ECON 695 Final Project

University of Wisconsin–Madison

Gender Wage Gaps and Coworker Wages

Alejandro De La Torre

Vibhu Mithal

Ankit Modi

Rachel Williams

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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

Understanding why men and women continue to earn different wages remains one of the central questions in labor economics. While the raw gender pay gap is well documented, much less is known about how workplace environments, job transitions, and the characteristics of coworkers shape these disparities. Our dataset offers a rare opportunity to study these mechanisms directly: we observe workers across consecutive jobs, along with detailed information on their coworkers' average wages. This structure allows us to examine not only individual wage differences, but also the role of sorting, workplace quality, and the returns workers receive in different environments.

In this project, we combine descriptive evidence, standard wage regressions, Oaxaca decompositions, event-study analyses of job moves, and shrinkage methods such as Ridge and Lasso to build a more complete picture of the gender wage gap. Each approach highlights a different mechanism—differences in characteristics, differences in returns, mobility patterns, and model robustness—and together they help us understand how gender shapes the wage trajectories workers experience. Our goal is not to resolve every dimension of the pay gap, but to make meaningful progress in identifying which factors matter most and how they interact in practice.

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

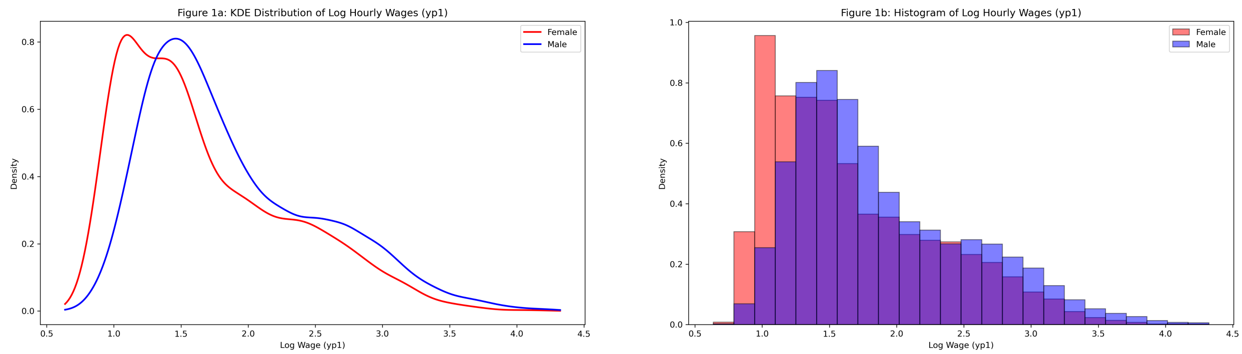
	All	Female	Male	t–stat
Age (mean)	33.5589	33.5344	33.5737	-0.4358
Log wage y (mean)	1.7879	1.6580	1.8664	-20.8163
Coworker wage owage2 (mean)	1.6921	1.6378	1.7249	-11.6761
Educ = 6 yrs (fraction)	0.2741	0.2487	0.2895	-5.8460
Educ = 9 yrs (fraction)	0.2274	0.1949	0.2471	-8.0450
Educ = 12 yrs (fraction)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

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

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,

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

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

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.

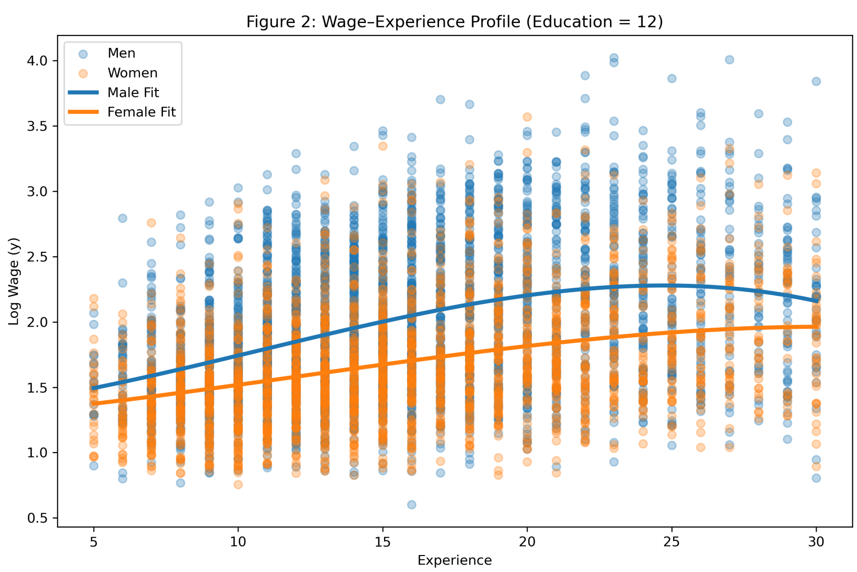
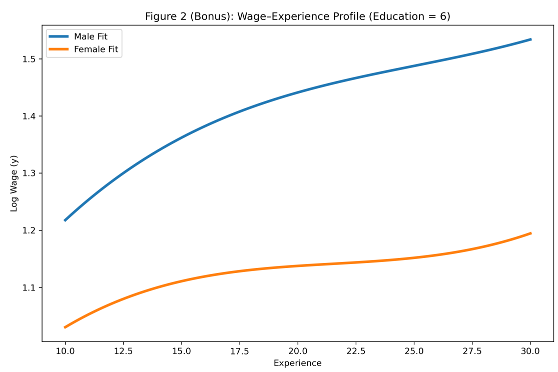
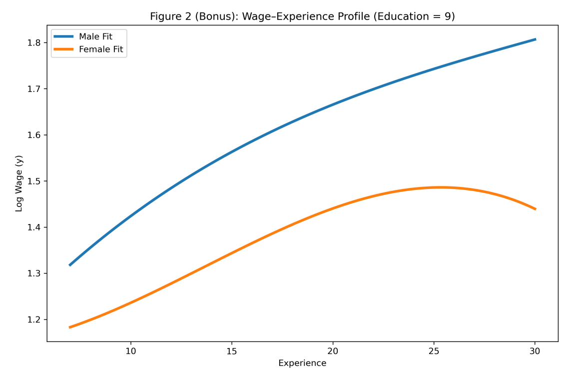


