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Can Education Reduce or Mitigate Discrimination? An Investigation on Earnings of PhD Recipients in the US

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ABSTRACT

Spence's signaling model (Spence, 1973) suggests that education can signal workers' unobserved ability to employers thereby mitigating discrimination. There have been several studies concerning education's impact on labor market discrimination against minority or disadvantaged groups. Our approach in this inquiry is unique in that we utilize the data of PhD recipients, a group of people with the highest education attainment, to test Spence's theory. Another novelty of this paper is that in addition to examining possible discrimination against women and foreign-born, as has been done in previous studies, we further explore possible discrimination against the physically challenged individuals. Our baseline results show conflicting results that Ph.D. education can reduce discrimination against disability and foreign-born but not against gender. Further analysis by the Blinder-Oaxaca Decomposition shows that the wage gaps of gender and disability come more from the unobserved part than the explained part, while the foreign-born wage gap come more from the observable human capital differences. Since prejudice is an unobserved factor and we know that the disadvantaged groups are likely to suffer from prejudice (Oaxaca, 1973; Blinder, 1973; Montes-Rojas et al., 2017; Deshpande and Khanna, 2018), we conjecture that prejudice might be attributable to the unexplained part of the wage gaps. Furthermore, prejudice might be deeply rooted in one's mind, thus difficult to remove even with the influence of education. Hence, our results reveal that it would be hard for Ph.D. education to eradicate the discrimination against gender and disability, but not against foreign-born.

KEYWORDS

Education; Discrimination; Doctorate recipients; Blinder-Oaxaca Decompositions

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1. Introduction

The number of Ph.D. graduates in the US has been trending up in the last few decades. Doctoral recipients in Science and Engineering subjects increased from about 32,000 in 1987 to almost 54,000 in 2017. Along with the general increase of PhD holders, proportionally more and more international, female and disabled students have received their PhD degree. From 1987 to 2017, while domestic US students receiving doctorate degree increased modestly from 24,000 to 35,000, international doctoral recipients almost tripled, from only 6,000 to 16,000. In the same period, we also see more and more women getting their PhD degrees. The female PhD recipients increased 13.3% from 2008 to 2017, compared to 10.9% increase of male doctorates. Moreover, doctoral recipients reporting functional limitations occupied more weights in the whole PhD graduates, from 5.8% in 2013 to 7.2% in 2017[1]. The rapid growth in the doctorate recipients of disadvantaged groups is noteworthy.

The signaling theory proposed by Spence (Spence, 1973) suggests that education can signal workers' unobserved or innate ability to employers, and hence it may serve as a tool to reduce discrimination. Following this logic, PhD recipients, as a representative group of workers with the highest education degree to signal high ability, may be subject to less or no discrimination. Specifically, foreign, female and other disadvantaged group of people are commonly suspected to suffer from discrimination. If these disadvantaged groups of workers obtain the PhD degree to signal possession of high skills, would this highest education attainment help them to escape being discriminated or face reduced discrimination? There have been several studies on earnings or wage gaps between native vs foreign, and male vs female. However, few investigate the issue focusing on earnings of PhD graduates. This study attempts to contribute to a quandary—Can Ph.D. education reduce discrimination? Our approach in this inquiry is unique in that we utilize the data of PhD recipients, a group of people with the highest education attainment, to test Spence's theory. Another novelty of this paper is that in addition to examining possible discrimination against women and foreign-born, as has been done in previous studies, we further explore possible discrimination against the physically challenged individuals.

There were two major pioneering scholarly articles on Ph.D. earnings, both using the U.S. National Science Foundations' Survey of Doctorate Recipients. Hanks and Kniffin (2014) investigated the effects of interdisciplinary dissertation on early career PhD salaries. They found that completing interdisciplinary dissertations seems to have no effect on doctorate graduates' earnings. Borjas (2006) found that foreign student influx may drag down the average salaries of Ph.D. holders, and that almost half of the adverse effects are attributable to the immigrants' choice or placement in low-pay postdoctoral appointments. There are some recent additions to the literature in this area, including Tao (2018) using the U.S. National Science Foundations' Survey of Doctorate Recipients, Alfano et.al (2021) using the Italian "Survey on the Employability of Ph.D. Holders", Nie (2023) using the American Community Survey, and Passaretta and Triventi (2023) using the Italian National Institute of Statistics' survey on Ph.D. graduates. This paper attempts to extend Borjas study on Ph.D. immigrant earnings with new and updated data. This paper also extends the literature analyzing the earnings effects of Ph.D. education by gender and disability status.

The rest of the paper is organized as follows. The next section describes the data with descriptive statistics. Section 3 gives detailed analysis of the heterogeneous earning gaps of gender, disability, and foreign-born, and explores sources of the gaps. Section 4 presents robustness checks, and Section 5 concludes with policy implications, limitations and future research directions.

