A Glass Escalator for Female UVA Graduates?

Gender Gaps Across the Starting Salary Distribution

Hema Shah

Duke University and University of Virginia

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Motivation

- The gender pay gap for US workers has narrowed significantly since the 1950's, driven in part by increases in women's college attendance (Blau & Kahn, 2017; Goldin, 2005)
- The pay gap has stagnated since the 1980's, along with gender gaps in the skills developed during college (Turner & Bowen, 1999)
- **This suggests an important link between gender differences in schooling content and in earnings**

Research Question

- To what extent can gender differences in pay for recent college graduates be explained by observed differences in graduates' skills and preparation?
- Does the explained share vary across the pay distribution?

This Paper

- I analyze new self-reported data on University of Virginia graduates' starting salaries
- Using Oaxaca-Blinder models and quantile decomposition methods, I evaluate the extent to which the gender pay gap can be explained by observable differences in qualifications

Contribution

Large existing literature on gender wage gap decomposition (Blau & Kahn, 2017)

Some previous work on career outcomes for graduates of a single selective university (Bertrand et al., 2010; Graham et al., 2000)

- Within this setting, little work analyzing gender gaps across the pay distribution
- Do female graduates face a “glass ceiling” immediately after graduation?

Contribution of pre-market human capital specialization to the gender wage gap (Black et al., 2008)

Preview of Results

Both the size and the explained share of the gender pay gap vary significantly across the distribution

- The pay gap is larger at the bottom of the distribution and ∼75% can be explained by differences in qualifications and industry choice
- Interestingly, at the upper end of the salary distribution, gender differences in these characteristics "over-explain" the gap

Data

First Destinations Survey

- Sent to students during their final year, available for 6 months after graduation
- Asks students about starting salary, career industry, major(s), minor(s), plans to enroll in higher education, and internship experience
- Despite sampling issues, this data provides the most accurate starting salary estimates
- The State Council of Higher Education for Virginia (SCHEV) reports wages only for graduates who are employed in Virginia.
    - Likely underestimates earnings (Foote & Stange, 2019)

My Sample

7,918 undergraduate degree recipients from 2016-2018

- 55.81% female, 44.19% male

Variable	Male	Female	Gender Gap
Log Annual Salary, Full-Time Workers	10.97	10.72	0.25***
Number of Internships Completed	2.59	2.71	-0.12***
Outcome Type Dummy Variables			
Working	0.5316	0.4911	0.0405***
Continuing Education	0.1569	0.1754	-0.0185**
Other	0.3115	0.3335	-0.0220**

Results of a two-sample t-test are indicated as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Gender Gap is defined as Male Mean - Female Mean

Gender Differences in Labor Force Participation?

- Do men and women differ in their propensity to join the labor force based on unobserved differences?
- If so, graduates who opt in to employment may have different salary offers than the general populations of male and female students
- This would necessitate some sort of correction procedure (Fang and Sakellariou, 2011; Gunewardena et al., 2008)

Gender Differences in Labor Force Participation

- The raw gender gap in labor force participation rate is 4.05%, significant at the 1% level.
- Using a simple linear probability model, I show that within majors, women are more likely to participate in the labor force

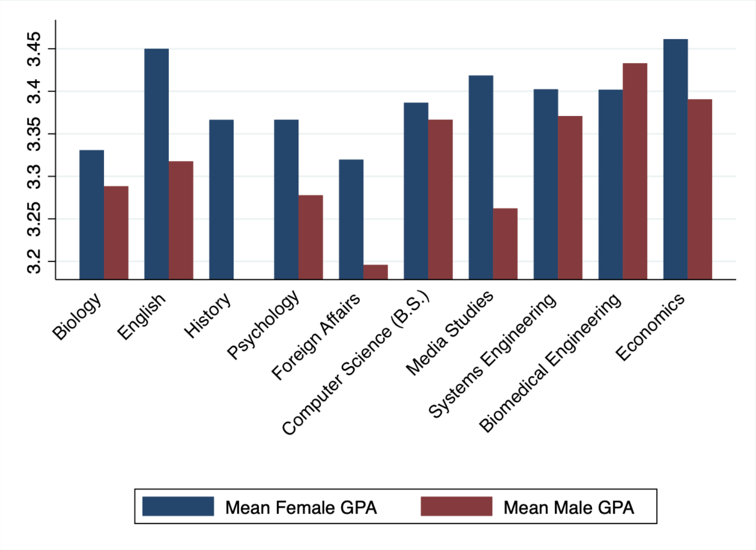
$$working_i = \beta_0 + \beta_1 male_i + \beta_2 \gamma_i + \epsilon_i$$

- $\hat{\beta}_1 = -.046$, significant at the 1% confidence level

Gender Differences in Academic Ability?

