IJIS: Vol.1, Issue1, February 2025, Page: 55-72 ISSN: 3049-3277

International Journal of Integrative Studies (IJIS)

Journal homepage:www.ijis.co.in

IS THERE A GENDER WAGE DIFFERENTIAL EVEN AMONG THE MOST HIGHLY EDUCATED?

Diyani Balthazaar

Research Scholar, School of Business, Woxsen University, Hyderabad, Telangana, India, *diyanimathews22@gmail.com*

Abstract

Even though gender wage discrimination is an extensively discussed topic, many questions remain unanswered, especially concerning the most highly skilled worker groups. This study estimates the gender wage differential of the most highly educated workers - PhD holders - in the United States. The findings suggest a gender wage gap of 17% and 21%, respectively, in 2013 and 2019. The wage differential was decomposed into observed and unobserved portions using the Oaxaca-Blinder decomposition method. The unobserved gender wage differential was 5% and 12%, respectively, in 2013 and 2019. The unexplainable portion of the wage gap was higher in the business/industry sector compared to the academic sector. Among the observed characteristics, less experience appeared to be a major factor for lower wages among women. Further, the results suggest that even highly educated women earned less than their male counterparts, partly due to occupational segregation – job category, employment category, and the field of study contributed to more than 40% of the observed wage gap in the business/industry sector.

Keywords: *Gender wage differential, Wage discrimination, Occupational segregation, Oaxaca-Blinder decomposition*

DOI: 10.63856/edvi6x58

INTRODUCTION

There is an extensive literature on the theories of gender wage discrimination and empirical analysis. Yet, many questions remain unanswered, especially concerning the most highly skilled worker groups. In the empirical realm, the gender wage gap of highly educated workers has been studied, merely focusing on the academic sector (Barbezat, 1987; Porter, Toutkoushian, and Moore III, 2008; Webber and Canche, 2015). Therefore, it is hard to make inferences about the wage gap and its trends in general. The academic sector alone does not represent all highly educated workers. PhD holders increasingly find jobs in non- academic related sectors. Hence, this paper expands the contemporary gender discrimination literature by estimating the gender wage gap of the PhD holders by incorporating both academic and business/industry sectors to its analysis.

The paper contributes to the literature in two ways. First, it provides a novel estimate for the gender wage gap of the most highly educated worker group in the business/industry sector. Second, it revisits and updates the gender wage gap in the academic sector with the most recent estimate. Previous estimates suggest that the gender wage gap in the academic labour market in the United States declined over the period from 1960 to 1970. The implementation of the Equal pay act, Civil Rights Act and Affirmative Action might have resulted in the above decline (Barbezat 1991).

However, the wage gap began to rise in the late 1980s. Since most recent studies are highly concentrated on a specific academic discipline or a specific group of academics, it is hard to make inferences about the wage gap and its trends in general (Ceci et al., 2014). For example, Ginther and Hayes (2003) suggest that the gender wage differential of the science discipline stagnated from 1973 to 1997 whereas Toumanoff (2005) suggests that the gender wage gap is not significant for the recently hired faculty in 1999. Thus, instead of focusing on a specific sector, this paper estimates the gender wage gap of the academic sector in general to provide a better comparison.

The findings suggest that gender wage gap among the most highly educated was 17% and 21%, respectively, in 2013 and 2019. The wage gap was higher in the business/industry sector compared to the academic sector for both the survey waves. The wage differential was decomposed into observed and unobserved portions using the Oaxaca-Blinder decomposition method. The unobserved gender wage differential was 5% and 12%, respectively, in 2013 and 2019.

Women employed in the academic sector faced less wage discrimination than those in the business/industry sector. Among the observed characteristics, less experience appeared to be a significant factor for lower wages among women. Most notably, the highly educated women earned less than their male counterparts partly due to occupational segregation – job category, employment category, and the field of study contributed to more than 40% of the observed wage gap in the business/industry sector.

LITERATURE REVIEW

Previous Estimates

Previous studies on the gender wage gap among PhD holders solely focused on the academic sector. In 1987, Barbezat, using Mincerian log-wage equations, estimated a gender wage gap of 23% in 1968 and 19% in 1977. The same author updated the estimate, underlining the rising wage gap of 20-23% in 1989 (Barbezat, 1991). McNabb and Wass (1997) estimated that the gender wage differential among academics in the UK was 16%, 13%, and 15% in 1975, 1989, and 1992, respectively. The Oaxaca decomposition method was widely used to decompose the estimated wage gap into observed (explainable) and unobserved (unexplainable) portions. Assuming all observed characteristics are included in the analysis, the unobserved portion of the Oaxaca decomposition method (Oaxaca, 1973) can be attributed to gender wage discrimination. The estimated gender wage discrimination was 17% in 1968 and 10% in 1977 (Barbezat, 1987). In 1989, 30-34% of the wage gap was attributed to unobservable characteristics (Barbezat, 1991). In the UK, the wage gap, due to unobservable characteristics, was 5.5%, 3.6%, and 4.7% in 1975, 1989, and 1992, respectively (McNabb and Wass, 1997). The estimates suggest that the gender wage gap in the academic labour market in the United States declined over the period from 1960 to 1970. However, the wage gap began to rise in the late 1980s.

Since most recent studies are highly concentrated on a specific academic discipline or a specific group of academics, it is hard to make inferences about the wage gap and its trends in general (Ceci et al., 2014). Ginther and Hayes (2003) found gender wage gap between assistant professors was lower compared to full professors. In particular, the wage gap was 9% in 1973 and 5% in 1977. In contrast, the gap was 20% in 1973 and 15% in 1997 for full professors. The unexplained portion of the total wage differential was almost zero for assistant professors after 1985. Thus, the gender wage gap was higher for senior faculty compared to recently hired faculty. Similar results were presented by Porter, Toutkoushian and Moore III (2008) for the period from 1988-2004. However, the estimated gender wage gap within an academic rank may obscure the actual wage gap since discriminatory preferences highly characterise the academic promotion process. For example, women are 25% less likely to be promoted than men in the academic sector (Ginther and Hayes, 1999). Further, women in economics are less likely to get promoted compared to other academic disciplines - the gender promotional gap was 21% for economists, 0.3% for statistics, 3% for physical sciences, and -4% for engineers (Ginther and Kahn, 2004). Thus, estimating separate log-wage equations for each academic rank masks the actual wage gender wage gap.

