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Gender Productivity Gap Among Star Performers in STEM and Other Scientific Fields

Herman Aguinis, Young Hun Ji, & Harry Joo (2018)

Journal of Applied Psychology
Vol. 103, No. 12, 1283-1306

Presentation by Young Hun Ji
18.01.2019

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Gender Representation Gap in STEM Fields

- In early education, boys and girls display similar participation in mathematics and science (e.g., Xie & Shauman, 2003).

- Nonetheless, women are increasingly underrepresented in higher-level STEM professions, e.g., level of associate and full professor (Wolfinger, Mason, & Goulden, 2008):

    - In chemistry, women earned about 50% of bachelor degrees and 35% of Ph.D. degrees in 2008, but represented only 17% of faculty members at US research universities in 2011.

    - A survey of the Association of American Universities showed that women chaired only 2.7% of engineering departments, 5.9% of math or physical science departments, and 12.7% of life science departments (Niemeier & Gonzalez, 2004).

- The persistent underrepresentation of women in STEM fields has tremendous societal, educational, and economic consequences.

Primary Research Question:

“Is there a gender productivity gap specifically among star performers in these fields?”

Star Performers in the 21st Century

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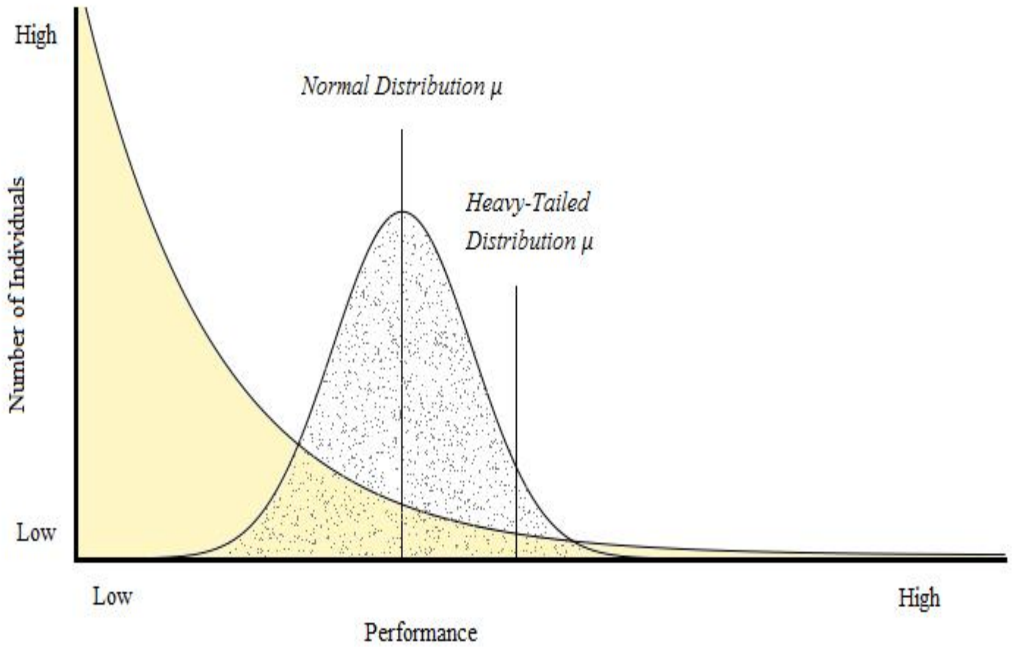
• **Star performers** are individuals who produce output and results many times greater than the rest of the individuals holding the same job or position (O'Boyle & Aguinis, 2012).

• These individuals are characterized by disproportionately high and prolonged **performance**, **visibility**, and **relevant social capital** (Call, Nyberg, & Thatcher, 2015).

• A recent set of studies demonstrated that star performers are more highly prevalent they would be under the assumption of normally distributed performance (Aguinis & O'Boyle, 2014).



A gender performance gap among star performers in favor of men is more detrimental to the success of all women performers than an equivalent gap among average performers.

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Research Questions & Overview

Research Questions:

- Is there a gender productivity gap among star performers in STEM and other scientific fields? If so, what causes it?
- Are there differences across scientific domains (e.g., mathematics versus genetics)?

Research Overview:

- **4 Samples**: S1: Mathematics, S2: Genetics, S3: Applied Psychology & Mathematical Psychology
- **Productivity data**: Number of papers published in top journals by individual researchers by gender and across scientific domains
- **Theory testing & development**: (1) Observe the shape of individual productivity distributions → (2) Identify the dominant generative mechanism for star performance → (3) Infer the most logical gender-based explanation for any gender productivity gaps among stars → (4) Generate recommendations for minimizing gender-star gaps

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Study Contributions

1. We show that the gender gap among stars in these fields is more severe than the total gender gap among all performers.

2. We identify the predominant mechanism that enables star performance across STEM fields and genders.

3. We infer the most-likely gender-based explanation for the gender productivity gap specifically among stars, based on the predominant mechanism identified.

4. We provide novel practical suggestions for minimizing the gender-star gap in STEM fields.

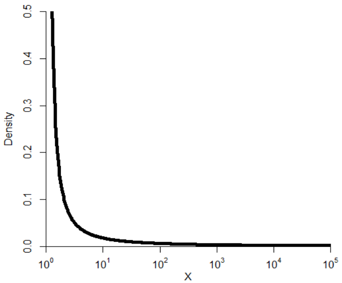
3 Competing Explanations for the Gender Gap

1. **Biological factors** *that lead to gender differences across cognitive domains* (e.g., Stoet & Geary, 2012)
   - Sex differences in brain lateralization patterns
   - Innate & fixed
2. **Gender differences in career and lifestyle choices**: *Women ‘opt out’ of STEM fields*
   - Gender differences in family and occupational values (Ceci, Ginther, Kahn, & Williams, 2014)
   - Psychological & volitional
3. **Gender discrimination**: *Women are ‘pushed out’ of STEM fields*
   - Gender biases in hiring, promotions, grant funding, journal reviewing (Chesler et al., 2010)
   - ‘Matilda effect’ among colleagues, supervisors, and reviewers, etc.
   - External & socio-cultural

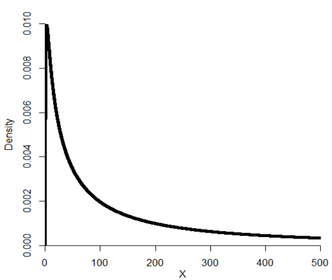
7 Theoretical Distributions & 4 Dominant Generative Mechanisms

Joo, Aguinis and Bradley (2017) provide a taxonomy of individual output distributions and their associated generative mechanisms.

