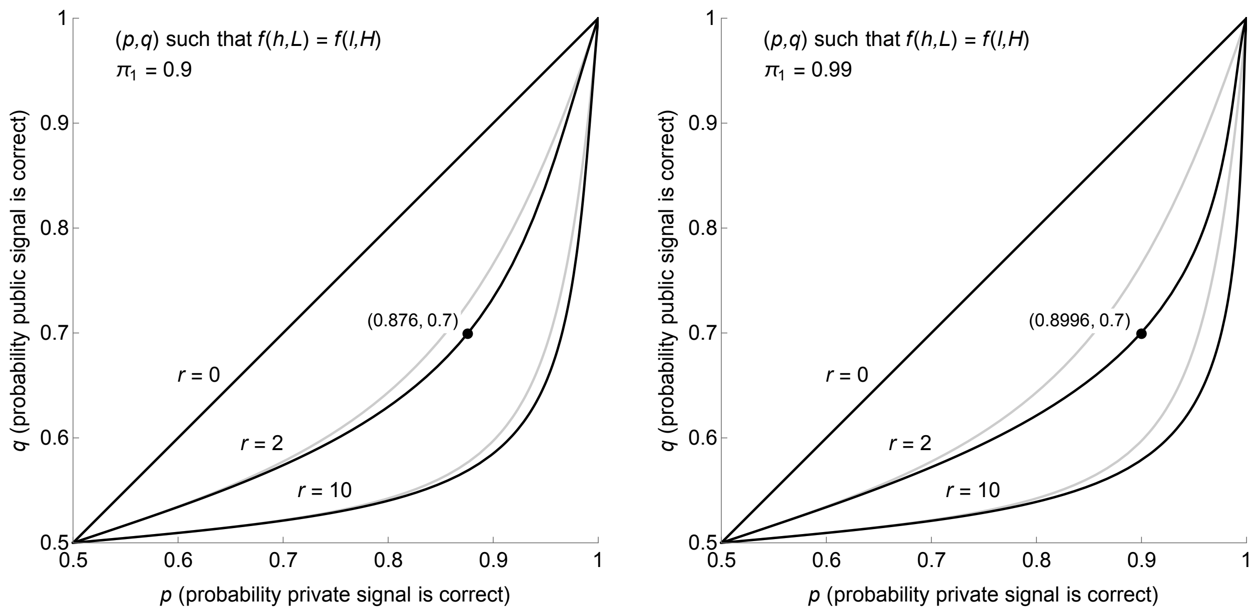

Figure 2. Each curve is the set of (p, q) that make $f(h, L) = f(l, H)$ (the public signal and private signal affect opinions equally), for $r = 0, 2, 10$, when $\pi_1 = 0.9$ and $\pi_1 = 0.99$ ($\pi_1 = 0.5$ is shown in gray)

Data

My unit of observation is an academic field, such as astronomy, chemical engineering, or sociology. Some fields, such as bioinformatics or polymer chemistry, might be considered "subfields" but I call them all "fields." Data are taken from three sources.

First, the percentages of women and different ethnic groups in a field are given by Table 16 and Table 22 of the NSF Survey of Earned Doctorates (SED), which considers all 49,010 people who received research doctoral degrees in the United States in 2011 (National Science Foundation, National Center for Science and Engineering Statistics 2012).

Second, the skewness of the distribution of citations in a field is taken from the working paper version of Albarrán, Crespo, Ortuño, and Ruiz-Castillo (2011), abbreviated here as ACORC, which analyzes 3.77 million papers published between 1998 and 2002 available from Thomson Reuters's Web of Science and the number of citations each paper received within five years of publication. Thomson Reuters defines more than 250 Web of Science subject areas (for a list see Web of Science Subject Areas 2016), and classifies each paper into one or more of these areas. ACORC combine some subject areas into a single field and exclude the humanities, because they find that citation distributions in humanities fields are quite different from those in non-humanities fields, and in the end report results on 219 fields.

Our measure of the skewness of the citation distribution in a field is simply the percentage of papers that receive fewer than the average number of citations in the field. For example, if papers in the field of oceanography are cited 7.2 times on average, the skewness of oceanography is the percentage of papers in oceanography that receive 7 or fewer citations. If the citation distribution is symmetric around the mean and thus not skewed at all, then skewness would be 50 percent. If almost all citations go to just a handful of papers and thus the distribution is maximally skewed, then skewness would be close to 100 percent.

Third, mathematical and verbal ability in each field is given by Table 4 (Extended), distributed by the Educational Testing Service (2016), which considers college seniors and nonenrolled college graduates who took the Graduate Record Examination (GRE) between August 1, 2011, and June 30, 2014, and who specified their intended major field in graduate school. Table 4 (Extended) provides mean GRE verbal reasoning, quantitative reasoning, and analytical writing scores across over 450 fields.

Bringing these three data sources together requires matching according to field. This can be challenging because each source defines fields differently. For example, the SED has the single field "Acoustics, optics/photonics" but there are two separate Web of Science subject areas, "Acoustics" and "Optics." To make the fields comparable, I combine "Acoustics" and "Optics" into a single field and say that its skewness is simply the average of the skewness of "Acoustics" and the skewness of "Optics." Some fields are included in one source but not others; for example, the SED includes the field "Wildlife/range management" but there are no corresponding Web of Science subject areas. I try to find as many commonalities between the first two data sources as possible and combine fields as little as possible to preserve fine distinctions between fields. After doing this, I have 119 fields. Then I assign average GRE scores as specifically as I can to each field.

Table 3 shows how the 119 fields fall into categories defined by the SED. With the exception of education and the humanities, my data cover fairly well the entire set of research doctorates granted in the United States. The category of education, which includes fields such as "Curriculum and instruction," "Educational leadership," "Art education" and "Physical education and coaching," is not covered well by my data. My data only cover three of the 32 education fields listed in the SED, and roughly half of the total doctorates awarded in education. My data do not include the humanities at all because ACORC exclude them. I should note that according to the SED, biophysics belongs to both the category of biological and biomedical sciences and the category of physical sciences, and educational psychology belongs to both psychology and education. We respect this dual classification elsewhere in the paper (in Figure 4 and in the regressions in Table 4 and Figures 5 and 7), but in Table 3, biophysics is included in biology and educational psychology is included in psychology. The complete data set of 119 fields is in Table A1 in the appendix.

The SED reports the number of people in each field with temporary visa status, which includes people who came to US universities from other countries and undocumented US residents. The SED reports the ethnicity of only US citizens and permanent residents, and so when we say that agricultural economics is 19.4 percent Asian, for example, we mean that 19.4 percent of US citizens and permanent residents receiving doctorates in agricultural economics are Asian. The percent of women in a field refers to all women, regardless of visa status.

	Doctorates awarded in the US	Doctorates awarded in my data set	Number of fields in NSF SED	Number of fields in my data set	Examples of fields in my data set
Life sciences					
Agricultural sciences and natural resources	1209	1159	12	10	Agronomy Environmental science
Biological and biomedical sciences	8135	8058	29	27	Neurosciences Biochemistry
Health sciences	2123	1851	10	8	Nursing science Epidemiology
Physical sciences					
Astronomy	288	288	3	1	Astronomy
Atmospheric science and meteorology	178	178	2	1	Atmospheric science and meteorology
Chemistry	2439	2181	8	6	Organic chemistry Analytical chemistry
Computer and information sciences	1711	1602	4	3	Computer science Information science and systems
Geological and earth sciences	453	453	5	5	Geology Geophysics and seismology
Mathematics	1607	1607	8	4	Mathematics Applied mathematics
Ocean/marine sciences	225	225	3	3	Oceanography Marine sciences
Physics	1777	1517	11	9	Condensed matter physics Particle physics
Psychology	3594	3330	14	10	Clinical psychology Counseling
Social sciences	4526	4303	13	11	Economics Political science
Engineering	8004	7295	14	13	Electrical engineering Mechanical engineering
Education	4691	2546	32	3	Education research Special education
Humanities	5214	0	30	0	
Other	2836	2386	20	5	Business management Communication Finance Social work Public administration
Total	49010	38979	218	119	

Table 3. Description of the 119 fields in my data set, organized into categories from the NSF Survey of Earned Doctorates (SED)

Analysis of data

My claim is that in academic fields in which people want to agree more with the opinions of others, sexist stereotypes are more powerful and difficult to overcome and thus there will be fewer women. The desire to agree with others is measured by the skewness of the citation distribution: the greater the desire to agree with others, the greater agreement on which papers should be cited, and thus a smaller number of papers receive the bulk of citations, making the citation distribution more skewed. Again, we measure skewness of the citation distribution in a field by the percent of papers in the field that receive fewer than the average number of citations in the field.

Figure 3 shows the percent of people in a field who are women for each of the 119 fields, as a function of the skewness of the citation distribution in the field and the average quantitative reasoning GRE in the field (some numbers have been "jittered" slightly leftward or rightward to make them readable, and I labeled as many fields as possible consistent with readability). Note that more mathematical fields tend to have fewer women: the numbers decrease as one moves "rightward." Also, more mathematical fields tend slightly to have higher skewness (the correlation is 0.20).

If my claim is true, the numbers should decrease as one moves "upward." We see this pattern, with some exceptions. At the upper right, computational biology, finance, and especially statistics do not fit the pattern. Even though computational biology is very mathematical, biological fields tend to have more women. Perhaps finance draws from a different student pool than equally quantitative fields in engineering and the physical sciences. Statistics, because of its great variety of applications, might attract a wider audience, including women. In the upper left, the most obvious exceptions are education research and educational psychology; perhaps people enter education fields after being primary and secondary school teachers, who are often women.