Mincerian Log-wage Equations and Observed Characteristics

The widely used observed characteristics in the Mincerian log-wage equations were the number of publications, academic discipline, characteristics of the employer, number of books published, academic rank, the field of study, type of the academic institution, demographic characteristics, and primary work activity (Barbezat, 1987; Barbezat,1991; Ginther and Hayes, 2003; Toutkoushian, Bellas, and John, 2007; Webber and Canché, 2015). The number of publications was widely employed as a measure of productivity. However, Barbezat's (1991) estimations showed that productivity and academic rank give rise to more or less similar results; the model with academic rank resulted in an 11% of the gender wage gap while it was 10% for the model with productivity measures. McNabb and Wass (1997) argued that the number of publications is a determinant of promotions, and promotions are directly related to academic rank. Therefore, academic rank indirectly measures the impact of productivity.

In addition to the number of publications/books and academic rank, some authors used detailed productivity measures. Carlin et al. (2013) used research output, grant output, teaching/service awards, and peer-review ratings as productivity related covariates. Their estimated wage gap was 9% for academics in 1996/1997. Further, the authors added market salary as a covariate and adding market salary reduced the gender wage differential to 4.7%. However, market salary is endogenous - market salary is determined by academic discipline and rank -, thus resulted a biased estimate. Binder et al. (2010) used non- conventional productivity measures such as teaching portfolio, undergraduate and graduate enrolment, grant count, life memberships in professional societies, type of publications, and impact of publications as covariates. Non- conventional productivity measures reduced the wage penalty by about 3%. Nevertheless, the authors concluded that adding non- conventional productivity measures reduces the wage penalty by only 1% than studies that estimate the gender wage gap using conventional productivity measures. Thus, the estimations with conventional productivity measures may overestimate the wage gap by 1%.

Other Methods

Even though the Mincerian log-wage equation is widely used to estimate the wage gap, some authors have used other approaches. Broder (1993) argued that academic remuneration is highly determined by academic rank and research output. Further, research output is a determinant of the academic environment. Hence, research output and the type of academic institution (a variable that captures the academic environment) are interrelated. Thus, estimated a multi-equation system to examine the gender wage differential of academics in the economics discipline. The first equation regressed the number of publications, experience, academic rank, a dummy variable for a public university, and gender on wage. The second equation regressed the number of publications, the tier of the employer department, experience, and gender on academic rank. The third equation regressed the number of publications, the tier of the PhD granting department, and gender on the tier of the current employer. The final equation regressed experience, the tier of the PhD granting university, the tier of the employer, and gender on total productivity. Lastly, the Oaxaca decomposition technique was applied to a system of equations. Results indicated that the model could not explain over 25% of the total wage differential despite its capability to address the simultaneity of explanatory variables.

Smart (1991) suggested that conventional regression techniques, such as the log-wage equation and the Oaxaca decomposition method, underestimate the total impact of gender on academic rank and salary. Thus, estimated a causal model using predictors such as gender, human capital variables, institutional characteristics, academic discipline, and variables to capture work-role segregation such as teaching, research and administrative work, and academic rank. Even though causal models can estimate the direct, indirect and total effects of salary determinants, they do not provide a precise estimate for gender discrimination.

METHODOLOGY

Theory of Discrimination

Becker's (1971) seminal work on discrimination identifies three channels in labour market discrimination: employer discrimination, co-worker discrimination, and consumer discrimination. Employer discrimination is employer's willingness to compensate a sure profit due to discriminatory preferences. Consequently, an employer with discriminatory preferences prefers to hire one group of workers over another, even if the marginal cost of the first group is greater than the marginal benefit. However, due to competitive market forces, employer discrimination diminishes in the long run. Co-worker discrimination is when one group of workers experiences a utility loss when they work with another group of workers. In such situations, higher wages should be paid to the first group to compensate for their utility loss. Again, competitive market forces can successfully eliminate co-worker discrimination in the long run as higher wages increase the marginal cost of the first group. The third type of discrimination is consumer discrimination. This is a situation where consumers suffer a utility loss when they acquire a product/ service from a group of workers. Competitive market forces fail to eliminate consumer discrimination, which is persistent and leads to labour market segregation.

Gender wage discrimination can be modelled as follows. Assume there are two groups of workers, male and female. If both male and female workers are equally productive, in the absence of labour market discrimination, the wage of a male worker $W M$, should be equal to the wage of a female worker, . Moreover, this wage should be equal to their respective marginal productivities. In contrast, in the presence of labour market discrimination, the wage of a female worker is equal to $W F + D$, where D represents the discriminatory preference. Thus, the wage of a female worker, $W F + D$ is equal to $W M$. If

D is greater than zero, male workers earn a higher wage than females. Thus, D represents the wage gap due to discrimination.

Oaxaca Decomposition Method

The gender wage discrimination discussion assumes that male and female workers are equally productive. Therefore, measuring productivity is crucial in estimating the wage gap. The Human Capital Theory (Becker, 1962) explains that investment in education results in higher productivity in the workplace. Also, higher productivity leads to higher wages. This relationship is empirically tested by Mincer (1958) using the widely famous Mincerian equation (regressing the number of years of schooling on log wage). Extended versions of the Mincerian equation were used to estimate the effect of productivity on wages.

The Oaxaca decomposition was used to decompose the raw wage gap into observable and unobservable characteristics. Oaxaca (1973) modified Becker's (1971) definition of the labour market discrimination coefficient, (D : the difference between observed wage ratio and the wage ratio that would prevail in the absence of discrimination) using wages and marginal productivities. Equation 1 shows Oaxaca (1973)'s definition in terms of marginal productivity.

$$D = \frac{\frac{\bar{W}_M}{\bar{W}_F} - \frac{MP_M}{MP_F}}{\frac{MP_M}{MP_F}} \quad (1)$$

Where $\frac{\bar{W}_M}{\bar{W}_F}$ is the observed wage ratio between male and female workers, $\frac{MP_M}{MP_F}$ and is the ratio between their respective marginal productivity. In logarithmic form, the equation (1) can be written as,

$$ln\bar{W}_M - ln\bar{W}_F = lnMP_M - \ln MP_F + \ln(D+1) \quad (2)$$

where $ln\bar{W}_M - ln\bar{W}_F$, is the log-wage difference due to productivity differences, and $\ln(D+1)$ is the log-wage difference due to discriminatory preference.