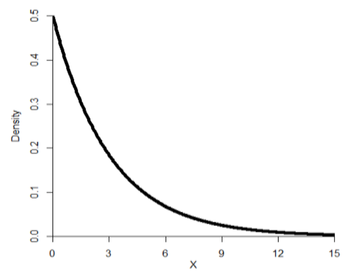
1. Pure power law



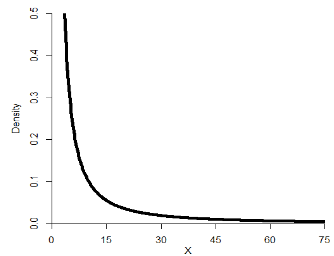
2. Lognormal



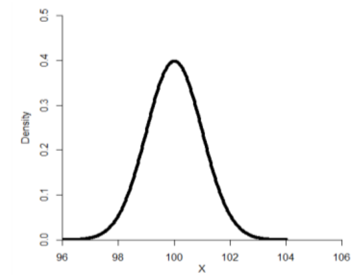
3. Exponential



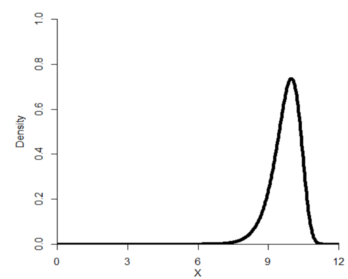
4. Power law with exponential cutoff



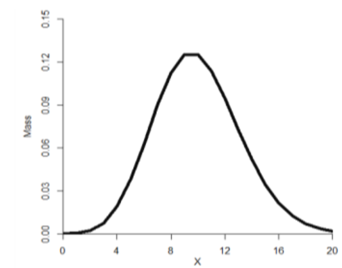
5. Normal



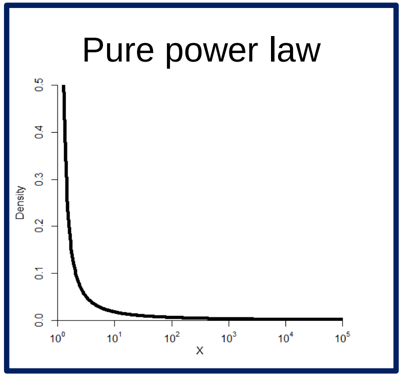
6. Weibull



7. Poisson



Pure Power Law & Self-Organized Criticality



Technical description:

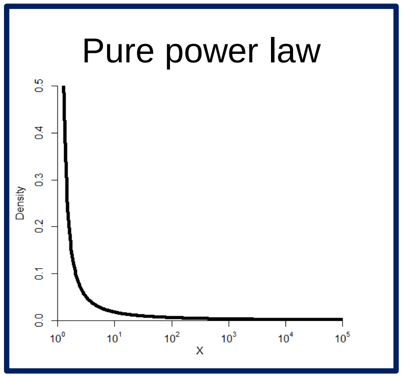
A set of values from a variable, or x, follows a **pure power law** if:

$$p(x) \propto x^{-\alpha}$$

Where **alpha (α) (> 1) is the rate of decay**. The lower the value of α, the heavier the distribution's right tail

Out of the seven distributions, the pure power law has the heaviest right hand tail (seemingly infinite).

Pure Power Law & Self-Organized Criticality



<u>**Generative mechanism**</u>**:** ***Self organized criticality***, a process where some individuals reach ‘critical states’ triggered by an interaction of events that lead to large ‘output shocks’ (Joo et al., 2017). Increases in output after reaching critical states are unpredictable and potentially extremely large.

<u>Examples:</u>

- A researcher may discover a unique set of findings by chance, which subsequently helps the scientist rapidly discover a much larger set of findings.
- Research in physics has found that the distribution of the magnitude of sand avalanches follows a power law distribution (Bak, 1996).

Pure Power Law & Self-Organized Criticality

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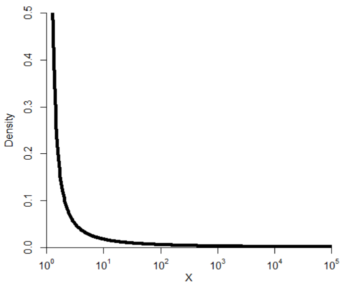
Pure power law



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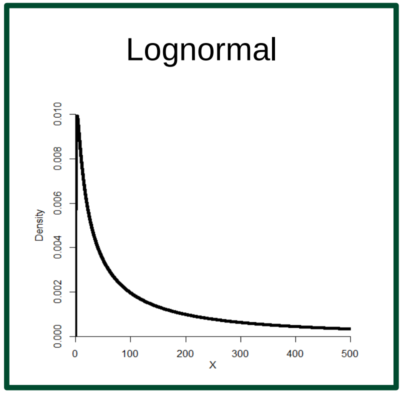
H1a: Individual productivity of women and men in STEM and other scientific fields follows a pure power law distribution.

H1b: The pure power law distribution of individual productivity will have a lighter right tail for women than men.

A lighter right tail for women likely reflects the impacts of gender discrimination and/or gender differences in career and lifestyle choices

Lognormal Distribution & Proportionate Differentiation



Technical description:

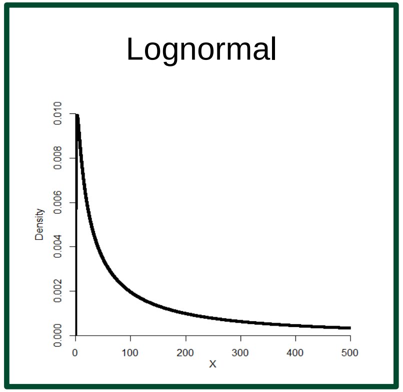
A set of values from a variable, or x, follows a **lognormal distribution** if:

$$p(x) \propto e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}}$$

Where ***μ* is the mean and *σ* (>0) is the standard deviation.** The higher the standard deviation, the heavier the right tail of the distribution.

Out of the seven distributions, the lognormal distribution has the second heaviest (but ultimately finite) right hand tail.

Lognormal Distribution & Proportionate Differentiation



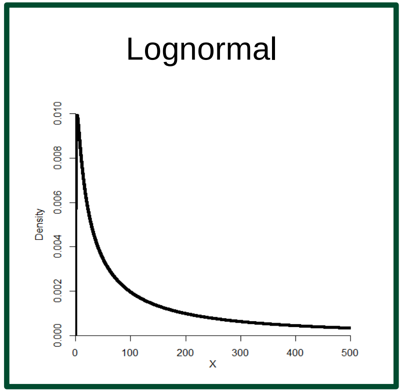
<u>Generative mechanism</u>: *Proportionate differentiation*. Individual differences in value on an outcome occur due to differences with respect to the accumulation rate and initial value on the outcome (Joo et al., 2017).

As such, some individuals experience large ‘output loops’ (i.e., increasingly larger output increases based on positive feedback between past and future output).

<u>Examples</u>:

- Community organizers with a higher number of initial signatures may find it easier to obtain additional signatures.
- Research in geology shows that a crystal’s initial size and its rate of exposure to additional minerals determine its subsequent sizes, creating a lognormal distribution of crystal sizes (Kile & Eberl, 2003).

Lognormal Distribution & Proportionate Differentiation



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As such, some individuals experience large 'output loops' (i.e., increasingly larger output increases based on positive feedback between past and future output).

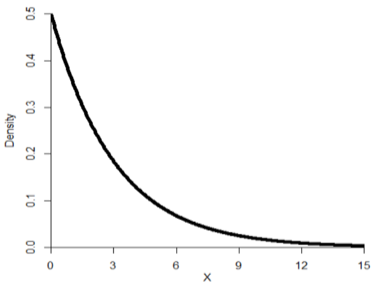
H2a: Individual productivity of women and men in STEM and other scientific fields follows a lognormal distribution.