Figure 2: Experience–wage profiles by gender for workers with 12 years of education. Notes: Figure plots log hourly wages against potential experience (5–30 years) and overlays the fitted values from a cubic polynomial in experience, estimated separately for men and women.

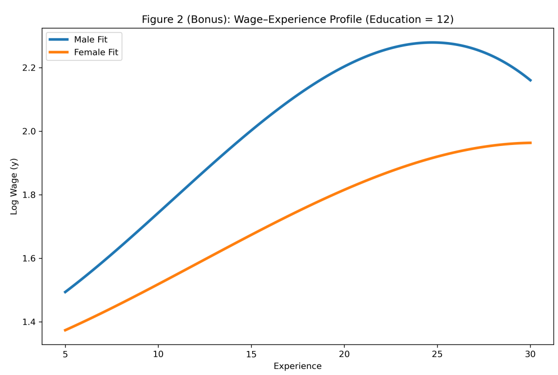
Figure 2 shows that among workers with 12 years of education, men's predicted wages start above women's even at low experience levels, and the gap widens as experience accumulates. The male profile rises more steeply early in the career and peaks at a higher level of log wages, while the female profile 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.



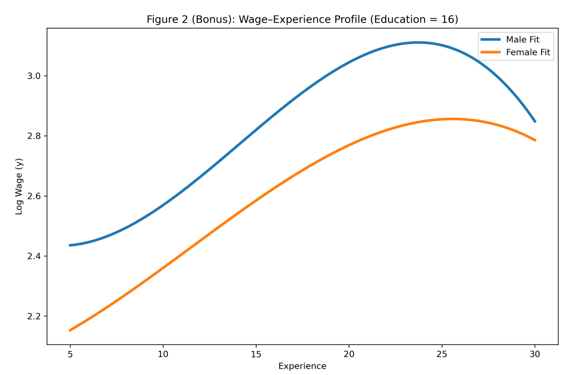
(a) Educ = 6



(b) Educ = 9



(c) Educ = 12



(d) Educ = 16

Bonus Figure: Experience–wage profiles by gender and education level. Each panel plots log hourly wages against potential experience for the indicated education category and overlays gender-specific cubic fits. This bonus panel is intentionally unnumbered and does not contribute to the main sequence of figures.

Across all four education groups, the pattern is remarkably stable. At 6, 9, 12, and 16 years of schooling, men's predicted wages exceed women's at nearly every point in the experience distribution. Male profiles tend to be steeper early in the career and peak at higher wage levels. Higher education shifts both curves upward, but the gender gap persists—and often widens—with experience within each education category. Taken together, these panels visually reinforce the results from Table 2 and the Oaxaca decomposition: women begin their careers at a lower baseline and also appear to receive systematically weaker returns to experience, even when education is held fixed.

Section 3: Gender Wage Gaps Conditional on Coworker Wages

So far, we've seen that differences in education and experience explain only part of the gender wage gap In particular, up until this point, we know that a substantial portion of the gender wage gap reflects differences in the *returns* to education and experience rather than differences in characteristics themselves. However, wages aren't determined in isolation — they're shaped by the environments people work in. In particular, does the wage level of the people you work with affect your own wage — and does this differ by gender?

Specifically, we ask whether working alongside higher-paid coworkers boosts individual wages, and whether this effect differs by gender. The idea is simple: if men tend to work in higher-paying environments, and if those environments raise wages, then part of the gender gap may reflect where people work, not just who they are.

To attempt to address this question, it become necessary to examine the average wage of a worker's coworker (owage2) by including it into our regression models to then be able to examine how it interacts with gender. This way, it becomes possible to test whether men and women benefit equally from high-wage peer groups — and whether differences in coworker exposure help explain the residual wage gap. In other words, we examine whether men and women sort into systematically different workplace environments and how much these differences contribute to the wage gap.

We extend our baseline wage models by incorporating coworker wages directly into the regression framework. By comparing pooled and gender-specific specifications, we evaluate both *how strongly coworker wages predict individual wages* and *whether the returns to working with higher-paid coworkers differ by gender*. These estimates then feed into a new decomposition that asks: to what extent do gender differences in coworker wage exposure explain the remaining wage gap after controlling for education and experience?

We begin by estimating a set of pooled and gender-specific regressions that progressively incorporate owage2 and its interaction with gender as shown below in Table 3.