$\ln\bar{W}$ can be empirically estimated by using Mincerian log-wage regression estimates, $\sum_j^k \beta_j.\bar{X}_J$, where $\bar{X}_J$, average productivity determinants such as the level of education, experience, etc. And β_j's are ordinary least-square regression coefficients. Therefore, $ln\bar{W}_M - ln\bar{W}_F$ can be expressed as,

$$ln\bar{W}_M - ln\bar{W}_F = \sum_j^k \beta_j^M \bar{X}_J^M - \sum_j^k \beta_j^F \bar{X}_J^F \quad (3)$$

Equation (3) can be manipulated by adding and subtracting $\sum_j^k \beta_j^M \bar{X}_J^F$ to the right-hand side of the equation:

$$ln\bar{W}_M - ln\bar{W}_F = \sum_j^k \beta_j^M (\bar{X}_y^M - \bar{X}_J^F) + \sum_j^k \beta_j^M (\beta_j^M - \beta_j^F) \quad (4)$$

Equation (4) resembles to equation (2), where $\sum_j^k \beta_j^M (\bar{X}_y^M - \bar{X}_J^F)$ is the empirical estimate of $lnMP_M - \ln MP_F$, and $\sum_j^k \beta_j^M (\beta_j^M - \beta_j^F)$ is the estimate for $\ln(D+1)$. Hence, the difference in β coefficients indicate discriminatory preference (Cotton, 1988).

RESULTS AND DISCUSSION

Data and Summary Statistics

Two waves of the "Survey of Doctorate Recipients" data, wave 2013 and 2019, were used to estimate the gender wage differential of PhD holders, the most educated labour category in the United States. The National Opinion Research Centre at the University of Chicago administers the survey every other year for the National Science Foundation and the National Institute of Health. The data set consists of demographic characteristics, education history, academic discipline, job characteristics, employer characteristics, and employment history of individuals who obtained a PhD from an academic institution in the United States. Those who obtained their PhDs in a foreign country but were employed in the United States are not included in the survey.

In total, the 2013-wave consisted of 30,696 observations. However, 4,157 observations were omitted due to missing values and outliers. The 2019 dataset contained 80,882 observations, but 11,535 observations were dropped due to missing values and outliers.

For Mincerian log-wage equations, the annual salary of a PhD holder was used as the dependent variable - the response to the survey question, “what is the basic annual salary of the principal job before deductions”. Unfortunately, the publicly available data set does not have the number of weeks worked per year. Hence, to compare annual salaries across PhD holders, a sample of PhD holders who work 52 weeks in a work year was selected. Note that a 52-week work year includes paid vacation and sick leave. Thus, the final sample consisted of 23,542 observations for 2013 and 54,327 observations for the 2019 wave.

The survey collects information on respondents’ employment sector. Further, if the respondent works in the education sector, the survey reports their academic position. For the analysis, PhD holders in the education and business/industry sectors were focused on. The academic sector sub-category was used to compare the results with the literature. The academic sector includes all the respondents who work in 2-year and 4-year colleges and medical institutions, and hold positions of a post-doc, administrative Job (dean or president), research faculty, teaching faculty, adjunct faculty, research assistant/teaching assistant/others. Table 1 provides a study sample summary for both the 2013 and 2019 waves.

Tables 2 and 3 present summary wages for the 2013 and 2019 waves, respectively. In 2013, a PhD holder earned USD100,481, and male and female PhD holders earned USD106,078 and USD90,349, respectively. The academic sector salaries were 28% less than the business/industry sector. As a percentage, more female workers were employed in the academic sector, 50.9%, compared to the business/industry sector – only 33.4% of females work in the business/industry sector in 2013. On average, a PhD holder earned USD122,585 in 2019. Mean wages in the academic and business/industry sector were USD100,155 and USD142,157, respectively.

Table 1: Study sample

Sample Description	2013 - Wave	2019 -Wave
Total number of observations	30,696	80,882
Missing values	4,157	11,535
Final sample with full-time workers (52-week year)	23,542	54,040
Male	15,164	32,050
Female	8,378	21,990
Final sample – academic sector	10,852	19,598
Male	6,589	10,914
Female	4,263	8,684
Final sample – Business/Industry sector	9,660	26,577
Male	6,858	16,819
Female	2,802	9,758

Many studies have examined the motherhood wage penalty (Staff and Mortimer, 2012; Gough and Noonan, 2013). Weeden, Cha and Bucca (2016) found that motherhood wage penalty has been persistent over the last three decades, especially among parents who work long hours. Female PhD holders with children were found to have earned less than their male counterparts.

However, this study does not suggest that women who have children earn less than those who do not have children. On average, U.S. citizens earned a higher wage than non-U.S. citizens. Among the racial/ethnic groups, White non-Hispanics earned the highest wage.

Figures 1 and 2 provide the experience-earnings profile for 2013 and 2019, respectively. Consistent with the literature, the experience was calculated as the number of years since completion of the PhD degree (Barbezat, 1991). For example, by the survey year 2013, an individual has 48 years of experience if he/she completed a PhD in 1965. The experience- earning profile confirms the quadratic relationship between experience and wage. At first, wages rise with experience; however, wages start to fall after reaching the inflexion wage point. In 2013, workers with 39-43 years of experience earned the highest salary 2013, whereas workers with 30-34 years of experience earned the most in 2019. Most remarkably, the gender wage gap is observed throughout the lifespan, for all experience categories, for both survey waves.

Tables 4 and 5 present the average wage by job category for 2013 and 2019 waves. The second column of the table presents the percentage of women in each job category out of the total workers in the respective job category. The third column calculates the percentage of women in each job category out of the total female workforce. For example, in 2013, among the total workforce of computer scientists and mathematicians, 26% were women.