[1] National Science Foundation, National Center for Science and Engineering Statistics, *Survey of Earned Doctorates, 2017*, Table 15, 17, 28; NSF, NIH, USED, USDA, NEH, NASA, *Survey of Earned Doctorates, 2013*, Table 28.

2. Data and Description of Variables

This paper uses data drawn from the Survey of Doctorate Recipients (SDR), 2017 cycle ((https://ncsesdata.nsf.gov/datadownload/). The SDR shows demographic, education, and career history information from individuals obtaining a Ph.D. degree within a science, engineering, or health (SEH) field in the US. Since 1973, the SDR has been conducted biennially by the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation. The individuals targeted for survey are those who earned SEH Ph.D. degrees within US prior to July 1, 2015, not institutionalized nor terminally ill on February 2, 2017, and less than 76 years of age as of February 2, 2017. The 2017 cycle is a compilation of the previous cycles with the new cycle data added. After data cleaning and management, we compile a total of 55,689 observations and 28 variables for analysis.

The total 28 variables comprise 1 dependent variable, 3 grouping variables, and 24 explanatory variables. The dependent variable is "earnings", representing the total earned income in terms of US dollars in the year 2016. Three grouping variables are "male", "disability" and "US_born", distinguishing the whole dataset into three groups in terms of gender, disability and foreign-born. The remaining 24 variables are explanatory variables. Among them, "age", "age2 (age squared)", "father_edu", "mother_edu" and "underrepresented_minority" can be labeled as personal characteristics. Family situation consists of three variables, which are "child", "married" and "spouse_working". Educational history is composed of "school_midwest", "school_northeast", "school_south", "major_engineering", "major_health" and "another_degree". Work related variables are "postdoc", "work_experience", "employ_midwest", "employ_northeast", "employ_south", "employ_abroad", "employ_government", "employ_industry", "job_satisfied" and "training". With the exception that "earnings", "age", "age2" and "work_experience" are numerical; most variables are categorical dummies.

For the variable "work_experience", since we do not directly have the exact data on the years of experience, we use the years after graduation to infer work experience. The dummy variables "school_midwest", "school_northeast" and "school_south" are created from the categorical variable—"school_region" with "school_west" as the reference group. The dummy variables "major_engineering" and "major_health" are created from the categorical variable--major with "major_science" as the reference group. The dummy variables "employ_northeast", "employ_south" and "employ_abroad" are created from the categorical variable—"employ_region" with "employ_west" as the reference group. The dummy variables "employ_goverment" and "employ_industry" are created from the categorical variable—"employ_sector" with "employ_academia" as the reference group. Table 1 displays the descriptive statistics of the variables.

3. Heterogeneous Earning Gaps and Their Sources

In each of the following three subsections, we show basic results of the respective earnings gap and compare with the literature. Then, we conduct OLS regression and perform the Blinder-Oaxaca Decomposition to explore the sources of earnings gaps. We also discuss and compare our findings with related studies.

3.1. Female vs Male

Our sample data contains 21,327 female and 34,362 male doctoral recipients. Out of them, the female's yearly median earnings is $85,000, while that of the male is $110,000. This indicates that the female Ph.D.'s yearly median earnings are about 77% of the males. However, the *Highlights of women's earnings in 2016* from US Bureau of Labor Statistics show that female workers' full-time weekly median wage was 82% of those of full-time male workers, higher than the 77% result here. Our result seems to dispute the argument that more education can increase women's relative wage and shrink gender pay gap. Our finding, however, coincides with some other scholarly research findings such as Blau and Kahn (2007) and AAUW (2014), in which they find that the gender gap exists at all educational levels and widens for people with more advanced degrees than high school degree.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
age	55,689	46.41078	11.58087	25	70
age2	55,689	2288.075	1118.742	625	4900
work_experience	55,689	19.01988	11.26097	2	52
child (have children = 1)	55,689	0.4822317	0.4996887	0	1
US_born (US_born = 1)	55,689	0.5973172	0.4904423	0	1
father_edu (no less than bachelor = 1)	55,689	0.5887339	0.4920677	0	1
mother_edu (not less than bachelor = 1)	55,689	0.4575589	0.4982	0	1
retired (previously retired = 1)	55,689	0.0755984	0.2643569	0	1
male (male = 1)	55,689	0.6170339	0.4861145	0	1
disability (disabled = 1)	55,689	0.0847923	0.2785749	0	1
job_satisfied (dissatisfied = 1)	55,689	0.0806443	0.2722905	0	1
married (married = 1)	55,689	0.9403652	0.236811	0	1
underrepresented_minority[1] (minority = 1)	55,689	0.1507838	0.3578412	0	1
postdoc (take postdoc = 1)	55,689	0.0359137	0.1860768	0	1
spouse_working (not working = 1)	55,689	0.2605182	0.4389213	0	1
another_degree (complete another degree = 1)	55,689	0.0050998	0.0712309	0	1
training (attended training = 1)	55,689	0.5575069	0.4966864	0	1
employ_midwest	55,689	0.1557399	0.3626118	0	1
employ_northeast	55,689	0.1880623	0.3907654	0	1
employ_south	55,689	0.2799476	0.4489772	0	1
employ_abroad	55,689	0.1355564	0.34232	0	1
employ_goverment	55,689	0.1063406	0.3082758	0	1
employ_industry	55,689	0.4024134	0.4903888	0	1
school_midwest	55,689	0.2474277	0.4315212	0	1
school_northeast	55,689	0.2397781	0.4269518	0	1
school_south	55,689	0.2830182	0.4504692	0	1
major_engineering	55,689	0.1883137	0.390966	0	1
major_health	55,689	0.0466699	0.2109327	0	1
earnings	55,689	121173.1	99855.01	0	652000

