ECON 695 Final Project

University of Wisconsin–Madison

Gender Wage Gaps and Coworker Wages

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Latest version and replication files

Acknowledgements. We thank Professor Alice Wu for guidance and comments. All errors are our own.

AI Disclaimer

AI tools (specifically ChatGPT) were used solely to assist with minor troubleshooting and formatting tasks, including resolving LaTeX and Python issues, and drafting descriptive tables for improved readability. All analysis, model specifications, interpretations, and the final written narrative are our own.

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Introduction

Data

We use administrative data provided to us by Professor Alice Wu for the ECON 695 final project that follow men and women who are observed for several consecutive years across exactly two jobs. The dataset (projectdata.csv) contains one record per individual, with each record summarizing the worker's demographic characteristics, education, potential labor market experience, and a sequence of annual wage observations surrounding a job transition. In total, the dataset includes 16,969 individuals—10,575 men and 6,394 women—who satisfy the sampling requirement of having at least three years of observations in their first job and three years in their second job. The timing convention indexes the first year on the second job as period 0, with years -3, -2, and -1 representing the three years prior to the move, and years 1 and 2 representing subsequent years on the second job.

A distinctive feature of the dataset is the inclusion of coworker wage measures: for each job spell, we observe a summary measure of the mean log wage of all other workers employed at the same firm. These coworker wage variables are recorded separately for the first job, where $owage1$ is defined as the average coworker wage across periods -1 and -2, and for the second job, where $owage2$ is defined as the average coworker wage across periods 0, 1, and 2. This structure enables us to investigate how the wage distribution among a worker's peers may influence their own wage outcomes. This richness makes the dataset particularly suitable for studying gender differences in wage determination and the role of workplace environments.

Sample Size and Structure

The dataset contains a total of 16,969 individuals, of whom 10,575 are men and 6,394 are women. Thus, approximately 38% of the sample consists of women. The sample is further restricted to workers who move between jobs where there are at least four coworkers at each job, so that coworker wage measures are well defined. Each individual record includes demographic characteristics, education, experience, and a sequence of wage observations around a job transition.

The timing convention follows the project instructions: period 0 is the first year on the second job, periods 1 and 2 are the subsequent years, and periods -1 through -3 correspond to the final three years on the first job. For each job spell, the dataset also includes a measure of the mean log wage of coworkers, which is central to our later analysis of coworker wage effects.

Variables

The dataset includes key demographic and human capital measures—age, years of education (taking values 6, 9, 12, or 16), gender (a binary indicator `female`), and potential experience constructed from age and schooling. Wage information is recorded as log hourly wages across multiple periods relative to a job transition: y denotes the wage in period 0 (the first year on the second job), $yp1$ and $yp2$ correspond to years 1 and 2 on the second job, and $yl1$, $yl2$, and $yl3$ capture wages in the final three years on the first job (periods -1 through -3). These coworker wage variables are summarized as $owage1$ (averaged over periods -1 and -2 for the first job) and $owage2$ (averaged over periods 0, 1, and 2 for the second job). Together, these variables allow us to link individual wage dynamics with characteristics of the worker's surrounding wage environment.

Section 1: Overview: Female vs. Male Workers

Female and male workers in our sample differ systematically in both pay and observed characteristics. Table 1 reports mean values for age, education, wages, and coworker wages for all workers and separately by gender, along with t–statistics comparing men and women at period 0 (the first year on the second job). Figure 1 then visualizes the distribution of log hourly wages by gender.