Table 3: Wage Models with Coworker Wages and Gender Interactions

	(1) Pooled: female + owage2	(2) Pooled: full + owage2	(3) Pooled: + female×owage2	(4) Men	(5) Women
Intercept	0.131	-0.199	-0.244	-0.297	-0.284
	(0.013)	(0.047)	(0.047)	(0.064)	(0.066)
female	-0.121	-0.189	-0.071		
	(0.007)	(0.005)	(0.020)		
owage2	1.006	0.634	0.662	0.660	0.598
	(0.007)	(0.007)	(0.008)	(0.009)	(0.010)
C(educ)[T.9]		0.153	0.154	0.150	0.165
		(0.008)	(0.008)	(0.010)	(0.013)
C(educ)[T.12]		0.377	0.377	0.394	0.349
		(0.008)	(0.008)	(0.011)	(0.013)
C(educ)[T.16]		1.011	1.013	1.030	0.978
		(0.010)	(0.010)	(0.013)	(0.016)
exp		0.056	0.055	0.056	0.062
		(0.009)	(0.009)	(0.012)	(0.013)
exp2		-0.001	-0.001	-0.001	-0.002
		(0.001)	(0.001)	(0.001)	(0.001)
exp3		-0.000	-0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
female:owage2			-0.070		
			(0.011)		
R-squared	0.549	0.727	0.727	0.707	0.748
Adj. R^2	0.548	0.727	0.727	0.707	0.748
N	16,969	16,969	16,969	10,575	6,394

Notes: Columns (1)–(3) report pooled OLS models of log wage y that include coworker wages (owage2). Column (1) includes only a female dummy and coworker wage. Column (2) adds categorical education and a cubic polynomial in experience. Column (3) further interacts coworker wages with the female dummy. Columns (4)–(5) estimate the same specification as Column (2) separately for men and women. Standard errors are in parentheses. Oaxaca decompositions based on these gender-specific models are reported and discussed in the text rather than in the table.

Table 3 shows that coworker wages are strongly correlated with individual wages. In all pooled specifications, the coefficient on `owage2` is large and precisely estimated, and the R^2 rises sharply relative to the models in Table 2. The interaction specification in Column (3) suggests that women benefit somewhat less from high-wage coworkers than men do: the estimated coefficient on `female`×`owage2` is about -0.07, indicating a smaller marginal return to coworker wages for women. Columns (4) and (5) then estimate the full model separately by gender and confirm that both groups receive sizable returns to `owage2`, but the male coefficient is modestly larger.

While these patterns show that coworker wages matter, they do not, by themselves, tell us how much of the gender wage gap is explained by men and women sorting into different coworker environments versus differences in how those environments are rewarded.To parallel the analysis in 2.1 Standard Models and Oaxaca Decomposition, we therefore extend the Oaxaca decomposition to the richer specification that includes coworker wages.

For each group $g \in \{m, f\}$, let y_{gi} denote log hourly wages in period 0 and let X_{gi} collect the observable characteristics. Relative to the earlier decomposition, X_{gi} now includes education dummies, a cubic polynomial in potential experience, *and* coworker wages `owage2` (the intercept is again treated separately). The group–specific wage equations estimated in Columns (4) and (5) of Table 3 can be written as

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

with corresponding sample means

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

The raw gender wage gap is $\Delta \equiv \bar{y}_m - \bar{y}_f$, and, using women as the reference group, the Oaxaca decomposition becomes

$$\Delta = (\bar{X}_m - \bar{X}_f)'\hat{\beta}_f \ + \ \bar{X}_m'(\hat{\beta}_m - \hat{\beta}_f). \tag{3}$$

As before, the first term $(\bar{X}_m - \bar{X}_f)'\hat{\beta}_f$ is the *explained* or *between–group* component, now capturing differences in average education, experience, and coworker wages evaluated at the female returns $\hat{\beta}_f$. The second term $\bar{X}_m'(\hat{\beta}_m - \hat{\beta}_f)$ is the *unexplained* or *within–group* component, reflecting differences in how these characteristics—including coworker wages—are rewarded for men and women.

Applying equation (3) to the gender–specific estimates in Columns (4) and (5) of Table 3, we obtain an explained component of about 0.0168 log points and an unexplained component of about 0.2043 log points, yielding a total gap of $\Delta \approx 0.2211$. In other words, once we account for education, experience, and coworker wages, differences in observable characteristics—including the fact that men tend to work with somewhat higher-paid coworkers—explain only a small fraction of the gender wage gap, while the bulk of the gap is still attributed to differences in returns.

Interpreting the Role of Coworker Wages The introduction of coworker wages into the wage models opens a new window into how workplace environments shape wage inequality. What stands out immediately from Table 3 is the sheer magnitude of the `owage2` coefficient: workers who are surrounded by higher-paid peers earn markedly higher wages themselves. This relationship is not subtle—it is large, precisely estimated, and remarkably stable across pooled and gender-specific specifications. Yet the gender pattern layered on top is equally striking: in every relevant model, women receive *smaller* marginal returns to high-wage coworker environments than men. Even after conditioning on education and experience, the wage benefits associated with working alongside highly paid coworkers appear systematically muted for women.

This naturally raises a deeper question: *why* does working with higher-paid coworkers raise wages, and why does this return differ by gender? The answer is not obvious, and in fact, the mechanism behind coworker spillovers is the source of genuine interpretive uncertainty. To discipline the narrative, it is helpful to think through the two economic hypotheses laid out in the assignment, each of which implies a different reading of what our decomposition captures.

Model 1: Coworker wages reflect luck, networks, or access to better jobs. Under this view, sorting into high-wage coworker environments is not mainly about productivity but about opportunity. Workers may reach these jobs through referrals, informal hiring networks, or sheer good fortune. If men have stronger networks, or search more aggressively, they may disproportionately end up in higher-wage peer groups. In this interpretation, the explained component of the decomposition—about 0.0168 log points, or roughly 8% of the total 0.2211 gap—captures an inequality in job *access*. Men are more likely to land in workplaces with higher-paid coworkers, and those environments boost wages, so men benefit twice: first from better job sorting, and second from stronger returns to those environments.