Notes: Respondents who are Non-Hispanic White and Non-Hispanic Asian are not underrepresented minorities.

Figure 1 shows the typical right-skewed pattern of earnings distribution. Thus, as has been done in other studies on earnings, we need to take logarithmic transformation of the earnings data to make the dependent variable normally distributed. Our earnings data contains a small number of (merely 247) zero earnings out of the total 55,689 observations. Wooldridge (2013, p.185) points out that, if the variable y contains a few zeros, log (1+y) is generally acceptable. Moreover, since the mean value of the earnings is $121,173, adding $1 on it should not have significant impacts. Therefore, we generate a new variable—"log_earnings" equal to log (earnings+1) to replace variable "earnings". In Figure 2, we can see that log_earnings is nearly normally distributed, verifying that our transformation is suitable.

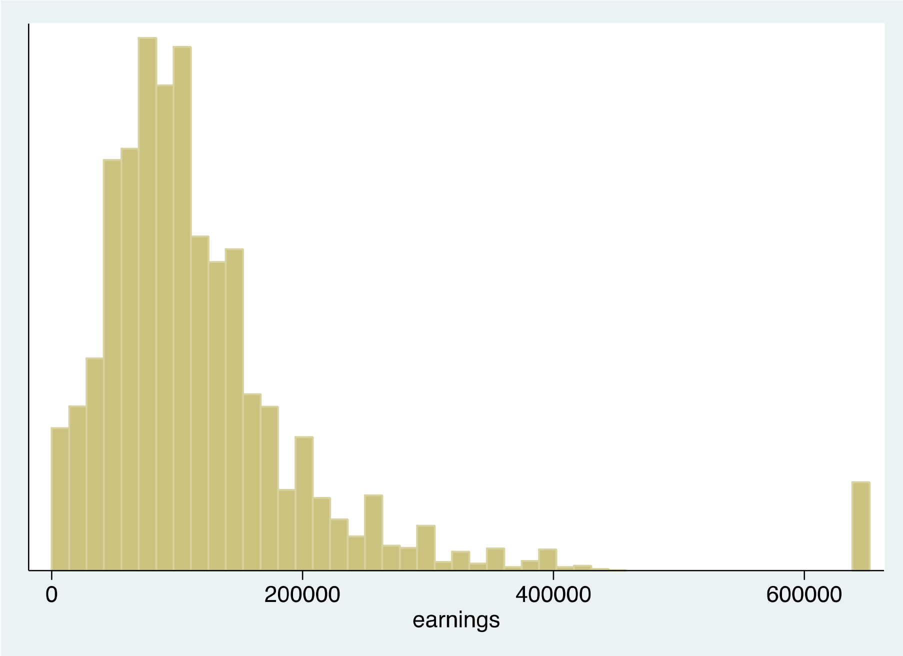

Figure 1. Histogram of earnings

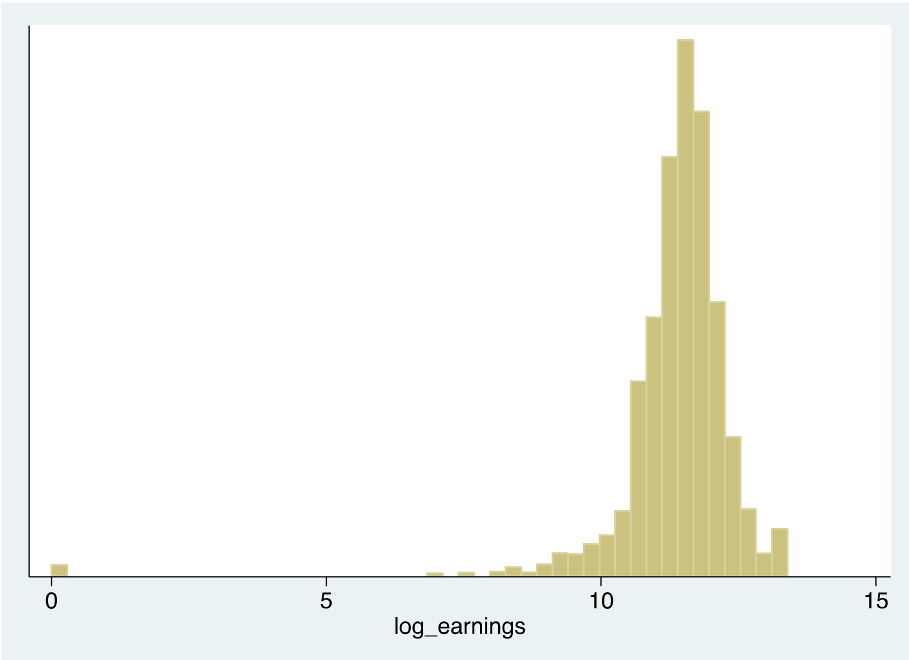

Figure 2. Histogram of log_earnings

We run OLS regression on the two (male and female) estimation equations (1) and (2) below:

$$\log\_\text{earnings}_{fi} = \theta_f \cdot X_{fi} + \varepsilon_{fi}\,, \qquad (1)$$

$$\log\_\text{earnings}_{mi} = \theta_m \cdot X_{mi} + \varepsilon_{mi}\,, \qquad (2)$$

Where log _earnings is the dependent variable, X is a set of independent variables including all explanatory variables plus the other two grouping variables—disability and foreign-born, ε represents error terms. Table 2 presents the regression results.

Table 2. OLS Regression of Gender

	Dependent Variable: log_earnings	
	(1)	(2)
Independent Variables	female	male
age	0.0677***	0.107***
	(0.00566)	(0.00429)
age2	-0.000874***	-0.00129***
	(6.10e-05)	(4.47e-05)
father_edu	0.00394	0.0341**
	(0.0167)	(0.0136)
mother_edu	0.0191	0.0235*
	(0.0163)	(0.0139)
underrepresented_minority	-0.0587***	-0.0643***
	(0.0192)	(0.0163)
child	-0.000273	0.0408***
	(0.0149)	(0.0121)
married	-0.0448*	0.0611**
	(0.0261)	(0.0272)
