# Productivity in Academic Economics

# Gender differences in sorting and institutions*

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**Abstract**

This paper contributes to the literature on gender inequalities in academia by analysing the difference in sorting patterns and the role of departments in economics. I find that the contribution of departments in research productivity are *significantly* lower for women compared to men. The sorting patterns of women also significantly differ. I find that top departments are very efficient in selecting the top productivity men, however they are less effective at doing the same for women. Consequently, this misallocation of talent leads to massive inefficiencies and upward mobility may be limited for talented female economists.

*- variance decomposition here -*

## 1 Introduction

There is substantial body of literature on gender disparities in academia. Valian (2005) identifies two key issues: women advance slower and that this is a widespread issue across disciplines. Economics is hardly an exception; even though entry into PhD programmes has increased over the past decades to the point where the majority of students enrolling in PhD programmes are women (Auriol et al., 2022), the proportion of women is ever diminishing as we look at more advanced stages of careers (Lundberg & Stearns, 2019).

The understanding of these gender differences is essential for both equity and efficiency reasons. Potential explanations have been extensively explored in the literature and this paper summarises the three most compelling and relevant hypotheses: discrimination competition aversion, and preferences. The focus of this paper is on the effect of departments and whether the gender differential in sorting – high-productivity researchers reaching high-productivity departments – explains the

*This paper is currently a work in progress and hence contains preliminary results.

variation in publication and placement outcomes. I use a matched department-author database of academics in economics to decompose research productivity into individual and department effects. I find that individual effects explain a large *(exact number here)* proportion of the variation

## Discrimination

Under discrimination we observe that women face barriers at various stages of their careers' and at each barrier a proportion erodes from the academic community. Eberhardt et al. (2022) provides evidence that advisors have different attitudes towards women. They look at reference letters for graduate students entering the job market and find that females are less recognised for their abilities and research skills due to unconscious biases. Wu (2018) also highlights the sexist and derogatory attitude of some people in the profession. This sentiment and toxicity in the profession is likely to deter women from pursuing a career in research.

Bagues et al. (2017) analyse the causal effect of gender composition on scientific committees in academic promotions by exploiting random variation in the gender composition of evaluating committees. They find no evidence for the presence of gender bias against women, both conditional and unconditional on candidates' observable characteristics.

Similarly, Abrevaya and Hamermesh (2012) find no evidence of gender bias in either direction by either gender in referee evaluations. Card et al. (2020) look at editorial decisions at 4 top journals and show that editors have no gender bias towards authors or referees. Their results are consistent with Abrevaya and Hamermesh (2012) finding no difference in evaluations by male and female referees, however they find that publications by women tend to be more cited than those of men. They interpret this result as evidence of female authors being held to higher standards regardless of referee and editor gender.

This line of literature might help explain why women are less likely to enter a career in academia, however the majority of evidence refutes the discrimination argument once already in academia. Even though the empirical literature finds no evidence of overt discrimination, some might still have either conscious or subconscious biases against women (Holmes & O'Connell, 2007; Winslow & Davis, 2016).

## Competition Aversion

Another branch of the literature analyses whether women have different attitudes toward and how they behave in competitive environments (detailed review in Croson & Gneezy, 2009). Gneezy et al. (2003) perform a laboratory experiment and show that women perform worse in competitive environments which results in a significant difference in outcomes, especially in a mixed-gender setting.

Since most fields in economics are heavily male dominated (Lundberg & Stearns, 2019) and academia is a very competitive environment (Carson et al., 2013), we should expect to observe differences in gender composition and research output by gender.

## Field Segregation

A potential implication of competition aversion is self-sorting into specific fields. If women do indeed prefer less male dominated fields, it follows logically that they we would observe a large concentration of women in certain fields. Dolado et al. (2012) show just this. They that women are unevenly distributed across disciplines within economics and attribute this segregation to women keeping away from male dominated areas rather than men not entering fields with more women. Their findings support for the competition aversion hypothesis as they find a negative correlation between the competitiveness and the share of women in a given field.

Hale and Regev (2014) use an IV strategy to find a causal link between the share of female faculty and the gender composition of graduates.

Women have also been shown to take on more responsibilities which are crucial for departments but are not considered during the evaluation of promotions (Babcock et al., 2017). They find that women are more likely to be requested and are also more likely to perform these low promotability tasks.

## Role of Departments

In all the various discussed theories there is one crucial unifying aspect: the role of academic institutions. Departments can make an effort not to disproportionately burden women with low promotability duties and institutional culture plays a large role in actively reducing discrimination, promoting diversity and inclusiveness. Dundar and Lewis (1998) review the literature on the productivity of departments and concludes that the culture of departments have an important effect on research performance both in the aggregate and individual level.

