Sorting Out the Gender Gap for High Skilled Workers

Seoyeon Jo
Visiting Assistant Professor
Wesleyan University
joseoy.econ@gmail.com

Donna K. Ginther
Roy A. Roberts & Regents Distinguished Professor
Research Associate, National Bureau of Economic Research
dginther@ku.edu

March 25, 2026

Abstract:

This study examines the gender salary gap and job transitions for skilled women using data from the National Survey of College Graduates (NSCG) spanning 2010 to 2023. We investigate the effect of major selection, occupations, job sector, and family characteristics on the gender salary gap for skilled workers. We find that women are only a third as likely as men to major in math-intensive science fields. We also find that women are 22 percentage points less likely to be employed in the private/for profit sector—the highest paying sector in the economy. We are the first to control for job sector in the analysis of the gender salary. Our results show that majors, job sector, and the marriage and child penalties for women together explain 74% of the gender salary gap. Job sector explains close to 40% of the gender gap. Given the large effect of job sector, we examine whether women are less likely to work in the private sector and more likely to leave. We find that women are 17 percentage points less likely to start working in the private sector, but this is mostly explained by college major. If a woman is first observed in a private sector job, she 1.8 times more likely to leave private sector employment compared with a man. We posit that the private sector has higher numbers of "greedy jobs," that discourage women from participation.

JEL Codes: J16, J31, J44

Key words: Gender gap, private sector, high skilled workers

Acknowledgements: Ginther also acknowledges funding from NIH grant 1P20GM152280 to Heather Desaire and Ginther. We thank Carlos Zambrana for assistance with hazard estimation. Any mistakes are our responsibility.

1. Introduction

Since 1995, women have earned the majority of bachelor's degrees in the U.S. and the gap continues to grow (Hurst 2024). Despite these significant human capital investments, our analysis shows that prime-aged women with a bachelor's degree or higher earn 25% less than men with similar education levels. This study examines the factors influencing the gender salary gap for skilled women using data collected on college graduates in the United States over the past decade. Our research shows that the gender gap for skilled women is associated with sorting out of math-intensive STEM majors and out of the private sector in part due to family considerations.

Previous research has shown that educational sorting plays a role in shaping occupational choices. Ceci et al. (2014) and Kahn and Ginther (2018) show that girls and college students are less likely to pursue math-intensive majors, which may influence their future career paths. They find that girls mathematics course-taking and interests diverge with boys in high school. Once in college, girls are less likely to major in the math-intensive fields of geoscience, engineering, economics mathematics and computer science, and physical sciences (GEMP fields) and are highly concentrated in life science, psychology and social sciences excluding economics (LPS) fields.

Other researchers have examined the role of college major in explaining the gender earnings gap. Humphries, Joensen, and Veramendi (2024) show that women sort into lower-paying majors in Sweden and these choices explain over half of the gender wage gap. Likewise, Sloane, Hurst, and Black (2021) use the American Community Survey data with reported undergraduate major and find that women sort into lower-paying majors. Using data from Texas on college graduates linked to earnings records, Imberman et al. (2026) show that women are less likely than men to major in high-earning fields such as business, economics, engineering,

and computer science and that these differences explain about one quarter of the gender gap. Using the same data employed in this study, Altonji et al (2025) found that controlling for major explained close to one quarter of the gender wage gap, and that controlling for highest degree also reduces the residual gap. Taken together, these studies show that gender differences in major explain between 25% - 50% of the gender gap for skilled workers.

Researchers have also found that occupations explain an additional portion of the gender wage gap. After adding controls for occupation in addition to major, Sloane, Hurst and Black (2021) explain 60% of the gender wage gap. Altonji et al (2025) and Imberman et al (2026) also find reductions in the gender gap after controlling for occupation. Rosenball et al (2025) show that 30% of the contribution of firms to the gender gap is due to omitting occupations from the analysis. They also attribute the gender pay gap to women being concentrated in lower-paying industries. Binder et al (2025) finds that among college graduates at elite institutions, controls for major, occupation, and hours of work explain almost all of the gender gap. However, at less selective institutions, these covariates explain less of the gap.

Some occupations and industries place greater demands on their workers than others. Coser (1974) and Goldin (2006)'s concept of "Greedy Institutions" argue that "greedy jobs" demand full attention and reduce the time available for competing roles such as family obligations. Bertrand, Goldin and Katz (2010) showed that female MBAs and lawyers were more likely to drop out of the labor force or work fewer hours after having children. Cortes and Pan (2017) used a panel of occupations requiring long hours (50+) across countries and found that married women were less likely to work in those occupations. Noonan, Corcoran and Courant (2005) found that female lawyers earn less and attribute this to fewer hours of work. Even if

they obtain a STEM major, Delaney and Devereux (2022) show that women in the UK are more likely to leave STEM occupations for jobs in health and education.