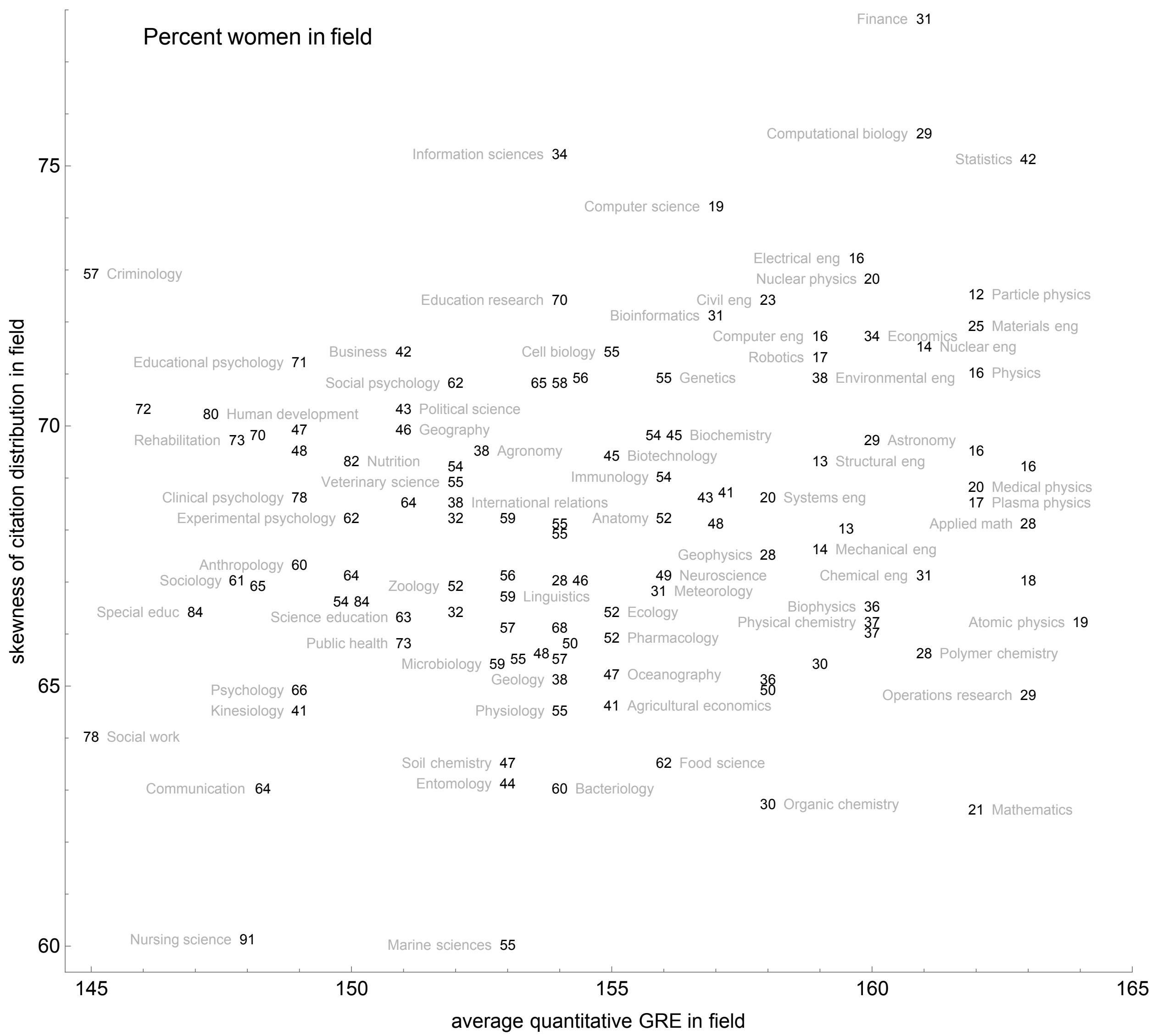

Figure 3. How percent women in field depends on skewness and quantitative GRE (skewness is defined as the percent of papers in the field that receive fewer citations than the average number of citations in the field)

Thus we should compare fields which belong to the same category. Figure 4 does this for the categories of engineering (13 fields), physical sciences (33 fields), biological sciences (27 fields), and agricultural sciences and natural resources (10 fields). These four categories altogether comprise 83 (70 percent) of our 119 fields. The data here are the same as in Figure 3 but separated by category. Now, within each category, the pattern is clearer. All of the engineering fields are quite quantitative but those with higher skewness tend to have fewer women (environmental engineering is a notable exception). There is a greater range of quantitative skills in the physical sciences, but again fields with higher skewness have fewer women (statistics being the main exception). The pattern holds, but less strongly, within the biological and biomedical sciences as well as within agricultural sciences and natural resources. If we do a similar plot for social sciences (11 fields), health sciences (8 fields) and the "other" category (5 fields), we see the pattern, but we do not see the pattern in psychology (10 fields) and education (4 fields).

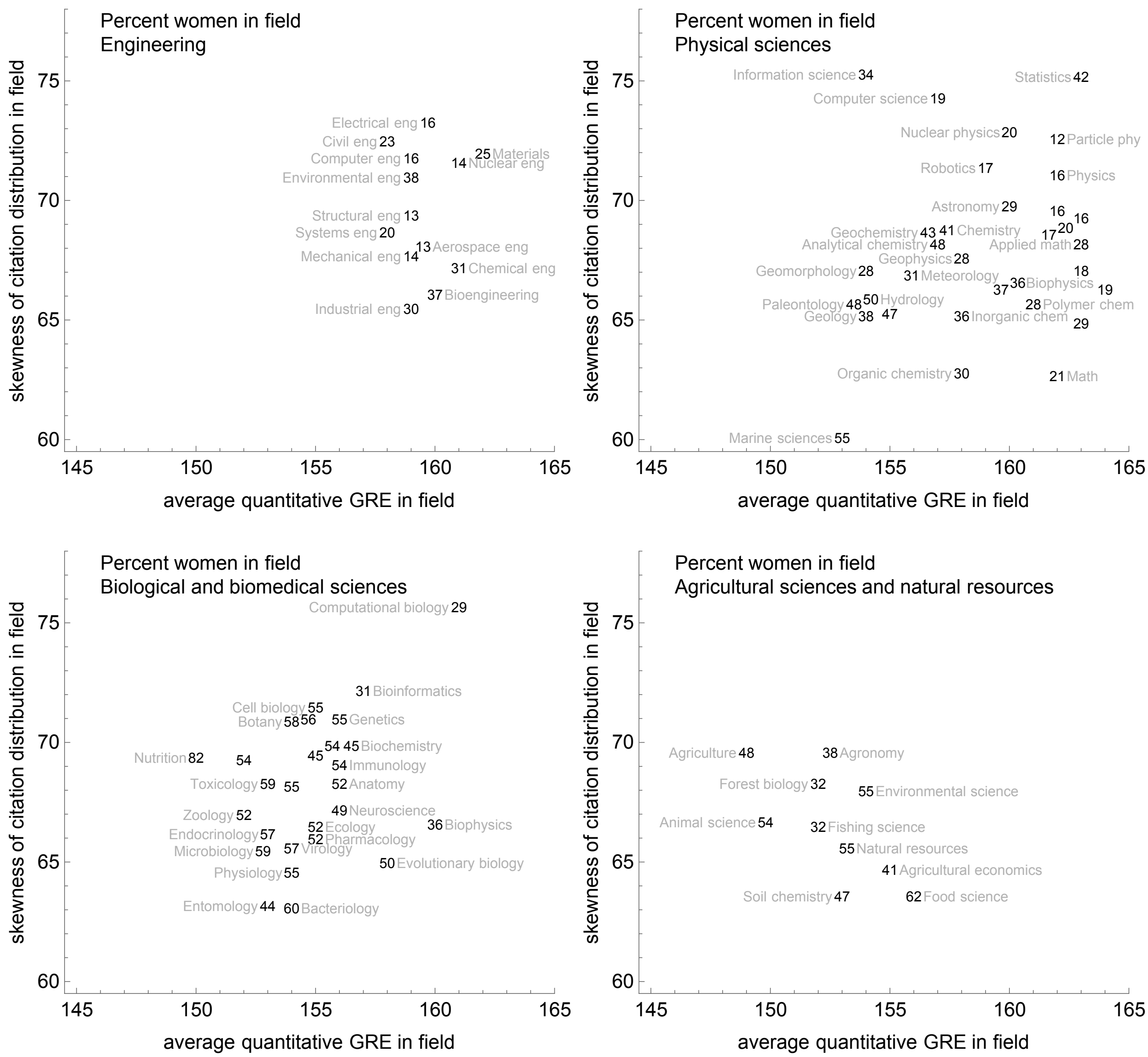

Figure 4. How percent women in field depends on
skewness and quantitative GRE, in different field categories

In Table 4, percent women in a field is regressed on variables including skewness, average verbal reasoning GRE, average quantitative reasoning GRE, and field categories. The analytical writing GRE is highly correlated with the verbal reasoning GRE (correlation 0.84) and thus I do not include it. Regression (i) regresses percent women on skewness alone, and finds that skewness is statistically significant at the 0.01 confidence level. In regression (ii), which adds verbal GRE and quantitative GRE as controls, skewness is no longer significant. The effect of quantitative GRE is very strong and statistically significant, and verbal GRE is significant in the opposite direction. When field categories are added in regression (iii), skewness is statistically significant at the 0.01 confidence level and the effect of verbal GRE goes away. Fields in physical science, engineering, and agricultural sciences and natural resources have fewer women and fields in psychology and education have more women (the omitted field category is "other"). Regression (iv) is a simplification of regression (iii).

Percent women in field regressed on	(i)	(ii)	(iii)	(iv)
Skewness	-1.60^{**}	-0.48	-0.96^{**}	-1.13^{***}
	(0.54)	(0.33)	(0.3)	(0.29)
Verbal GRE		1.04^{**}	0.11	0.0003
		(0.39)	(0.39)	(0.37)
Quantitative GRE		-3.38^{***}	-1.95^{***}	-1.74^{***}
		(0.23)	(0.34)	(0.32)
Agricultural sciences and natural resources			-7.13	-10.75^{**}
			(4.60)	(3.21)
Biological and biomedical sciences			4.80	
			(4.01)	
Health sciences			6.19	
			(4.80)	
Physical sciences			-9.77^{*}	-14.15^{***}
			(4.45)	(2.78)
Psychology			12.02^{**}	9.72^{**}
			(4.44)	(3.28)
Social sciences			-0.85	
			(4.56)	
Engineering			-14.58^{**}	-19.22^{***}
			(5.06)	(3.71)
Education			13.60^{*}	11.50^{*}
			(5.31)	(4.73)
Constant	154.80^{***}	442.60^{***}	397.85^{***}	397.29^{***}
	(36.66)	(63.63)	(61.47)	(56.20)
R^2	0.071	0.681	0.795	0.786
N	119	119	119	119

Table 4. Coefficients from regressing percent women in field on skewness, average GRE scores, and field category (standard errors in parentheses, stars indicate significance at 0.05^{*}, 0.01^{**}, 0.001^{***} level)

From Table 4, if skewness in a field increases by one percent, the percent of women in the field decreases by roughly one percent, controlling for GRE scores and field category. Figure 5 shows the size of this effect, using the coefficients from regression (iii) in Table 4 to show the effect on the percent of women as each variable goes from minimum to maximum. The minimum skewness is 60 (Marine science) and the maximum is 77.8 (Finance), and as skewness goes from 60 to 77.8, all other things being the same, the percent of women declines by 17.12 percent. The minimum average quantitative GRE is 145 (Criminology and Social work) and the maximum is 164 (Atomic physics), and as the average quantitative GRE goes from 145 to 164, all other things being the same, the percent of women declines by 37.02 percent. The effect of skewness is not as large as the effect of quantitative GRE, but is larger than any of the field category effects.