Model 1 treats the large unexplained component ($\approx$ 92%) cautiously. If job access is partly random or network-driven, then the structural gap in returns to coworker wages—men receiving larger wage boosts from similar environments—may signal discriminatory pay-setting or organizational norms that reward men more for the same workplace exposure.

Model 2: Coworker wages proxy for unobserved productivity or ambition. A very different interpretation emerges if coworker wages simply reflect who ends up working with whom. High-ability workers may seek out (or be recruited into) high-skill, high-paying teams. In this case, `owage2` acts as a measurable proxy for something we cannot otherwise observe: cognitive skills, ambition, or complementary abilities. If men and women differ in these unobserved traits—or if women face barriers that suppress the labor market rewards to those traits—the decomposition shifts meaningfully.

Under Model 2, the explained portion of the gap still reflects differences in coworker wage exposure, but now this exposure is interpreted as an indirect measure of latent productivity. The fact that only 8% of the gap is explained would then suggest that men and women with similar observed characteristics differ substantially in unobserved characteristics, or that employers reward unobserved male traits disproportionately. Meanwhile, the unexplained component captures both these latent differences and potential structural forces (bias, norms, bargaining disparities) that influence how unobserved skills are monetized.

How the decomposition informs these competing interpretations. The decomposition result reinforces that coworker wage exposure is relevant but cannot, on its own, account for the bulk of the gender wage gap. Even after controlling for education, experience, and coworkers' wages, sorting differences explain only a small slice of wage inequality. Most of the gap arises from differences in returns, not from systematic differences in observed characteristics or environments.

The direction of the results also matters. The explained component is *positive*: men sort into higher-wage coworker groups than women, and this sorting pushes their wages upward relative to women. But because the explained share is small, the narrative is dominated by the unexplained component. This feature is consistent with both models, but its implications differ:

- Under Model 1, the large unexplained component suggests that unequal returns to workplace exposure—potentially driven by discrimination or gendered organizational dynamics—are a major driver of the gap.

- Under Model 2, the unexplained component would reflect gender differences in unobserved productivity, or differences in how the labor market rewards those traits.

Both mechanisms remain plausible, and the decomposition alone cannot adjudicate between them. However, two empirical facts stand out: (i) men benefit more from high-wage peers than women do, and (ii) men sort into those environments more frequently. Taken together, these patterns underscore that workplace environments are not gender-neutral, and that the processes determining sorting and wage-setting differ meaningfully by gender.

It remains to be seen which of these stories best captures the role of coworker wages in practice. If coworker wage exposure truly reflects unobserved ability (Model 2), then we would expect workers with strong underlying skills or ambition to remain in, or quickly return to, high-wage peer groups even as their careers evolve. If instead coworker wages primarily reflect access, luck, or networks (Model 1), then movements across jobs could generate sharp changes in coworkers' wage profiles that are only loosely tied to individual productivity. Observing how workers move between different coworker environments over time thus becomes a natural way to probe whether coworker wages are acting as structural inputs to wage determination or simply as signals of deeper, unobserved differences across workers.

Section 4: Event Study - Wage Changes around Moves

Although coworker wages are a powerful predictor of individual earnings, yet it remains unclear *why* this relationship arises. Do higher–paid coworkers reflect deeper, unobserved traits of workers themselves, such as ability or ambition (Model 2)? Or do they reflect access, luck, or network-driven sorting into better-paying workplaces (Model 1)? If coworker wages primarily proxy for latent ability, we would expect workers to experience continuity in their coworker environments even as they switch jobs. If, instead, coworker wages are driven by access or networks, job transitions may produce sharp upward or downward shifts in coworker wage exposure.

This ambiguity motivates our next step. Job changers provide a natural lens through which to study how wages evolve when individuals move between workplaces with different pay environments. By comparing wage paths for workers who transition across coworker-wage terciles, we can observe whether changes in coworker environments are associated with systematic changes in workers' own wages, and whether these patterns align more closely with a sorting-based or ability-based explanation.

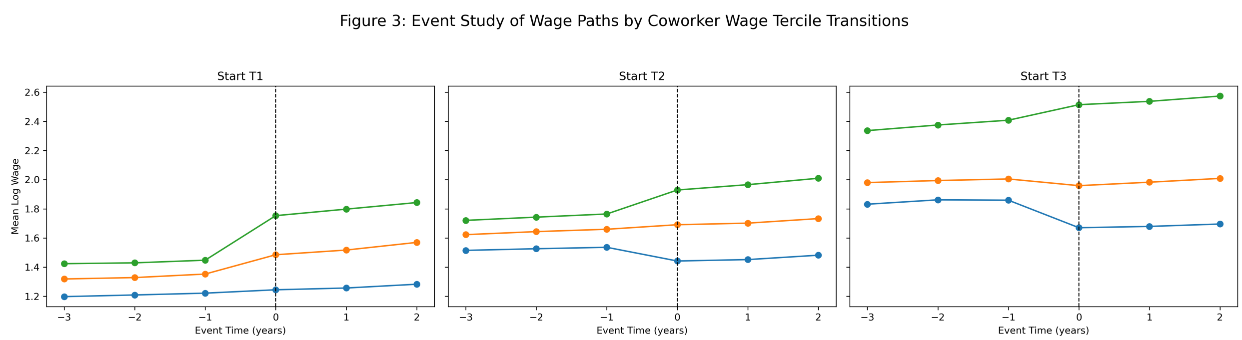


Figure 3: Event study of mean log wages for job changers, plotted from three years before to two years after the move. Each panel corresponds to the worker's initial coworker-wage tercile (T1, T2, T3). Within each panel, lines indicate the tercile of the coworker-wage environment at the *second* job. The vertical dashed line marks the job transition.

