Abstract—Women are underrepresented in academia in general and economics in particular. I introduce a test to detect an underresearched form of hiring bias: implicit quotas. I derive a test under the null hypothesis of gender-blind hiring that requires no additional information about individual hires and can be used to analyze hiring bias in a variety of other hiring settings. I derive its asymptotic distribution and propose a parametric bootstrap procedure that resamples from the exact distribution. I analyze the distribution of female professors at German universities and find an implicit quota of one or two women on the department level.

I. Introduction

Although the share of women among university graduates and women’s labor market participation has increased dramatically, the share of women among high-ranking professionals has remained low. For example, in 2019, women accounted for just 27.8% of board members of the largest publicly listed companies registered in EU countries, and only about 17% of senior executives are women (Eurostat, 2020a). In Germany, the share of female board members among the 30 largest publicly traded companies in the DAX even fell and is currently at only 12.5% (Berlin AllBright Stiftung, 2020).

It is crucial to understand the role that candidate gender plays in hiring to increase the representation of women. One possible channel through which gender may influence hiring decisions might be implicit quotas. Implicit quotas, similar to explicit quotas, are quantity restrictions on hiring but without explicit targets. They can be seen as a form of discrimination, as candidate gender is taken into account in the hiring decision, both positive and negative. However, proving discrimination in hiring is difficult, as researchers rarely observe enough information on hiring committees and candidates to make definitive judgments (Arcidiacono, Kinsler, & Ransom, 2022). To detect discrimination against women in academia, we would need detailed information on individual candidates’ qualifications, the preferences and information set of the hiring committee, and the number of women already in the department.

In this paper, I introduce a statistical test to detect implicit quotas. This test requires relatively little information in order to make statements about possible hiring bias. I develop a test for gender-blind hiring with implicit quotas as alternatives. I characterize both the small sample distribution, which can be approximated numerically, and the asymptotic distribution under the null of gender-blind hiring. In my application I study the distribution of women in German universities.

My main results show that (i) the current allocation of women across departments is highly improbable under the null hypothesis where candidates are drawn gender-blind from a Bernoulli distribution with the share of female professors $p$. Specifically, there are “too few” departments with no female professors and “too many” with one or two female professors across disciplines. This result holds both using the exact distribution, which can only be approximated numerically, and the critical values using the asymptotic distribution. (ii) I find no evidence that disciplines with a higher share of women are different in their implicit quotas, and I can show that the distribution of female shares across all disciplines could be well explained by a two-women quota per department. This test can be used in many different settings where one can reasonably assume that hiring probabilities for underrepresented groups are approximately the same across units, such as management levels across different firm locations or on the partner level in top law firms.

German universities are ideal for studying this topic. Germany has a homogeneous nationwide university system that is entirely publicly funded, and almost all universities offer a wide array of disciplines. This homogeneity is essential to identifying potential implicit quotas because the assumptions, especially an approximately constant hiring probability within disciplines, are more likely to be met.

This paper adds to several strands of literature on the representation of women in top positions. One policy measure that has, by design, significant effects on the representation of women in the short run is explicit quotas. However, even in the absence of explicit quotas, there may still be quantity restrictions on diversity—what I call implicit quotas in this paper. Donors, politicians, NGOs, and society put pressure on organizations and institutions to commit to increasing the representation of women. Crucially, however, these pressures rarely have explicit targets. Evidence on implicit quotas is sparse, with the notable exception of Chang et al. (2019), who study female representation in boards and find evidence for an implicit quota on the boards of the largest publicly listed companies in America.
A large and growing literature shows positive effects in that explicit quotas raise female participation. Explicit quotas have, for example, been analyzed in the context of company boards or election lists; for example, Bertrand et al. (2018) evaluate a Norwegian board reform, and Maida and Weber (2019) examine an Italian board reform. Bagues and Campa (2021) analyze a Spanish quota where at least 40% of candidates on ballots were mandated to be of either gender. Balafoutas and Sutter (2012) show that explicit quotas increase willingness for competition without decreasing group performance. However, evidence of other potential benefits of explicit quotas, such as firm performance or potential spillover effects on lower-level managerial or electoral positions, is mixed. Additionally, there are some significant drawbacks associated with explicit quotas. Talent might be misallocated, which would harm both employers as well as female professionals who will not necessarily be matched with an employer where they can develop their full potential, as Bagues and Campa (2021) pointed out.