Summary Statistics

Table 1: Summary Statistics by Gender

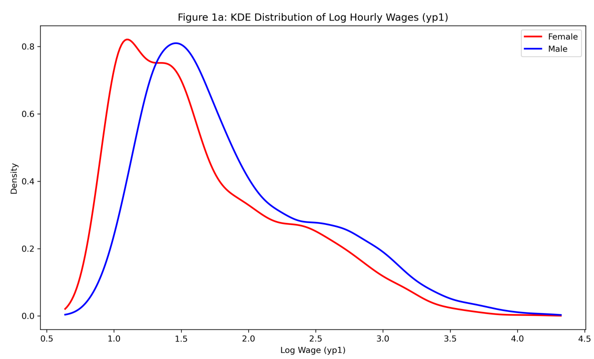
	All	Female	Male	t–stat
Age (mean)	33.5589	33.5344	33.5737	-0.4358
Log wage y (mean)	1.7879	1.6580	1.8664	-20.8163
Coworker wage owage2 (mean)	1.6921	1.6378	1.7249	-11.6761
Educ = 6 yrs (fraction)	0.2741	0.2487	0.2895	-5.8460
Educ = 9 yrs (fraction)	0.2274	0.1949	0.2471	-8.0450
Educ = 12 yrs (fraction)	0.2958	0.3286	0.2759	7.2054
Educ = 16 yrs (fraction)	0.2027	0.2279	0.1875	6.2317

Notes: Each column reports sample means for the listed variables across all workers, and separately by gender. Education is coded as categorical dummies for 6, 9, 12, and 16 years of schooling. The final column reports t–statistics from independent two-sample tests comparing male and female means. All values are measured at period 0 (first year on the second job).

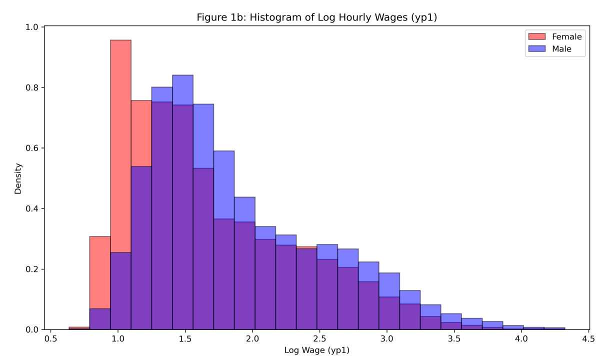
Women comprise approximately 38% of the sample. As shown in Table 1, average age is nearly identical across genders, but women tend to have slightly higher educational attainment: they are more likely to have completed 12 or 16 years of schooling, whereas men are more concentrated in the 6- and 9-year categories. These differences in educational composition are large and statistically significant, with t–statistics in the range of about 6 to 8 in absolute value.

Despite women's modest advantage in formal schooling, men earn substantially higher wages at period 0. The mean log hourly wage is 1.866 for men compared to 1.658 for women, corresponding to a large and statistically significant gender gap (the t–statistic is about -20.8). Coworker wages show a similar pattern: men are more likely to work alongside higher-paid coworkers (mean owage2 of 1.725 for men versus 1.638 for women), suggesting systematic gender differences in the types of jobs or firms where workers are employed.

Wage Distributions



(a) Kernel density of log hourly wages ($yp1$) by gender.



(b) Histogram of log hourly wages ($yp1$) by gender.

Figure 1: Distribution of log hourly wages in period 1 on the second job ($yp1$) for women and men. Panels (a) and (b) show kernel densities and histograms, respectively.

Figure 1 provides additional detail on the distribution of wages by gender. In panel (a), the kernel density curves indicate that the female wage distribution lies to the left of the male distribution, with women clustering more heavily around log wages of roughly 1.0–1.4. Panel (b) shows a similar pattern in the histograms: women are more prevalent at lower wage levels, while men are overrepresented in the upper tail, particularly above a log wage of 2.0. The male distribution also exhibits greater spread, consistent with higher dispersion in men's wage outcomes.

Taken together, Table 1 and Figure 1 document a sizable raw gender wage gap and meaningful differences in educational attainment and coworker wage exposure, even before controlling for other observable characteristics. These descriptive patterns motivate the regression analysis and Oaxaca decompositions in Section 2: Gender Wage Gaps.