H2b: The lognormal distribution of individual productivity will have a lighter right tail for women than men.

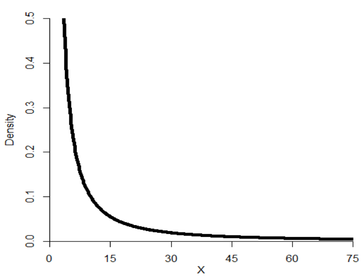
A lighter right tail for women likely reflects the impacts of gender discrimination.

Exponential-tail Distributions & Incremental Differentiation

Exponential



Power law with
exponential cutoff



Technical descriptions:

- A set of values from a variable, or x, follows an **exponential distribution** if:

$$p(x) \propto e^{-\lambda x}$$

Where ***λ* (>0) is the rate of decay.** The lower the value of λ, the heavier the distribution's right tail.

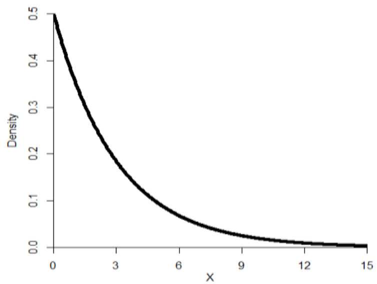
- A set of values from a variable, or x, follows a **power law with exponential cutoff** if:

$$p(x) \propto x^{-\alpha} e^{-\lambda x}$$

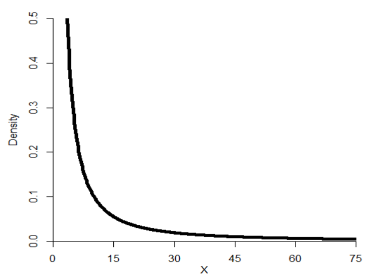
Where ***α* (>1) and *λ* (>0) are the rates of decay.** The lower the values of α and λ, the heavier the distribution's right tail. Between the two rates of decay, λ is stronger in shaping the distribution's right hand tail.

Exponential-tail Distributions & Incremental Differentiation

Exponential



Power law with exponential cutoff



Generative mechanism: *Incremental differentiation*. Individual differences in total output differ due to differences with respect to output accumulation rates, i.e., output generated per opportunity to perform (Joo et al., 2017).

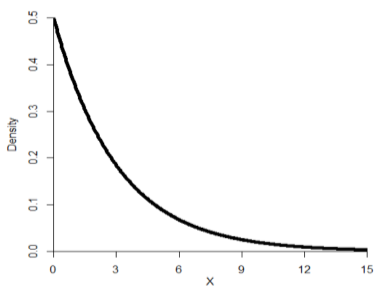
Due to differences in accumulation rates, some individuals enjoy larger 'output increments,' i.e., larger linear increases in output.

Examples:

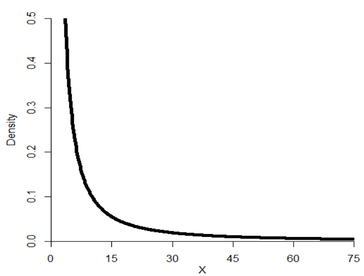
- Differences across individuals in terms of labor productivity lead them to accumulate wages at different linear rates (Nirei & Souma, 2007).
- The accumulation of links with other nodes (e.g., between airports) follows a power law with exponential cutoff (Amaral et al., 2000).

Exponential-tail Distributions & Incremental Differentiation

Exponential



Power law with
exponential cutoff



<u>Generative mechanism:</u> *Incremental differentiation*. Individual differences in total output differ due to differences with respect to output accumulation rates, i.e., output generated per opportunity to perform (Joo et al., 2017).

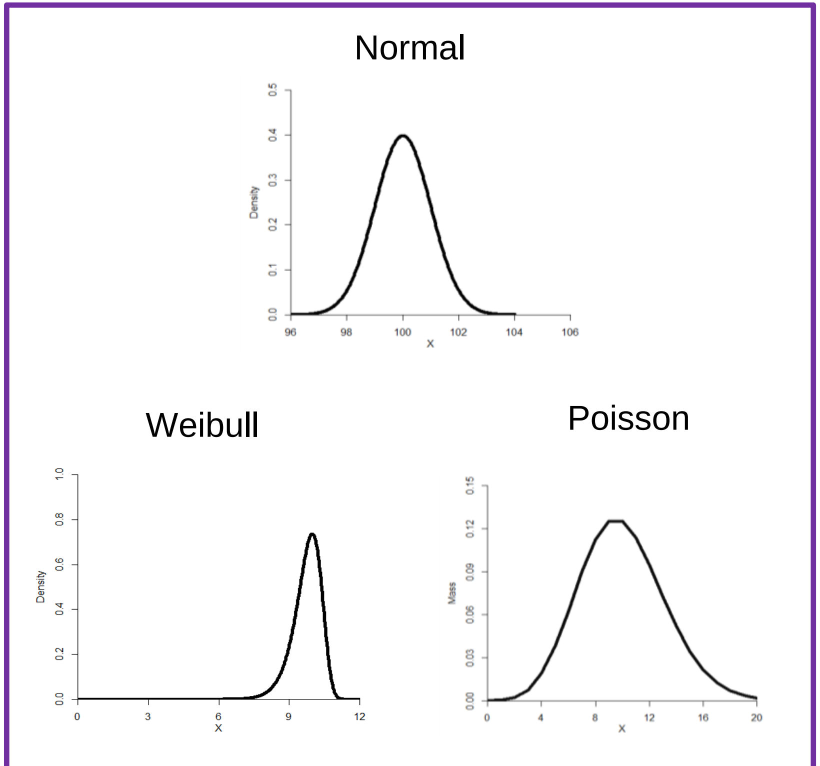
Due to differences in accumulation rates, some individuals enjoy larger 'output increments,' i.e., larger linear increases in output.

H3a: Individual productivity of women and men in STEM and other scientific fields follows an exponential tail distribution.

H3b: The exponential tail distribution of individual productivity will have a lighter right tail for women than men.

A lighter right tail for women likely reflects the impacts of gender discrimination.

(Potentially) Symmetric Distributions & Homogenization



Technical descriptions:

- **Normal distribution:**

$$p(x) \propto e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

The lower the value of $\boldsymbol{\sigma}$, the lighter the distribution's symmetric tails.