Diversity pressure, as an alternative to explicit quotas, seems to be quite common: many political institutions, professional organizations, and firms explicitly mention that they want to increase the share of women. Universities are particularly prone to implicit quotas, as the share of female professors is low (Lundberg & Stearns, 2019, and Au- riol, Friebel, & Wilhelm, 2020), and increasing the share of women via explicit quotas is, for legal and political reasons, difficult to implement. A low share of female professors in universities probably has substantial costs for society. First, male professors might focus on different content and methods than women do. Second, many young professionals study and receive their education from professors in universities, which might affect many decisions across their professional life. Related, female professors provide role models, which might affect the decisions of young female (and also male) professionals. For example, female role models might affect educational choices and aspirations (Beaman et al., 2012), specialization choices (Porter & Serra, 2020; Buser, Niederle, & Oosterbeek, 2014), labor supply in later life, or even the allocation of paid and unpaid labor in households. Unsurprisingly, politicians, student representations, donors, third-party funding agencies, and the general public pressure universities to increase the share of women.

My results imply that politicians and donors have to be aware of potential implicit quotas that could become entrenched without the accountability of an explicit target. This likely requires different monitoring to detect whether the shares are increasing beyond certain thresholds. While the analysis in this paper is not dynamic and does not predict whether in a few years implicit quotas will increase too (to, for example, three or four women), we can make inferences based on another statistic: the implicit quota is centered around the number of women in the department, not around the discipline mean. This implies that administrative pressures to conform to a particular number of women are on large and small departments alike.

In the presence of implicit quotas, it is doubtful whether analyzing productivity indicators, such as publications and citations, is informative for two reasons. First, match quality might be worse for women, as the probability of being hired at a particular institution relies on factors outside their control, namely, on the sum of the women already in the department. In addition, if women are more likely to be hired when there are no women but less likely to be hired when there are already two, then the characteristics of the third woman in a department will potentially be very different from those of the first one. Hence, analyses that analyze productivity patterns of scientists in different disciplines, such as Huang et al. (2020), will mask significant heterogeneity.

The presence of implicit quotas can also be informative about how employers, the public, or other stakeholders perceive diversity. There is evidence as well that implicit quotas can be self-reinforcing. In a recent experimental paper, Paryavi, Bohnet, and van Ge (2019) analyze how descriptive norms in gender composition are acted on by men and find that descriptive norms do not lead to prescriptive norms and can even lead to backlash if male “employers” are informed that others have hired more women. Suppose tokenism plays a role, and implicit quotas result from a shift in social pressure (by either the university administration or funding agencies). In that case, it is unclear whether the “acceptable number” of women will increase over time or whether there will be stagnation since there is no explicit target.

This paper proceeds as follows. In section II, I describe the data and the institutional background in Germany. Section III introduces the method. In section IIIA, I develop the test statistic, in section IIIB, I derive the asymptotic normality result for the test statistic, and in section IIIC, I introduce the parametric bootstrap procedure. Section IV presents the results from the application. Section V concludes and discusses some implications.

II. Data and Institutional Background

In this section I briefly describe the general institutional setup in Germany and the data I use.

A. Universities in Germany

There are about 70 universities in Germany, and most offer the full spectrum of academic disciplines. Seventeen universities of technologies more tailored toward the natural sciences and engineering but employ faculty in the social sciences and humanities. This feature of the German

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2See, for example, the recent ruling against the Eindhoven University of Technology’s gender quota program by the Dutch human rights commission (Netherlands Institute for Human Rights, 2020).

3In fact, one of their key findings, that research productivity differences have increased over time, could at least partially be explained by an increase in quality heterogeneity.
For professors, the data offer, among other things, information on the discipline, their gender, their salary category, their university, the year of their first appointment as a professor, and their year of birth.

University. I only consider universities and not universities of applied sciences because these do not overlap in their hiring pool and have different populations of students and working conditions.

Professors. According to the administrative classification, I restrict the sample to professors, both tenured and untenured, including assistant, associate, and full professor level, but not substitute professors. I do not condition on civil servant status or full-time employment, although neither of these would change the sample in a significant way.

Discipline. I define discipline according to the administrative three-digit classification of the statistical office. The disciplines are listed on the x-axis of figure 1. I consider only disciplines with at least three departments. Some disciplines did not meet this minimum threshold and were excluded.