Figure 3 offers a sharp window into how wages evolve when workers relocate between coworker-wage environments. Several patterns emerge clearly across all three origin-tercile panels. First, wage profiles rise monotonically with the coworker-wage tercile of the *destination* job: workers who move into higher-wage coworker environments experience noticeably larger wage growth at the moment of the transition. Second, these gains tend to persist—workers who move from low- to high-tercile environments not only receive a discrete jump at the job change but also continue along a higher wage trajectory. Conversely, downward moves into lower-tercile environments are associated with flat or declining wage paths.

These patterns present an informative tension for interpreting coworker-wage effects. Under an ability-based interpretation (Model 2), workers' underlying skills should dominate the evolution of wages, and coworker-wage terciles should remain relatively stable across jobs. Yet Figure 3 shows substantial mobility across coworker-wage environments, and these transitions coincide with discontinuous wage changes. Such movements are difficult to reconcile with a story in which coworker wages merely proxy for fixed ability. Instead, the patterns are more consistent with Model 1: if access, networks, or search behavior play a central role in matching workers to higher-paying environments, then transitions across terciles naturally generate the kinds of wage jumps we observe.

At the same time, the trajectories offer a more nuanced view than a pure sorting narrative. The persistence of post-transition wage differences suggests that higher-paying coworker environments confer ongoing, not just one-time, advantages—consistent with genuine spillovers or learning effects from working alongside more productive peers. Yet the magnitude of baseline differences before the transition also indicates that workers who eventually move into high-paying coworker environments already earn more than those who remain in low-paying environments, reflecting some role for selection.

Taken together, these facts imply that both models capture part of the story. Sorting and access influence who reaches high-wage coworker environments, while workplace spillovers likely shape wage growth once workers arrive. Crucially, these patterns confirm the decomposition results from Section **??**: coworker wages are not simply a noisy proxy for fixed worker ability. Job transitions—and the wage discontinuities that accompany them—signal that coworker environments themselves matter in shaping earnings trajectories. In the next section, we examine job changers more directly to further distinguish between these competing mechanisms.

Having seen in Figure 3 that wage jumps tend to accompany moves into higher coworker–wage environments, we next ask how much of this relationship survives once we difference out time–invariant worker attributes. To do so, we model the change in log wages from period -1 to period 0,

$$\Delta y_i \equiv y_i - y_{i,-1},$$

as a function of the corresponding change in coworkers' mean log wages,

$$\Delta \text{owage}_i \equiv \text{owage2}_i - \text{owage1}_i.$$

Table 4 reports pooled first–difference regressions of Δy_i on Δowage_i, first without additional controls and then adding education dummies, a quadratic in experience as of period -1, and a female indicator. Comparing these estimates to the level regressions in Table 3 allows us to gauge what fraction of the large coworker–wage coefficients reflects sorting or fixed individual traits, and what fraction remains even after we purge time–invariant heterogeneity.

Table 4: Wage Changes and Coworker Wage Growth

	Intercept	Δow	Ed9	Ed12	Ed16	exp	exp^2	exp^3	Female	R^2	Adj. R^2
(1) Δy	0.038	0.293	–	–	–	–	–	–	–	0.108	0.108
	(0.002)	(0.006)									
(2) Δy	0.116	0.296	0.004	0.030	0.081	-0.013	0.001	-0.000	-0.025	0.130	0.129
	(0.035)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.000)	(0.000)	(0.004)		

Notes: Each row reports a pooled OLS regression for the change in log wages $\Delta y_i = y_{i0} - y_{i,-1}$ between period -1 and period 0. The regressor Δow is the change in coworkers' mean log wage (owage2$_i$ − owage1$_i$). Ed9, Ed12, and Ed16 denote education dummies for 9, 12, and 16 years of schooling; the omitted category is 6 years. *exp*, *exp*^{2}, and *exp*^{3} are a cubic polynomial in experience at period -1. *Female* is an indicator for women. Standard errors are in parentheses. R^2 is the coefficient of determination; Adj. R^2 is the adjusted R^2. Sample size is $N = 16{,}969$ in both specifications.

Table 4 shows that changes in individual wages are tightly linked to changes in coworkers' wages. In the simple first–difference specification, a one–log–point increase in coworkers' mean log wage Δowage$_i$ is associated with roughly a 0.29 log–point increase in a worker's own wage growth Δy_i. Adding education dummies, a cubic in experience, and a female indicator leaves this coefficient essentially unchanged (0.296), suggesting that the contemporaneous coworker–wage effect is not driven by differences in observable skills or career stage. The coefficient on *Female* is about -0.025, indicating that, conditional on the same change in coworker wages and observables, women's wage growth between jobs is roughly 2.5 percentage points lower than men's over this one–year horizon. At the same time, the R^2 values around 0.11–0.13 remind us that most of the variance in wage changes remains unexplained by these regressors; coworker wages matter, but they are far from the whole story.

