

The Effect of Occupational Feminization on the Returns to Education

Paul E. Gabriel
Loyola University Chicago

Susanne Schmitz
Dominican University

This study explores whether workers in female-dominated occupations have lower returns to schooling than workers in integrated or male-dominated occupations. Our analysis of 2023 CPS earnings data for year-round full-time workers indicates that the earnings benefits to additional schooling decline as the female density of occupations increases. This finding is consistent with the occupational feminization literature. However, we also find that females have higher returns to schooling than males in integrated and male-dominated occupational categories. Overall, women have achieved the highest labor market success in terms of returns to schooling in male-dominant occupations.

Keywords: occupational segregation, returns to schooling, gender wage differences

INTRODUCTION

It is well established in labor markets throughout the world that females have lower earnings than males. Although relative female earnings improved during the late 1970s in the United States, by the early 2000s the gender earnings ratio stabilized at approximately 80 percent (Blau and Kahn, 2017; Kochhar, 2023). A second trend was that more women moved into traditional ‘male’ occupations and gender differences in occupational distributions declined (Blau et al., 2013; Blau and Kahn, 2017; Mandel 2018; Rio and Alonso-Villar, 2015). However, like the wage gap trend, gender occupational differences have also stabilized over the last twenty years (Blau and Kahn, 2017, Rio and Alonso-Villar, 2015).

Although gender wage and occupation differences have been stable for nearly twenty years, there is one notable demographic trend that seems paradoxical to these labor market outcomes: female educational attainment now surpasses that of males. In 2022, 39.1% of US women aged 25 and older had completed a bachelor’s degree or more, while the rate was 36.2% for men (Institute Education Sciences, 2022). The accepted view in the human capital literature is that education enhances earnings and occupational mobility, although there are variations in outcomes across race, gender, and ethnicity. From an investment perspective, higher education levels for females might be due to improved labor market returns to schooling. However, some remain convinced that labor market discrimination reduces the valuation of women’s human capital relative to men (Blau and Kahn, 2017; Goldin, et al., 2017). For example, occupational segregation may result in women being excluded from higher-paying male-dominated occupations, compelling them to pursue employment in lower-paying jobs. As suggested by Laing (2011) and others (Addison et al., 2018; Bartnik, et al., 2022), the higher level of feminization in more accessible occupations

may decrease wages and devalue the returns to human capital. Discrimination, coupled with cultural norms about home production (e.g., childcare), may push women towards occupations with fewer hours, more flexible scheduling, and fewer opportunities for training and promotions (Weeden et al., 2016; Addison et al., 2018).

The primary focus of this paper is whether the relationship between earnings and education differs according to the degree of occupational feminization. In the analysis below, we explore the returns to education for three classifications of occupations: male, integrated, and female.

DATA AND EMPIRICAL METHODOLOGY

Our sample of year-round full-time, non-agricultural wage and salary workers is drawn from the 2023 March Current Population Survey (CPS).¹ The use of year-round, full-time workers suggests that males and females have similar levels of labor-market attachment. A worker’s occupation is classified on the basis of gender density using criteria from recent occupational feminization studies: *female* (60-100% female), *male* (0-39% female), and *integrated* (40-59% female) (see Strawinski et. al., 2018; Grönlund and Magnusson, 2013; Blau et. al., 2013; Cozzi, 2017; Bartnik et.al., 2022). Thus, we consider an occupation as gender dominant when at least 60% of that occupation is represented by males or females. Table 1 list examples of occupations by category based on CPS occupational classifications.