Department. I define a department as all faculty employed within a discipline at the same university, as there is no direct department designator in the administrative data. However, professorships are allocated according to a so-called position plan (Stellenplan). This means that the ministry of culture in each state allocates the number of professorships to universities and the respective teaching and research units (so-called Lehr- und Forschungsbereiche). The discipline code that I use here corresponds to these Lehr- and Forschungsbereiche. Universities cannot independently create professorships without approval. Once a position is created, a specific teaching load (depending on the state and the seniority of the position—assistant, associate, or full professor—is allocated to this Lehr- und Forschungsbereich (e.g., economics). Hence, these organizational units are then responsible for this increase in the overall teaching load, and there is no incentive to “give away” this position to a different department. Furthermore, what I observe here is the allocation of the position to the teaching and research unit (e.g., economics), not the actual classification of the researcher. Therefore, the unit the position is allocated to is most likely also the unit that makes the hiring decision.

Figure 1 shows the (ordered) shares of female professors by discipline. Economics is highlighted for reference. The black horizontal line indicates 0.5, meaning there is no discipline where women hold most professorships. The final sample contains 1,737 departments across 50 disciplines.

III. Method

Analyzing implicit quotas is difficult: First, whether hiring is gender blind is in most cases unobservable and the decision rule employers use can only be inferred from observed outcomes using mostly unobservable individual characteristics (Arcidiacono et al., 2022). Second, because the implicit quota itself is not known, the probability of hiring a woman but it does mean that some officially published statistics are not directly comparable.
is not uniformly lower given the same observable characteristics. Here, I exploit the fact that many departments at different universities offer the same discipline and thus hire from the same hiring pool. Let \( s \in \{1, \ldots, S\} \) be an index for the discipline. For a given probability of hiring a woman \( p_s \) in discipline \( s \), which I treat as known and which corresponds to the observed share of women within a discipline (see figure 1)—the distribution of women across departments should follow a known distribution. Intuitively, if the number of departments is large enough, even for \( p_s \) quite low or quite high, we would expect tail events such as departments with no women or departments with many women to occur. The challenge then becomes how to quantify and formally argue what an “unusual distribution” looks like.

A. Testable Predictions

If the distribution of female faculty across departments is gender blind and depends only on the overall discipline probability \( p_s \), I make testable statements about the deviations of the observed number of departments with \( z \) female faculty from their expected value. Let \( z \) denote the number of women in each department, for example, \( z = 0 \) denotes 0 women in the department and \( z = 1 \) denotes one woman in the department.

We can formalize this by thinking about each employment decision as a separate Bernoulli experiment with associated success probability—\( X_i \sim \text{Bernoulli}(p_s) \). The success probability corresponds to the average share of women in the discipline, so that every employment decision is like tossing a coin with the outcome “woman is hired” occurring with probability \( p_s \), which I treat as known.

**The null hypothesis.** Let \( n \) denote the number of departments over all disciplines. Let \( n_s \) denote the number of professorships in discipline \( s \), for \( s = 1, \ldots, S \). I test the joint null hypothesis of whether the hiring process is random (i.e., gender blind) across all departments. In terms of this application, this means that the null hypothesis

\[
H_0 : X_i \overset{i.i.d.}{\sim} \text{Bernoulli}(p_s) \text{ for each } i \in 1, \ldots, n_s \text{ and } s = 1, \ldots, S
\]

assesses whether the hiring process is gender blind for all departments over all disciplines.

Let \( d \) be the index for each department, such that \( d = 1, \ldots, n \). Let \( n_d \) be the number of department members of department \( d \in \{1, \ldots, n\} \). For each department \( d \), the number of women is given by

\[
Y_d = \sum_{i=1}^{n_d} X_i
\]
Under the null of gender-blind hiring, the number of female professors in each department is $Y_d \sim\text{Bin}(n_d, p_d)$, where $p_d$ is the $p$ for discipline $s$ that department $d$ belongs to. Thus, we can calculate for each department the probability of observing exactly $z$ women explicitly as

$$p_d(z) := P(Y_d = z) = \binom{n_d}{z} p_d^z (1 - p_d)^{n_d - z},$$

$$z = 0, 1, 2, \ldots, n_d.$$  \hfill (2)

For every department, I define the random variable

$$H_d(z) = 1(Y_d = z)$$

under the null of gender-blind hiring, it follows directly that $H_d(z) \sim \text{Bernoulli}(p_d(z))$ for $z = 0, 1, \ldots, n_d$.

