Self-Image Bias and Lost Talent

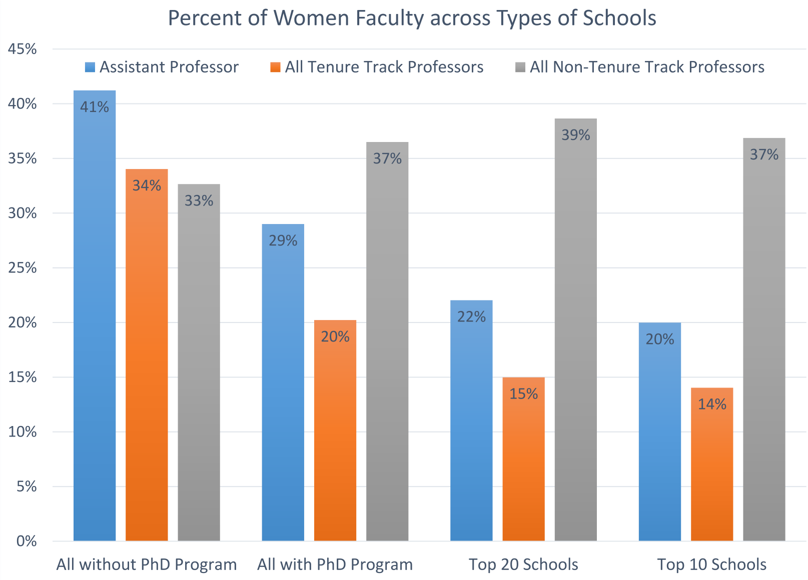
Marciano Siniscalchi[1] Pietro Veronesi[2]

[1]Northwestern University

[2]University of Chicago, NBER and CEPR

ASSA / NAWM 2022

Gender imbalance in Economics



Source: CSWEP Report, 2020.

Our Contribution

Large literature on discrimination

- Taste-based: Becker (1957)
- Implicit bias: e.g. Bertrand and Mullainathan (2004)
- Statistical: Phelps (1972), Arrow (1973)

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Key force: self-image bias

Related Literature

Economics (a very small selection!):

- Economics of discrimination: Becker (1952), Phelps (1972), Arrow (1973); see Fang and Moro (2011)
- Gender pay gap: see Bertrand (2011), Blau and Kahn (2017)
- Implicit bias: Bertrand, Chugh and Mullainathan (2005)
- Discrimination in economics: Bayer and Rouse (2016), Sarsons (2019), Card, della Vigna, Funk and Iriberri (2019)
- Small vs. large differences: Bardhi, Guo and Strulovici (2020)

Psychology / Social Psychology:

- Self-image bias: Levicki (1982), Hill (1988);
- Self-serving prototypes Dunning and co., (1991), (2000)
- "Rational" self-image bias: Story and Dunning (1998)
- Hiring as cultural matching: Rivera (2012)

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- Probability of producing quality research (paper, JMP):

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Characteristics are equally valuable: More "1"s $\rightarrow \gamma^\theta \uparrow$

$\rho =$ effect of characteristics on ability to produce quality research

Group (M vs. F) does not affect probability of success

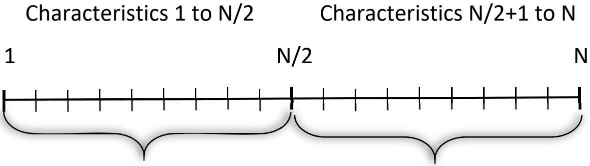
Research Characteristics

Many positive characteristics affect research quality:

- Economic motivation
- "Nose" for good questions
- Institutional knowledge
- Ability to find new data sources
- Solid identification strategy
- Sophisticated empirical analysis
- Clever experimental design
- Skilful theoretical modelling
- Ability to highlight insights, strategic effects...
- Mathematical sophistication / proof techniques...
- Ability to position within the literature
- Presentation skills
- Ability to address questions from audience

...

Young Researchers: Key Distributional Assumption



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$F: pr(\theta_n = 1) = 1 - \phi$ $\quad$ $F: pr(\theta_n = 1) = \phi$

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- large within-group differences;
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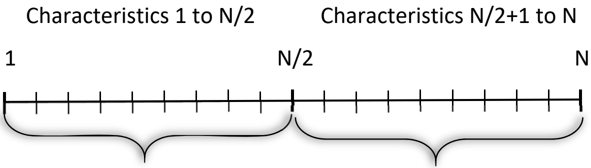

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Note: not necessarily innate!