Table 2: Summary wages in 2013

	Male		**Female**	
	Mean	**SD**	**Mean**	**SD**
Wage	106,078	36,328	90,349	35,167
Wage in the academic sector	92,812	35,573	80,083	31,385
Wage in the business/industry sector	119,370	33,131	105,416	36,740
Age (years)	49	11	46	11
Experience (years)*				
Less than 2	73,654	32,308	62,360	24,616
3-8	82,858	32,093	74,933	28,467
9-13	99,536	32,673	87,732	31,070
14-18	111,367	33,435	98,672	34,387
19-23	116,494	33,022	101,657	36,273
24-28	118,224	32,703	106,077	34,974
29-33	121,054	32,546	111,162	35,315
34-38	117,984	35,954	112,242	36,931
39-43	121,998	33,891	115,431	41,615
44-48	117,241	40,630	105,000	44,154
Above 48	119,405	38,821	104,400	52,243
Employment sector**				
Business/Industry	119,370	33,131	105,416	36,740
2-year college or other school system	77,245	28,896	71,082	25,925
4-year college or medical institution	93,252	35,615	80,318	31,513
Government	108,084	30,526	98,025	29,922
Having Children				
0	104,050	37,406	89,159	35,758
1	105,993	35,885	91,537	34,887
2 or above	109,519	34,500	92,330	33,784
Citizenship				
U.S. Citizen	108,586	36,052	91,810	35,324
Non-U.S. citizen	92,205	34,689	80,811	32,564
Race				
White, non-Hispanic	108,169	36,272	92,438	35,539
Asian, non-Hispanic	106,064	35,916	91,252	35,721
Under-represented minorities***	96,348	35,683	83,675	32,686
Number of observations	15,164		8,378	

Notes: Total Number of observations is 23,542.
Mean is the average annual salary measured in U.S. dollars.
Average of a PhD holder is USD 100,481, average wage in the academic sector is USD 87,812, and average wage in the Business/Industry sector is USD 115,322.
*Experience is measured as the number of years since PhD.
**The survey collects data on four employment sectors. PhD holders in the academic sector belong to either 2-year college or 4-year college categories.
***The data set for 2013 consists of only three race/ethnicity categories: White non-Hispanic, Asian non-Hispanic, and Under-represented minorities.

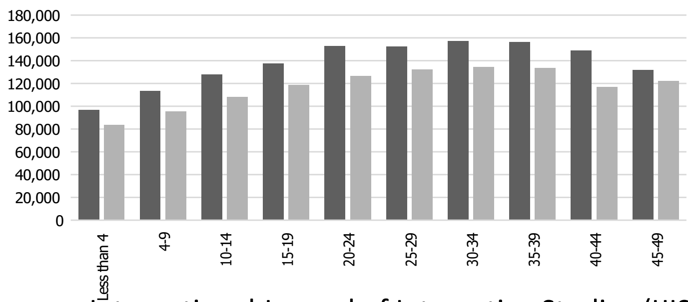
Table 3: Summary wages in 2019

Wage Description	Male		Female	
	Mean	SD	Mean	SD
Wage of a PhD holder	132,446	77,055	10,8212	63,888
Wage academic sector	106,092	69,355	92,694	56,244
Wage - business/industry sector	153,235	80,935	123,063	71,243
Age(years)	47	12	44	11
Experience(years)*				
Less than 4	96,813	51,276	83,587	40,301
4-9	113,163	60,762	95,417	50,690
10-14	127,685	68,767	108,053	57,448
15-19	137,486	75,248	118,698	66,245
20-24	152,933	81,053	126,454	71,178
25-29	152,523	82,651	132,368	81,901
30-34	157,066	88,911	134,467	83,576
35-39	156,422	92,052	133,657	95,119
40-44	148,674	103,468	116,780	87,087
45-49	131,721	103,301	121,893	85,742
Employment sector**				
Business/Industry	153,235	80,935	123,063	71,243
Education sector	105,764	69,306	92,010	56,082
Government sector	119,774	51,026	108,916	47,591
Having Children				
0	128,323	77,985	105,892	64,817
1	133,939	74,975	108,891	61,979
2 or above	138,758	76,251	112,664	63,099
Citizenship				
U.S. Citizen	141,421	77,489	112,846	64,305
Non-U.S. Citizen	103,835	68,180	86,291	56,988
Race				
White, non-Hispanic	137,962	78,395	110,535	64,645
Asian, non-Hispanic	130,134	75,696	110,022	66,380
Black, non-Hispanic	117,122	70,267	102,424	56,787
Hispanic, any race	114,480	74,326	94,458	57,255
Other races	126,155	64,718	104,336	59,631
Number of observations	32,050		21,990	

Notes: Total Number of observations is 54,040.
Mean is the average annual salary measured in U.S. dollars.
Average of a PhD holder is USD 122,585, average wage in the academic sector is USD 100,155, and average wage in the Business/Industry sector is USD 142,157
*Experience is measured as the number of years since PhD.
**The survey collects data on three employment sectors. PhD holders in the academic sector belong to the Education sector.

However, only 5% of total women were employed in the computer scientist and mathematicians job category. The top five highest-paying job categories were 1) science and engineering managers, 2) top and middle-level managers, executives, and administrators, 3) electrical or computer hardware engineers, 4) economists, and 5) computer scientists and mathematicians 2013. However, only 17% of the total female PhD holders were employed in the above job categories.

Figure 1: Experience-Earnings profile for male and female PhD holders – 2013



■ Male ■ Female

Figure 2: Experience-Earnings profile for male and female PhD holders – 2019

In contrast, 55% of women were employed in the five least-paying job categories altogether. A majority (38%) of them worked as post-secondary teachers. Similarly, in 2019, workers employed as 1) non-science and engineering managers, 2) science and engineering managers, 3) electrical or computer hardware engineers, 4) computer and information scientists and 5) aerospace, aeronautical, or astronautical engineers earned the most. Only 15% of female workers were employed in the top five highest-paying job categories.

Table 4: Female concentration by job-category – 2013 wave

Job category	[1]Female %e out of total workforce in a job category	[2]Female % out of total female workforce	Mean	SD
Science and engineering Managers (969)	28	3	126,346	2,856
(1858)	32	7	125,769	3,235
Electrical or computer hardware engineers (630)	12	1	124,038	25,548
Economists (251)	36	1	123,275	30,100
Computer scientists and mathematicians (1589)	26	5	115,548	30,723
Chemical engineers (271)	16	1	114,524	30,352
Other management related occupations (693)	40	3	112,815	35,206
Other engineers (1014)	20	2	111,997	31,467
Mechanical engineers (304)	9	0	111,293	27,736
Health-related occupations (1510)	49	9	104,652	37,235
Postsecondary teachers - engineering (728)	19	2	104,191	29,417
Physicists and astronomers (416)	14	1	103,815	37,972
Other physical and related scientists (552)	28	2	103,415	35,292
Chemists, except biochemists (667)	26	2	103,361	33,315
Civil engineers (137)	11	0	102,336	30,333
Science and engineering post-secondary teachers (99)	18	0	102,323	37,704
Psychologists (1191)	58	8	92,604	32,856
Other social scientists (404)	61	3	91,792	33,412
Other non-science and engineering occupations (812)	45	4	90,211	45,098
Other life-related scientists (897)	42	4	88,948	36,141
Postsecondary teachers-life related sciences (1364)	36	6	88,198	33,113
Postsecondary teachers-computer and mathematics (888)	28	3	87,667	29,604
Biological and medical scientists (2390)	43	12	87,638	39,126
Non-science and engineering pre-college and post-secondary Teachers (608)	50	4	87,512	35,124
Postsecondary teachers-physical and related sciences (1077)	28	13	83,698	31,653
Postsecondary teachers-social and related Sciences (2088)	47	25	82,791	29,590
Science and engineering pre-college teacher (135)	44	1	63,896	21,076