Waldinger (2012) shows a positive casual effect of faculty quality within a department on graduate student outcomes, accentuating the importance of peer-effects and mentorship for young academics. However, the paper finds no evidence for the presence of peer-effects for senior faculty. On the other hand, the dismissal of a co-author or a successful peer reduces research productivity (Waldinger, 2012, 2016). Azoulay et al. (2010) document the same negative shock to productivity upon the death of a "superstar" co-author due to the loss of new ideas. They further discuss the idea of "gatekeeping". Azoulay et al. (2019) further investigate this hypothesis and confirm that indeed publications by non-coauthors increase after the death of a star leading to the diversification and expansion of research in the field.

In this context, superstars might act as gatekeepers in their respective fields by influencing (or being) journal editors. It follows from this line of reasoning that established researchers might act in a similar fashion at the departmental level; they might have influence over research agendas, funding allocation, hiring decisions, and even peer-effects.

I confirm the findings of Ductor et al. (2018) identifying a large gender gap in research productivity. Women in my sample produce

# 2 Data

My panel database of economists contains observations at an author-year level over the period of 2000-2020. I infer the gender of authors based on forenames and publication quality from journal metrics and construct departments based on the affiliations of the authors.

## 2.1 Publications

I extract publications and affiliations from OpenAlex, *"a fully open catalog of the global research system"* (Priem et al., 2022). The full database contains 240 million publications from 213 million authors at over 100,000 institutions.[1] I limit my analysis to research active economists in departments with at least 15 active authors between 2000-2020, obtaining a sample of 35,000 authors across 1,500 institutions.

I also obtain some potential proxies for quality from this database. First of all the number of publications per author and the number of citations for each publication, which already provide for useful summary statistics. I also infer the number of authors on each publication and use that to construct weighed measures of contribution by equally dividing the measures across co-authors. (This measure is imperfect as some co-authors have more contribution than others, however that cannot be extracted from the data.)

## 2.2 Journals

I define my sample of economists as academics that publish in economics journals based on EconLit and Web of Science classifications. I merge these to the OpenAlex journals based on iSSN and

[1] See Appendix for data processing steps and replication codes.

eiSSN numbers and journal names in the cases where the id numbers do not provide a match.

Once I have the list of OpenAlex IDs for economics journals I filter the publications and get all authors that have published in economics. For these authors I extract all of their publications and classify authors as economists if at least one third of their published works are in economics journals. These academics make up the sample that I use to construct the author-year panel for my analysis.

### 2.3 Research Quality

I collect measures for journal quality from Claviate's Journal Citation Reports. The key indicator that I use is the *Article Influence Score* which is the best predictor of a Top 5 publication in economics.[2] The AIF is calculated based on papers' citations (and quality of those citations) in the first 5 years after publication. AIF also has the highest correlation with the probability that a paper is published in a Top 5 journal, hence it serves as an appropriate measure of quality. I define the quality of a paper $p$ by author $i$, published in journal $j$ in year $y$ in Equation 1. I weigh the AIF by a paper specific quality measure as AIF is only defined at the journal level.

$$quality_{ipy} = \frac{AIF_j}{} \frac{citations_p}{average\_citations_j} \tag{1}$$

### 2.4 Gender Classification

I classify gender in a two stage process. First I collect a list of forenames and corresponding gender probabilities from the The United States Social Security Administration and the World Gender Name Dictionary (Raffo, 2021).

### 2.5 University Rankings

I compile rankings data from QS, CWUR, and THE. These sources provide overall and economics specific rankings. These sources aggregate measures of research quality, reputation and graduate employability to form their rankings. I merge and disambiguate universities based on the names and abbreviations.

## 3 Empirical Strategy

I build on the seminal work of Abowd et al. (1999) and adapt their model to decompose research productivity into individual and institutional effects. The AKM model has been widely used in

[2]Other indicators include the *Journal Citation Indicator* and the *Journal Impact Factor*.

labour and health economics economics to study the gender wage gap, however recently the method has also been used to decompose productivity directly by Bhaskarabhatla et al. (2021) who analyse the relative contribution of firms and inventors in research output.

### 3.1 Two-period Model

I construct a two-period model of the profession containing N authors and K departments using a sample of research active economists between 2000 and 2020. I restrict the sample to departments with more than 15 people and authors with at least 3 publications. For a detailed description of the sample see the Appendix.