To make testable statements about the sum over all departments, I need to know the distribution of the sum of the $H_d(z)$ over $d$, that is, $\sum_{d=1}^n H_d(z)$. If $p_d = p$ (i.e., if the success probabilities for each department were identical), the sum would follow a binomial distribution. However, because this is not the case, the sum of all $H_d(z)$ follows a so-called Poisson binomial distribution with mean $\mu_n = \sum_{d=1}^n p_d(z)$ and variance $\sigma_n^2 = \sum_{d=1}^n \sigma_d^2$ with $\sigma_d^2 = (1 - p_d(z)) p_d(z)$ (see Hong, 2013). I will show that this distribution converges to a normal distribution as $n \to \infty$. There exist other approximations for Poisson binomial random variables, and if $n$ is very small, it might be feasible to calculate exact expressions of the mean and variance based on convolution (see Liu & Quertermous, 2018). However, we are ultimately interested in the distribution of the sum across many different disciplines and departments, and it is not clear that any reasonable closed-form solution exists in that case.

I am interested in alternatives that imply implicit quotas at specific values of $z$. This entails that the observed realizations differ systematically across departments from their expected value under the null. I formulate the following test statistic for different specific values $z$, where $z$ indicates the number of women in the department:

$$T_n(z) = \frac{\sum_{d=1}^n H_d(z) - p_d(z)}{\sqrt{\sum_{d=1}^n \sigma_d^2(z)}}.$$  \hfill (4)

For the joint null hypothesis of gender-blind hiring across departments, I want to quantify the uncertainty around the sum of the deviations.

B. Asymptotic Distribution of the Test Statistic

Let $B_d(z) = H_d(z) - p_d(z)$ be a sequence of centered, independent Bernoulli random variables and $s_n^2 = \text{Var}(\sum_{d=1}^n B_d) = \sum_{d=1}^n \sigma_d^2$. Although the distributions of the $B_d(z)$ do not depend on $n$ if the $n_d$ are fixed, we could generalize this setup to $B_{n,d}(z)$ as a row-wise triangular array of independent Bernoulli random variables. This would be the case if, for example, the $n_d$ could vary. I will use this more general setup in the subsequent asymptotic analysis, although here I treat the $n_d$ as fixed. Clearly, $\sum_{d=1}^n B_{n,d}/s_n^2$ has mean 0 and variance 1 if $H_0$ is true. $\hat{T}_n(z) = \sum_{d=1}^n B_{n,d}$, given by equation (4), is then asymptotically standard normal with limiting distribution given by

$$\hat{T}_n(z) \to N(0, 1), \text{ for } n \to \infty.$$  \hfill (5)

It is sufficient to show that the Lyapunov condition holds to ensure equation (5) (see e.g., theorem 2.7.1 in Lehmann, 2004).

Lyapunov condition. Let $\{W_{n,d}\}$ be a row-wise independent triangular array of random variables, with $E(W_{n,d}) = 0$ and $E(\ell_{n,d}^2) = s_n^2$, for $d = 1, \ldots, n$ and $s_n^2 = \sum_{d=1}^n \ell_{n,d}^2$. There exists $\delta > 0$ such that

$$1 \geq \frac{\sum_{d=1}^n \text{Var}(W_{n,d})}{\ell_{n,d}^2} \geq \sum_{d=1}^n \text{Var}(W_{n,d}) = \frac{1}{s_n^2}$$

as $n \to \infty$.

If the Lyapunov condition holds, then $\hat{T}_n$ converges in distribution as in equation (5). I established above that $E(B_{n,d}) = 0$ and $E(B_{n,d}^2) = \sigma_n^2$. It holds that for any $\delta > 0$,

$$1 \geq \frac{\sum_{d=1}^n \text{Var}(B_{n,d})}{\ell_{n,d}^2} \geq \sum_{d=1}^n \text{Var}(B_{n,d}) = \frac{1}{s_n^2}.$$  \hfill (6)

Therefore,

$$1 \leq \frac{1}{s_n^2} \sum_{k=1}^n \text{Var}(B_{n,d}) \leq \frac{1}{s_n^2} \sum_{k=1}^n \text{Var}(B_{n,d}) = \frac{1}{s_n^2}.$$  \hfill (7)