- **Weibull distribution:**

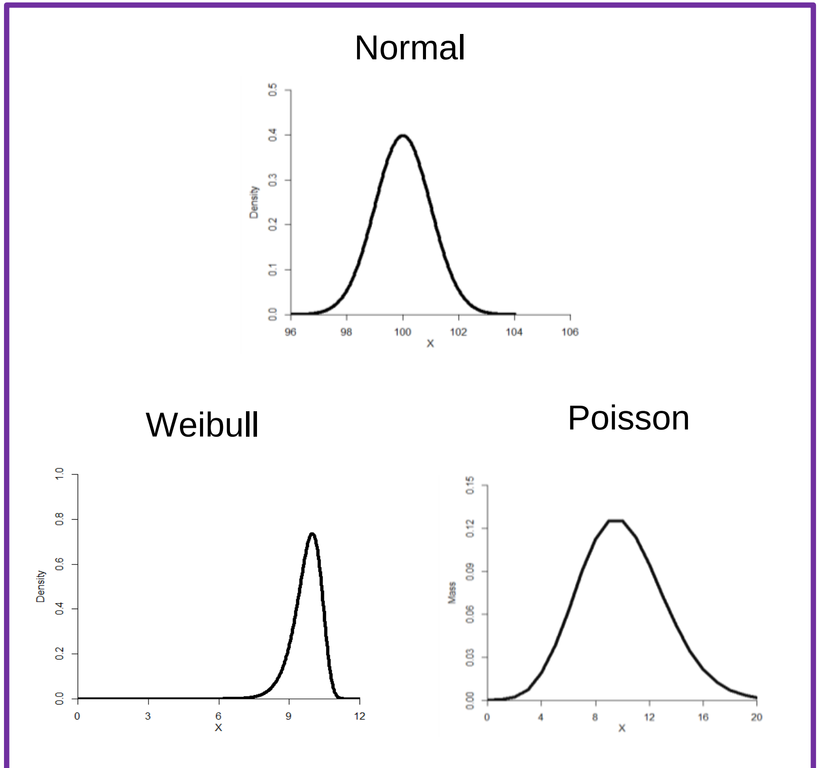
$$p(x) \propto \left(x/\lambda\right)^{\beta-1} e^{\left(x/\lambda\right)^{\beta}}$$

The lower the value of $\boldsymbol{\beta}$ **(>0)**, the heavier the distribution's left tail.

- **Poisson distribution:** $p(x) \propto \mu^x / x!$

The lower the value of $\boldsymbol{\mu}$ **(>0)**, the heavier the distribution's right tail.

(Potentially) Symmetric Distributions & Homogenization

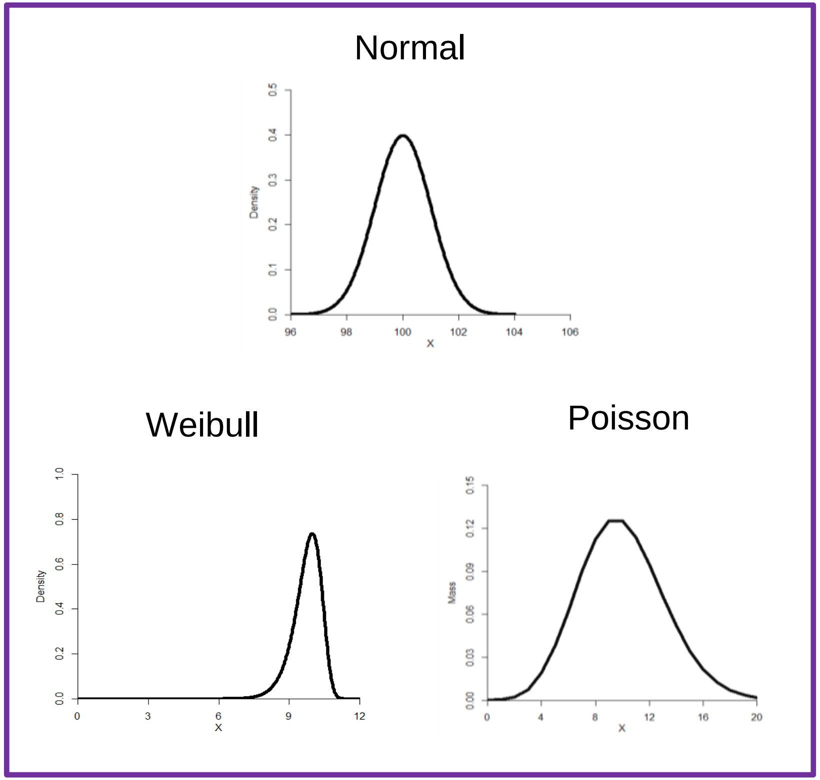


<u>Generative mechanism:</u> ***Homogenization***, a process where individuals undergo output homogenization leading to lower variability in individual output over time (Joo et al., 2017).

<u>Examples:</u>

- Uniform expectations of production and service reduce the variability of output among assembly line workers and service workers.
- Research in entomology found that mouth-to-mouth feeding, social grooming, and other physical contact among ants homogenized their scent (Lenoir et al., 2001).

(Potentially) Symmetric Distributions & Homogenization



<u>Generative mechanism:</u> ***Homogenization***, a process where individuals undergo output homogenization leading to lower variability in individual output over time (Joo et al., 2017).

H4a: Individual productivity of women and men in STEM and other scientific fields follows a (potentially) symmetric distribution.

H4b: The (potentially) symmetric distribution of individual productivity will have a lighter right tail for women than men.

A lighter right tail for women likely reflects the impacts of gender differences in career and lifestyle choices.

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Method—Samples

<u>Study 1:</u> All researchers who have published at least one article in the top ten most influential journals in the field of **Mathematics (3,161 articles)** from 2006 to 2015.

- **N = 3,853** unique authors of whom **360** (**9%**) were women.

<u>Study 2:</u> All researchers who have published at least one article in the top five most influential journals in the field of **Genetics from (7,746 articles)** 2006 to 2015.

- **N = 45,007** unique authors of whom **14,685** (**32.6%**) were women.

<u>Study 3:</u> All researchers who have published at least one article in the top five most influential journals in the field of **Applied Psychology (2,807 articles)** and of **Mathematical Psychology (3,796 articles)** from 2006 to 2015.

- Applied Psychology: **N = 4,081** unique authors of whom **1,595** (**39.1%**) were women.
- Mathematical Psychology: **N = 6,337** unique authors of whom **2,117** (**34.4%**) were women.

Method—Journal Selection Criteria

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Identifying the most influential journals in each field:

• Journals in each field (mathematics, genetics, applied psychology, and mathematical psychology) were ranked based on their **average journal impact factor over the past five years**.

• **Journal impact factor**: the average number of citations received per publication in that journal in the two preceding years.

Impact Factors of Top Genetics Journals (2011 to 2015)

Journal	2011	2012	2013	2014	2015	Average
Nature Reviews Genetics	38.075	41.063	39.794	36.978	35.898	**38.3616**
Nature Genetics	35.532	35.209	29.648	29.352	31.616	**32.2714**
Annual Review of Genetics	22.233	17.436	18.115	15.724	12.235	**17.1486**
Trends in Ecology & Evolution	15.748	15.389	15.353	16.196	16.735	**15.8842**
Genome Research	13.608	14.397	13.852	14.63	11.351	**13.5676**
Genes & Development	11.659	12.444	12.639	10.798	10.042	11.5164
Americal Journal of Human Genetics	10.603	11.202	10.987	10.931	10.794	10.9034
Molecular Biology and Evolution	5.55	10.353	14.308	9.105	13.649	10.593
Genome Biology	9.036	10.288	10.465	10.81	11.313	10.3824
Trends in Genetics	10.064	9.772	11.597	9.918	9.858	10.2418
Annual review of Genomics and Human Genetics	14.829	9.5	9.132	8.957	8.347	10.153

Method—Measures

Individual Research Productivity: An individual's total count of the number of papers published in the top 5 journals in their field (top 10 for mathematics) from 2006 to 2015. All articles and associated metadata were collected using the Web of Science database.