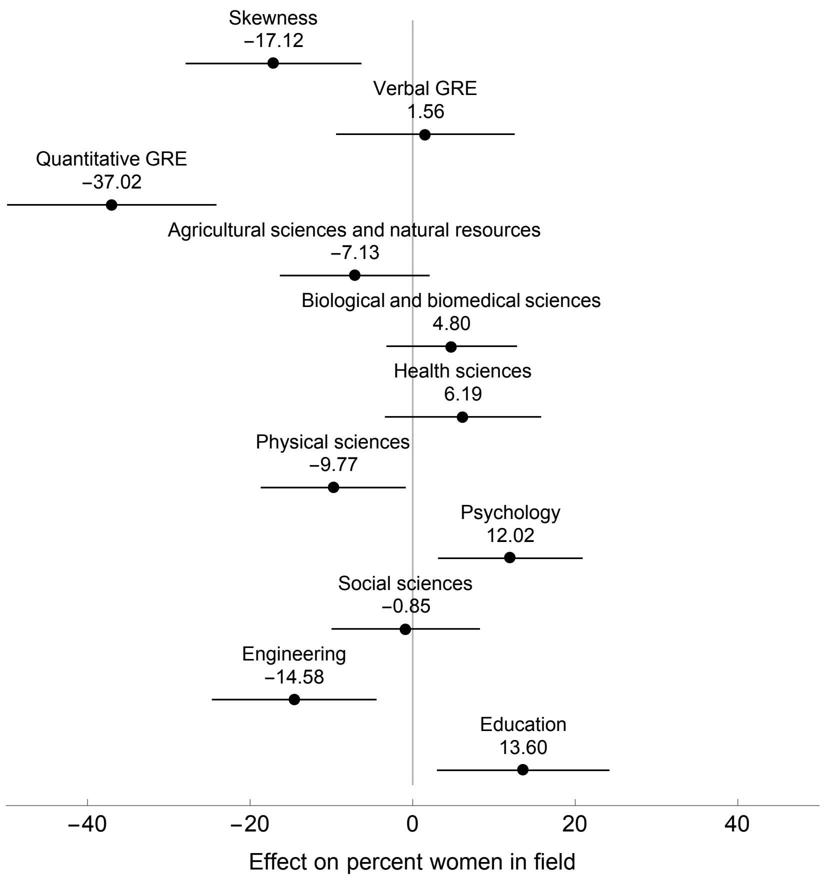

Figure 5. Effect on percent women in field as variable goes from minimum to maximum (estimates from regression (iii) in Table 4, with 0.95 confidence intervals)

We can also look at the percentage of different ethnic groups and temporary visa holders in each field. Figure 6 shows the distribution of percent Asian, Black, Hispanic, White, temporary visa holders, and women in each of our 119 fields.

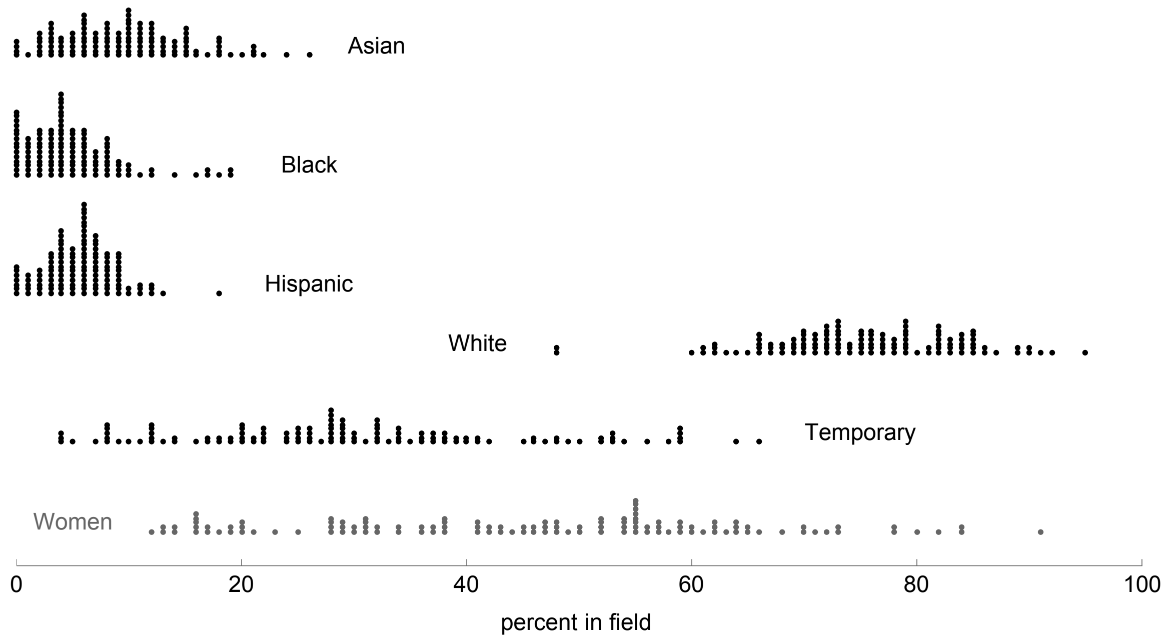

Figure 6. Distribution of percent Asian, Black, Hispanic, White, temporary visa holders, and women in field

When we regress percent Asian, Black, Hispanic, White, temporary visa holders, and women on skewness, GRE scores, and field category, we get Figure 7. This is the equivalent of Figure 5 but with a different regression done for percent of each ethnic group and for percent temporary visa holders (details of each regression are in Table A2 in the appendix). Skewness affects percent Asians positively (significant at 0.05 level), Hispanics negatively (significant at 0.05 level), and Blacks also negatively (not quite significant at 0.05 level). These effects are smaller in absolute terms than the effect on percent women, but are comparable in relative terms: as shown in Figure 6, percent women has a much larger range (from 13 to 91 percent) than percent Asian, Hispanic, and Black (from 0 to roughly 20 percent). Skewness has no effect on percent White and percent temporary visa holders. These results are consistent with Hispanics and Blacks being hindered by negative stereotypes, Whites and temporary visa holders being free from stereotypes, and Asians benefitting from positive stereotypes. My claim that stereotypes are more powerful when people want to agree with each other more appears to be confirmed for ethnic groups as well as for women.

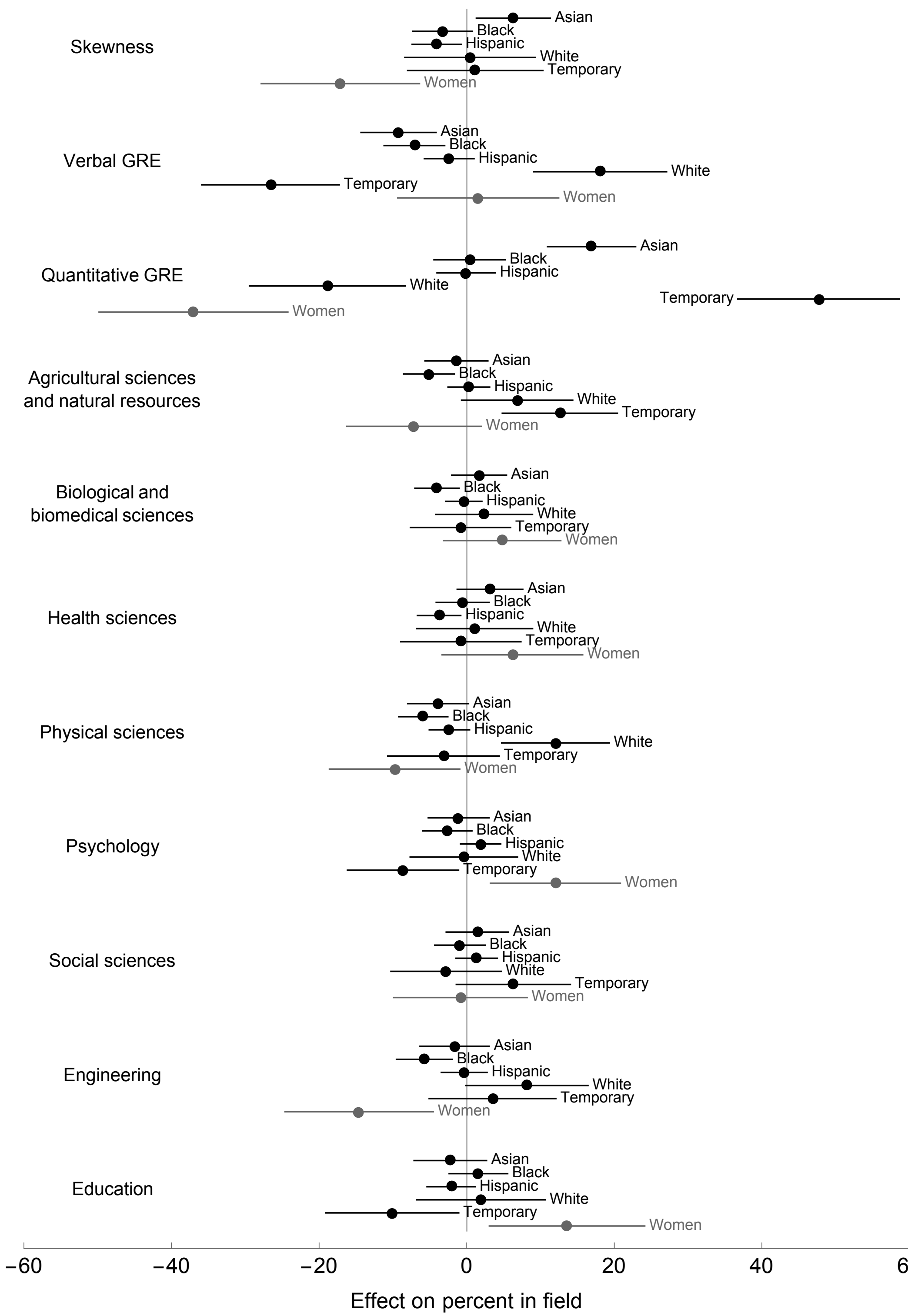

Figure 7. Effect on percent Asian, Black, Hispanic, White, temporary visa holders, and women in field as variable goes from minimum to maximum (with 0.95 confidence intervals)

Competing explanations

This paper does not try to provide a comprehensive theory of stereotypes or why some fields have fewer women than others (for a recent survey see Ceci, Ginther, Kahn, and Williams 2014). What is novel about the paper is the finding that there are fewer women in fields with more skewed citation distributions. I explain this with a model that shows that stereotypes, which are public signals, are harder to overcome when people like to agree with each other. Are there other possible explanations?