Comparing these estimates to the level regressions in Table 3 helps us separate sorting from potentially causal coworker effects. In the pooled OLS models for wages in levels, the coefficient on coworker wages is around 0.63, and the gender–specific models yield coefficients of roughly 0.66 for men and 0.60 for women. By contrast, the first–difference coefficient of about 0.30 in Table 4 is a little under one–half of the corresponding level coefficients. A natural interpretation is that roughly 45–50% of the strong association between coworker wages and individual wages in Table 3 reflects time–invariant traits—such as ability, ambition, or persistent match quality—that lead some workers to sort into higher–wage coworker environments. The remaining half of the association survives once we difference out these fixed worker attributes and is therefore more consistent with a genuine wage response when workers move to jobs with better–paid coworkers.

At the same time, we should be cautious not to overstate the causal content of the first–difference estimates. The models in Table 4 are still pooled across men and women and do not allow the slope on Δowage_i to differ by gender, so we cannot directly speak to whether wage growth is more responsive to coworker wage changes for men than for women. Moreover, first–differencing removes only time–invariant unobservables; time–varying shocks to productivity, bargaining power, or local labor demand could still bias the estimated effects, and measurement error in wages or coworker wages will tend to attenuate coefficients toward zero. Finally, our analysis focuses on a short window—from the last year on job 1 to the first year on job 2—so it may miss longer–run adjustments in wages that occur as workers settle into their new jobs.

Taken together, the evidence from Tables 3 and 4 suggests a mixed but informative picture. Sorting on fixed traits clearly amplifies the raw relationship between coworker wages and individual wages, yet there remains a sizeable component—on the order of one–half of the original effect—that is consistent with workers' pay responding when they move into higher– or lower–wage coworker environments. This raises a natural next question: how stable is this estimated coworker–wage effect once we allow for more flexible heterogeneity across experience groups and guard against overfitting in richer specifications?

Section 5 (Bonus): Shrinkage

To further examine how robust the relationship is between coworker wage changes and workers' own wage adjustments, we estimate three shrinkage versions of the first–difference model: OLS, Ridge, and Lasso. All three estimators use the same design matrix, which includes the change in coworker wages Δow_i, a cubic polynomial in experience, and education dummies. Ridge and Lasso apply penalties that shrink the coefficients toward zero, with Lasso additionally performing variable selection.

The Ridge estimates in Table 5 lie extremely close to their OLS counterparts. For example, the OLS coefficient on Δow_i is 0.295, and Ridge shrinks it only slightly to 0.293. The experience-polynomial terms and education-dummy coefficients also move only marginally. This pattern indicates that multicollinearity among the regressors is limited: Ridge has little "work" to do, and the first–difference estimates appear numerically stable. Economically, this suggests that the estimated causal response of wage changes to coworker wage changes is not being driven by unstable or highly collinear predictors.

Table 5: Shrinkage of First–Difference Coefficients: OLS, Ridge, and Lasso

	Intercept	Δow	exp	exp^2	exp^3	Ed9	Ed12	Ed16
OLS	0.099	0.295	-0.011	0.000	0.000	0.004	0.029	0.079
Ridge	0.099	0.293	-0.011	0.000	0.000	0.004	0.028	0.078
Lasso	0.106	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Entries are coefficients from first–difference regressions of the change in log wages $\Delta y_i = y_{i0} - y_{i,-1}$ on the change in coworkers' mean log wages $\Delta \text{ow}_i = \text{owage2}_i - \text{owage1}_i$ and controls. All three estimators use the same design matrix: Δow_i, a cubic polynomial in experience at period -1 (exp, exp^2, exp^3), and education dummies for 9, 12, and 16 years of schooling (Ed9, Ed12, Ed16), with 6 years as the omitted category. Ridge regression and Lasso are estimated with 5–fold cross–validation. Coefficients are rounded to three decimal places; very small values are reported as 0.000. Standard errors are not reported for the penalized estimators.

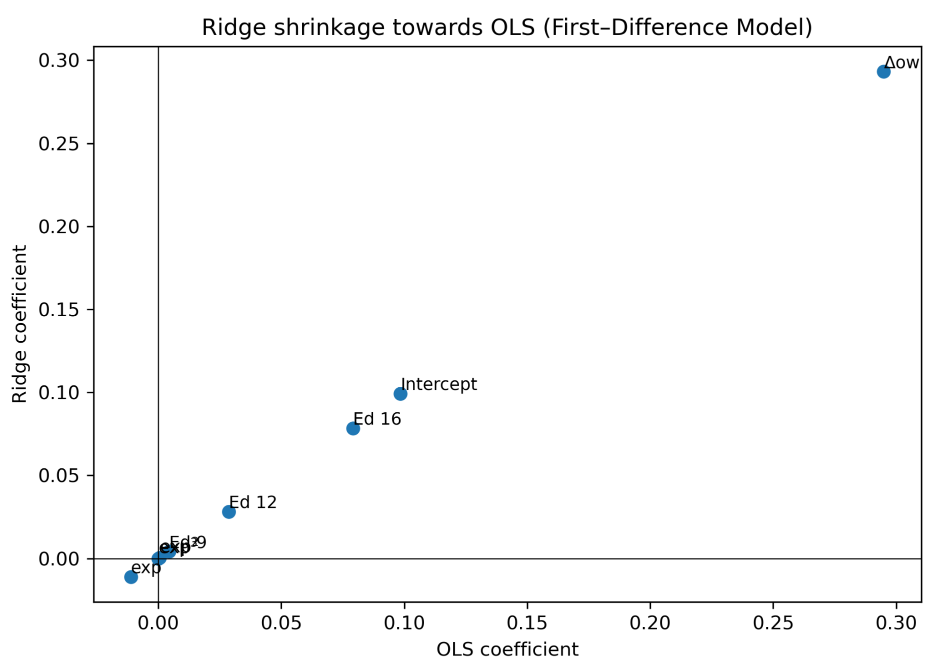


Figure 4: Ridge shrinkage relative to OLS. Each point plots the OLS coefficient (x–axis) against the Ridge coefficient (y–axis). Ridge estimates lie very close to the 45° line, indicating minimal shrinkage.