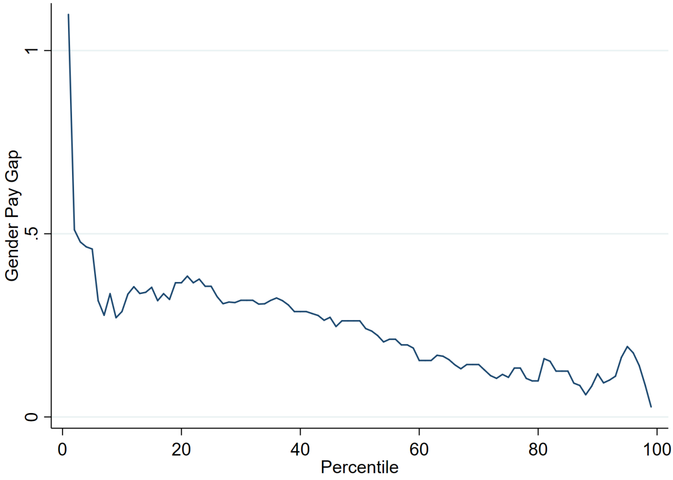
- My data does not include any individual-level measure of academic ability.
- However, within-major comparisons of average GPA between male and female graduates suggest that, if anything, my model will overestimate the "explained share" of the pay gap.

Within-Major Gender Differences in Mean GPA



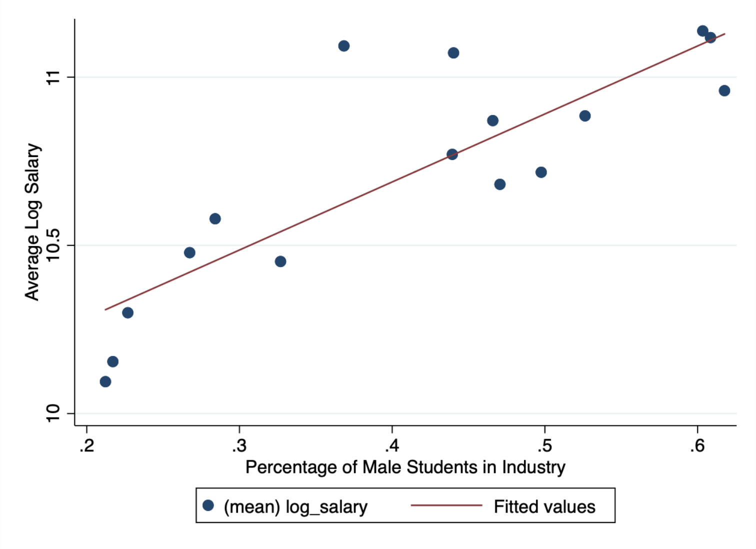
Kernel Density Estimates of the Log Earnings Distribution

Gender Pay Gap by Percentile



Gender Segregation of Majors

Gender Segregation of Industries



Empirical Specifications

Standard Oaxaca-Blinder Decomposition

$$\overline{Y}_M - \overline{Y}_F = [(\overline{X}_M - \overline{X}_F) \times \hat{\beta}] + [(\hat{\beta}_M - \hat{\beta}_F) \times \overline{X}]$$

with

- $\overline{Y}$ = average log salary
- $\overline{X}$ includes undergraduate major, internship experience, and career industry
- M and F index males and females, respectively, and variables without subscripts refer to pooled base group

Unconditional Quantile Regression

- To estimate the pay gap at various quantiles of the pay distribution, I use the reduced influence function (RIF) regression model (Firpo et al., 2009; Fortin et al., 2011)
- This procedure allows for the generalization of linear decomposition models to distributional statistics other than the mean (Firpo et al., 2018)