Perhaps a field has a more skewed citation distribution because of its method of inquiry, not because people in the field want to agree with each other. In more mathematical fields, perhaps the greater abstraction and generality provided by mathematics make it more possible for a single paper to have a wide impact and receive many citations, which makes the citation distribution more skewed. Since there are fewer women in more mathematical fields, this is an alternative explanation. As illustrated in Figure 3, more mathematical fields do tend slightly to have greater skewness (correlation 0.20). However, as shown in Figures 3 and 4 and in the regressions in Table 4, there are fewer women in fields with greater skewness even after controlling for quantitativeness. More evidence that a field's quantitativeness and its skewness are not the same thing comes from Figure 7: more mathematical fields have significantly more temporary visa holders and significantly fewer Whites, but fields with greater skewness do not have more temporary visa holders or fewer whites.

Perhaps skewness influences a person's choice to enter a field through risk preferences. Fields with more skewed citation distributions are riskier in that your paper is either a dud, with few citations, or a hit, with many citations. If men are more tolerant of risk than women, this is an alternative explanation. However, Figure 7 shows that there are fewer Hispanics and Blacks, and more Asians, in fields with greater skewness. So if this alternative explanation is true, we would have to argue that Asians are more risk-tolerant than Whites, who are more risk-tolerant than Hispanics and Blacks. When surveying people about whether they would take a new job that could provide possibly higher or lower income, Barsky, Juster, Kimball, and Shapiro (1997) find that men are more risk-tolerant than women and that Asians are most risk-tolerant, followed by Hispanics, Blacks and Native Americans, and finally Whites; they also find that immigrants are more risk-tolerant than nonimmigrants. Fang, Hanna, and Chatterjee (2013) also find that men are more risk-tolerant than women, but find that Whites are more risk-tolerant than Blacks and Hispanics and that nonimmigrants are more risk-tolerant than immigrants. In sum, the evidence that Whites are more risk-tolerant than Hispanics and Blacks is probably more mixed than the evidence that negative stereotypes exist about Hispanics and Blacks. Also, immigrants might be more or less risk-tolerant than nonimmigrants, but Figure 7 shows that temporary visa holders are neither more nor less likely to enter fields with greater skewness.

Perhaps fields with more skewed citation distributions differ in other ways. They might be seen as more competitive in the sense that success depends on doing better than others rather than just doing well personally. Buser, Niederle, and Oosterbeek (2014) find that high school girls like competition less than their male classmates, that this preference is distinct from risk preferences, and that this to some degree explains why girls choose less mathematical academic tracks. Fields with more skewed citation distributions might require "systemizing" skills, which men seem to be better at, as opposed to "empathizing" skills, which women seem to be better at (Wright, Eaton, and Skagerberg 2015; Varella, Ferreira, Pereira, Bussab, and Valentova 2016). So far studies of preferences over competition, and systemizing versus empathizing skills, compare women's participation across very broad career categories, such as sciences versus humanities or management versus education. Our analysis looks at finer distinctions, such as among the thirteen engineering fields in Figure 4. If there is a difference in competitiveness or systemizing skills between electrical engineering and industrial engineering, for example, it is surely smaller than the difference between science and the humanities. But electrical engineering has 16 percent women while industrial engineering has 30 percent women, a large difference.

Perhaps the skewness of the citation distribution in a field results from the field's centralized social organization. If the main gatekeepers of a field form a tighter "cabal," they might be able to better keep out women and also promote a single way of thinking which allows a paper to receive many citations. In fields with multiple "centers of power," it might be more difficult for a paper to receive citations from across the field, and more difficult to shut out outsiders. Han (2003) looks at the hiring network (which departments hire from which graduate programs) in seven fields and finds, for example, that English and economics are dominated by a single faction of top departments while psychology and history have multiple competing factions (see also Papoutsaki, Guo, Metaxa-Kakavouli, Gramazio, Rasley, Xie, Wang, and Huang (2016), who find that roughly half of the faculty in top 50 US computer science departments received their doctorates from just ten departments). Among the five non-humanities fields which Han considers, the most hierarchical is mathematics, followed by economics, political science, sociology, and psychology (Han 2003, Table 6, p. 269). Among these five fields, the one with the most skewed citation distribution is economics, followed by political science, sociology, psychology, and mathematics (see Figure 3). Excepting mathematics, these rankings are the same, which suggests a connection between a field's social structure and skewness.

One's incentive to agree with others in a field and its degree of centralization might be related. If a field has multiple competing factions, the incentive to agree with others might be lower because it is impossible to agree with everybody. If there is greater inherent uncertainty about whether a given research direction is good, people might be happier if others agree with them and also seek out more the quality assurance of a centralized prestige system.

Finally, one simple alternative explanation of why fields with greater skewness have more men is if men write more papers that receive very few or no citations. Men might write less appealing papers or pursue a riskier strategy of writing papers that have a small chance of being heavily cited but are most likely not cited at all. Thus if there are more men in a field, skewness, which we measure as the percentage of papers with fewer than average citations, will be higher. However, in general papers written by women are cited less than papers written by men (Larivière, Ni, Gingras, Cronin, and Sugimoto 2013).

Related phenomena

Anyone who fears public speaking already knows this paper's main argument: given that people in a group like to agree with each other, your public performance has a particularly strong effect on others' opinion of you. You can either triumph or bomb. A person who performs perfectly would rather do so in front of a group all together, and a person who makes a mistake would rather do so in individual interactions with each of the group's members.

There is experimental evidence that information that all members of a group already share overly influences group decision-making (see Tindale and Kameda 2000 for a review of the "common knowledge effect"). Stasser and Titus (1985) ask a group of students to select a student body president based on facts they provide about the candidates; however, they give some facts to all of the students, and distribute some facts to only a few students each. The group is then asked to discuss the information and make a decision. Even though the facts initially known by a few can be shared in discussion so that everyone knows them (presumably this is what discussion is for), and these facts, when shared and taken together, are numerous and strong enough to carry the decision, the group's discussion and decision are typically dominated by the facts initially given to everyone. In other words, instead of allowing the group to bring together disparate information, discussion re-emphasizes information everyone already knows.

Similarly, Clark and Kashima (2007) tell students a story and then ask each student which facts they would include if they were to retell the story to another student at the same university. Students tend to include facts consistent with stereotypes (in their experiment, about maleness) rather than facts inconsistent with stereotypes, which are presumably more unexpected and therefore more informational. When students are told that many students at their university share these stereotypes, this tendency increases. The interpretation is that communication is not just about conveying information but also reinforcing social connectivity among a community. Perhaps one aspect of social connectivity is wanting to express an opinion similar to those of others, as in our model.

More broadly, Roithmayr (2014) and Ridgeway (2011) look at how people wanting to comply with social convention perpetuates racial and gender inequality. For example, US law schools rely heavily on the Law School Admissions Test (LSAT), which disadvantages African-Americans and Latinos, even though the LSAT was adopted in the mid-twentieth century as part of a trend to exclude ethnic minorities, and LSAT scores poorly predict law school grades (Marks and Moss 2016). The LSAT is "locked in": each individual law school requires the LSAT mainly because every other law school requires it, because a law school that does not use it cannot compete in national rankings with others (Roithmayr 2014, p. 79).

Ridgeway (2011, p. 159) finds that gender inequality persists even as material conditions, including entire industries and the organization of the workplace, change rapidly. "[W]hen people . . . construct some new form of business or new type of relationship and sex-categorize one another in the process, the cultural beliefs about gender that are activated in the background are more traditional than the innovative circumstances they confront. . . . [T]hey implicitly inscribe trailing assumptions about gender into the procedures and social forms that they create." For example, high-tech start-up firms that emphasize "company culture, fitting in, and informal peer-group control" employ fewer women scientists than firms that are more bureaucratic and rule based, because fitting in and peer-group interactions, as in our model, are especially vulnerable to gender stereotypes (Ridgeway 2011, p. 179, Baron, Hannan, Hsu, and Kocak 2002).

Finally, people often "revert" to sex roles during disasters: men tend to work on search and rescue while women clean up households, provide supplies, and take care of children (Fothergill 1998). For example, during the 1977 Beverly Hills Supper Club fire in Kentucky, in which 165 people died, employees largely acted according to their occupational roles, with servers helping patrons escape the building while non-server employees helped fight the fire. But sex roles also emerged, with male non-servers more likely to help fight the fire than female non-servers (Johnston and Johnson 1989). Perhaps stereotypical sex roles emerge during disasters because of the obvious and immediate need to coordinate.

Skewness and belief in innate talent

Recently Leslie, Cimpian, Meyer, and Freeland (2015), abbreviated here as LCMF, surveyed members of 30 academic fields and found that fields in which people believe that inherent intellectual talent or "brilliance" is necessary for success, as opposed to hard work, effort, or dedication, tend to have fewer women. LCMF suggest that academic fields should "downplay talk of innate intellectual giftedness and instead highlight the importance of sustained effort" in order to increase diversity (p. 265). But they do not try to explain why some fields believe more in innate talent than others.

I find that LCMF's measure of a field's belief in innate talent, what they call "field-specific ability beliefs," is positively correlated with the skewness of the field's citation distribution. This might explain why some fields believe more in innate talent than others.

LCMF measure field-specific ability beliefs for each field by asking 1820 faculty, postdoctoral fellows, and graduate students in 30 fields whether they agree with statements such as "If you want to succeed in [your field], hard work alone just won't cut it; you need to have an innate gift or talent." Nine of LCMF's fields are in the humanities and thus ACORC do not provide skewness numbers for those fields; LCMF also includes Middle Eastern studies, which is not covered by Thomson Reuters's Web of Science and hence not analyzed by ACORC. Hence I can compare LCMF's field-specific ability beliefs with skewness for 20 fields. Figure 8 shows how the percent women in a field depends on skewness and field-specific ability beliefs, separated into STEM (science, technology, engineering, and mathematics) fields, and non-STEM fields. I use LCMF's field names. Note that some of LCMF's fields (for example engineering and psychology) are aggregations of some of our 119 fields earlier; fortunately, ACORC provide skewness numbers for these aggregated fields.