spouse_working	0.101***	0.0705***
	(0.0213)	(0.0122)
school_midwest	-0.0222	-0.0162
	(0.0225)	(0.0171)
school_northeast	0.0224	0.0477***
	(0.0223)	(0.0174)
school_south	-0.0396*	-0.0351**
	(0.0218)	(0.0170)
major_engineering	0.191***	0.125***
	(0.0243)	(0.0136)
major_health	0.143***	0.0896***
	(0.0282)	(0.0313)
another_degree	-0.271***	-0.0895
	(0.0837)	(0.0885)
postdoc	-0.299***	-0.411***
	(0.0344)	(0.0350)
work_experience	0.0225***	0.0233***
	(0.00129)	(0.00108)
employ_midwest	-0.0434*	-0.0810***
	(0.0243)	(0.0196)
employ_northeast	0.0578**	0.00331
	(0.0229)	(0.0187)
employ_south	0.0173	-0.0360**

	(0.0214)	(0.0170)
employ_abroad	-0.627***	-0.659***
	(0.0283)	(0.0201)
employ_government	0.204***	0.144***
	(0.0236)	(0.0193)
employ_industry	0.123***	0.238***
	(0.0152)	(0.0124)
job_satisfied	-0.148***	-0.187***
	(0.0244)	(0.0213)
training	0.0417***	0.0487***
	(0.0144)	(0.0114)
disability	-0.120***	-0.137***
	(0.0276)	(0.0192)
US_born	-0.000831	0.00792
	(0.0160)	(0.0131)
Constant	9.685***	8.901***
	(0.131)	(0.104)
Observations	21,327	34,362
R-squared	0.080	0.117

*Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

From Table 2, we can see that many independent variables are significant for both genders. Particular noteworthy is the estimation result for the variable "whether a postdoc was taken", which is not only highly negative significant but also has big impacts in scale for both female and male earnings. Take the coefficient estimate -0.299 as an example, in practical sense, we can infer from this coefficient that a postdoctoral work entails lowering the typical Ph.D. earnings by almost 30%. This is consistent with the finding of Borjas (2006). For male, parents' education levels have significant impact on their earnings; while for female, whether completed another degree is significant for their earnings. Interestingly, having children is significant and conducive to earnings of male PhDs. Having kids probably induces a sense of responsibility of being a father, which in turn increases their working impetus.