Section 2: Gender Wage Gaps

From our descriptive analysis, it is self evident that there exists substantial raw differences in wages, education, and coworker wage environments between men and women. These gaps raise a natural question: to what extent do observable characteristics—such as education and potential experience—account for the wage differences we see, and how much remains unexplained by these factors? Here we begin to attempt to formally investigate these questions by estimating standard wage models and applying the Oaxaca decomposition to separate the portion of the gender wage gap attributable to differences in characteristics from the portion attributable to differences in returns to those characteristics.

2.1 Standard Models and Oaxaca Decomposition

Table 2: Wage Models and Oaxaca Decomposition of the Gender Wage Gap

	(1) Female Dummy	(2) Full Model	(3) Men	(4) Women
Intercept	1.866	0.557	0.491	0.327
	(0.006)	(0.056)	(0.078)	(0.080)
Female	-0.208	-0.271		
	(0.010)	(0.007)		
C(educ)[T.9]		0.275	0.259	0.314
		(0.009)	(0.012)	(0.015)
C(educ)[T.12]		0.680	0.692	0.667
		(0.009)	(0.012)	(0.014)
C(educ)[T.16]		1.515	1.508	1.525
		(0.011)	(0.014)	(0.016)
exp		0.067	0.072	0.069
		(0.011)	(0.015)	(0.015)
exp2		-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)
exp3		-0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)
R-squared	0.024	0.588	0.556	0.618
Adj. R^2	0.024	0.588	0.556	0.618
N	16,969	16,969	10,575	6,394

Notes: Columns (1)–(2) report pooled OLS models; Columns (3)–(4) estimate the same specification separately by gender. Standard errors in parentheses. Oaxaca decomposition uses gender-specific models.

Across the pooled models, the coefficient on the female indicator is negative and statistically significant, indicating that women earn lower wages on average even before conditioning on observable characteristics. In the baseline model that includes only a constant and the female dummy, the coefficient of approximately -0.208 suggests that women earn roughly 20% lower wages than men at period 0. After adding categorical controls for education and a cubic polynomial in experience, the wage gap widens to about 27%, reflecting that women in our sample tend to have slightly higher educational attainment and similar experience levels. Thus, once controlling for these favorable characteristics, the remaining wage gap attributable to gender becomes larger.

The separate regressions by gender show broadly similar returns to education and experience for men and women. Returns to schooling rise with each additional educational category, while experience exhibits diminishing marginal returns. The largest difference lies in the intercepts: men have a higher baseline log wage than women, implying that even at comparable education and zero experience, men start from a higher predicted wage level.

Yet this baseline gap is muddied between differences in the composition of the characteristics of each group (e.g., average education levels) and differences in the returns to those characteristics (e.g., how much additional education translates to wage increases). In other words, while these regressions quantify the wage gap and its relationship to observable traits, part of the wage gap may be due to differences in the average education and experience levels (composition effects), while another being due to differences each group being paid differently for the same education or experience, or actual gender discrimination, which is the object of our study.

To separate the portion of the wage gap arising from differences in average characteristics from the portion arising from differences in how those characteristics are rewarded in the labor market, we apply the Oaxaca decomposition of Oaxaca (1973) using the gender-specific regressions in Columns (3) and (4). Let y_{gi} denote log hourly wages for individual i in group $g \in \{m, f\}$ and let X_{gi} be the vector of observable characteristics (education dummies and a cubic polynomial in potential experience).[1] We model wages as

$$y_{gi} = \alpha_g + X_{gi}'\beta_g + \varepsilon_{gi}, \qquad g \in \{m, f\}. \tag{1}$$

Taking sample means yields

$$\bar{y}_g = \hat{\alpha}_g + \bar{X}_g'\hat{\beta}_g.$$

[1] The intercept is excluded from X_{gi} and treated separately.