Gender: We coded the gender of all individuals manually.

1. Identify the author's gender via their **first name.**
2. If the first name is 'gender-ambiguous,' search for the author's **web page** (personal, faculty, ResearchGate, Google Scholar, etc.) for a **photo or other information** that would reveal the author's gender.
3. If first name is ambiguous AND there is no web page for the author, use the **Namepedia.org** database to record the most likely gender given the author's first name and geographical/ethnic information.

Method—Data Analytic Approach

1. Distribution Pitting: A falsification-based approach that pits each of the theoretical distributions against one another in terms of their fit with the observed distribution.

- The R package **Dpit** performs **pairwise comparisons of distribution fit** between the seven theoretical distributions.
- **3 decision rules**: (1) Log-likelihood ratio (LR) values, (2) Principle of parsimony, and (3) Principle of triangulation. The 'last one standing' is deemed the theoretical distribution with the best fit with the observed data.

2. Fit Parameters and Descriptive Statistics: Fit parameters describe the heaviness of the distribution's right tail. Differences in the size of the fit parameters for men versus women reflect the size of the gender-star gap.

3. Bootstrapping and Permutation: *Bootstrapping*: 5,000 replications (50,000 for Study 2) of each best-fitting distribution's parameter value to compute its 95% confidence interval. *Permutation*: Significance test of the difference between actual versus expected number/proportion of women among top producers based on 20,000 simulations.

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Distribution Pitting Results

- In all groups, the **power law with exponential cutoff distribution** had the best fit with the observed data.
- Individuals differentiate their research productivity predominantly via **incremental differentiation**.

Table 1
Distribution Pitting Results for Research Productivity of Female and Male Researchers in Study 1 (Mathematics)

Gender	*N*	Norm vs. PL	Norm vs. Cut PL vs. Cut	Norm vs. Weib PL vs. Weib Cut vs. Weib	Norm vs. LogN PL vs. LogN Cut vs. LogN Weib vs. LogN	Norm vs. Exp PL vs. Exp Cut vs. Exp Weib vs. Exp LogN vs. Exp	Norm vs. Pois PL vs. Pois Cut vs. Pois Weib vs. Pois LogN vs. Pois Exp vs. Pois
Women	360	−5.69 (0)	−6.10 (0) −3.46 (.01)	−6.14 (0) −1.66 (.10) .54 (.59)	−6.09 (0) −1.55 (.12) 1.08 (.28) .03 (.97)	−6.77 (0) .63 (.53) 1.76 (.08) 1.80 (.07) 1.67 (.10)	−7.71 (0) 1.73 (.08) 2.42 (.02) 2.40 (.02) 2.40 (.02) 2.87 (0)
Men	3,493	−16.55 (0)	−18.28 (0) −83.30 (0)	−18.18 (0) −7.72 (0) .31 (.75)	−18.09 (0) −7.76 (0) .88 (.38) 1.71 (.09)	−20.25 (0) 1.49 (.14) 6.16 (0) 6.17 (0) 5.88 (0)	−26.48 (0) 6.53 (0) 8.46 (0) 8.46 (0) 8.34 (0) 9.21 (0)

Note. *N* = sample size; LR = loglikelihood ratio. Distribution pitting results are presented in the final six columns of the table. For each instance of distribution pitting, the LR value is presented followed by its *p* value in parentheses. Distribution names are abbreviated as follows: Norm = normal; PL = pure power law; Cut = power law with exponential cutoff; Weib = Weibull; LogN = lognormal; Exp = exponential; Pois = Poisson. Distribution pitting titles are presented such that the first distribution is pitted against the second distribution (e.g., Norm vs. PL = normal distribution versus pure power law). Positive LR = superior fit for first distribution as listed in the distribution pitting title. Negative LR = superior fit for second distribution as listed in the distribution pitting title.

Fit Parameters, Bootstrapping, and Permutation Results for Studies 1 and 2

	Study 1: Mathematics		Study 2: Genetics	
	Women ($N = 360$)	Men ($N = 3{,}493$)	Women ($N = 14{,}685$)	Men ($N = 30{,}322$)
Parameter alpha and 95% CI	$\alpha = 2.94$ [2.74, 3.16]	$\alpha = 2.39$ [2.35, 2.44]	$\alpha = 2.43$ [2.41, 2.46]	$\alpha = 2.30$ [2.28, 2.31]
Parameter lambda and 95% CI	$\lambda = 0.57$ [0.54, 0.59]	$\lambda = 0.47$ [0.46, 0.48]	$\lambda = 0.44$ [0.43, 0.45]	$\lambda = 0.40$ [0.40, 0.41]
Actual vs. expected number and percent among the top 10% of producers	24 vs. 36 6.2% vs. 9.3%	361 vs. 349 93.8% vs. 90.7%	1,377 vs. 1,467 30.6% vs. 32.6%	3,123 vs. 3,033 69.4% vs. 67.4%
Actual vs. expected number and percent among the top 5% of producers	10 vs.18 5.2% vs. 9.3%	183 vs. 175 94.8% vs. 90.7%	637 vs. 734 28.3% vs. 32.6%	1,614 vs. 1,517 71.7% vs. 67.4%
Actual vs. expected number and percent among the top 1% of producers	0 vs. 4 0% vs. 9.3%	39 vs. 35 100% vs. 90.7%	118 vs. 147 26.2% vs. 32.6%	332 vs. 303 73.8% vs. 67.4%

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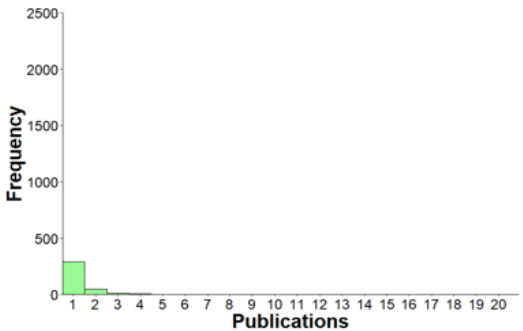
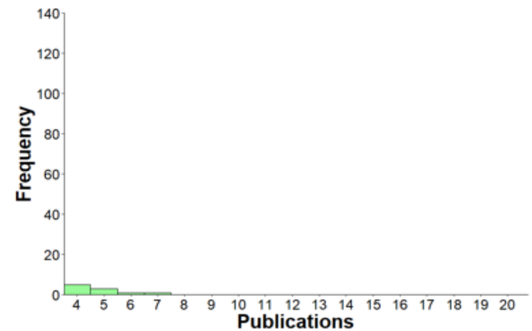
Histograms and Kernel Density Plots for Study 1 (Mathematics)