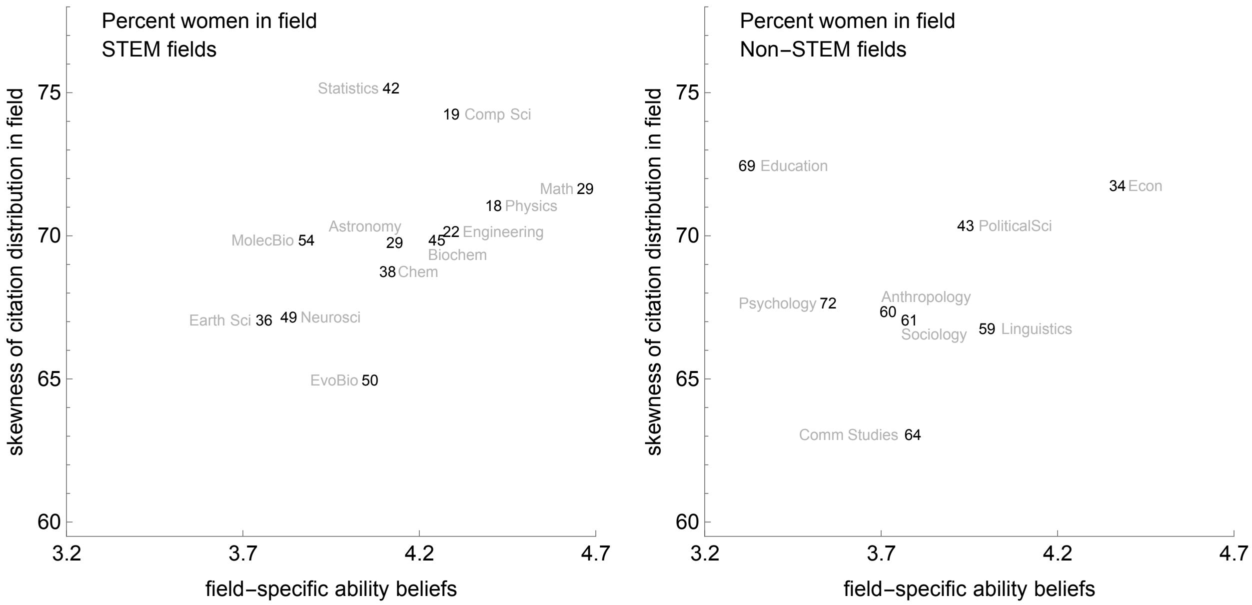

Figure 8. How percent women in field depends on skewness and field-specific ability beliefs, for STEM and non-STEM fields

Among all fields, fields with greater skewness have higher field-specific ability beliefs (correlation 0.39). Education is an outlier, with low field-specific ability beliefs and high skewness. This might be due to a measurement issue, because I use ACORC's measure of skewness for the Web of Science field "Education and Educational Research," which might not correspond well with LCMF's survey of education, which as mentioned earlier, covers many diverse fields. If education is excluded, the correlation is 0.62. Within STEM fields, and within non-STEM fields, fields with greater skewness and higher field-specific ability beliefs have fewer women, although statistics is an outlier.

Why do fields with greater skewness believe more in talent? A person's success in a field is due to many things, including skills, habits, hard work, dedication, creativity, imagination, patience, personal relationships, entrepreneurship, and luck, which all combine in complicated, random, and nonobvious ways. "Talent" is a radical simplification of this process. "Talent" is understood to be unconditional; it is inherent and inborn, not the result of a process. "Talent" is understood to explain excellence in a clear and direct way; the effect of a teacher's instruction, for example, depends on the personality of the student, but talent is almost always understood to be directly beneficial. "Talent" is understood to be easily observable, visible in a single moment, even striking.

In a field with higher skewness, people have a greater desire for their opinions to be similar to each other. If a person thinks that a scholar's success is due to many contingent interacting factors that are difficult to observe, she does not expect others to necessarily have a similar opinion. However, if a person thinks that a scholar's success is the result of an unconditional, clear, and easily visible attribute such as talent, she can expect that others share the same opinion. In other words, if people believe that excellence is explained by a clear and obvious attribute called "talent," then people can base their opinions on "talent" and thereby coordinate their opinions.

For example, when I see a musician performing, if I explain her excellence in terms of years of lessons and dedicated study, this does little to coordinate my opinion with the opinions of others, because her years of lessons and dedicated study are not publicly observable: even if I know she has studied for years, I know that few others know that. If I explain her excellence as the result of talent, which seems to be an obvious and inherent attribute that everyone can see, our opinions are better coordinated.

A similar phenomenon is how political leadership is strongly associated with inherent physical aspects of a leader's body. Each person is more likely to obey or consent to a political authority if he thinks that everyone else does too. Thus political systems, from monarchies to democracies to authoritarian states, install their leaders in large public mass ceremonies such as inaugurations, parades, or progresses. These mass ceremonies create common knowledge of the leader's ascension; each person watching knows that many other people watch too (Chwe 2001). In these ceremonies, the image of the leader's face and the leader's physical presence are essential, even though the leader's facial features and other physical aspects of her body are not very relevant to her ability or how she was chosen.

Physical aspects of a leader's body are, however, unconditional, clear, and easily visible. When you see a leader being crowned, or taking an oath with her hand on a religious text, you know that other people see the same thing you do. Of course the reason that she is the leader, in a democracy for example, is a long and complicated process of nominations and elections that depends on many factors; even if you are a political junkie who followed and understood it all, you have little confidence that others do.

In monarchies, the idea of a leader's authority as having an inherent physical basis is especially strong. For example, one "form of distribution of the kingly body was the feudal kiss on the mouth, with a light emission of saliva into the mouth of the vassal. With this, vassals would take with them a part of the royal body that would serve, wholly and for all, as a representation of the king in a peripheral and distant territory" (Bertelli 2001, p. 34). The political authority of the king was carried through his saliva. According to Norwegian legend, after the king Halfdan the Black died, his subjects cut his body "into four pieces, and buried each portion under a mound in each of the four principal districts of the country" in order to guarantee good harvests in each district (Bloch 1973, p. 32). The idea that a political leader's authority comes from his body, even inanimate, might seem an amusing superstition to us today, but it persists in the modern secular period, in for example the reverential display of Lenin's preserved body in Red Square (Bertelli 2001, p. xvii). Perhaps the idea that excellence results from inborn talent will one day seem as antiquated.

A recent example of how people mistakenly reduce excellence to inherent "brilliance" and physical characteristics is the case of "America's youngest female billionaire" Elizabeth Holmes, CEO of the blood diagnostics company Theranos (Crane 2014). Channing Robertson, a chemical engineering professor who taught Holmes when she was an undergraduate, stated: "When I finally connected with what Elizabeth fundamentally is, I realized that I could have just as well been looking into the eyes of a Steve Jobs or a Bill Gates" (Parloff 2014). When Robertson uses the phrase "fundamentally is," he sees Holmes's excellence as due to something fundamental and inherent in her person, something she is as opposed to something she does. Her similarity to other legendary entrepreneurs is manifest through a part of her body, her eyes. Press coverage of Holmes often showed her wearing black turtlenecks, as Steve Jobs did (Weisul 2015). The idea that Holmes possessed inherent brilliance and talent served Theranos well, as investors are more likely to believe in a company's promise if others also believe. In 2016, Theranos came under federal criminal investigation for fraud (Stockton 2016).

Finally, another way to tell that people believe more in talent when they care more about having similar opinions is to look at the frequency of terms like "talented" in everyday English usage. For example, it seems that the term "talented artist" is used more frequently than "talented lawyer" even though lawyers of course can be just as talented as artists. I start with a list of 1,110 occupations from O*NET Online, a web site sponsored by the US Department of Labor (O*NET Online 2016), which includes occupations such as "Architectural and Civil Drafters," "Dredge Operators," "Economics Teachers, Postsecondary," and so forth. I reduce each occupation to a single word, such as "drafter," "operator," and "teacher," and thus the list of occupations is reduced to a list of 376 words. For word usage I use the HathiTrust Digital Library (2016), a collection of around 15 million books and other documents. Among this collection, roughly 5.5 million documents are public domain and can be searched in an automated manner (Organisciak 2016). I find how many of these documents contain terms like "talented drafter," "talented operator," and "talented teacher." The term "talented drafter" might appear in fewer documents than "talented teacher" simply because "drafter" appears less often than "teacher." To correct for this, I take the number of documents that contain "talented drafter" and divide it by the number of documents that contain "drafter," and compute this ratio similarly for all occupations. I exclude occupations that appear in fewer than 2000 documents, such as "geoscientist" and "cosmetologist," because they might have a high ratio even if "talented geoscientist" appears only in one or two documents.

Table 5 shows the results. For example, "musician" appears in 401920 documents and "talented musician" appears in 3420 documents, and thus the ratio is $3420/401920 = 0.0085$. Among all the documents that contain "musician," just under one percent (0.0085) contain the term "talented musician." The term "musician" has the highest ratio, "artist" has the second highest, and so forth, with the thirtiest highest, "mathematician," having ratio 0.0007.

talented . . .	brilliant . . .	skilled . . .	dedicated . . .	hard-working . . .
musician (0.0085)	strategist (0.0129)	anesthetist (0.0657)	conservationist (0.0061)	farmer (0.0038)
artist	writer	mechanic	projectionist	mechanic
author	performer	laborer	processor	laborer
writer	lawyer	worker	urologist	clergyman
editor	mathematician	technician	researcher	member
composer	leader	woodworker	hydrologist	lawyer
lyricist	escort	veterinarian	teacher	developer
sculptor	historian	obstetrician	educator	cartographer
painter	author	operator	scientist	practitioner
etcher	scientist	cabinetmaker	pediatrician	secretary
performer	technician	machinist	phlebotomist	paramedic
illustrator	editor	orthodontist	therapist	officer
engraver	investigator	musician	worker	artist
lawyer	officer	molder	member	teacher
actor	member	ophthalmologist	legislator	legislator
architect	musician	welder	fundraiser	physician
singer	hostess	neurologist	psychiatrist	official
engineer	physicist	physician	firefighter	pharmacist
member	operator	pharmacist	epidemiologist	clerk
physician	teacher	pathologist	leader	typist
correspondent	etcher	electrician	archivist	brickmason
poet	artist	patternmaker	optometrist	rancher
announcer	poet	performer	controller	roustabout
teacher	surgeon	gynecologist	physician	dressmaker
officer	actor	coremaker	technician	historian
translator	representative	dietitian	server	manicurist
salesperson	psychologist	accountant	officer	orthodontist
leader	painter	internist	operator	editor
conductor	illustrator	surgeon	counselor	orderly
mathematician (0.0007)	radiologist (0.0012)	optician (0.0066)	planner (0.0001)	naturalist (0.0002)

Table 5. Occupations most likely to be described as "talented," "brilliant," "skilled," "dedicated," and "hard-working," ranked from first most likely to thirtiest

Table 5 shows that occupations most often called "talented" are predominantly occupations that have an audience, such as musician, artist, author, writer, composer, and lyricist. Within an audience, as opposed to a clientele of separate individuals, people can more directly influence each other in a self-confirming manner: a person is more likely to enjoy a musician, artist, or author if she thinks other people in the audience like them too. There are a handful of "star" musicians, artists, and authors whom everyone thinks are great; the distribution of attention, or "citations," is highly skewed. Presumably talent is important for engineers, physicians, and salespeople, but they are not as often called talented. Lawyers and teachers are perhaps intermediate, with an audience to some degree but not to the same extent as musicians and authors.