Notes: Total number of observations = 23,542.
Mean is the average annual salary measured in U.S. dollars.
Number of observations in each job category is given in parentheses.
[1]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ job-category_i}{Total\ No\ of\ workers\ in\ job-category_i} \times 100$
[2]The formula used to calculate percentages $\frac{No\ of\ female\ workers\ in\ job-category_i}{Total\ No\ of\ female\ workers\ in\ the\ sample} \times 100$

Table 5: Female concentration by job-category – 2019 wave

Job category	[1]Female % out of total workforce in a job category	[2]Female % out of total female workforce	Mean	SD
Non-science and engineering managers (4,103)	39	7	178,137	100,483
Science and engineering managers (1,935)	36	3	162,444	73,968
Electrical or computer hardware engineers (1,447)	15	1	151,462	56,738
Computer and information scientists (3,659)	22	4	151,430	67,985
Aerospace, aeronautical, or astronautical engineers (504)	19	0	146,486	49,071
Other S&E related occupations (67)	31	0	145,955	64,109
Health related occupations (3,453)	56	9	138,664	95,608
Economists (693)	39	1	137,364	74,120
Mathematical scientists (1,728)	39	3	136,368	62,195
Management related occupations (2,459)	48	5	135,392	80,672
Chemical engineers (435)	24	0	135,225	55,541
Mechanical engineers (676)	16	0	131,941	51,250
Other engineers (2,300)	27	3	131,158	56,425
S&E technicians and technologists (516)	23	1	122,242	63,166
Physicists and astronomers (979)	19	1	120,621	55,541
Other physical and related scientists (353)	34	1	116,938	51,987
Sales and marketing occupations (634)	43	1	116,366	77,991
Chemists, except biochemists (1357)	30	2	116,009	49,961
Earth scientists, geologists, and oceanographers (1620)	35	3	111,335	57,101
Non S&E postsecondary teachers (1,010)	48	2	108,590	71,812
Biological and medical scientists (7,757)	50	18	107,342	59,621
Other social and related scientists (837)	69	3	105,465	51,617
Psychologists (2,285)	66	7	105,401	58,387
Political scientists (121)	41	0	103,289	43,816
Agricultural and food scientists (1,409)	37	2	102,417	52,832
Civil, architectural or sanitary engineers (614)	21	1	101,963	43,409
Other non S&E occupations (1,124)	49	2	101,507	90,297
Postsecondary teachers – life and related sciences (2,035)	45	4	94,615	59,917
Postsecondary teachers- computer and math sciences (1,116)	32	2	92,770	53,790
Postsecondary teachers – engineering (1,043)	19	1	92,253	58,343
Postsecondary teachers – social and related scientists (2,342)	51	5	91,718	53,852
Environmental life scientists (373)	43	1	88,488	40,410
Sociologists and anthropologists (286)	67	1	87,448	50,075
Post-secondary teachers – physical and related sciences (1,288)	32	2	86,742	54,476
Art, humanities, and related occupations (691)	70	2	78,340	58,301
Social services and related occupations (396)	64	1	68,265	41,618
Non S & E pre-college teachers (72)	79	0	66,583	64,259
S&E pre-college teachers (199)	53	0	65,935	26,753
Industrial engineers (124)	34	0	12,312	52,386

Notes: Total number of observations = 54,040
Mean is the average annual salary measured in U.S. dollars.
Number of observations in each job category is given in parentheses.
[1]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ job-category i}{Total\ No\ of\ workers\ in\ job-category_i} \times 100$
[2]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ job-category i}{Total\ No\ of\ female\ workers\ in\ the\ sample} \times 100$

The average annual salary by the field of specialisation of the highest degree is shown in Tables 6 and 7. Most females earned PhDs in the field of biological sciences (27%) and psychology (19%). Psychology (56%) and sociology and anthropology (54%) appeared to be female dominant fields. However, the highest wages were observed for individuals who obtained PhDs in electrical, electronics and communications engineering, management and administration, chemical engineering, economics, and other engineering fields in 2013. Only 10% of females specialised in the fields mentioned above. In 2019, non-science and engineering fields, electrical and computer engineering, computer and information sciences, Aerospace, aeronautical, and astronautical engineering, and economics PhDs earned the most. Only 6% of females specialised in the above high- earning fields.

Table 6: Female concentration by field of study – 2013 wave

Field of specialisation	[1]Female % out of total workforce in a field of study	[2]Female % out of total female workforce	Mean	SD
Electrical, electronics and communications engineering (1,091)	14	2	121,27	30,267
Management and administration (2)	0	0	120,00	42,426
Chemical engineering (557)	20	1	117,30	32,043
Economics (787)	31	3	116,23	32,638
Other engineering (1,713)	20	4	111,81	32,997
Mechanical engineering (644)	10	1	110,52	32,431
Physics and astronomy (1,334)	15	2	105,47	37,456
Civil engineering (355)	14	1	105,05	33,047
Computer and mathematical sciences (1,863)	26	6	104,53	34,468
Chemistry, except biochemistry (1,931)	27	6	102,99	36,859
Health-related fields (1,248)	63	9	99,659	33,851
Other physical and related sciences (707)	33	3	98,187	34,474
Biological sciences (5,360)	42	27	95,745	39,742
Political and related sciences (674)	37	3	92,914	35,335
Other biological/agricultural/environmental life sciences (848)	33	3	92,132	34,945
Psychology (2,862)	56	19	91,389	33,840
Sociology and anthropology (994)	54	6	85,139	33,863
Other non-science and engineering (4)	25	0	84,750	46,119
Other social sciences (568)	50	3	83,840	32,349

Notes: Total number of observations = 23,542.
Number of observations of each field is given in parentheses.
[1]The formula used to calculate percentages : $\frac{No\ of\ female\ workers\ in\ field\ of\ studyi}{Total\ No\ of\ workers\ in\ field\ of\ sstudyi} \times 100$
[2]The formula used to calculate percentages $\frac{No\ of\ female\ workers\ in\ field\ of\ studyi}{Total\ No\ of\ female\ workers\ in\ the\ sample} \times 100$