We conduct the standard Blinder-Oaxaca Decomposition to explore the sources of gender earnings gap. Blinder (1973) and Oaxaca (1973) independently developed a technique to decompose the raw earnings gap between two groups of workers into a portion that explains the earnings gap by differences in characteristics related to productivity, and another portion that remains unexplained and constitutes an estimate of discrimination. Table 3 shows the decomposition results (We do not show here the detailed result of each variable's contribution in the explained portion to save space). From Table 3, we can see that the total gender differential is -0.26, with the explained portion -0.06 while the unexplained portion accounting for -0.2. Similar to most studies of gender earnings differential decomposition, such as Altonji and Blank (1999)[2], the unexplained part is about 3 times as much as the explained part, showing that more earnings differentials stem from unobserved or unexplained factors

[2] A notable exception is Nie (2023). That paper examines gender wage differentials of doctorate recipients from 2014-2018 using the American Community Survey data, and finds total gender wage differentials being 0.29 but with the explained portion 0.12 and unexplained portion 0.17. The different decomposition results could be due to the use of different dataset, and possibly due to Nie (2023) includes all doctorate recipients in analysis whereas our sample only includes those in the science, engineering or health field. Nevertheless, in that paper the unexplained portion is still larger than the explained portion.

than the observed human capital differences. As speculated by Alfano et al (2021) and Passaretta & Triventi (2023), the unobserved factors, including women's child-bearing and rearing responsibilities or other stereotypical perceptions over female, might account for a large part of discrimination (the unexplained part of earnings gap) on female workers.

Table 3. Blinder-Oaxaca Decomposition of Gender

log_earnings	Coef.	Robust Std. Err.
overall		
difference	-0.2655914	0.0093188
explained	-0.0605348	0.0046294
unexplained	-0.2050565	0.0081413

3.2. Disabled vs Non-disabled

Our sample contains 50,967 non-disabled and 4,722 physically challenged (disabled) doctorate graduates, with the ratio of disabled versus non-disabled about 1/10. While the mean earnings of the non-disabled is $121,731, the disabled's is $115,154. Our sample show that the disabled Ph.D. graduates "only" earn 5% less than the non-disabled Ph.Ds. This is in sharp contrast to Yin et al. (2014)'s finding on all workers. They find that the disabled people earn 37% (or $10,700) less than non-disabled people, after controlling for certain personal characteristics or labor maker factors. Therefore, it appears that having a Ph.D. does help to reduce earnings gap between disabled and non-disabled people. In other words, Ph.D. education appears to mitigate the extent of discrimination against the disabled.

Table 4 presents the OLS regression results of the earnings of disabled and non-disabled separately. We can tell from Table 4 that almost all variables are significant. Gender plays the same role for both disabled and non-disabled people in that males earn more than females. While parents' education levels are significant for non-disabled persons' earnings, they do not exert impacts on the disabled. For disabled people, training seems to have greater impacts for them than the non-disabled.

Table 4. OLS Regression of Disability

	Dependent Variable: log_earnings	
	(1)	(2)
Independent Variables	non-disabled	disabled
age	0.0883***	0.134***
	(0.00340)	(0.0152)
age2	-0.00109***	-0.00160***
	(3.61e-05)	(0.000155)
father_edu	0.0220**	0.0322
	(0.0107)	(0.0469)
mother_edu	0.0230**	0.00578
	(0.0107)	(0.0489)
underrepresented_minority	-0.0652***	-0.0313
	(0.0126)	(0.0544)
child	0.0208**	0.0679
	(0.00952)	(0.0424)

married	0.00186	0.0467
	(0.0191)	(0.0821)
spouse_working	0.0806***	0.0752*
	(0.0107)	(0.0443)
school_midwest	-0.0264*	0.0650
	(0.0138)	(0.0584)
school_northeast	0.0327**	0.110*
	(0.0139)	(0.0631)
school_south	-0.0455***	0.0793
	(0.0136)	(0.0587)
major_engineering	0.136***	0.238***
	(0.0119)	(0.0540)
major_health	0.121***	0.127
	(0.0210)	(0.104)
another_degree	-0.225***	0.278
	(0.0613)	(0.299)
postdoc	-0.356***	-0.257*
	(0.0245)	(0.133)
work_experience	0.0225***	0.0255***
	(0.000841)	(0.00327)
employ_midwest	-0.0735***	0.0140
	(0.0154)	(0.0682)
employ_northeast	0.0168	0.0800
	(0.0146)	(0.0680)
employ_south	-0.0201	0.0172
	(0.0134)	(0.0595)
employ_abroad	-0.630***	-0.861***
	(0.0165)	(0.0724)
employ_government	0.166***	0.177***
	(0.0151)	(0.0653)
employ_industry	0.213***	0.00397
	(0.00972)	(0.0433)
job_satisfied	-0.178***	-0.107*
	(0.0165)	(0.0638)
training	0.0403***	0.112***
	(0.00904)	(0.0400)
male	0.235***	0.256***
	(0.00966)	(0.0453)
US_born	0.00719	-0.0176
	(0.0102)	(0.0485)
Constant	9.160***	7.921***
	(0.0811)	(0.380)