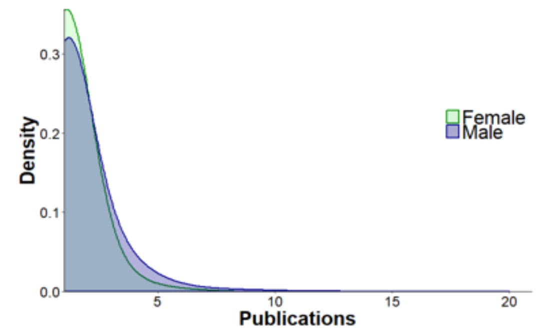
Female Researchers



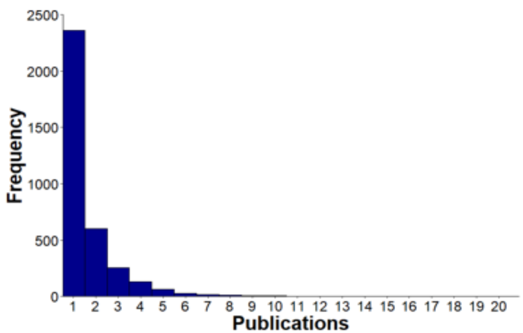
Female Researchers with Four or More Publications



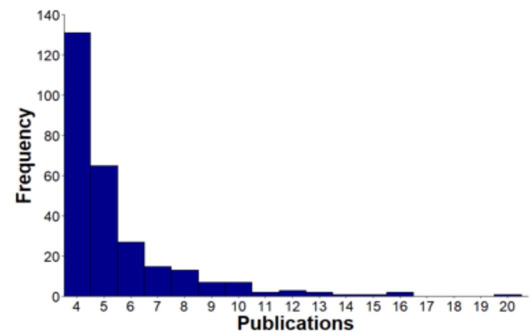
Kernel Density Plots for Female and Male Researchers Combined



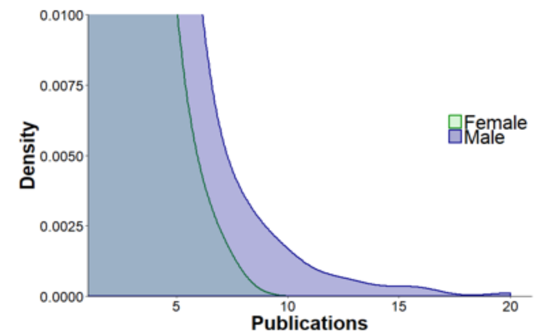
Male Researchers



Male Researchers with Four or More Publications

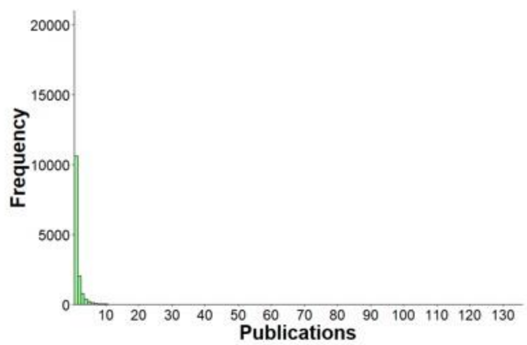


Kernel Density Plots for Female and Male Researchers Combined (Close-Up of Right Tails)

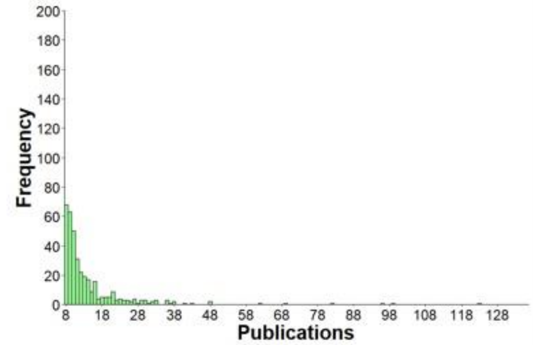


Histograms and Kernel Density Plots for Study 2 (Genetics)

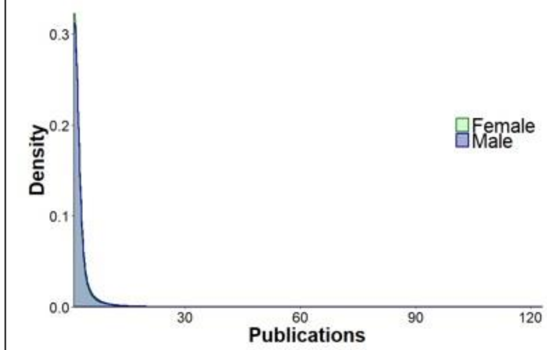
Female Researchers



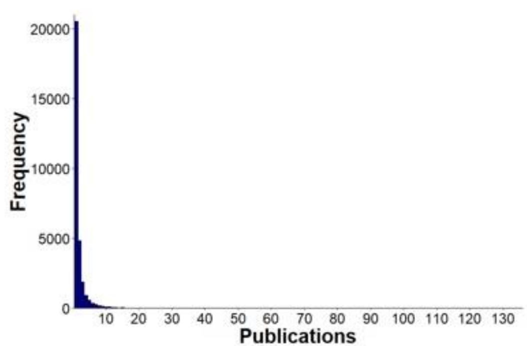
Female Researchers with Eight or More Publications



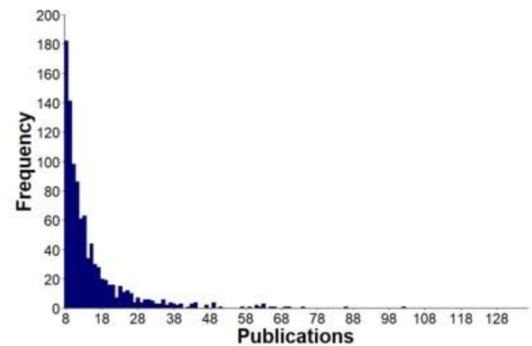
Kernel Density Plots for Female and Male Researchers Combined



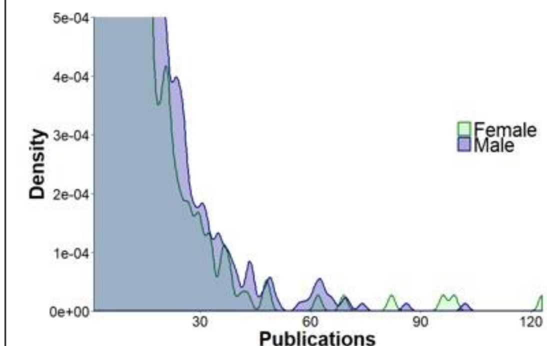
Male Researchers



Male Researchers with Eight or More Publications



Kernel Density Plots for Female and Male Researchers Combined (Close-Up of Right Tails)



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Fit Parameters, Bootstrapping, and Permutation Results for Study 3

	Study 3: Applied Psychology		Study 3: Mathematical Psychology	
	Women ($N = 1{,}595$)	Men ($N = 2{,}486$)	Women ($N = 2{,}177$)	Men ($N = 4{,}160$)
Parameter alpha and 95% CI	$\alpha = 2.40$ [2.33, 2.47]	$\alpha = 2.14$ [2.10, 2.18]	$\alpha = 2.95$ [2.86, 3.04]	$\alpha = 2.41$ [2.37, 2.45]
Parameter lambda and 95% CI	$\lambda = 0.46$ [0.44, 0.47]	$\lambda = 0.37$ [0.36, 0.39]	$\lambda = 0.56$ [0.55, 0.57]	$\lambda = 0.45$ [0.44, 0.47]
Actual vs. expected number and percent among the top 10% of producers	133 vs. 160 32.6% vs. 39.1%	275 vs. 249 67.4% vs. 60.9%	214 vs. 304 24.3% vs. 34.4%	668 vs. 579 75.7% vs. 65.6%
Actual vs. expected number and percent among the top 5% of producers	63 vs. 80 30.9% vs. 39.1%	141 vs. 124 69.1% vs. 60.9%	90 vs. 152 20.5% vs. 34.4%	351 vs. 289 79.5% vs. 65.6%
Actual vs. expected number and percent among the top 1% of producers	6 vs. 16 14.6% vs. 39.1%	35 vs. 25 85.4% vs. 60.9%	6 vs. 30 6.3% vs. 34.4%	83 vs. 58 93.7% vs. 65.6%