From the occupational samples we then estimate the parameters of a Mincer wage equation for men and women in each of the three occupational groups:

$$\ln W_i = \alpha + \beta \text{SCHOOLING}_i + \delta X_i + \varepsilon_i \quad (1)$$

where W_i is the logarithm of regional CPI-adjusted weekly wage and salary income for each worker ($i = 1, \dots, N$), SCHOOLING_i is years of schooling completed, X_i is comprised of additional variables linked to earnings (see Table 2), α, β, δ , are parameters and ε is a stochastic error term [$\varepsilon_i \sim N(0, \sigma^2)$]. Our primary focus is the estimated coefficient $\hat{\beta}$, used to approximate the expected earnings premium for an additional year of schooling.² Heckman’s (1974) two-stage selectivity bias correction is employed to estimate the parameters of the Mincer equation. In the first stage, a labor force participation logistic regression is estimated, with the resulting Inverse Mill’s Ratio included in the wage regressions to control for the endogeneity of labor force status (in versus out).

TABLE 1
OCCUPATIONAL CATEGORY EXAMPLES – CPS

Male (227 Occupations)	Integrated (87 Occupations)	Female (120 Occupations)
Pilots	Admin Service Manager	Childcare Workers
Train Engineers	Bartenders	Dental Hygienists
Automotive Mechanics	Cashiers	Elementary and Middle School Teachers
Carpenters	Chiropractors	Home Health Aides
Computer Engineers	Dentists	Optometrists
Truck Drivers	Janitors	Receptionists
Electricians	Physicians	Nurses
Construction Managers	Retail Salespersons	Administrative Assistants
Police Officers	Secondary School Teachers	Social Workers
Mechanical Engineers	Restaurant Servers	

TABLE 2
VARIABLES AND COVARIATES FOR MINCER WAGE EQUATIONS

LWKEARN:	Logarithm of weekly wage and salary. Weekly wage and salary income is adjusted for the regional CPI (1982-1984=100).
SCHOOLING:	Years of schooling completed
EXPER:	Years of potential labor market experience: (Age – SCHOOLING – 5)
EXPERTSQ:	EXPER*EXPER

Categorical variables:

Census	
Region:	NORTHEAST, MIDWEST, SOUTH, WEST (omitted category)
MSP:	married, spouse present
UNION:	covered by a collective bargaining agreement
Race:	white (omitted category), black, and other
VETERAN:	prior service in US military
URBAN:	resides in an urban area

Sample selection:

INVMILLS:	Inverse Mill's ratio from a Heckman two-stage sample-selection correction logit equation of labor force participation
-----------	---

EMPIRICAL RESULTS

Table 3 shows the estimated rates of return to schooling for females and males are lowest in female occupations and highest in male occupations.³ This outcome is consistent with the segregation hypotheses that returns to human capital are discounted in female occupations. However, in two occupation groups (integrated and male), the return to schooling is higher for females than males, and the differences are statistically different at conventional levels. Thus, recent increases in the relative educational attainment of women may be a logical response to their higher returns to schooling – even in occupations where women are under-represented.

TABLE 3
ESTIMATED RETURNS TO EDUCATION BY OCCUPATIONAL GENDER DENSITY

<i>Female Occupations:</i>				
	Sample Size	Coefficient on Years of Schooling	Years of Schooling	Rate of Return to Schooling (%) ^a
<i>Males</i>	3,941	0.1054	15.05	11.11
<i>Females</i>	12,997	0.1108	14.62	11.72
<i>Integrated Occupations:</i>				
	Sample Size	Coefficient on Years of Schooling	Years of Schooling	Rate of Return to Schooling (%) ^a
<i>Males</i>	6,352	0.1222	15.06	12.99
<i>Females</i>	5,733	0.1573*	15.18	17.04
<i>Male Occupations:</i>				
	Sample Size	Coefficient on Years of Schooling	Years of Schooling	Rate of Return to Schooling (%) ^a
<i>Males</i>	16,766	0.1271	13.40	13.55
<i>Females</i>	3,813	0.2025*	13.95	22.44

Notes to Table 3:

*The differences in the estimated female-male regression coefficients are significant at the 1 percent level.

^a Rate of return to schooling (%) is calculated as $e^{(\beta_{\text{Schooling}} - 1)} \times 100$.