Therefore, if $s_n \to \infty$, which is true as long as $p_d(z)$ is bounded away from 0 and 1, the Lyapunov condition is satisfied and I can conclude that $\sum_{d=1}^n B_{n,d}/s_n \to N(0, 1).$\footnote{As a technical aside, if the distribution of $B_{n,d}$ actually depends on $n$ though varying $n_d$, this condition is only ensured if the $n_d$ are bounded in some way.}

Rejection of the null hypothesis indicates that the joint null of gender-blind hiring across all departments is rejected, but does not indicate which departments or disciplines engaged in nongender-blind hiring.

For the normal approximation to work well in this context, we only need to assume that $n$ is large, which means that either or both the number of departments within disciplines or the number of disciplines are large, but we cannot make statements about particular departments or disciplines.

C. Parametric Bootstrap

As an alternative to the asymptotic test procedure, I introduce a type of parametric bootstrap procedure, or, more precisely, a numerical approximation of the exact distribution. I first draw a random value from a Bernoulli
distribution for each position \( X_i \), with the \( p_i \) from the data and calculate \( H_d(z) \) for all \( d = 1, \ldots, n \) (collected in a vector \( H(z) \)) according to equation (3) with \( n = 1,737 \) from the data. I center the resulting data using \( p_d(z) \) for each \( d \) and calculate the sum over all departments \( B(z) = \sum_{d=1}^{n} B_d(z) \). I treat the resulting value as one bootstrap observation. I denote the vector of department sizes \( n^d = (n_1, n_2, \ldots, n_n) \).

In detail, the procedure is the following. Let \( B \) be the number of bootstrap draws and \( ^* \) denote a bootstrap sample.

for \( z = 0, \ldots, 10, b = 1^*, \ldots, B^* \) do
  Draw each position \( X_i \) for \( i = 1, \ldots, n_s \) over all disciplines \( s = 1, \ldots, S \) from a \( \text{Bernoulli}(p_s) \) and collect these in a vector denoted by \( X^{b^*} \).
  for \( d = 1, \ldots, n \) do
    calculate \( Y_d^{b^*} \) (according to (1)) using the vector of department sizes \( n^{d^*} \) from the data. Calculate \( B_d(z)^{b^*} \) as described above.
  end

Calculate \( B(z)^{b^*} = \sum_{d=1}^{n} B_d(z)^{b^*} \) and compare the empirical distribution of the Bootstrap realizations \( B(z)^{b^*} \) with the actual \( B(z) \) from the data.

end

IV. Results

A. Descriptives

Share of female professors across disciplines. The mean share of female professors varies significantly across disciplines. Traditional STEM subjects, law, and economics have a relatively low share of female professors, ranging from about 7% in electrical engineering, 16% in mathematics, and 18% in economics. The share is higher in other disciplines in the social sciences or the humanities. For example, political science has a share of 26%; history has 30% and German 40%. However, it is notable that there is no discipline where women hold a majority of positions: the highest share of female professors is in cultural studies, where women hold about 48% of positions. In 2015, 50% of male employed professors were appointed in 2004 or after, while 50% of currently employed female professors were appointed in 2008 or after.

Average department size. Departments in the humanities, where the average share of women is higher than in STEM subjects, law, and economics, tend to be much smaller. In cultural studies, the average department has only 6 professors, where as the average electrical engineering department has about 19, and the average economics department has about 22. Again, the other social sciences are in between. This is broadly consistent across countries in Western Europe and the United States; for example, in 2010, the average physics department employed 29.2 full-time faculty versus history, which had an average department size of 16.5 in 2007 among PhD-granting institutions.\(^8\)

B. Testing for Implicit Quotas

Here, I present the deviations from the expected value as outlined above, both overall and by discipline. To characterize whether the distribution of women is unusual and violates the null of gender-blind hiring, I present both the result from calculating the value of the test statistic, equation (4), and the critical values from a two-sided test using the standard normal distribution and the quantiles from the parametric bootstrap procedure. Overall, both procedures clearly indicate that there are too many departments with exactly two women and too few with zero-, and three, four, or five women. Based on this evidence, I can reject the joint null of gender-blind hiring with a similar \( p \)-value for both the normal approximation and the parametric bootstrap procedure.