The pattern is similar but less pronounced for "brilliant": we often speak of brilliant writers and performers, but we also speak of brilliant mathematicians, technicians, investigators, and surgeons. The pattern disappears completely, however, for "skilled," "dedicated," and "hard-working." Many occupations are called skilled, including musician, but occupations that have audiences are not especially among them. Skill is not just a lesser kind of talent: many occupations called skilled are high-status positions that require extensive training and expertise, such as anesthetist, technician, obstetrician, and ophthalmologist. In other words, there is something about being "talented" which is not the same thing as being "skilled," and has to do with having an audience.

The terms "dedicated" and "hard-working" of course describe something different than "talented" or "skilled," and are not especially used to describe occupations with audiences, even though being an author or musician of course requires dedication and hard work. How are "talented" and "brilliant" different from "skilled," "dedicated," and "hard-working"? Talent and brilliance are more singular than skill: one can have many skills but not as many talents or kinds of brilliance. When one calls a person skilled, the response is "skilled at what?" but calling a person talented or brilliant does not evoke a similar question; a person is simply talented, or simply brilliant. Talent and brilliance are also understood as more inborn: one can become skilled over time, but one does not become talented or become brilliant. Being skilled can result from a process. Similarly, "dedicated" and "hard-working" refer to a process of steady improvement, not an static inborn property.

Again, academic fields that have a more skewed citation distribution tend to believe more in inborn talent. My explanation for this is that people in fields with a more skewed citation distribution evidently want to agree with each other more, and thus are more likely to explain excellence in terms of inborn talent instead of a more realistic and complicated process, because talent is a clear, unconditional, and visible attribute to coordinate on while a complicated process is not.

Conclusion

How can stereotypes best be countered? If stereotypes are powerful because they are public, they must be countered publicly. Everyone doing their own small bit to counteract stereotypes is not going to work. Stereotypes must be countered in a mass, public, manner. Women scholars as public role models not only help motivate young people join a field but also help balance the public, common knowledge, perception of women in the field so that young people are evaluated more correctly. If stereotypes are more powerful when people like to agree with each other, then making hiring and admissions committees more diverse might help not just because a greater variety of opinions are represented but also because doing so decreases people's incentives to agree with each other.

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Appendix

Fact 1. The unique Nash equilibrium of $\Gamma(\pi_1, p, q, r)$ is (f, f), where f is given by

$$f(h,H) = \frac{\pi_1 pq[\pi_1(1-p)q + \pi_0 p(1-q) + r(1-p)(\pi_1 q + \pi_0(1-q))]}{p(1-p)(\pi_1 q - \pi_0(1-q))^2 + \pi_1\pi_0 q(1-q) + rp(1-p)(\pi_1 q + \pi_0(1-q))^2}$$

$$f(l,H) = \frac{\pi_1(1-p)q[\pi_1 pq + \pi_0(1-p)(1-q) + rp(\pi_1 q + \pi_0(1-q))]}{p(1-p)(\pi_1 q - \pi_0(1-q))^2 + \pi_1\pi_0 q(1-q) + rp(1-p)(\pi_1 q + \pi_0(1-q))^2}$$

$$f(h,L) = \frac{\pi_1 p(1-q)[\pi_1(1-p)(1-q) + \pi_0 pq + r(1-p)(\pi_1(1-q) + \pi_0 q])}{p(1-p)(\pi_1(1-q) - \pi_0 q)^2 + \pi_1\pi_0(1-q)q + rp(1-p)(\pi_1(1-q) + \pi_0 q)^2}$$

$$f(l,L) = \frac{\pi_1(1-p)(1-q)[\pi_1 p(1-q) + \pi_0(1-p)q + rp(\pi_1(1-q) + \pi_0 q)]}{p(1-p)(\pi_1(1-q) - \pi_0 q)^2 + \pi_1\pi_0(1-q)q + rp(1-p)(\pi_1(1-q) + \pi_0 q)^2}$$

and $\pi_0 = 1 - \pi_1$.

Proof. Since EU_1 and EU_2 are quadratic and concave, person 1's best response is given by $\partial EU_1/\partial f(h,H) = 0$, $\partial EU_1/\partial f(l,H) = 0$, $\partial EU_1/\partial f(h,L) = 0$, $\partial EU_1/\partial f(l,L) = 0$ and person 2's best response is given by $\partial EU_2/\partial g(h,H) = 0$, $\partial EU_2/\partial g(l,H) = 0$, $\partial EU_2/\partial g(h,L) = 0$, $\partial EU_2/\partial g(l,L) = 0$. These eight first-order conditions are linear in $f(h,H)$, $f(l,H)$, $f(h,L)$, $f(l,L)$ and $g(h,H)$, $g(l,H)$, $g(h,L)$, $g(l,L)$ and so we have a linear system of eight equations and eight unknowns.

We simplify this first by noting that the four conditions $\partial EU_1/\partial f(h,H) = 0$, $\partial EU_1/\partial f(l,H) = 0$, $\partial EU_2/\partial g(h,H) = 0$, $\partial EU_2/\partial g(l,H) = 0$ involve only four variables, $f(h,H)$, $f(l,H)$, $g(h,H)$, $g(l,H)$. So we can solve for a linear system of four equations and four unknowns. (Solving for $f(h,L)$, $f(l,L)$, $g(h,L)$, $g(l,L)$ is similar.) We abbreviate by writing $f_h = f(h,H)$, $f_l = f(l,H)$, $g_h = g(h,H)$, $g_l = g(l,H)$.

The first order condition $\partial EU_1/\partial f_h = 0$ is $-2P(hhH1)(f_h - 1 + r(f_h - g_h)) - 2P(hhH0)(f_h - 0 + r(f_h - g_h)) - 2P(hlH1)(f_h - 1 + r(f_h - g_l)) - 2P(hlH0)(f_h - 0 + r(f_h - g_l)) = 0$, where we remove the commas between arguments of P for brevity. Thus we have

$$(1+r)P(h \cdot H \cdot)f_h = P(h \cdot H1) + rP(hhH\cdot)g_h + rP(hlH\cdot)g_l \qquad (*)$$

where the argument $\cdot$ stands for summing over the possible values of that argument (for example, $P(h \cdot H1) = P(hhH1) + P(hlH1)$). Thus

$$f_h = \frac{1}{1+r}\frac{P(h \cdot H1)}{P(h \cdot H\cdot)} + \frac{r}{1+r}\frac{P(hhH\cdot)}{P(h \cdot H\cdot)}g_h + \frac{r}{1+r}\frac{P(hlH\cdot)}{P(h \cdot H\cdot)}g_l.$$

We know that the coefficients on g_h and g_l above are less than 1, because $r/(1+r) \leq 1$ since $r \geq 0$, and $P(hhH\cdot) < P(h \cdot H\cdot)$ and $P(hlH\cdot) < P(h \cdot H\cdot)$. Hence if we think of this equation as a function from g_h, g_l to f_h, it is a contraction. We can write a similar equation for f_l starting with $\partial EU_1/\partial f_l = 0$, and similarly for g_h and g_l, and similarly show that they are contractions. Hence the f_h, f_l, g_h, g_l which satisfies these equations is the fixed point of a contraction mapping. Hence if a solution exists, it is unique.

We now show that there exists a solution which is symmetric. Assume that $f_h = g_h$ and $f_l = g_l$. Hence $\partial EU_1/\partial f_h = 0$ and $\partial EU_2/\partial g_h = 0$ are equivalent, and $\partial EU_1/\partial f_l = 0$ and $\partial EU_2/\partial g_l = 0$ are also equivalent. So we have a linear system of two equations, $\partial EU_1/\partial f_h = 0$ and $\partial EU_1/\partial f_l = 0$, and two unknowns, f_h and f_l.

Our equation $(*)$ above becomes

$$(1+r)P(h \cdot H\cdot)f_h = P(h \cdot H1) + rP(hhH\cdot)f_h + rP(hlH\cdot)f_l$$

or in other words

$$((1+r)P(h \cdot H\cdot) - rP(hhH\cdot))f_h - rP(hlH\cdot)f_l = P(h \cdot H1).$$

Since $P(h \cdot H\cdot) - P(hhH\cdot) = P(hlH\cdot)$, we have

$$(P(h \cdot H\cdot) + rP(hlH\cdot))f_h - rP(hlH\cdot)f_l = P(h \cdot H1).$$

If we start with $\partial EU_1/\partial f_l = 0$, we similarly get the equation

$$(P(l \cdot H\cdot) + rP(lhH\cdot))f_l - rP(lhH\cdot)f_h = P(l \cdot H1).$$

Hence we can write

$$\begin{bmatrix} P(h \cdot H\cdot) + rP(hlH\cdot) & -rP(hlH\cdot) \\ -rP(lhH\cdot) & P(l \cdot H\cdot) + rP(lhH\cdot) \end{bmatrix} \begin{bmatrix} f_h \\ f_l \end{bmatrix} = \begin{bmatrix} P(h \cdot H1) \\ P(l \cdot H1) \end{bmatrix}$$

and thus

$$\begin{bmatrix} f_h \\ f_l \end{bmatrix} = \frac{1}{D} \begin{bmatrix} P(l \cdot H\cdot) + rP(lhH\cdot) & rP(hlH\cdot) \\ rP(lhH\cdot) & P(h \cdot H\cdot) + rP(hlH\cdot) \end{bmatrix} \begin{bmatrix} P(h \cdot H1) \\ P(l \cdot H1) \end{bmatrix}$$

where D is the determinant of the matrix. So

$$\begin{bmatrix} f_h \\ f_l \end{bmatrix} = \frac{1}{D} \begin{bmatrix} P(l \cdot H\cdot)P(h \cdot H1) + rP(lhH\cdot)P(h \cdot H1) + rP(hlH\cdot)P(l \cdot H1) \\ rP(lhH\cdot)P(h \cdot H1) + P(h \cdot H\cdot)P(l \cdot H1) + rP(hlH\cdot)P(l \cdot H1) \end{bmatrix}.$$

Since $P(lhH\cdot) = P(hlH\cdot)$ and $P(h \cdot H1) + P(l \cdot H1) = P(\cdot \cdot H1)$, we have

$$\begin{bmatrix} f_h \\ f_l \end{bmatrix} = \frac{1}{D} \begin{bmatrix} P(l \cdot H\cdot)P(h \cdot H1) + rP(hlH\cdot)P(\cdot \cdot H1) \\ P(h \cdot H\cdot)P(l \cdot H1) + rP(hlH\cdot)P(\cdot \cdot H1) \end{bmatrix}. \qquad (**)$$

Therefore

$$\begin{bmatrix} f_h \\ f_l \end{bmatrix} = \frac{1}{D} \begin{bmatrix} (\pi_1(1-p)q + \pi_0 p(1-q))\pi_1 pq + r(\pi_1 p(1-p)q + \pi_0(1-p)p(1-q))\pi_1 q \\ (\pi_1 pq + \pi_0(1-p)(1-q))\pi_1(1-p)q + r(\pi_1 p(1-p)q + \pi_0(1-p)p(1-q))\pi_1 q \end{bmatrix}$$

and so

$$\begin{bmatrix} f_h \\ f_l \end{bmatrix} = \frac{1}{D} \begin{bmatrix} \pi_1 pq[\pi_1(1-p)q + \pi_0 p(1-q) + r(1-p)(\pi_1 q + \pi_0(1-q))] \\ \pi_1(1-p)q[\pi_1 pq + \pi_0(1-p)(1-q) + rp(\pi_1 q + \pi_0(1-q))] \end{bmatrix}.$$