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Each agent has type $\theta \in \{0, 1\}^N$ and belongs to group $g \in \{m, f\}$

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- $a_t^{\theta,g}$: "accepted" young researcher of type θ in group g at t
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- $\lambda_t^{\theta,g}$: old researchers of type θ in group g at t
- $\lambda_t^\theta = \lambda_t^{\theta,m} + \lambda_t^{\theta,f}$: total mass of old researchers of type θ
- $\Lambda_t^g = \sum_\theta \lambda_t^{\theta,g}$: total mass of old researchers of group g

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Some old researchers "retire" to keep total mass $\lambda_t = 1$

$$\lambda_{t+1}^{\theta,g} = \lambda_t^{\theta,g}(1 - a_t) + a_t^{\theta,g}$$

Benchmark: Objective Evaluation

- Young researchers enter the model
- If they produce quality research, they get hired

Implies $a_t^{\theta,g} = p_g^{\theta} \cdot \gamma^{\theta}$, so

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Proposition

The limiting distribution of researchers (across types and groups) does not depend upon initial conditions $(\lambda_0^{\theta,g})_{g\in\{m,f\},\theta\in\{0,1\}^N}$

In the limit, group balance obtains, and all types survive.

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Matching and evaluation are completely group-blind:

- Young researcher's group not taken into account
- Both M and F old researchers use same rule

Type Dynamics: Basics

Proposition

The sequences $(\lambda_t^g)_{t\geq 0}$ *(*$g \in \{m, f\}$*) converge.*

Only three types can potentially survive in the limit: either

(i) *the type most likely to be successful in research,*

$$\theta^* = (1, \dots, 1); \quad \textit{or}$$

(ii) *the type most prevalent across young M and F researchers,*

$$\theta^m = (1, \dots, 1, 0, \dots, 0) \quad \textit{and} \quad \theta^f = (0, \dots, 0, 1, \dots, 1).$$

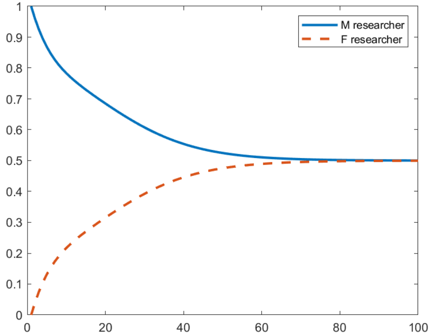
θ^m, θ^f have frequency ϕ^N; θ^* has frequency $\phi^{N/2}(1-\phi)^{N/2}$, so less prevalent among both M and F researchers.

Type Dynamics: Meritocracy

Proposition

If $\rho > \overline{\rho}(\phi, N) \equiv \frac{1}{4}\left[\left(\frac{1-\phi}{\phi}\right)^{N/2} + \left(\frac{\phi}{1-\phi}\right)^{N/2}\right]^2$ *then, for all initial conditions, only type* θ^* *survives.*

$N = 2$, $\phi = 0.8$, $\gamma_0 = 0.1$, $\rho = 9$; initial population all M



Total mass of M and F researchers

Type Dynamics: Limiting Gender Imbalance

Proposition

If $\rho < \overline{\rho}(\phi, N)$ then only θ^m and θ^f survive in the limit. In particular, the best type θ^* disappears.

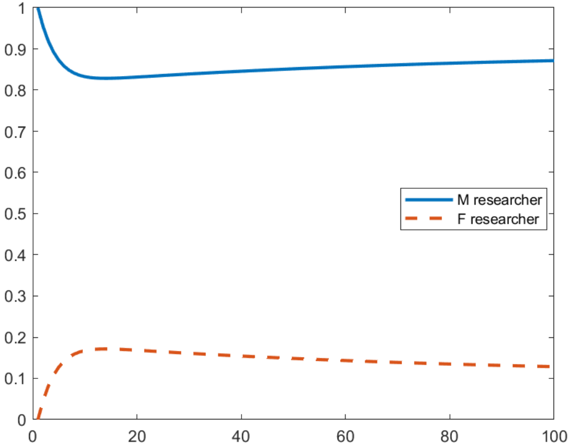
Proposition

If $\rho < \overline{\rho}(\phi, N)$ and all referees are initially M, i.e., $\lambda_0 = p_m$, then the limit mass of M researchers is

$$\bar{\Lambda}^m = 1 - \bar{\Lambda}^f = \frac{1 + \left(\frac{\phi}{1-\phi}\right)^{2N}}{1 + \left(\frac{\phi}{1-\phi}\right)^{2N} + 2\left(\frac{\phi}{1-\phi}\right)^{N}} > 0.5.$$