Observations	50,967	4,722
R-squared	0.117	0.099

*Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Table 5 presents Blinder-Oaxaca Decomposition results of the earnings gap of disability (To save space we do not show here the detailed result of each variable's contribution in the explained portion). From Table 5, we can see that the overall earnings differential between the disabled and non-disabled is 0.15, with the explained portion comprising 0.02 whereas the unexplained part accounting for 0.13. The unexplained part of earnings differential is 6 times more than the explained part, which shows that more weights of earnings gap are attributable to unobserved factors. Since we know that the disadvantaged groups are likely to suffer from prejudice, one of the unobserved factors is possibly coming from employers' prejudice. According to Yin et al. (2014)'s calculation, if the prejudice is corrected, an additional $141 billion can be created for the US economy, representing about 1% of the GDP. This implies that there are potentially substantial gains to the economy if policy makers can implement effective educational and labor market reform measures to deal with prejudice and discrimination against disability.

Table 5. Blinder-Oaxaca Decomposition of Disability

log_earnings	Coef.	Robust Std. Err.
overall		
difference	0.1507281	0.0208288
explained	0.0203811	0.0061426
unexplained	0.130347	0.0195022

3.3. Foreign vs Native

Following Borjas (2006), we define "natives" as US-born citizens and "non-natives" or "foreign born" as naturalized citizens, permanent residents or temporary visa holders. Our sample contains 22,425 observations of foreign-born PhDs and 33,264 observations of US-born PhDs. Like female and the disabled, non-natives are a relatively disadvantaged group compared to natives in labor market. Their disadvantages stem from either being unfamiliar with the cultural setting, or lack of language fluency, or working permit restrictions. According to the Bureau of Labor Statistics[3], in 2016, the median weekly earnings of foreign-born full-time workers ($715) were 83.1 percent of their US-born counterparts ($860). Our sample shows that the median annual earnings of foreign-born PhD ($96,000) were 96 percent of their US-born counterparts ($100,000) in 2016, higher than the 83.1 percent foreign/native earnings ratio for all full-time workers. It appears that Ph.D. education helps to shrink the pay gap between natives and non-natives.

Table 6 presents the regression results of earnings for natives and non-natives. From Table 6, we can see that almost all the independent variables are significant. While father's education levels are more important for foreign-born PhDs, whether spouse is working are more important for the US-born counterparts. Besides these, whether complete another degree and whether having postdoc experience are significant for both foreign-born and US-born PhDs.

Table 6. OLS Regression of Foreign-born vs US-born

	Dependent Variable: log_earnings	
	(1)	(2)
Independent Variables	foreign-born	US-born

[3] *Foreign-born workers: Labor Force Characteristics — 2016* released by Bureau of Labor Statistics

age	0.0706***	0.105***
	(0.00591)	(0.00405)
age2	-0.000950***	-0.00124***
	(6.36e-05)	(4.24e-05)
father_edu	0.0329*	0.0122
	(0.0176)	(0.0131)
mother_edu	0.0276	0.0115
	(0.0184)	(0.0129)
underrepresented_minority	-0.0898***	-0.0251
	(0.0184)	(0.0173)
child	0.0615***	-0.00163
	(0.0150)	(0.0121)
married	-0.0267	0.0301
	(0.0340)	(0.0225)
spouse_working	0.0464***	0.112***
	(0.0168)	(0.0134)
school_midwest	-0.0210	-0.0216
	(0.0219)	(0.0172)
school_northeast	0.0226	0.0416**
	(0.0220)	(0.0175)
school_south	-0.0659***	-0.0158
	(0.0216)	(0.0170)
major_engineering	0.0753***	0.204***
	(0.0166)	(0.0171)
major_health	-0.00755	0.181***
	(0.0367)	(0.0253)
another_degree	-0.198**	-0.177**
	(0.0914)	(0.0822)
postdoc	-0.388***	-0.316***
	(0.0370)	(0.0332)
work_experience	0.0304***	0.0192***
	(0.00153)	(0.000961)
employ_midwest	-0.124***	-0.0311*
	(0.0275)	(0.0183)
employ_northeast	-0.0394	0.0618***
	(0.0248)	(0.0178)
employ_south	-0.0849***	0.0170
	(0.0231)	(0.0163)
employ_abroad	-0.733***	-0.332***
	(0.0219)	(0.0346)
employ_government	0.157***	0.168***

	(0.0256)	(0.0182)
employ_industry	0.280***	0.131***
	(0.0161)	(0.0119)
job_satisfied	-0.184***	-0.154***
	(0.0251)	(0.0209)
training	0.0535***	0.0446***
	(0.0146)	(0.0112)
male	0.242***	0.242***
	(0.0165)	(0.0117)
disability	-0.129***	-0.130***
	(0.0267)	(0.0193)
Constant	9.583***	8.765***
	(0.139)	(0.0964)
Observations	22,425	33,264
R-squared	0.157	0.083

*Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Table 7 presents the Blinder-Oaxaca Decomposition results of the wage gap between US-born and foreign-born PhDs. It shows that the total earnings differential is -0.13, with the explained part consisting of about -0.12 while the unexplained part comprising less than -0.01. The explained part of earnings differential is 12 times more than the unexplained part, indicating that the observable factors account more for the wage gap than the unobserved factors. Among all the observable factors, “age”, “age2” and “employ_abroad” contribute most to the wage gap (detail results of each variable’s contribution to the explained part not shown in Table 7 to save space), which indicates that the gap is driven by the discrepancies like age and employment locations of US-born and foreign-born PhDs. Hence, different from the gender and disability wage gaps in the preceding subsections, it is possible to substantially mitigate or even eradicate the foreign-born wage gap if the discrepancies like age and employment locations are improved.

Table 7. Blinder-Oaxaca Decomposition of Foreign-born

log_earnings	Coef.	Robust Std. Err.
overall		
difference	-0.132058	0.0096026
explained	-0.1274245	0.0060831
unexplained	-0.0046335	0.0073416

4. Robustness Check

Figure 1 (the earnings histogram) in Section 3.1 shows that there are outliers in the data. There are 247 observations with $0 income (0.4% of the total observations) and 999 observations reporting the highest value of $652,000 (1.8% of the total observations). These outliers might distort the analysis results. We perform a robustness check eliminating the top and bottom 5% observations from the sample and conducting the Blinder-Oaxaca Decomposition analysis on the outlier-excluded data.

Table 8 shows that total gender earnings differential is -0.18, with the explained part accounting for -0.06 while the unexplained part comprising -0.12. Here, the unexplained part is doubled from the explained part, which is smaller than the earlier result that the unexplained part is almost 3 times as much as the explained part. Hence, we can still conclude that Ph.D. education cannot reduce and eradicate gender wage discrimination.

Table 8. Robustness Check for Blinder-Oaxaca Decomposition of Gender

log_earnings	Coef.	Robust Std. Err.
overall		
difference	-0.184369	0.0046251
explained	-0.0694983	0.0028516
unexplained	-0.1148707	0.00376

Table 9 shows that the total disability differential is 0.022, with the explained part -0.013 while the unexplained part 0.036. Since the unexplained part accounts more of total differential, the results are similar to the baseline results in Table 5.

Table 9. Robustness Check for Blinder-Oaxaca Decomposition of Disability

log_earnings	Coef.	Robust Std. Err.
overall		
difference	0.0223731	0.0086028
explained	-0.0134888	0.0044787
unexplained	0.0358618	0.0074374

Table 10 shows that the total foreign-born differential is -0.079, with the explained part being -0.083 whereas the unexplained part 0.004. The explained part practically captures all differentials. Again, similar to the baseline results, among all the explained factors, “age”, “age2” and “employ_abroad” contribute most to the gap, which implies that it is possible to reduce or remove the discrimination against foreign-born PhDs if these factors are improved.

Table 10. Robustness Check for Blinder-Oaxaca Decomposition of Foreign-born

log_earnings	Coef.	Robust Std. Err.
overall		
difference	-0.0793964	0.0047981
explained	-0.0832124	0.0033394
unexplained	0.003816	0.0033926

In sum, the three robustness checks of earnings differentials regarding gender, disability and foreign-born generate similar results and consistent with the baseline findings, indicating that the presence of outliers did not bias the earlier baseline results and our previous conclusions are robust.

5. Conclusions, Policy Implications, Limitations and Future Research

We investigate whether Ph.D. education can shrink the wage gap to reduce discrimination, and significantly reduce the extent of prejudice-originated discrimination.

The data comes from the Survey of Doctorate Recipients (SDR), consisting of 55,689 observations and 24 variables. We find that the gender earnings gap of PhDs is larger than the overall gender earnings gap for all workers, while the disability and foreign-born gaps of PhDs are smaller than their corresponding overall average earning gaps. This shows that Ph.D. education shrinks wage gaps of disability and foreign-born but does not help close the gender earnings gap. Further analysis with Blinder-Oaxaca Decomposition shows that more of the earnings gap can be attributed to the unexplained part than the explained part for the gender and disability earnings gaps, but the opposite for the foreign-born earnings gap. Given that prejudice is an unobserved factor, and follow Oaxaca (1973), Blinder (1973), Montes-Rojas et al. (2017) and Deshpande and Khanna (2018) that they all attribute the unexplained wage gaps to discrimination and prejudice, we conjecture that prejudice could be a possible factor for the unexplained portion of the three earnings gaps analyzed here. Moreover, since all the three groups pass the robustness check, we can conclude that Ph.D. education has conflicting effects on both discrimination reduction and prejudice-based discrimination elimination.