C. Main Results

The top panel of figure 2 graphically shows the summed deviations \( (B(z) = \sum_{d=1}^{1737} B_d(z)) \) of the number of departments with exactly \( z \) women, for \( z = 0, 1, \ldots, 10 \), summed over all departments. To indicate the uncertainty around these estimates, the bars are shaded by the \( p \)-values with the critical values from a two-sided test from a standard normal distribution. Darker shades indicate lower \( p \)-values. The deviations and \( p \)-values can also be found in table 1.

The results indicate that the joint hypothesis of gender-blind hiring can be rejected for several values of \( z \). Specifically, there are too few departments with exactly zero women (there are about 20 departments fewer than expected with an associated \( p \)-value of 0.03) and too few departments with three women (\( p \)-value 0.09), four women (\( p \)-value 0.28), five women (\( p \)-value 0.08), and seven women (\( p \)-value 0.18). There are also about 12 departments too many with precisely one woman (\( p \)-value 0.21) and 47 too many departments with two women (\( p \)-value 0.01). This indicates a two-women implicit quota and that departments specifically try to avoid having no female professors. As an alternative to the test above, I depict the results from the parametric bootstrap procedure described in figure 3. The transparent diamonds represent individual bootstrap draws \( B(z)^{b^*} \), the gray triangles represent the empirical 90% interval, and the black dots are the observed \( B(z) \) from the data. The results are generally in line with the results from the test in terms of the empirical \( p \)-values. Both the observed deviations for zero women and two and three women lie unambiguously outside the 90% interval. Therefore, the results from the bootstrap procedure confirm the presence of a two-women department implicit quota and an aversion against zero women in the department.

When I compare the two methods, the bootstrap implies that for larger \( z \), there is more uncertainty than the

\(^8\) See White, Ivie, and Ephraim (2012) and Townsend (2010).
Figure 2.—Deviation from Expected Number of Departments with 0 to 10 Women

Mean over all 50 disciplines, shaded by $p$-value; $p_{\min} = 0.011$, $p_{\max} = 0.27$. Deviation from expected value (in absolute numbers), shaded by joint $p$-value. The darker the shading, the lower the $p$-value. Lowest $p$-value corresponds to the deviation from exactly two-women departments with a $p$-value of 0.011.

Table 1.—Summed Deviations and $p$-Values for the Asymptotic Test in Equation (4) for $z = 0, \ldots, 1$

| $z$ | $B(z)$ | $p$-value |
|-----|-------|----------|
| 0   | −20.080 | 0.031 |
| 1   | 12.350 | 0.212 |
| 2   | 46.940 | 0.012 |
| 3   | −29.270 | 0.092 |
| 4   | −10.060 | 0.283 |
| 5   | −10.460 | 0.083 |
| 6   | 3.670 | 0.230 |
| 7   | −13.690 | 0.181 |
| 8   | 4.340 | 0.025 |
| 9   | 2.590 | 0.270 |
| 10  | −0.060 | 0.084 |

Asymptotic approximation would suggest. Intuitively this makes sense, as with the overall small $p_s$, we would expect very few departments with many women. Therefore, even minor deviations (because actual observations are integers and expected values are not) would be significant compared to the normal distribution. There exist continuity adjustments for normal approximations of the binomial distribution (Feller, 2015), and this could probably be applied in this situation if one wanted to avoid the parametric bootstrap procedure.

D. Independence and Constant Hiring Probabilities

Both the asymptotic normality result and the parametric bootstrap rely on the independence of hiring decisions across departments, both within and across disciplines. This assumption is usually justified in this context, as the hiring of professors is essentially sampling with replacement—that is, the success probability is approximately constant, and knowledge of the outcome of a previous hiring decision at a different department should not influence the gender of the next hire. However, I also assume that hiring probabilities are constant across departments, and because it is not possible to hire the same person twice, this assumption might be problematic. With the overall number of departments and professors large, the change in the overall probability of
hiring a woman is mostly unchanged when the women already in “own-department” do not count toward the hiring probability. To verify that this is a reasonable assumption in this application, I calculate the leave-one-out probability $p_{d,o}$ of hiring a woman and how $p_{d,o}$ differ from the overall probability $p_s$. They are all (very) small and only for 0.041% of departments (with 1,737 departments from 50 different disciplines) is the $t$-test for equality of means of the leave-one-out mean and the overall mean rejected with $\alpha = 0.05$. Thus, the constant probability assumption appears to be reasonable in the context of this application.