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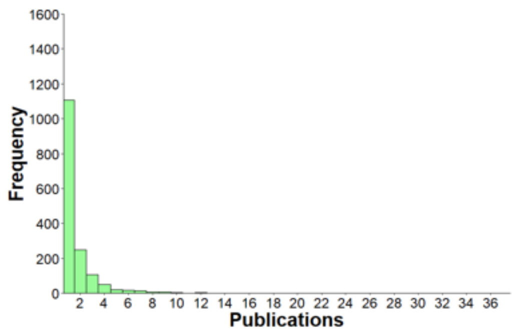
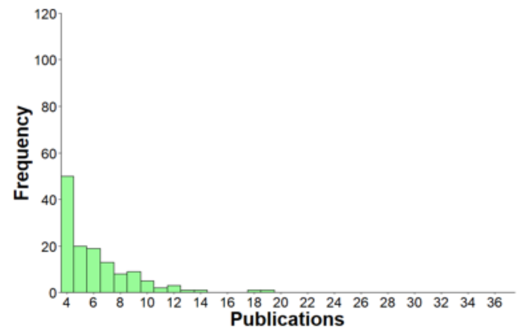
Histograms and Kernel Density Plots for Study 3 (Applied Psychology)

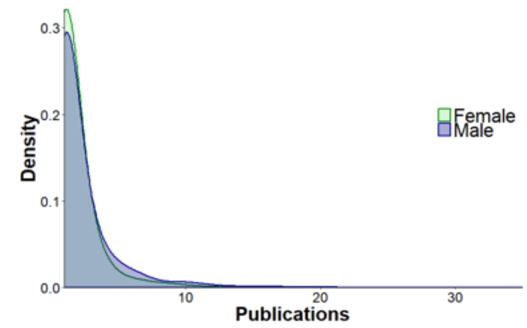
Female Researchers



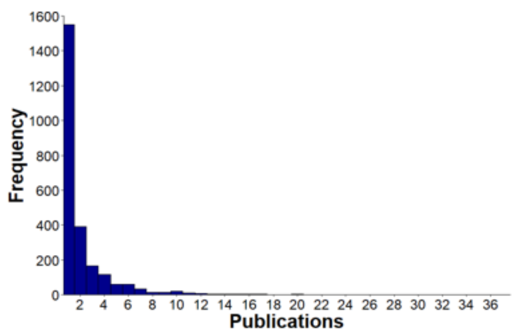
Female Researchers with Four or More Publications



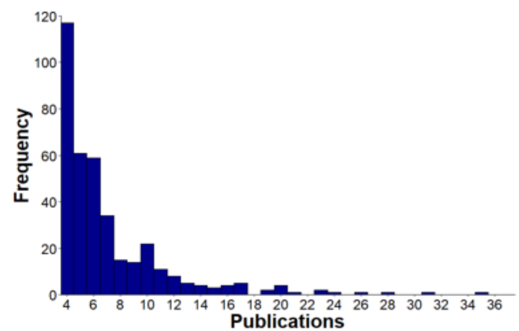
Kernel Density Plots for Female and Male Researchers Combined



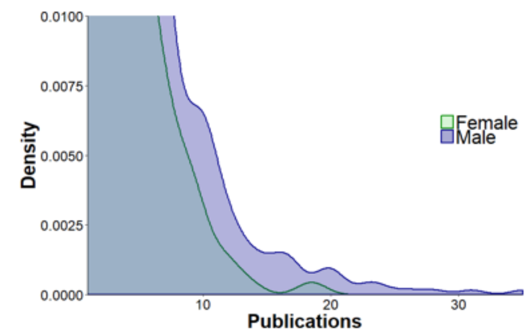
Male Researchers



Male Researchers with Four or More Publications



Kernel Density Plots for Female and Male Researchers Combined (Close-Up of Right Tails)



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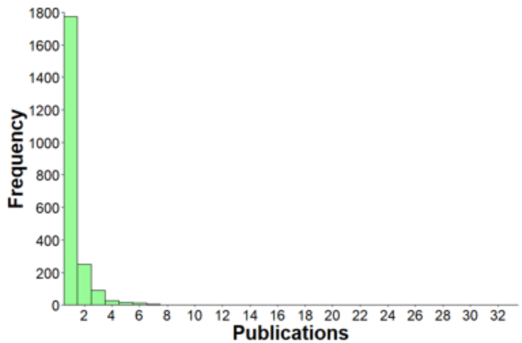
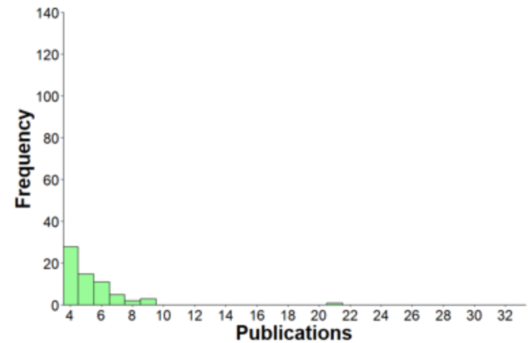
Histograms and Kernel Density Plots for Study 3 (Mathematical Psychology)

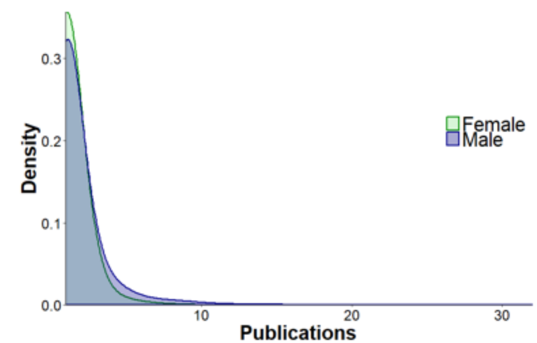
Female Researchers



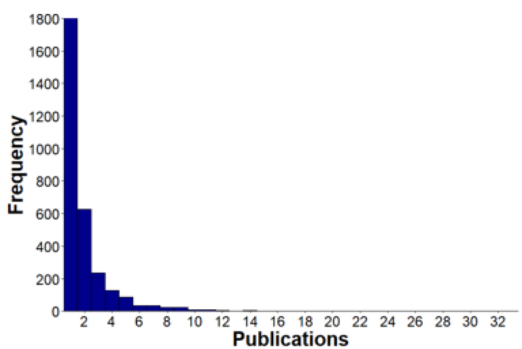
Female Researchers with Four or More Publications