Quantile Decomposition Model

Linear group specifications:

$$\nu_{M,\tau} = E[RIF(Y; q_{M,\tau}|X)] = \hat{\gamma}_{M,\tau}\overline{X}_M$$

$$\nu_{F,\tau} = E[RIF(Y; q_{F,\tau}|X)] = \hat{\gamma}_{F,\tau}\overline{X}_F$$

$$\nu_{C,\tau} = E[RIF(Y; q_{C,\tau}|X)] = \hat{\gamma}_{C,\tau}\overline{X}_C$$

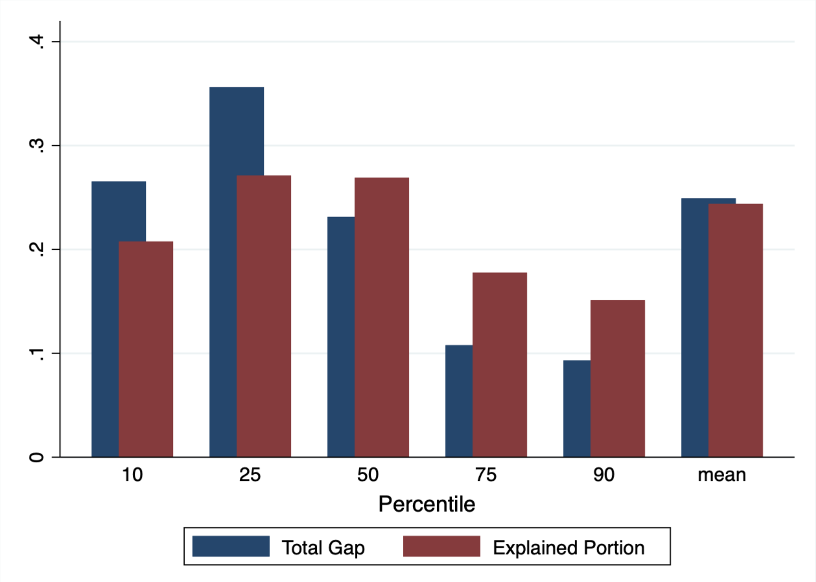
Similarly to the linear Oaxaca-Blinder model, I estimate the following decomposition:

$$\nu_{M,\tau} - \nu_{F,\tau} = [(\overline{X}_M - \overline{X}_F) \times \hat{\gamma}_{C,\tau}] + [(\hat{\gamma}_{M,\tau} - \hat{\gamma}_{F,\tau}) \times \overline{X}_C]$$

Benefits of RIF Model

- Used often in recent wage gap literature (Carrillo et al., 2014; Chi & Li, 2008; Kassenboehmer & Sinning, 2014; Xiu & Gunderson, 2014)
- Unlike conditional quantile regression methods, allows for quantiles to be decomposed non-sequentially
  - Analogous to the Oaxaca-Blinder model

Results: Explained Share Across the Pay Distribution



Results

		Gap Explained by				
Statistic	Raw Pay Gap	Controls	Major	Industry	Internships	Total Explained
10th Percentile	0.2654	-0.0097	0.0770	0.1407	-0.0003	0.2077
25th Percentile	0.3563	-0.0007	0.1322	0.1400	-0.0004	0.2711
Median	0.2314	-0.0194	0.1487	0.1400	-0.0003	0.2690
Mean	0.2492	0.0105	0.1340	0.0997	-0.0003	0.2439
75th Percentile	0.1078	-0.0666	0.1304	0.1141	-0.0002	0.1777
90th Percentile	0.0932	0.0037	0.1067	0.0410	-0.0002	0.1512

n = 3649

- Below the median, the gap cannot be entirely explained by observable characteristics
- Above the median, differences in characteristics "over-explain" the gap
- The role of major and industry vary across the distribution

Conclusions

- My results contradict prior literature confirming the existence of a "glass ceiling" for highly skilled female workers (Blau & Kahn, 2017)
  - A "glass escalator" for female graduates?
  - Either female graduates are more qualified on dimensions not measured in my data, or they receive preferential labor market treatment
- Given the literature on women's life cycle earnings, results are less surprising.
- My findings indicate that early career earnings are largely driven by major and industry choice
  - Suggests that pre-market human capital specialization plays an important role