If Bias Dominates: Fraction of M and F researchers

$N = 2$, $\phi = 0.8$, $\gamma_0 = 0.2$, $\rho = 4$; initially all M: only θ^m, θ^f survive

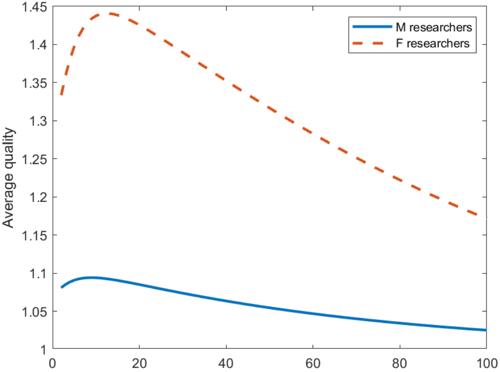


Total mass of M and F researchers

If Bias Dominates: Higher Average Quality of Accepted F's

Proposition

Let $N = 2$ and $\lambda_0 = p_m$. Then the average quality of accepted F researchers is higher.



Average Quality of accepted M and F researchers

A "calibration:" Effect Size

A common measure in psychology and other fields:

Cohen's d

Given population means μ_1, μ_2 and pooled standard deviation σ:

$$d = \frac{\mu_1 - \mu_2}{\sigma}$$

In our model:

$$d = \frac{\mathrm{E}[\theta_n^i | i \in M] - \mathrm{E}[\theta_n^i | i \in F]}{\sigma_{\text{pooled}}(\theta_n^i)} = \frac{2\phi - 1}{\sqrt{\phi(1-\phi)}}$$

Small: $d \approx 0.2$; medium : $d \approx 0.5$; large: $d \approx 0.8$ or larger

With $\phi = 0.8$, $d \approx 1.5$, so too large

Within- vs. across-group differences

- Hyde (2006): small *d* for most cognitive traits
- Hyde (2001): small-to-medium *d* for big-5 personality traits
  - Extraversion, Agreebleness, Openness, Conscientiousness, and Neuroticism
- Croson and Gneezy (2009): "robust" differences for risk, social, and competitive preferences
- Borghans and Heckman (2009): differences in risk and ambiguity aversion (smaller)
- Dittrich and Leipold (2014): differences in time preferences
- Drebner and Johannesson (2008): men more likely to lie
- Niederle and Vesterlund (2010): greater gender gap at highest levels of math competition

Across-group differences exist, but are smaller than within-group

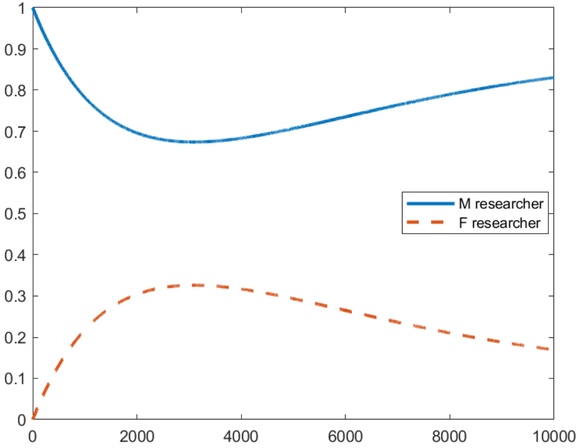
A "calibration:" parameterization

- $N = 10$ characteristics
- $\phi = 0.5742$, so $d = 0.3$ (i.e. small)
- As before, $\gamma_0 = 0.2$, $\rho = 4$
  - Approx. % Ph.D.'s working at 4-yr institutions, $\approx 45\%$
    NSF Survey of Doctoral Receipients, 2017
  - $\theta^* = (1, \ldots, 1)$ 4 times as productive than $(0, \ldots, 0)$
    Conley and Önder, 2014

With these parameters, bias dominates

Calibration: Fraction of M and F researchers

$\gamma_0 = 0.2$, $\rho = 4$; initial population all M: only θ^m, θ^f survive



Total mass of M and F researchers

Conclusion

- Novel model of discrimination based on:
  - (Small) heterogeneity in research characteristics
  - Self-image bias of referees
  - Initial asymmetry
- Extensions (see paper):
  - Other distributional assumptions
  - Endogenous entry / selection by employers
  - Junior and senior faculty: leaky pipeline
- Policy implications
  - Mentoring (but may increase talent loss)
  - Affirmative action: diverse referee population
  - Broadening referees
  - Specific criteria vs. discretion in refereeing?