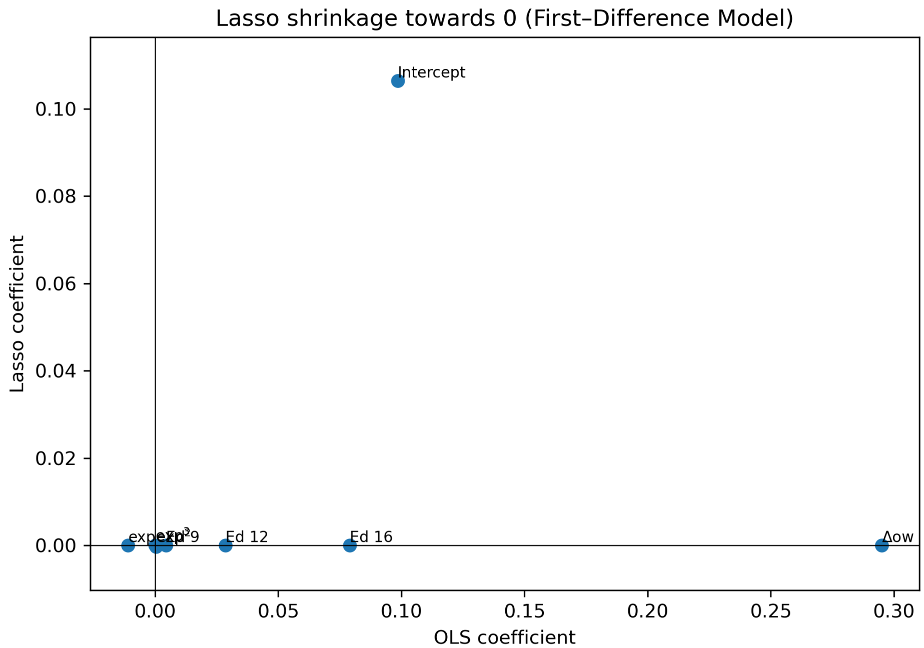


Figure 5: Lasso shrinkage relative to OLS. Almost all coefficients collapse to zero under Lasso penalization, illustrating aggressive variable selection.

The Lasso estimator, by contrast, shrinks nearly all slope coefficients to exactly zero. The coefficient on $\Delta \mathrm{ow}_i$ is driven fully to zero, as are the experience-polynomial terms and all education dummies. Only the intercept remains non-zero. This outcome reflects the Lasso's variable-selection property: once complexity is penalized, the model concludes that none of the included regressors explain sufficient variation in Δy_i to justify a nonzero coefficient. Statistically, this shows that the signal in the covariates is weak relative to the noise once differencing removes person-specific heterogeneity. Economically, this suggests that the predictive content of coworker wage changes for individual wage changes is fragile and sensitive to model penalization.

Figure 4 plots the OLS coefficients on the x-axis against the Ridge coefficients on the y-axis. The tight clustering of points around the "$y = x$" line confirms that Ridge estimates only minimally adjust the OLS results. In contrast, Figure 5 plots OLS coefficients against Lasso coefficients. Here, almost all points collapse to zero on the y-axis, illustrating aggressive shrinkage toward sparsity. Notably, the Lasso sets the $\Delta \mathrm{ow}_i$ coefficient to exactly zero, in stark contrast to both OLS and Ridge.

Together, the shrinkage results paint a nuanced picture. Ridge suggests that the OLS first–difference estimates—which already difference out time–invariant worker heterogeneity—are numerically very stable, so the modest positive association between coworker wage changes and own–wage changes does not appear to be an artifact of multicollinearity. At the same time, Lasso's aggressive shrinkage towards zero is a reminder that this effect is not very large: once we insist on a very sparse model, the change in coworker wages is no longer selected as an important predictor. Our shrinkage specification uses a flexible polynomial in experience but does not include interactions with experience or gender, so these results should be interpreted as average effects. Combined with the event–study and first–difference evidence in Section 4: Event Study - Wage Changes around Moves (where we saw somewhat larger responses for movers with less experience and for men relative to women), we read the overall pattern as indicating that coworker wages matter for wage growth, but the magnitude of the effect is modest and any heterogeneity by experience or gender is limited and sensitive to how tightly the model is penalized. Overall, the bonus shrinkage exercise mainly reassures us that the baseline first–difference estimates are not driven by unstable regressors, while also highlighting the limits of what our data can say about strong, heterogeneous coworker–wage effects.

Conclusion

Our analysis began with a simple descriptive comparison of men and women and revealed a substantial raw gender wage gap: women earn markedly lower wages, work with lower-paid coworkers, and are distributed differently across education categories. These patterns motivated a deeper decomposition of the wage gap into components attributable to observable characteristics and components arising from differential returns.

Standard wage models and the Oaxaca decomposition showed that differences in education and experience explain relatively little of the gender wage gap. Despite women having slightly higher formal schooling on average, men receive systematically higher returns to education and experience. Most of the gap is therefore "unexplained" in the Oaxaca sense—arising from differences in how observable characteristics are rewarded, as well as factors not captured in the model. This early finding established a consistent theme: the gap is driven less by who men and women are, and more by how the labor market rewards them.