Table 7: Female concentration by field of study – 2019 wave

Field of specialisation	[1]Female % out of total workforce in a field of study	[2]Female % out of total female workforce	Mean	SD
Non-science and Engineering fields (21)	24	0	173,333	97,239
Electrical and computer engineering (2,698)	17	2	153,022	70,222
Computer and information sciences (1960)	25	2	151,672	80,129
Aerospace, aeronautical, and astronautical engineering (555)	19	0	140,595	66,127
Economics (1,452)	34	2	140,112	88,690
Chemical engineering (748)	25	1	140,099	72,308
Mechanical engineering (919)	18	1	138,620	69,900
Other engineering (4,278)	27	5	132,462	70,930
Mathematics and statistics (2,235)	29	3	131,162	75,249
Physics and astronomy (3,035)	21	3	130,618	69,477
Chemistry, except biochemistry (3,403)	35	5	128,270	72,334
S&E related fields (3,073)	64	9	124,413	72,167
Industrial engineering (258)	31	0	123,395	65,343
Biological sciences (11,837)	50	27	119,551	78,765
Political and related sciences (1,166)	43	2	115,388	70,930
Earth, atmospheric, and ocean sciences (2,382)	36	4	113,389	63,118
Psychology (5,249)	63	15	111,035	67,895
Civil and architectural engineering (1,037)	22	1	110,828	58,441
Other physical sciences (552)	41	1	106,757	60,856
Agriculture and food sciences (2,480)	39	4	103,539	61,211
Other social sciences (1,799)	54	4	100,130	64,441
Sociology and anthropology (1,408)	63	4	96,111	60,920
Environmental life sciences (1,495)	37	2	94,625	49,473

Notes: Number of observations = 54,040
Number of observations of each field is given in parentheses.
Number of observations in each job category is given in parentheses.
[1]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ field\ of\ study i}{Total\ No\ of\ workers\ in\ field\ of\ sstudy_i} \times 100$
[2]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ field\ of\ study i}{Total\ No\ of\ female\ workers\ in\ the\ sample} \times 100$

Tables 8 and 9 present the average wages of academics by academic position. Men dominated all academic positions in 2013. The highest percentage of female PhD holders are employed either as adjunct faculty (48%) or in post-doctoral positions (45%). In contrast, in 2019, adjunct faculty positions, teaching assistants/research assistants or other positions were dominated by females.

However, still the highest-paying positions were dominated by males. The highest percentage of female PhD holders in the academic sector worked as teaching faculty; 61% in 2013 and 44% in 2019.

Table 8: Female concentration by academic position – 2013 wave

Academic position	[1]Female % out of total workforce in an academic position	[2]Female % out of total female workforce	Mean	SD
Administrative (dean or president) (482)	36	4	119,635	31,779
Teaching faculty (6931)	38	61	90,876	32,398
Research faculty (1833)	39	17	87,974	33,788
research assistant, teaching assistant or other (734)	51	9	84,936	34,551
Adjunct Faculty (124)	48	1	57,137	38,221
Post-doc (748)	45	8	46,416	97,941

Notes: Total number of observations = 10,852
Number of observations of each academic position is given in parentheses.
[1]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ academic\ position_i}{Total\ No\ of\ workers\ in\ academic\ position_i} \times 100$
[2]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ academic\ position_i}{Total\ No\ of\ female\ workers\ in\ the\ sample} \times 100$

Table 9: Female concentration by academic position – 2019 wave

Academic position	[1]Female % out of total workforce in an academic position	[2]Female % out of total female workforce	Mean	SD
Administrative (dean or president) (1,108)	44	6	161,949	87,325
Teaching faculty (9,315)	41	44	103,015	64,788
Research faculty (4,948)	43	24	99,425	56,420
Research assistant, teaching assistant or other (2,540)	57	17	94,810	57,850
Post-doc (1,366)	47	7	53,989	15,126
Adjunct Faculty (321)	53	2	53,879	48,539

Notes: Total number of observations = 19,598
Number of observations of each academic position is given in parentheses.
[1]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ academic\ position_i}{Total\ No\ of\ workers\ in\ academic\ position_i} \times 100$
[2]The formula used to calculate percentages: $\frac{No\ of\ female\ workers\ in\ academic\ position_i}{Total\ No\ of\ female\ workers\ in\ the\ sample} \times 100$

Mincerian Log-wage Regressions

A series of Mincerian log wage regressions - a pooled regression, and separate regressions by gender and employment sector categories (for academic and business/industry sectors)- were estimated. The pooled regression suggested a gender wage differential of 5% in 2013 and 11% in 2019. However, a pooled regression captures only the variation in intercept coefficients between men and women but ignores the variation in slope coefficients. Therefore, two separate log-wage regressions were estimated for male and female PhD holders. The estimated gender wage gap was decomposed into an observed portion (the difference between slope coefficients) and an unobservable portion (the difference between intercept coefficients) using the Oaxaca-Blinder decomposition method. The number of years of experience, size of the employer, job category, employment sector, having children, children's age, academic position, employer benefits, the field of specialisation of the highest degree, attending training programs, the number of memberships in professional associations, having another degree, enrolled in additional courses related to employment, work history (previously retired), primary work activity, citizenship, and race/ethnicity were included as covariates in the log-wage regressions.

The regression coefficients concerning experience dummy variables are highly significant in male only and female only regressions in both waves. Accordingly, more experience results in higher wages for PhD holders. The magnitude of the coefficients indicates that having higher experience was more important for women than for men in both 2013 and 2019. The regression coefficients for employment sector dummies suggest that both men and women in the business/industry sector earned higher wages than the government and education sectors in both 2013 and 2019.

PhD holders who work as computer scientists and mathematicians earned significantly higher wages than those who worked as post-secondary teachers in computer sciences and mathematics in 2013. Females earned 14% more in the computer science and mathematics job category than females who work as post- secondary teachers. Also, male PhD holders who work in computer science and mathematics earned 9% higher than males who work as post-secondary teachers. In addition, working as an economist result in higher wages for both male and female PhD holders. Women earned 19% higher in the economics job category than other post-secondary teachers, which was 7% for men. Similar results were obtained for electrical engineers. Specifically, male electrical engineers earned 12% higher than male post-secondary teachers in computer sciences and mathematics.