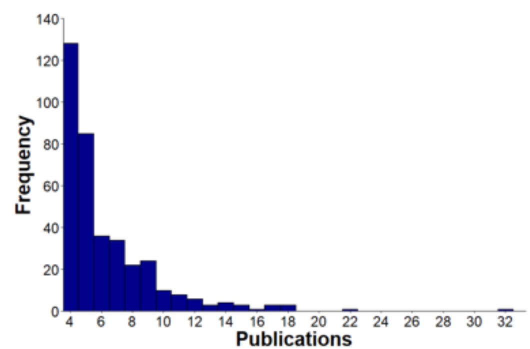
Kernel Density Plots for Female and Male Researchers Combined



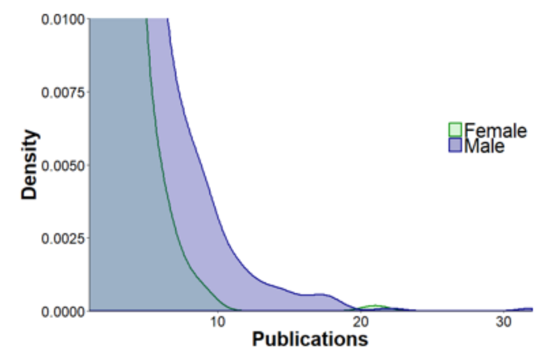
Male Researchers



Male Researchers with Four or More Publications



Kernel Density Plots for Female and Male Researchers Combined (Close-Up of Right Tails)



Implications for Theory

1. Individuals differentiate their research productivity predominantly via incremental differentiation.

2. The consistency of the dominance of incremental differentiation across genders and academic domains

3. Gender discrimination is the most likely cause for the observed gender-star gaps.

4. Gender productivity gaps among stars may be prevalent in fields that do not have the reputation of being traditionally masculine (e.g., applied psychology).

5. Gender-star gaps may explain a chain of consequences that could ripple throughout entire domains.

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Implications for Practice

1. A difference of 1 or 2 papers in top journals can be huge for individual researchers' careers.
2. Women need to accumulate input components at a greater rate than men in order to achieve the same level of increase in total outputs.
3. Simply encouraging greater female participation in science is not enough. Organizations need to do more to address the gender gap specifically among stars.
4. What can organizations do to 'de-constrain' incremental differentiation among women?
    - Cluster hiring
    - Greater emphasis on fairness and transparency regarding policies
    - Greater utilization of stars as a source of mentoring and coaching
    - Policies aimed at increasing female star retention (e.g., idiosyncratic work arrangements)

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Limitations & Future Directions

1. Incremental differentiation was revealed to be the most dominant mechanism, not the *sole* mechanism at play.
2. We did not directly examine ability, gender discrimination, and gender differences in career & lifestyle choices.
3. Future studies could:
   - Examine research productivity growth longitudinally
   - Explore the effects of researchers’ collaborative network ties
   - Identify the forms of gender discrimination most pertinent to female stars

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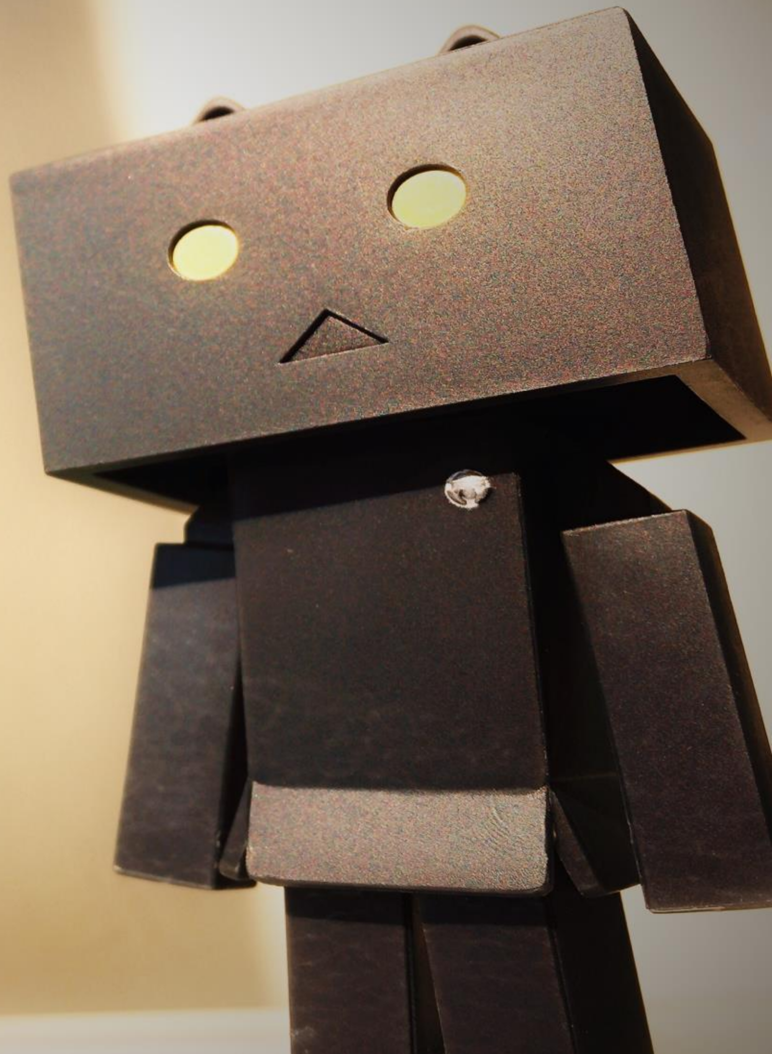
Questions?



Appendix: LR values

Log likelihood (i.e., Absolute Fit) Values of Each Sample to Each Theoretical Distribution

	Study 1: Mathematics		Study 2: Genetics		Study 3: Applied Psychology		Study 3: Mathematical Psychology	
	Women ($N = 360$)	Men ($N = 3{,}493$)	Women ($N = 14{,}685$)	Men ($N = 30{,}322$)	Women ($N = 1{,}595$)	Men ($N = 2{,}486$)	Women ($N = 2{,}177$)	Men ($N = 4{,}160$)
Pure power law	-256	-3,892	-15,836	-36,883	-1,772	-3,514	-1,534	-4,582
Lognormal	-287	-4,189	-18,772	-42,520	-1,983	-3,895	-1,793	-5,220
Power law with exponential cutoff	-253	-3,808	-15,812	-36,756	-1,752	-3,474	-1,526	-4,547
Exponential	-570	-6,172	-26,982	-58,056	-2,855	-4,963	-3,464	-7,482
Normal	-423	-6,207	-37,041	-78,207	-3,076	-6,063	-3,001	-8,401
Poisson	-447	-5,372	-28,774	-64,848	-2,603	-5,385	-2,785	-6,997
Weibull	-407	-5,378	-26,116	-56,706	-2,582	-4,814	-2,699	-6,878

Note. N = sample size. The smaller the log likelihood's negative value, the better is the sample's fit to the theoretical distribution (see Equation 8). As a cautionary note, it is not appropriate to compare log likelihood values across different samples with different sizes because a log likelihood value is a function of not only fit but also sample size. So, a log likelihood value indicates how well a theoretical distribution fits a sample as long as it is compared with other log likelihood values for other theoretical distributions given the same sample size.