CONCLUSION

This study investigates whether current labor market returns to education are affected by occupational gender density. Our analysis of 2023 CPS data for year-round full-time workers reveals that the earnings benefits to an additional year of school decline as the female density of occupations increases. This finding is consistent with the occupational feminization and labor market segregation literature. However, we also find that women have higher returns to education in two occupational categories (integrated and male dominated). This outcome may help explain why the educational attainment of US females (in years and degree completion) is now higher than males. Overall, women appear to have the highest labor market success in terms of returns to schooling in male-dominant occupations where the representation of females is the lowest.

ENDNOTES

1. The 2023 IPUMS-CPS (Flood, et al., 2023) sample is the non-institutionalized civilian labor force, ages 18 – 64. The samples are limited to workers with positive earnings and complete data on relevant characteristics. Workers with weekly earnings below the 1st and above the 99th percentiles were omitted to reduce outliers.
2. The rate of return to additional schooling is calculated as $(e^{(\hat{\beta} - 1)} \times 100)$ (see van Garderen and Shah, 2002).
3. The complete empirical tables with descriptive statistics and wage regressions are shown in the appendix.

REFERENCES

- Addison, J.T., Ozturk, O.D., & Wang, S. (2018). The occupational feminization of wages. *ILR Review*, 71(1), 208–241.
- Blau, F.D., & Kahn, L.M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3), 789–865.
- Blau, F.D., Brummund, P., & Liu, A.Y.-H. (2013). Trends in occupational segregation by gender 1970-2009: Adjusting for the impact of changes in the occupational coding system. *Demography*, 50(2), 471–492.
- Cozzi, M. (2017). The gender wage gap: Does it pay to follow the crowd? *The Park Place Economist*, 25, 1–14.
- Dominica, B., Gabriel, P.E., & Schmitz, S. (2022). The impact of occupational feminization on the gender wage gap and estimates of wage discrimination. *Applied Economics Letters*, 29(17), 1605–1609.
- Flood, S., King, M., Rodgers, R., Ruggles, S., & Warren, J.R. (2023). *Integrated Public Use Microdata Series, Current Population Survey: Version 8.0* [dataset]. Minneapolis, MN: IPUMS.
- Goldin, C., Kerr, S.P., Olivetti, C., & Barth, E. (2017). The expanding gender earnings gap: Evidence from the LEHD-2000 Census. *American Economic Review: Papers and Proceedings*, 107(5), 110–114.
- Grönlund, A., & Magnusson, C. (2013). Devaluation, crowding or skill specificity? Exploring the mechanism behind the lower wages in female professions. *Social Science Research*, 42(4), 1006–1017.
- Heckman, J. (1974). Shadow prices, market wages, and labor supply. *Econometrica*, 42(4), 679–694.
- Institute of Education Sciences, & National Center for Education Statistics. (2022). *Table 104.30: Number and percentage distribution of persons aged 18 and over, by highest level of educational attainment, sex, race/ethnicity, and age*.
- Kochhar, R. (2023, March 1). *The Enduring Grip of the Gender Pay Gap*. Pew Research Center.
- Laing, D. (2011). *Labor Economics: Introduction to Classic and the New Labor Economics*. New York: W. W. Norton & Company.
- Mandel, H. (2018). A second look at the process of occupational feminization and pay reduction in occupations. *Demography*, 55(2), 669–690.
- Río, C., & Alonso-Villar, O. (2015). The evolution of occupational segregation in the United States, 1940–2010: Gains and losses of gender–race/ethnicity groups. *Demography*, 52(3), 967–988.
- Strawinski, P., Majchrowska, A., & Broniatowska, P. (2018). Occupational segregation and wage differences: The case of Poland. *International Journal of Manpower*, 39(3), 378–397.
- van Garderen, K.J., & Shah, C. (2002). Exact interpretation of dummy variables in semilogarithmic equations. *The Econometrics Journal*, 5(1), 149–159.
- Weeden, K.A., Cha, Y., & 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: The Russell Sage Foundation Journal of the Social Sciences*, 2(4), 71–102.