In contrast, female electrical engineers earned 15% higher than female post-secondary teachers in computer sciences and mathematics. The wage premiums for female PhD holders in science and engineering managers, top managers, and other managers were 18%, 22%, and 14 %, respectively. The respective male wage premiums were 10%, 14%, and 10%. Accordingly, employment in the job categories such as computer scientist, mathematician, economist, electrical engineer, and manager was more important for women. Similarly, in 2019, computer scientists and mathematicians earned higher wages than post- secondary pre-college teachers – men earned 16% higher, and women earned 18% higher. Female PhD holders who work as sociologists and anthropologists earned significantly less than post-secondary pre- college teachers – 34% less. Management- related job categories were gratifying; men in non-science and engineering management jobs earned 29% more than men in pre-college teaching jobs, and it was 30% higher for women.

The size of the employer is another significant determinant of the wage. It was measured as the number of employees at the workplace. Both male and female PhD holders earned higher wages at larger institutions than those who work in institutions with fewer employees. Employed in workplaces that provide employee benefits such as health insurance, profit-share schemes, pension schemes and paid vacation increased wages for both men and women compared to those who do not work in such workplaces.

Primary work activity is another determinant of wages in the log-wage equation. Those who spend more than 10% of their time in applied research (study directly toward gaining scientific knowledge to meet a recognised need) earned higher salaries compared to those who do not. For instance, the wage premium in the applied research was 6% for men and 7% for women in 2013. Further, individuals primarily work on development activities such as using knowledge gained from research to produce materials and devices and design equipment processes and those who deliver professional services such as health care, counselling, financial, and legal services earned higher salaries. Conversely, salaries were significantly lower for primary work activities such as teaching and production, operations, and maintenance activities.

Having memberships in professional associations was beneficial for both men and women. For instance, a wage premium for being a member of 6 professional associations was 13% for men and 12% for women. Memberships can be considered proxies for intense professional engagement, which is a factor that leads to higher remuneration. PhD holders who previously retired from an institution earned significantly lower wages. The wage penalty for the previous retirement was 16% for women and 12% for men in 2013. In 2019, the wage penalty was 34% and 30% for men and women, respectively. Among the demographic factors, U.S. citizens earned significantly more than non-U.S. citizens. Citizenship was more important for men than women, where the individual wage premiums for men and women are 5% and 3%, respectively. Black and Hispanic women earned significantly less than White women in 2019. A selected portion of the regression outputs for the 2013 and 2019 waves are presented in Appendix A and B.

Decomposition Results

The Oaxaca decomposition results suggest that the gender wage differential of PhD holders was 17% and 21% in 2013 and 2019, respectively. Out of the total wage gap, 12% was due to observable characteristics, and 5% was due to unobservable characteristics in 2013. In 2019, 9% was due to observable characteristics, and 12% was due to unobservable characteristics.

Table 10: Oaxaca decomposition results

	Full sample		Academic sector		Business / Industry sector	
	2013	**2019**	**2013**	**2019**	**2013**	**2019**
Panel A summary						
Total gender wage differential[1]	17	21	15	11	15	27
Explained portion	12	9	11	2	9	11
Unexplained portion	5	12	4	9	7	16
Panel B percentage of the explained portion[2]						
Experience	43	45	60	249	34	31
Employment sector	27	32	0	0	0	0
Field of study	17	19	21	100	23	19
Employer benefits	3	13	4	3	15	26
Job category	3	19	-4	-87	24	41
Primary work activity	9	1	8	20	7	-12
Academic job	1	-0	NA[b]	NA[b]	NA[b]	NA[b]
Academic position	NA[a]	NA[a]	9	52	NA[a]	NA[a]
Training	3	1	3	-0	3	0
Race/ethnicity	2	1	2	-4	4	1
Employer size	-1	-2	2	-33	9	9
Having children/number of children	2	3	2	11	2	2
Child age	0	-3	0	-8	0	-2
Additional courses	0	0	0	3	0	0
Additional degree	0	0	0	1	0	0
Citizenship	-1	-18	-1	-188	-1	-6
Memberships	-3	-3	-2	8	-3	-2
Previously retired	-2	-9	-1	-29	-2	-8
Number of observations	23,542	54,040	10,852	19,598	9,660	26,577

Notes: [1]Gender wage differential is measured as the percentage of wage gap between female and male workers. The explained portion implies the percentage of wage gap that can be explained by observed characteristics whereas the unexplainable portion indicates the percentage of wage gap that cannot be explained by observed characteristics.
[2]Sub-categories of the explained portion describe the portion of the explained portion that is explained in the model.
NA - Not applicable.
[a]*Academic position* is not included since it is not available for PhD holders employed in the business/industry sector.
[b]*Academic job* is omitted for the models estimated separately for business/industry sector and the academic sector

More than 40% of the explainable variation in both 2013 and 2019 was attributed to the differences in experience levels among men and women PhD holders. In addition, the employment sector, field of specialisation, and job category accounted for most of the observed wage gap. Hence, it appears that most highly educated women are employed in lower-paying employment sectors and specialise in fields that are less rewarding at work.

The gender wage differential between the business/industry and academic sectors was 15% in 2013. However, the explained portion (due to observable characteristics) was higher (11%) in the academic sector compared to the business/industry sector (9%). A higher unexplained portion of the gender wage gap indicates modestly higher discrimination in the business/industry sector. In 2019, the academic sector's wage gap slowed to 11%. In contrast, the business/industry sector exhibited a higher wage gap, 27%, compared to 2013.

The above estimates are comparable to previous studies that used national-level data to study the gender wage gap among academics. In 1968, 23% of the gender wage gap was observed in the academic sector. It declined to 19% in 1977 but further increased to 20- 23%in 1989. The findings of this study suggest gender wage gap has declined since 1989. The gender wage gap due to unobservable characteristics was 17%, 11%, and 6% in 1968, 1977, and 1989, respectively (Barbezat, 1987; Barbezat, 1991). The current estimates suggest that the wage gap due to unobservable characteristics has fallen at first; however, later, it appears to increase.

Panel B of Table 10 further describes the explainable portion of the wage gap. Among the observable characteristics, experience explained more than 40% of the total explained variation both for the full sample and for the academics. This finding indicates that females earned less (in the academic sector and in the full sample), mainly because their experience is fewer compared to male counterparts. In addition, the field of specialization, employment sector, and job category contributed to a higher portion of the explained wage gap. This implies that female PhD holders tend to specialize in fields, dominate job categories, and find employment characterised by lower wages.