### E. Effects of a Fictional Quota

Given the analysis above, we might speculate about implicit quotas in specific disciplines or we might hypothesize that disciplines that have a low share of female professors provide a more hostile environment and therefore are more likely to discriminate against women. However, the correlation $\rho_z$ between having a negative deviation from the expected number of zero women departments and the share of women is $\rho_0 = -0.035$ (p-value 0.86) and for $z = 3$ women is $\rho_3 = 0.07$ (p-value 0.62). Equally, there is no clear correlation with being a STEM or non-STEM discipline. These results suggest that the type of discipline with an implicit quota is not easily categorized. This result might seem puzzling at first glance, but when considering the bimodal distribution of average department sizes, it becomes clear that an implicit quota would have heterogeneous effects on the share of women within the discipline, depending on the average department size. Most of the non-STEM fields (with the notable exceptions economics and law) with the largest share of female faculty have average department sizes below 10 professors: this implies that a two-women quota would mechanically lead to a much higher female share in these disciplines than in mathematics or economics, where the average department size is much larger. This example shows that we cannot rule out that non-STEM disciplines in the humanities have a larger share of female professors because an implicit quota has a heterogeneous effect depending on average department sizes in the discipline rather than discipline-specific characteristics. To illustrate this point, consider figure 4. Here I simulate the hypothetical shares of women
V. Conclusion and Discussion

This paper introduced a test to detect an underresearched form of hiring bias: implicit quotas. I derive a test under the null of gender-blind hiring that requires no additional information about individual hires under some assumptions. I derive the asymptotic distribution of this test statistic and, as an alternative, propose a numerical approximation of the exact distribution, which is known but infeasible to calculate in most cases. This test can be used to analyze a variety of other hiring settings.

Analyzing employment patterns of female professors across departments and disciplines allows me to show that there exists a one- to two-women quota on the department level. This type of discrimination or hiring bias cannot be explained with traditional explanations for discrimination—for example, either pure statistical or taste-based discrimination.9 I also show that this type of implicit quota can

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9Bayer and Rouse (2016) categorize research findings in economics into supply-side factors (i.e., hostile work environments; Wu, 2018) and demandside factors (such as a lower probability of getting published or accepted at conferences (conditional on paper quality and a range of controls; Card et al., 2020; Hospido & Sanz, 2021), higher discounting of women’s contributions when working with male coauthors (Sarsons, 2017), more “unfair” questions during seminars (Dupas et al., 2021) or lower teaching evaluations (Boring, 2017; Mengel, Sauermann, & Zölitz, 2019). Neither of these is a sufficient explanation for the presence of implicit quotas.
potentially explain part of the gap in the female professor share among disciplines. The fact that I can distinguish between the implicit quota being centered around the mean (i.e., around the relative share of female professors in a discipline, which is not the case) and a specific discrete number poses exciting questions that I have not seen addressed before: how humans perceive structures that have the “correct level” of diversity.

It is important to emphasize that the observed patterns described above allow me only to make statements about whether the observed distribution is gender blind: we cannot say whether the “real” or “natural” proportion of female professors \( p_s \) (without the implicit quota) would be larger, smaller, or precisely the same. Furthermore, direct discrimination in implicit quotas (which leads to discrimination in both directions) and gender differences in personal attributes, preferences, and implicit biases are not mutually exclusive. There is even a plausible link between biases and direct discrimination; as Goldin (2014) argues, if men perceive women as less qualified and care about the prestige of their profession, they may fear that a woman’s entering a profession signals a change in the prestige of the profession and therefore might block entry to otherwise qualified women.

The analysis in this paper is sufficient to show that hiring is not gender blind. My work therefore has several implications for both further research and policy.

Concerning research, any further analysis of performance measures and researcher productivity should be conducted only with the caveat in mind that there might be implicit quotas. Implicit quotas could potentially lead to substantially more quality heterogeneity among the underrepresented groups that might be obscured when researchers only consider averages.

Concerning policy, my results imply that funders and organizations that engage in diversity pressure without explicit targets should be conscious of the potential for implicit quotas and carefully monitor progress. My results also imply that if policymakers have a specific diversity target in mind, then an explicit quota might be more effective, as implicit quotas might incur the same societal and private costs as explicit quotas while not achieving the same level of progress.

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