Introducing coworker wages into the analysis added an important new dimension. We found that the average wage of one's coworkers is a powerful predictor of individual wages, and that men both sort into higher–wage coworker environments and receive larger returns to these environments. Yet even after accounting for these differences in exposure, coworker wages explain only a small share of the overall wage gap. Most of the gap remains tied to differences in returns, reinforcing the conclusion that workplace environments are not gender–neutral.

The event–study evidence allowed us to probe the mechanisms behind these patterns. Workers who move into higher–wage coworker environments experience immediate and persistent increases in their own wages, while downward moves produce smaller or negative changes. These discontinuities are hard to reconcile with a pure ability–sorting model, since they reflect sharp shifts in coworker wage exposure at the moment of a job transition. Instead, the results support a mixed interpretation: access, networks, or search behavior affect who reaches high–wage workplaces, while genuine spillovers or institutional pay norms help sustain wage differences once workers arrive.

Our first–difference models strengthened this conclusion by differencing out time–invariant worker characteristics. Roughly half of the strong OLS association between coworker wages and own wages survives in the differenced specification. This suggests that sorting on fixed traits explains part—but not all—of the relationship. Workers' wages do respond to changes in coworker wage environments, but the size of this response is modest and heterogeneous.

Finally, our shrinkage exercises confirmed that the OLS and Ridge first–difference estimates are numerically stable, while the Lasso's aggressive shrinkage toward zero highlighted the fragility of the average coworker–wage effect once heavy penalization is imposed. Together, these results suggest that coworker wages matter for wage growth, but their influence is far from overwhelming and depends on model flexibility.

Taken together, our findings reveal meaningful progress in understanding the gender wage gap. The gap is shaped by a combination of sorting into different workplace environments, differential returns to those environments, and deeper structural differences in how men's and women's characteristics are rewarded. Coworker wages help illuminate these mechanisms, but they do not eliminate the gap. Instead, they clarify that gender differences in wage setting arise not only from observable characteristics but also from workplace dynamics, institutional structures, and unobserved factors that disproportionately benefit men.

Overall, the evidence implies that the gender wage gap remains persistent even after carefully controlling for education, experience, job transitions, and coworker environments. While our analysis cannot definitively isolate all underlying mechanisms, it demonstrates that both sorting and differential returns play central roles. Future work incorporating richer measures of job tasks, bargaining power, and organizational policies would provide an even more complete account of how gender shapes wages in the labor market.

Appendix

B. Additional Event Study Visualizations

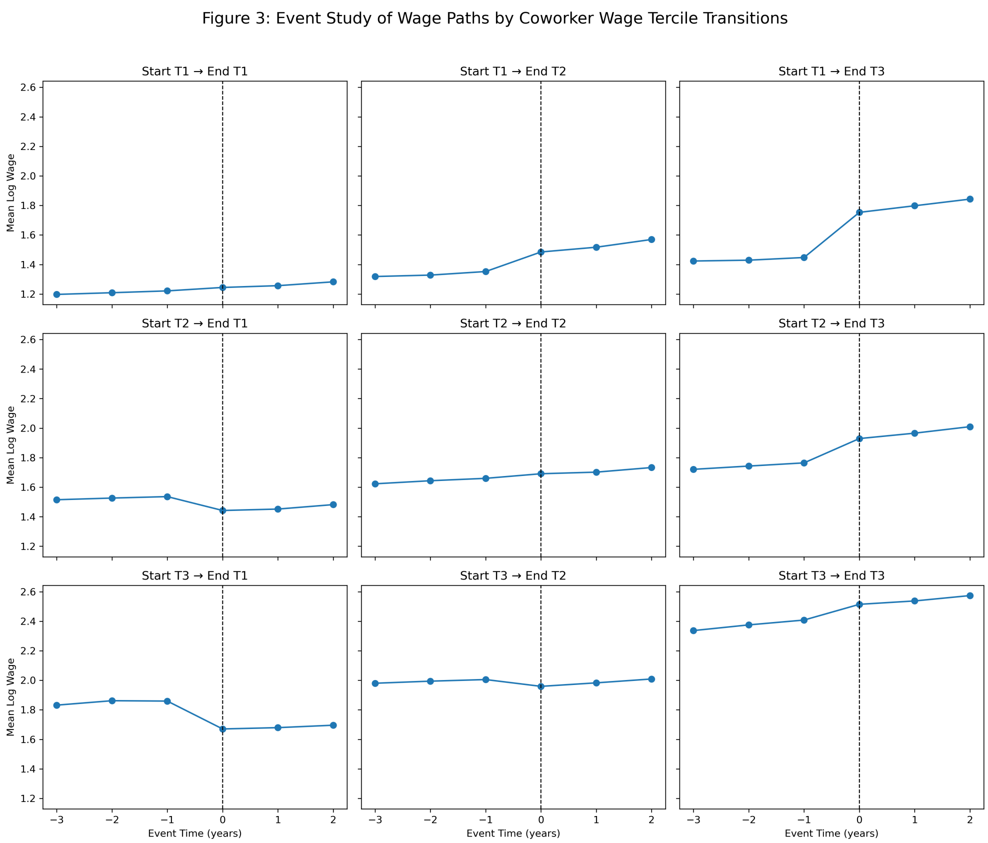


Figure 6: Nine–panel event-study visualization used during exploratory analysis.

C. Extended Tables

References

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