APPENDIX

TABLE 3
DESCRIPTIVE STATISTICS – 2023 CPS SAMPLE

<i>Occupational Category:</i>	Female		Integrated		Male	
	<i>Sample Mean or Proportion</i>		<i>Sample Mean or Proportion</i>		<i>Sample Mean or Proportion</i>	
<i>Variable</i>	Males	Females	Males	Females	Males	Females
WKLYWAGE (\$)	515.00	456.00	634.00	626.00	521.00	470.00
LOGWAGE	6.03	5.95	6.20	6.18	6.02	5.89
SCHOOLING	15.05	14.62	15.06	15.18	13.40	13.95
EXP	20.55	21.98	22.02	21.04	23.03	22.91
EXPSQ	555.45	627.26	631.58	588.80	676.98	674.94
SOUTH	0.35	0.38	0.37	0.39	0.37	0.39
NORTHEAST	0.17	0.16	0.18	0.19	0.15	0.14
MIDWEST	0.18	0.20	0.21	0.19	0.20	0.20
WEST (base category for regressions)	0.30	0.27	0.24	0.23	0.29	0.28
MSP	0.57	0.53	0.58	0.53	0.59	0.51
DISAB	0.02	0.03	0.02	0.03	0.02	0.03
WHITE (base category for regressions)	0.74	0.75	0.78	0.74	0.79	0.70
NONWHT	0.12	0.14	0.10	0.14	0.10	0.14
OTHER	0.14	0.11	0.12	0.12	0.11	0.16
UNIONWKR	0.02	0.02	0.01	0.02	0.02	0.01
VETERAN	0.08	0.01	0.07	0.01	0.08	0.02
URBAN	0.30	0.25	0.31	0.32	0.24	0.27
Sample size	3,941	12,997	6,351	5,733	16,766	3,813

TABLE 4
WAGE REGRESSIONS – 2023 CPS SAMPLE

<i>Dependent Variable: Log of Weekly Earnings</i>						
<i>Occupational Category:</i>	Female		Integrated		Male	
	<i>Estimated Coefficients</i>		<i>Estimated Coefficients</i>		<i>Estimated Coefficients</i>	
<i>Variable</i>	Males	Females	Males	Females	Males	Females
Constant	3.961*	4.057*	3.704*	3.088*	3.587*	1.972*
SCHOOLING	0.105*	0.111*	0.122*	0.157*	0.127*	0.2025*
EXP	0.025*	0.018*	0.032*	0.037*	0.028*	0.028*
EXPSQ	-0.0003*	-0.0003*	-0.0005*	-0.0005*	-0.0004*	-0.0002*
NORTHEAST	0.008	-0.013	-0.016	0.010	0.042*	-0.046
MIDWEST	0.070*	0.057*	0.085*	0.048**	0.097*	0.080*
SOUTH	0.031	0.002	0.002	-0.044**	0.026*	0.006
MSP	0.220*	0.066*	0.317*	0.090*	0.301*	0.207*
DISAB	-0.092	0.025	-0.027*	-0.130	-0.348*	-0.629*
NONWHT	-0.092*	-0.017	-0.154*	-0.019	-0.219*	-0.127*
OTHER	-0.101*	-0.019	-0.072*	0.026	-0.008	-0.008
UNIONWKR	-0.054	0.023	-0.037	0.018	0.099*	0.069
VETERAN	0.049	0.0021	-0.048***	0.048	0.0039*	0.007
URBAN	0.004	0.046*	0.013	0.093*	0.012	0.035
INVERSEMILLS	-0.277	-0.0312	1.064***	2.015*	2.077*	5.786*
R-squared (adjusted)	0.301	0.268	0.348	0.338	0.295	0.323

*, **, ***: significant at the 1%, 5%, and 10% level, respectively