Now all that remains is to simplify the determinant D. We have

$$D = (P(h \cdot H\cdot) + rP(hlH\cdot))(P(l \cdot H\cdot) + rP(lhH\cdot)) - r^2 P(hlH\cdot)P(lhH\cdot)$$

and again since $P(lhH\cdot) = P(hlH\cdot)$, we have

$$D = P(h \cdot H\cdot)P(l \cdot H\cdot) + rP(hlH\cdot)(P(h \cdot H\cdot) + P(l \cdot H\cdot)) + r^2 P(hlH\cdot)^2 - r^2 P(hlH\cdot)^2$$

and thus

$$\begin{aligned} D &= P(h \cdot H\cdot)P(l \cdot H\cdot) + rP(hlH\cdot)(P(h \cdot H\cdot) + P(l \cdot H\cdot)) \\ &= P(h \cdot H\cdot)P(l \cdot H\cdot) + rP(hlH\cdot)P(\cdot \cdot H\cdot) \qquad (***) \\ &= (\pi_1 pq + \pi_0(1-p)(1-q))(\pi_1(1-p)q + \pi_0 p(1-q)) \\ &\qquad + r(\pi_1 p(1-p)q + \pi_0(1-p)p(1-q))(\pi_1 q + \pi_0(1-q)) \\ &= p(1-p)(\pi_1^2 q^2 + \pi_0^2(1-q)^2) + \pi_1\pi_0 q(1-q)(p^2 + (1-p)^2) \\ &\qquad + rp(1-p)(\pi_1 q + \pi_0(1-q))^2 \\ &= p(1-p)(\pi_1^2 q^2 + \pi_0^2(1-q)^2) + \pi_1\pi_0 q(1-q)(1 - 2p(1-p)) \\ &\qquad + rp(1-p)(\pi_1 q + \pi_0(1-q))^2 \\ &= p(1-p)(\pi_1^2 q^2 + \pi_0^2(1-q)^2 - 2\pi_1\pi_0 q(1-q)) + \pi_1\pi_0 q(1-q) \\ &\qquad + rp(1-p)(\pi_1 q + \pi_0(1-q))^2 \\ &= p(1-p)(\pi_1 q - \pi_0(1-q))^2 + \pi_1\pi_0 q(1-q) + rp(1-p)(\pi_1 q + \pi_0(1-q))^2. \quad \square \end{aligned}$$

Fact 2. When $r = 0$ we have

$$f(h, H) = \frac{\pi_1 pq}{\pi_1 pq + \pi_0(1-p)(1-q)}$$

$$f(h, L) = \frac{\pi_1 p(1-q)}{\pi_1 p(1-q) + \pi_0(1-p)q}$$

$$f(l, H) = \frac{\pi_1(1-p)q}{\pi_1(1-p)q + \pi_0 p(1-q)}$$

$$f(l, L) = \frac{\pi_1(1-p)(1-q)}{\pi_1(1-p)(1-q) + \pi_0 pq}$$

Proof. When $r = 0$, from $(**)$ and $(***)$ in the proof of Fact 1, we have

$$f(h, H) = \frac{P(l \cdot H\cdot)P(h \cdot H1)}{P(h \cdot H\cdot)P(l \cdot H\cdot)} = \frac{P(h \cdot H1)}{P(h \cdot H\cdot)}$$

and we are done. The expressions for $f(h, L)$, $f(l, H)$, and $f(l, L)$ are similar. $\square$

Fact 3. When $\pi_1 = 1/2$ and $p = q$, $(f(h,H) - f(h,L))/(f(h,H) - f(l,H)) = r + 1$.

Proof. When $\pi_1 = 1/2$, we have $\pi_0 = \pi_1$, and since $p = q$, from Fact 1 we have

$$\begin{aligned}
f(h,H) &= p^2 \frac{(1-p)p + p(1-p) + r(1-p)}{p(1-p)(2p-1)^2 + p(1-p) + rp(1-p)} \\
f(l,H) &= (1-p)p \frac{p^2 + (1-p)^2 + rp}{p(1-p)(2p-1)^2 + p(1-p) + rp(1-p)} \\
f(h,L) &= p(1-p) \frac{(1-p)^2 + p^2 + r(1-p)}{p(1-p)(1-2p)^2 + (1-p)p + rp(1-p)} \\
f(l,L) &= (1-p)(1-p) \frac{p(1-p) + (1-p)p + rp}{p(1-p)(1-2p)^2 + (1-p)p + rp(1-p)}.
\end{aligned}$$

So we have

$$f(h,H) - f(h,L) = (2p^3(1-p) + rp^2(1-p) - p(1-p)^3 - p^3(1-p) - rp(1-p)^2)/E$$

$$f(h,H) - f(l,H) = (2p^3(1-p) + rp^2(1-p) - p^3(1-p) - p(1-p)^3 - rp^2(1-p))/E$$

where $E = p(1-p)(2p-1)^2 + p(1-p) + rp(1-p)$.

Thus

$$\begin{aligned}
\frac{f(h,H) - f(h,L)}{f(h,H) - f(l,H)} &= \frac{p^3(1-p) + rp^2(1-p) - p(1-p)^3 - rp(1-p)^2}{p^3(1-p) + rp^2(1-p) - p(1-p)^3 - rp^2(1-p)} \\
&= \frac{p^2 + rp - (1-p)^2 - r(1-p)}{p^2 + rp - (1-p)^2 - rp} \\
&= \frac{p^2 - (1-p)^2 + r(p - (1-p))}{p^2 - (1-p)^2} \\
&= \frac{2p - 1 + r(2p-1)}{2p-1} \\
&= 1 + r. \quad \square
\end{aligned}$$

Table A1. Data on 119 academic fields.

Column [1]: Name of field, abbreviated.
Column [2]: Among all people receiving doctorates in field, percent who have temporary visas.
Columns [3]–[6]: Among US citizens and permanent residents receiving doctorates in field, percent who are Asian, Black, Hispanic, White.
Column [7]: Among all people receiving doctorates in field, percent who are women.
Column [8]: Skewness, the percent of papers in the field that receive fewer than the average number of citations received by a paper in the field.
Columns [9]–[11]: The average GRE scores of people intending to enter the field: Verbal reasoning, Quantitative reasoning, Analytical writing.
Column [12]: The category of the field.

[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Ag econ	64.5	19.4	11.1	5.6	61.1	41.1	64.6	151	155	3.6	agri
Agronomy	46.8	6.3	1.8	6.3	83	37.7	69.5	152.1	152.5	3.61	agri
Animal sci	32.2	2.1	1	4.2	89.6	53.7	66.6	151	150	3.7	agri
Enviro sci	27.7	8.9	5.2	11.1	71.1	54.9	67.9	154	154	3.9	agri
Fishing sci	25.4	2.3	0	2.3	83.7	32.2	66.4	153	152	3.7	agri
Food sci	58.9	14.6	7.3	7.3	68.3	61.6	63.5	149	156	3.5	agri
Forest bio	37.3	3.1	4.6	6.2	84.6	31.8	68.2	154	152	3.7	agri
Nat resources	20	5.2	2.6	6.5	84.4	55	65.5	155	153	3.9	agri
Soil chem	53.4	8.8	5.9	11.8	70.6	46.6	63.5	154	153	3.8	agri
Agriculture	21.7	0	5.9	11.8	82.4	47.8	69.5	146	149	3	agri
Anatomy	31.7	18.2	3.4	6.8	66.2	52.2	68.2	154.4	156	3.87	bio
Bacteriology	18.8	7.7	0	2.6	84.6	60.4	63	153	154	3.9	bio
Biochem	34	10.6	5	7.5	72.6	45.4	69.8	155	156	3.9	bio
Bioinformatics	29.3	21.3	1.3	6.3	68.8	31.4	72.1	153	157	3.7	bio
Biomed sci	27.4	17.7	6.2	8.6	63.6	56.1	70.9	153	154	3.9	bio
Biophysics	42.5	14	2.2	5.6	72.1	35.7	66.5	157	160	4	bio, physical
Botany	29.4	14.7	0	4.2	72.6	58	70.8	155	154	3.9	bio
Cancer bio	27.6	14.8	6.3	7.7	68.3	55.2	68.1	153	154	3.9	bio
Cell bio	26.5	11.2	5.8	6.5	72.3	55.2	71.4	154	155	3.9	bio
Compu bio	33.8	16.3	0	0	79.1	29.2	75.6	159	161	4.2	bio
Ecology	15.9	3.3	0.9	1.2	90.9	51.7	66.4	158	155	4.1	bio
Endocrinology	21.9	14.6	8.5	7.3	65.9	57	66.1	153	153	3.7	bio
Entomology	30.1	5.1	0	7.7	84.6	44.2	63.1	155	153	3.8	bio
Toxicology	25.2	2.3	7	3.5	82.6	59.1	68.2	153	153	3.9	bio
Evo bio	24.4	3.2	0	5.1	85.4	49.8	64.9	160	158	4.3	bio
Genetics	29.4	12.5	4.1	4.1	73.8	55.4	70.9	156	156	4	bio
Immunology	20.5	12.4	5	9.1	68.5	54.3	69	155	156	3.9	bio