Specifically, we conclude that Ph.D. education can eradicate prejudice-based discrimination for foreign-born workers but not for female and disabled workers. In the analysis of earnings gap between foreign-born and natives our findings imply that if the discrepancies like age and employment locations are improved, the prejudice-based discrimination against the foreign-born is likely to be eradicated. Another policy implication from our analysis is that there is potentially substantial gains to the economy if policy makers can implement effective educational and labor market reform measures to deal with prejudice and discrimination against disability.

Lastly, we list some caveats or limitations of this study as follows. First, the sample size of the disabled doctorates is small (4,722 observations), only 1/10 of the non-disabled ones (50,967). The small sample may limit generalization of the findings regarding disability here. Second, the focus of our study is on Ph.D. holders in the science, engineering and health field. While extending the study to include Doctorate recipients in humanities may introduce more heterogeneities or noises, it is possible to gain more insights and hence might be worthwhile to pursue in future research. Third, we can only speculate that prejudice might be the possible source of the unexplained portion of the wage gaps, but there is no direct evidence to prove this. In the future, if more data indicating employer's attitudes on gender, disability or foreign-born can be added, we may be able to make stronger conclusions. Fourth, for future research, we would also explore other factors affecting earnings disparities among PhD holders or explore appropriate data to conduct longitudinal studies on PhD earnings.

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Conflict of interest

The authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

References

Alfano, V., L. Cicatiello, G. Gaeta, and M. Pinto (2021). The Gender Wage Gap among Ph.D. Holders: Evidence from Italy. *BE Journal of Economic Analysis and Policy*, 21(3): 1107-1148. http://dx.doi.org/10.1515/bejeap-2020-0319

Altonji, J.G. and R. M. Blank (1999), "Race and Gender in the Labor Market" in *Handbook of Labor Economics*, Vol. 3C, 3143-3259. https://doi.org/10.1016/S1573-4463(99)30039-0

American Association of University Women (AAUW). (2014). *The simple truth about the gender pay gap*. ERIC Clearinghouse.

Blau, F. D., & Kahn, L. M. (2007). The gender pay gap: Have women gone as far as they can? *Academy of Management Perspectives*, *21*(1), 7-23. http://dx.doi.org/10.4324/9781003071709-31

Blinder, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human resources*, 436-455. https://doi.org/10.2307/144855

BLS, U. (2017). Highlights of women's earnings in 2016. *US Department of Labor, Bureau of Labor Statistics, BLS Reports, Report*, *1064*.

Borjas, George J. (2006) Immigration in High-Skill Labor Markets: The Impact of Foreign Students on the Earnings of Doctorates. *Journal of Human Resources*, 2006, 41(2), 221-258.

Deshpande, A., Goel, D., & Khanna, S. (2018). Bad Karma or Discrimination? Male–Female Wage Gaps among Salaried Workers in India. *World Development*, *102*, 331-344. https://doi.org/10.1016/j.worlddev.2017.07.012

Galor, O., & Weil, D. (1996). The Gender Gap, Fertility, and Growth. *American Economic Review*, *86*(3), 374-87.

Grogger, J., & Hanson, G. (2013). The scale and selectivity of foreign-born PhD recipients in the US. *American Economic Review*, *103*(3), 189-92. https://doi.org/10.1257/aer.103.3.189

Grogger, J., & Hanson, G. H. (2015). Attracting talent: Location choices of foreign-born PhDs in the United States. *Journal of Labor Economics*, *33*(S1), S5-S38.

Hanks, A. S., & Kniffin, K. M. (2014). Early career PhD salaries: The industry premium and interdisciplinary debate. *Applied Economics Letters*, *21*(18), 1277-1282. http://dx.doi.org/10.1080/13504851.2014.922664

Montes-Rojas, G., Siga, L., & Mainali, R. (2017). Mean and quantile regression Oaxaca-Blinder decompositions with an application to caste discrimination. *The Journal of Economic Inequality*, *15*(3), 245-255.

Nie, Qing, (2023). Immigration in High-Skill Labor Markets: The Impact of Foreign Students on the Earnings of Doctorates by Gender. *Journal of Business and Social Sciences Review,* 4(1), 28-37. https://doi.org/10.3386/w12085

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International economic review*, 693-709.

Passaretta, G. and M. Triventi (2023). Inequality at the Top. The Gender Earnings Gap among the Italian Educational Elite. *Research in Social Stratification and Mobility*, 85, 100796. https://doi.org/10.1016/j.rssm.2023.100796

Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, *87*(3), 355-374.

Tao, Y. (2018). Earnings of Academic Scientists and Engineers: Intersectionality of Gender and Race/Ethnicity Effects. *American Behavioral Scientist*, 62(5), 625-644. https://doi.org/10.1177/0002764218768870

Wooldridge, J. M. (2013). Introductory econometrics: a modern approach 5th edition. *Mason, OH: South-Western*.

Yin, M., Shaewitz, D., & Megra, M. (2014). An uneven playing field: The lack of equal pay for people with disabilities. *Washington, DC: American Institutes for Research*.