The raw gender wage gap is defined as

$$\Delta \equiv \bar{y}_m - \bar{y}_f.$$

Using women as the reference group, the Oaxaca decomposition expresses Δ as

$$\Delta = (\bar{X}_m - \bar{X}_f)'\hat{\beta}_f \; + \; \bar{X}_m'(\hat{\beta}_m - \hat{\beta}_f). \tag{2}$$

The first term,

$$(\bar{X}_m - \bar{X}_f)'\hat{\beta}_f,$$

is the *explained* or *between-group* component: it reflects how differences in average education and experience across men and women would translate into a wage gap if both groups received the same returns estimated for women.

The second term,

$$\bar{X}_m'(\hat{\beta}_m - \hat{\beta}_f),$$

is the *unexplained* or *within-group* component: it captures differences in the returns to these characteristics, evaluated at men's mean characteristics.

Applying equation (2) to our estimates, we obtain an explained component of approximately -0.0623, indicating that women's observable characteristics would predict *higher* wages than men if both groups were rewarded according to the female returns. The unexplained component is about 0.1071, showing that men receive higher returns to education and experience than women. This unexplained component dominates, yielding a total wage gap of roughly 0.0448 log points, or about 4.5%, in favor of men.

2.2 Gender Difference in Experience Profiles

Of course, the existence of a wage gap we identified in 2.1 Standard Models and Oaxaca Decomposition is not monotone–behaviors, attitudes, lawsuits, macro-trends, and many other of the world's moving parts can influence changes in any such gap we have identified and maybe too effects people differently. As such, it become necessary to ask how it evolves over the life cycle. Here, we explore gender differences in the relationship between log wages and potential experience, focusing first on workers with 12 years of education and then extending the comparison across the full education distribution.

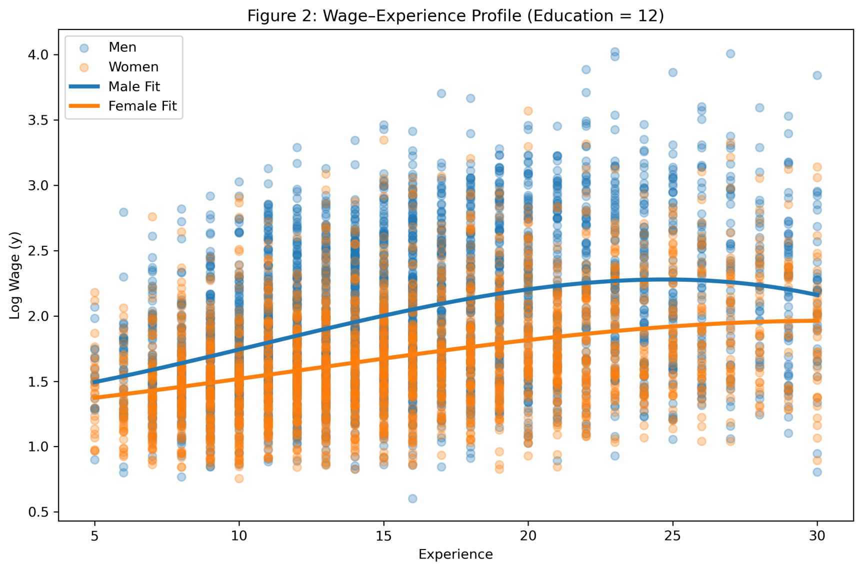
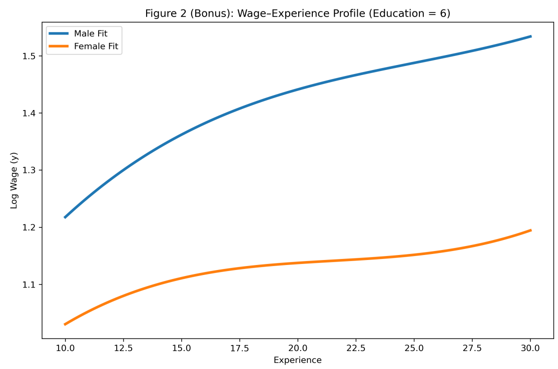
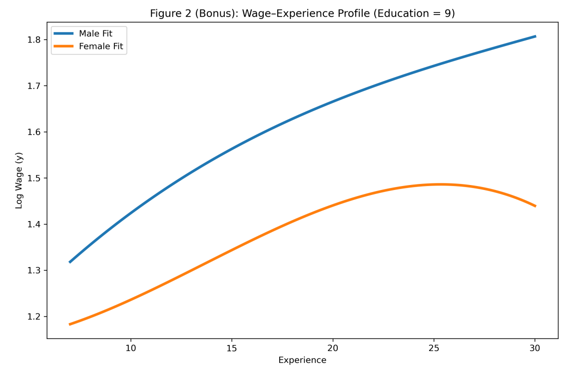