Let $a_{iy}$ denote the affiliation of author $i$ in year $y$ and let $m_i$ denote the year of the move of author $i$ between institutions in year $y$.

$$m_i = y \quad if \quad a_{iy-1} \neq a_{iy}$$

For repeated movers defining $m_i$ is slightly more complicated as some authors might not stay at an institution for 4 years before they move again. In these cases I take the closes available move to 2010 with sufficient time periods both before and after the move.

For non-movers let $m_i = 2010$ or in the case that there are missing observations between 2006-2013, the closest year with sufficient surrounding productive years.

Define two time periods as $t_1 = [m_i - 4; m_i - 1]$ and $t_{i2} = [m_i; m_i + 3]$. I construct the research productivity of author $i$ in period $t$ by taking the average of $quality_{ipy}$ across years to obtain $Y_{ikt}$.

$$Y_{ikt} = \alpha_i + \varphi_k + \varepsilon_{ikt} \tag{2}$$

I run the regression with author and department fixed effects in Equation 2 using the ZigZag method proposed in Guimarães and Portugal (2010). I utilise this estimation method because due to very large number of parameters, performing the matrix inversion used by the classic OLS estimator is not feasible.

For the valid estimation of fixed effects there must be enough heterogeneity in research productivity. I observe a large variation in research output both across institutions and individuals. The second requirement is a sufficient mobility across departments and that departments are connected to each other by movers (Abowd et al., 2002). I develop an algorithm to identify the largest network of connected institutions which includes 95% of the overall sample.

Bonhomme et al. (2022) discuss the importance of Limited Mobility Bias and its' effects on estimates. It is highly probable that the results from Model 2 are affected due to the low number of movers across departments and hence to avoid overestimating department fixed effects, I estimate results using Model 3. I follow the methodology of Bonhomme et al. (2019) to construct a two-period model with latent classes where each institution $k \in \{c_1, c_2, ...c_j\}$.

$$Y_{ict} = \alpha_i + \varphi_c + \varepsilon_{ict} \tag{3}$$

## 3.2 Identifying Assumptions

The fixed effects model also relies on the assumption of random timing in movements. This assumption is very strong and likely to be violated as moves in academia are usually associated with promotions and are endogenous. I will have to analyse the reasons for moving and ease this assumption.

A crucial criteria for identification is that institutions are connected in a network via movers.

Mobility is independent of current research productivity

**Estimation Method**

**Extensions**

# 4 Results

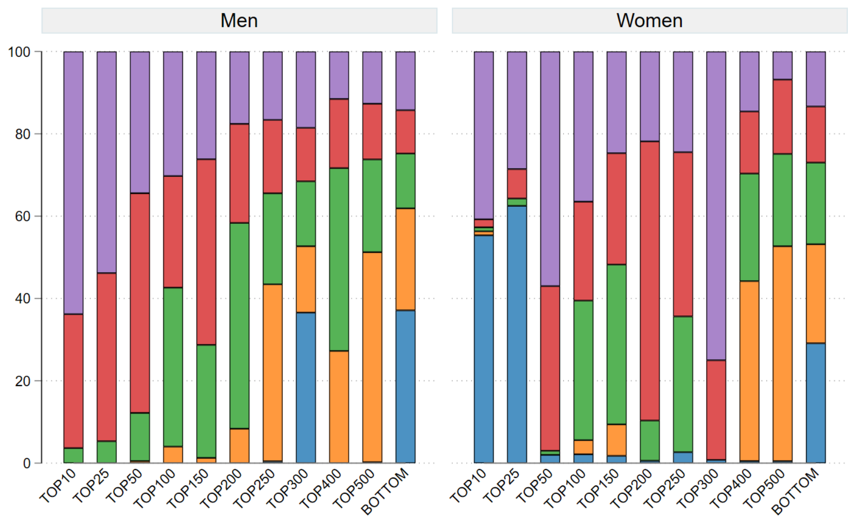


Figure 1: Sorting across classes globally, by gender

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2022 Journal Impact Factor, Journal Citation Reports (Clarivate, 2021)

# Appendix

## Data Processing

### Identifying Gender

First, I merge forenames to OpenAlex authors. These matches are likely to be accurate since the WGND contains data on names from every country on the planet and the SSA data contains data on all US-born baby names (with a frequency over 5 that given year) where a vast majority of research production happens.

Second, for those unmatched I develop a Neural Network trained on the SSA and WGND databases. The neural network has an accuracy over 85% on the validation data and there seems to be no systematic bias in the incorrect predictions.

## Sample Restrictions

I impose an additional restriction, removing those with more than 5 moves over 20 years, since these are likely to be due to noise in the data and might potentially introduce artificial moves.