Microbio	21.1	9.5	7.7	7.7	72.3	58.8	65.4	154	153	3.9	bio
Molec bio	26.1	10.8	4.6	7	73.3	54.4	69.8	155	156	3.9	bio
Neurosci	17.3	12.9	4.3	6.6	72.1	49.4	67.1	157	156	4.1	bio
Nutrition	29.3	9.2	5.5	3.7	81.7	81.7	69.3	151	150	3.8	bio
Pharma	25.2	12.7	7.6	5.1	70.1	52.3	65.9	151	155	3.6	bio
Physiology	21.1	14	2.9	7.6	70.8	54.8	64.5	154	154	4	bio
Virology	26.4	10	3.1	9.2	70	56.7	65.5	153	154	3.9	bio
Zoology	9.2	0	0	3.6	89.1	52.3	66.9	154	152	3.9	bio
Biology	31.7	11.2	7.9	5.6	71.9	54.5	69.2	152	152	3.8	bio
Biotech	36.2	5.7	7.5	5.7	75.5	44.7	69.4	149	155	3.3	bio
Public health	11.3	11.7	16.5	6.4	61.3	72.7	65.8	152	151	3.9	health
Epidemiology	13.7	15.3	8.1	4.8	66.9	67.6	66.1	155	154	4	health
Health sys	25.6	12.5	17.9	3.6	62.5	65.1	66.9	148	148	3.6	health
Kinesiology	19.2	4	3.3	4	84	40.9	64.5	149	149	3.7	health
Medicinal sci	45.5	21.3	18.9	4.1	47.5	45.5	67	148	154.3	3.3	health
Nursing sci	11.5	5	9.3	3.2	78.9	91.1	60.1	151	148	3.7	health
Rehab	18.3	6.1	2	0	91.8	73.3	69.7	149	148	3.5	health
Vet sci	36.7	8.3	2.8	2.8	86.1	55	68.9	152	152	3.8	health
Astronomy	28.1	6.1	1.5	5.6	83.8	29.2	69.7	156	160	3.9	physical
Meteorology	34.3	8.3	0.9	1.9	85.2	30.9	66.8	152.9	155.9	3.9	physical
Analytic chem	39.2	11.3	3.9	3	78.7	47.9	68.1	151	157	3.6	physical
Inorg chem	29.4	7.9	6	4.2	77.8	36.3	65.1	154	158	3.8	physical
Org chem	41.1	10.2	3.7	7.3	75.4	30.1	62.7	154	158	3.8	physical
Phys chem	37.9	7.4	3.5	7.8	77.1	36.7	66.2	155	160	3.8	physical
Polymer chem	40.3	9.9	9.9	0	78.9	28.2	65.6	151	161	3.4	physical
Chem	32.1	9.8	3	7.5	75.2	41.4	68.7	153	157	3.8	physical
Comp sci	47.6	19.9	3.3	3.3	69.7	18.6	74.2	148	157	3.2	physical
Info sci	29.5	13.6	5.7	2.3	71.6	33.7	75.2	149	154	3.4	physical
Robotics	28.3	17.2	0	0	79.3	17.4	71.3	147	159	3.1	physical
Geology	24.8	1.1	2.3	1.1	95.4	38.4	65.1	154	154	3.7	physical
Geophys	41.1	8.5	2.1	6.4	80.9	28.4	67.5	153	158	3.7	physical
Geochem	29.2	11.5	0	6.6	82	42.7	68.6	155	157	4	physical
Paleontology	20.4	0	2.5	2.5	90	48.1	65.6	157	154	4.1	physical
Geomorphology	20	6.3	1.6	0	82.8	27.8	67	155	154	3.8	physical
Math	37.2	5.7	1.7	3.1	86.4	21.2	62.6	155	162	3.8	physical
Applied math	48.8	10.8	3	5.9	75.4	28.5	68.1	153	163	3.6	physical
Stats	50	18.4	5.4	0	69.4	41.6	75.1	152	163	3.5	physical
Op research	36	13.4	3.6	2.7	73.2	28.9	64.8	156	163	4	physical
Marine sci	14.5	0	5.8	11.5	76.9	55.1	60	153	153	3.8	physical
Oceanography	31.5	8.2	0	8.2	82	46.7	65.2	155	155	3.9	physical
Hydrology	35.9	8.1	0	2.7	89.2	50	65.8	154.9	154.2	3.8	physical
Acoustics/Optics	47.8	9.7	1.1	6.5	77.4	18.3	67	150	163	3.4	physical
Applied phys	38.6	11.8	5.3	9.2	61.8	15.9	69.5	155	162	3.9	physical
Atomic phys	44.8	9	1.3	1.3	84.6	18.6	66.2	154	164	3.7	physical
Cond matter phys	53.5	8.6	0.6	4.3	82.2	16.4	69.2	154	163	3.6	physical
Med phys	28.4	18.2	0	4.5	75	20.3	68.8	156	162	3.9	physical

Nuclear phys	38.3	12.8	0	0	78.7	19.8	72.8	153	160	3.7	physical
Particle phys	40.2	9.2	0.8	3.1	78.6	11.8	72.5	156	162	3.7	physical
Plasma phys	31.3	3.6	3.6	3.6	83.9	16.9	68.5	157	162	3.9	physical
Physics	33.9	6.7	2.2	1.1	82.2	15.9	71	156	162	3.9	physical
Clinical psych	3.5	7.3	5	10.7	73.1	77.8	68.6	153	149	4	psych
Counseling	4.6	5.1	10	9.5	69.5	72.2	70.3	150	146	3.7	psych
Dev psych	11.5	3.8	6	9.3	75.3	83.5	66.6	152	150	3.9	psych
Educ psych	6.6	6.5	5.4	5	76.3	71.3	71.2	151	149	3.8	psych, educ
Exp psych	12.3	3.2	2.4	4.8	81.5	62.3	68.2	154	150	3.9	psych
Human dev	8.2	4	8.8	7.2	74.4	80.1	70.2	150.3	147.3	3.77	psych
Psychobio	7.7	1.5	4.5	3	86.6	64.1	67.1	154	150	3.9	psych
Social psych	7.9	9.8	7.4	9.3	68.6	62.3	70.8	155	152	4.1	psych
Psych	4.3	3.4	10.1	12.8	64.9	66.5	64.9	152	149	3.9	psych
Psychometrics	10.1	3.3	3.7	8.8	78.6	64.6	70.8	155.2	153.9	4.02	psych
Anthro	13	6.3	4.2	9.4	74.2	59.6	67.3	156	149	4.1	social
Econ	55.5	14.7	4	5.6	73	34.4	71.7	155	160	3.9	social
Pol sci	21.9	7.4	5.7	4.9	76.5	43.1	70.3	156	151	4.2	social
Sociology	17.2	6.1	7.9	9.2	72.1	61.3	67	152	148	3.9	social
Area stud	18	9.6	16.9	18.1	48.2	70.3	69.8	150	148	3.7	social
Criminology	8.2	2.7	7.4	5.4	80.5	56.8	72.9	147	145	3.5	social
Geography	24.4	3	3	6	83.2	46.2	69.9	154	151	3.8	social
Intl rel	28.1	10	4.3	1.4	81.4	37.7	68.5	156	152	4.1	social
Linguistics	34.6	10.7	3.1	6.3	75.5	59.2	66.7	157	153	4.1	social
Urban planning	29.8	14.7	7.4	7.4	66.2	55.8	67.1	154	153	4	social
Demography	27.7	5.3	17.2	8.9	62.7	63.6	68.5	152.7	151.1	3.93	social
Aero eng	38.3	9.7	3.5	5.6	77.1	13	68	152.2	159.5	3.71	eng
Chem eng	46	12.7	3.5	7.3	73.2	31.2	67.1	152	161	3.7	eng
Civil eng	59	14.4	4.6	8.3	69	23.1	72.4	149	158	3.4	eng
Elec eng	58.8	25.9	4.7	5.7	60.4	16	73.2	148.1	159.7	3.21	eng
Industrial eng	58.9	11.9	7.9	10.9	67.3	30	65.4	148	159	3.29	eng
Materials eng	52.7	17.6	4.3	4	66.9	25.1	71.9	153	162	3.65	eng
Mech eng	52.5	11	3.7	5.5	75.3	13.8	67.6	150	159	3.4	eng
Bio eng	32.3	21.6	3.5	4.6	66.3	37.2	66	155	160	3.9	eng
Compu eng	66.4	21.2	0.9	3.5	70.8	16.1	71.7	149	159	3.3	eng
Enviro eng	52.7	8.3	8.3	1.7	78.3	38.4	70.9	152	159	3.6	eng
Nuclear eng	28	6.8	0	8.1	78.4	14	71.5	155	161	3.9	eng
Struc eng	58	10.3	0	6.9	75.9	13	69.3	151	159	3.5	eng
Systems eng	24.1	15.9	4.5	6.8	72.7	20.3	68.6	153	158	3.7	eng
Educ research	12.5	5.5	11.7	6.4	71.2	70	72.4	154	154	4.2	educ
Special ed	8.2	4.4	9.4	5.4	75.9	84.1	66.4	149	147	3.7	educ
Sci ed	4.3	2.3	13.6	2.3	78.4	63.4	66.3	154	151	4	educ
Business	32.9	12.4	8.8	5.1	69.9	41.9	71.4	151	151	3.7	other
Finance	52	24.4	3.5	7	61.6	31.2	77.8	151	161	3.5	other
Communication	20.3	4.6	7.4	5.1	77.2	64.2	63	149.9	148.3	3.63	other
Public admin	22	2.4	19	7.1	70.2	46.6	69.9	152	149	3.8	other
Social work	12.5	6.6	12.4	10.2	65.5	77.5	64	149	145	3.6	other

Table A2. Coefficients from regressing percent Asian, Black, Hispanic, White, and temporary visa holders on skewness, average GRE scores, and field category (standard errors in parentheses, stars indicate significance at 0.05*, 0.01**, 0.001*** level).

Regressing on	Percent Asian	Percent Black	Percent Hispanic	Percent White	Percent temporary visa holders
Skewness	0.35*	−0.18	−0.23*	0.026	0.065
	(0.14)	(0.11)	(0.09)	(0.25)	(0.26)
Verbal GRE	−0.66***	−0.51***	−0.17	1.29***	−1.90***
	(0.18)	(0.15)	(0.12)	(0.32)	(0.34)
Quantitative GRE	0.89***	0.02	−0.0037	−0.99***	2.51***
	(0.16)	(0.13)	(0.10)	(0.28)	(0.29)
Agricultural sciences and natural resources	−1.39	−5.11**	0.29	6.84	12.62**
	(2.15)	(1.73)	(1.42)	(3.80)	(3.93)
Biological and biomedical sciences	1.68	−4.02**	−0.40	2.36	−0.84
	(1.87)	(1.51)	(1.24)	(3.31)	(3.42)
Health sciences	3.16	−0.55	−3.75*	1.06	−0.79
	(2.24)	(1.81)	(1.48)	(3.96)	(4.10)
Physical sciences	−3.87	−5.88***	−2.34	12.03**	−3.14
	(2.08)	(1.68)	(1.37)	(3.68)	(3.81)
Psychology	−1.09	−2.61	1.88	−0.39	−8.63*
	(2.07)	(1.67)	(1.37)	(3.67)	(3.80)
Social sciences	1.45	−0.92	1.35	−2.80	6.32
	(2.13)	(1.72)	(1.41)	(3.76)	(3.90)
Engineering	−1.64	−5.74**	−0.34	8.15	3.50
	(2.36)	(1.91)	(1.56)	(4.18)	(4.33)
Education	−2.22	1.59	−2.12	1.93	−10.08*
	(2.48)	(2.00)	(1.64)	(4.38)	(4.54)
Constant	−50.85	95.65***	48.59*	24.65	−72.75
	(28.68)	(23.15)	(18.98)	(50.75)	(52.55)
R^2	0.490	0.426	0.284	0.281	0.752
N	119	119	119	119	119