Figure 2: Experience–wage profiles by gender for workers with 12 years of education. Notes: Figure plots log hourly wages against potential experience (5–30 years) and overlays the fitted values from a cubic polynomial in experience, estimated separately for men and women.

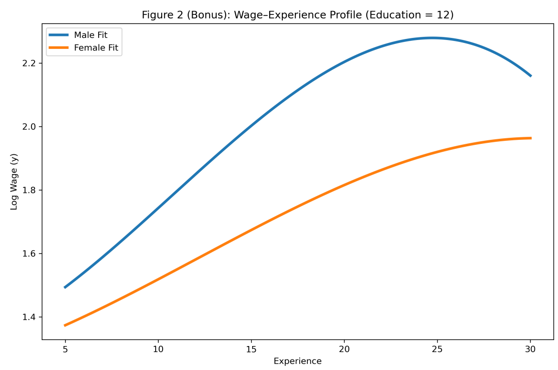
Figure 2 shows that among workers with 12 years of education, men's predicted wages start above women's even at low experience levels, and the gap widens as experience accumulates. The male profile rises more steeply early in the career and peaks at a higher level of log wages, while the female profile is flatter and turns over earlier. For both genders, returns to experience are largest in the early years and then level off, consistent with the diminishing marginal effects of experience estimated in Table 2. Taken together, these patterns are consistent with the Oaxaca result that differences in returns, rather than differences in observed characteristics, play an important role in sustaining the wage gap.



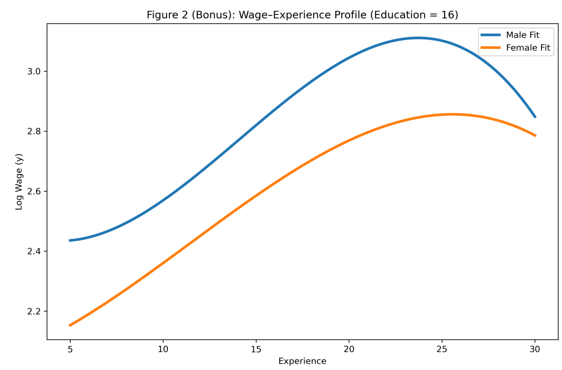
(a) Educ = 6



(b) Educ = 9



(c) Educ = 12



(d) Educ = 16

Figure 3: Experience–wage profiles by gender and education level. Notes: Each panel plots log hourly wages against potential experience for the indicated education category and overlays gender-specific cubic fits in experience.

The bonus panels in Figure 3 show that this pattern is remarkably stable across education groups. At 6, 9, 12, and 16 years of education, men's predicted wages exceed women's at nearly every experience level, and male profiles tend to be steeper in the early career years and peak at higher wage levels. Higher education shifts both curves up, but the gender gap persists and often grows with experience within each education category. These figures complement Table 2 and the Oaxaca decomposition by illustrating, in a more visual way, that women do not only start from a lower baseline but also appear to receive weaker returns to experience over the life cycle, even when we hold education fixed.

Section 3: Gender Wage Gaps Conditional on Coworker Wages

Section 4: Event Study - Wage Changes around Moves

Section 5 (Bonus): Shrinkage

Conclusion

Appendix

References

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review 14*(3), 693–709.