In the academic sector, academic position accounted for 9% and 52% of the variation in 2013 and 2019, respectively. This variation is due to higher male dominance in the high- paying academic positions. The years of experience explained more than 30% of the total observable variation in the business/industry sector in both survey waves. In addition, the job category explained more than 20% of the variation. Thus, female PhD holders tend to find employment in lower-paying jobs.

CONCLUSION AND POLICY RECOMMENDATIONS

This study estimated the gender wage differential of the most highly educated labour segment using data from the Survey of Doctorate Recipients. The Oaxaca decomposition method was used to decompose the gender wage differential into observable and unobservable characteristics. Wage differential due to unobservable characteristics can probably be attributed to gender discrimination, assuming all the wage determinants are included in the model.

The findings suggest that female PhD holders earned 17% less than their male counterparts in 2013 and 21% in 2019. The estimated gender wage differential due to unobservable characteristics was 5% in 2013 and 12% in 2019. Less experience, employment in sectors with low remuneration, and specialisation in the academic fields less rewarded in the job market were the most contributing factors to the observed gender wage gap. The years of experience was important for both sectors, yet it was more important for women in the academic sector.

Female PhD holders faced a sizable gender wage gap in academic and business/industry sectors. In 2019, the gender wage differential in business/industry sector was 27%. Hence, women who leave academia faced a larger gender wage gap than those who remained. Among the covariates, experience (measured as the number of years since PhD) explained the highest variation of the gender wage gap. Less experience observed among women led to a sizable wage penalty for women in both academic and business/industry sectors. Moreover, female PhD holders were employed in low-paying job categories and employment sectors. Also, segregated into academic fields with low remunerations. Therefore, policies to address the above issues, such as encouraging women to specialise in non-conventional high rewarding academic fields, job categories, and employment sectors, could lessen the gender wage gap.

Interesting future extensions to the study would be to explore why women are less experienced compared to men (women may apply for more leave due to childbirth, childcare, elderly care, etc) and an investigation into motherhood wage penalty among highly skilled workers. Further, estimations for gender wage gap in the developing countries would be helpful to understand the gender wage dynamics in the developing country setting.

REFERENCES

1. Barbezat, D. A. (1987). Salary differentials by sex in the academic labour market. The Journal of Human Resources, 22(3), 422-428.
2. Barbezat, D. A. (1991). Updating estimates of male-female salary differentials in the academic labour market. Economics Letters, 36(2), 191-195.
3. Becker, G. (1971). The economics of discrimination (Studies in economics (University of Chicago. Economics Research Centre)). Chicago: University of Chicago Press.
4. Becker, G. S. (1962). Investment in human capital: A theoretical analysis. Journal of Political Economy, 70(5, Part 2), 9-49.
5. Binder, M., Krause, K., Chermak, J., Thacher, J., and Gilroy, J. (2010). Same work, different pay? evidence from a US public university. Feminist Economics, 16(4), 105-135.
6. Broder, I. E. (1993). Professional achievements and gender differences among academic economists. Economic Inquiry, 31(1), 116-127.
7. Carlin, P. S., Kidd, M. P., Rooney, P. M., and Denton, B. (2013). Academic wage structure by gender: The roles of peer review, performance, and market forces. Southern Economic Journal, 80(1), 127-146.
8. Ceci, S. J., Ginther, D. K., Kahn, S., and Williams, W. M. (2014). Women in academic science: a changing landscape. Psychological Science in the Public Interest, 15(3), 75-141.
9. Cotton, J. (1988). On the decomposition of wage differentials. The Review of Economics and Statistics, 236-243.
10. Ginther, D. K., and Hayes, K. J. (1999). Gender differences in salary and promotion in the humanities. American Economic Review, 89(2), 397-402.
11. Ginther, D. K., and Hayes, K. J. (2003). Gender differences in salary and promotion for faculty in the humanities 1977–95. Journal of Human Resources, 38(1), 34-73.
12. Ginther, D. K., and Kahn, S. (2004). Women in economics: moving up or falling off the academic

career ladder? Journal of Economic Perspectives, 18(3), 193-214.
13. Gough, M., and Noonan, M. (2013). A review of the motherhood wage penalty in the United States. Sociology Compass, 7(4), 328-342.
14. Long, J. S., Allison, P. D., and McGinnis, R. (1993). Rank advancement in academic careers: sex differences and the effects of productivity. American Sociological Review, 703-722.
15. McNabb, R., and Wass, V. (1997). Male-female salary differentials in British universities. Oxford Economic Papers, 49(3), 328-343.
16. Mincer, J. (1958). Investment in human capital and personal income distribution. Journal of Political Economy, 66(4), 281-302.
17. Oaxaca, R. (1973). Male-female wage differentials in urban labour markets. International Economic Review, 693-709.
18. Ospino, C. G., Roldan Vasquez, P., and Barraza Narvaez, N. (2010). Oaxaca-blinder wage decomposition: methods, critiques, and applications. A literature review. Revista de Economía del Caribe, (5), 237-274.
19. Porter, S. R., Toutkoushian, R. K., and Moore III, J. V. (2008). Pay inequities for recently hired faculty, 1988-2004. The Review of Higher Education, 31(4), 465-487.
20. Riach, P. A., and Rich, J. (2002). Field experiments of discrimination in the marketplace. The Economic Journal, 112(483).
21. Smart, J. C. (1991). Gender equity in academic rank and salary. The Review of Higher Education, 14(4), 511-525.
22. Staff, J., and Mortimer, J. T. (2012). Explaining the motherhood wage penalty during the early occupational career. Demography, 49(1), 1-21.
23. Toumanoff, P. (2005). The effects of gender on salary-at-hire in the academic labour market. Economics of Education Review, 24(2), 179-188.
24. Toutkoushian, R. K., Bellas, M. L., and Moore, J. V. (2007). The interaction effects of gender, race, and marital status on faculty salaries. The Journal of Higher Education, 78(5), 572-601.
25. Umbach, P. D. (2007). Gender equity in the academic labour market: an analysis of academic disciplines. Research in Higher Education, 48(2), 169-192.
26. Webber, K. L., and Canché, M. G. (2015). Not equal for all: gender and race differences in salary for doctoral degree recipients. Research in Higher Education, 56(7), 645- 672.
27. Weeden, K. A., Cha, Y., and Bucca, M. (2016). Long work hours, part-time work, and trends in the gender gap in pay, the motherhood wage penalty, and the fatherhood wage premium. RSF.