Additionally, jobs requiring client contact or long hours have fewer women, and there is a growing gender earnings gap over time (Goldin and Katz 2011). These findings suggest that factors related to work-family balance and occupational sorting contribute to the gender salary and employment gaps. Furthermore, Goldin et al. (2017) highlight the expanding gender earnings gap over the lifecycle, with most of the widening occurring in the first seven years after leaving school. They attribute 44% of the gap to disproportionate shifts by men into higher-earning positions, industries, and firms, and 56% to differential advances within firms. The widening gap is greater for married individuals and certain sectors, while high school graduates without college degrees experience less widening but with similar patterns.

Bayard et al. (2003) find that women tend to sort into low-paying occupations, establishments, and industries, explaining a significant portion of the gender gap in the 1990s. Card et al. (2016) observe a similar pattern in Portugal, where women sort into lower-paying firms. Sorkin (2017) reveals that women have different offer distributions, often with a higher concentration of lower-paying firms. Faberman, Mueller, and Şahin (2026) further show that women are more likely to work in higher-amenity occupations and experience larger amenity gains but smaller wage gains when switching occupations, consistent with systematic movement toward "family-friendly," lower-pay jobs over time. Similarly, Goldin (2016) finds that pharmacy attracts women because technological changes and the growth of pharmacy employment in retail chains and hospitals has contributed to a narrower gender earnings gap in pharmacy.

The current literature shows significant evidence of women sorting away from higher-paying, mathematics-intensive majors as well as demanding occupations such as law and business. Using data from the National Survey of College Graduates (NSCG) we investigate the inter-related roles of major selection, occupations, employment sector sorting, and family characteristics on the gender salary gap for skilled workers. Unlike previous studies, we control for employment sector—whether the employer is in the private sector, government, education, or non-profit. Our analysis finds that majors and employment sector explain the majority of the gender gap. Using the 2023 NSCG, the private, for-profit sector has a significantly lower representation of women compared to men (69% compared with 46%), but the private sector has the highest salaries among all sectors. Our results show that gender differences in major contribute to one-third of the explained salary gap, and gender differences in employment sector contribute to 38%. Adding controls for family characteristics contributes to 27% of the explained gender gap. Controlling for marital status, children under the age of six, and children ages 7-18, we find a significant marriage and older child penalty for women onlly. After adding these rich levels of controls, the unexplained gender salary gap falls from 25% to just under 4%.

Additional analysis shows that the gender salary gap differs significantly by age. Older women face a larger salary gap of 31% and after controlling for covariates the unexplained gap is 6%. Major and employment sector contribute less to the explained salary gap while the female marriage and child penalties contribute to 40% of the explained gap.

Given the importance of employment sector, we use panel data from the 2010—2019 waves of the NSCG to examine gender differences in job mobility. We find that women are less likely to start their careers in the private sector and most of the gender gap is explained by major. Conditional on private sector employment, women are more likely to leave that sector, more

likely to leave the labor force, and more likely to change jobs. Taken together our results suggest that the disamenities of working in greedy professions such as business or law found in the previous literature, may generalize to the entire for-profit sector.

The remainder of the paper is organized as follows. Section 2 explains data and section 3 describes the methods. Section 4 examines the gender salary gap, and section 5 investigates job mobility. Section 6 concludes.

2. Data on Prime-Aged Skilled Workers

This study utilizes data from the National Survey of College Graduates (NSCG) to examine the distribution of skilled women across major fields and investigate gender differences in salaries. The NSCG is a biennial survey that provides comprehensive data on individuals with a bachelor's or higher degree, with a specific focus on those with education and employment in science or engineering. The survey collects detailed information on various demographic characteristics, educational background, and employment status. The NSCG has a decade-long panel structure, allow us to follow workers over time. For this analysis, we use data from the 2010—2023 waves of the NSCG.

The dataset includes demographic characteristics such as sex, age, race and ethnicity, citizenship status, foreign-born status, marital status, and the number of children, particularly whether they have children under the age of six. Educational background information covers the degree attained (bachelors, master's or professional) and the field of study (major) for their highest degree. The data includes the major of the highest degree including the life sciences, physical sciences, engineering, social sciences, arts and humanities and nonscience degrees such as business and education. Employment status variables include labor force status, hours of

work, whether individuals work part-time or full-time, occupation, work experience, and job tenure.

Unlike other surveys, the NSCG categorizes employer by sector and size. Employment sector is classified as higher education, K-12 education, business and industry, for-profit (private sector), business and industry, not for profit (non-profit) business and industry, federal government, and state and local government. Employment sector is not measured in other federal surveys, and ours is the first study to consider its impact on the gender salary gap.

We limit our analysis sample for salaries to prime-aged workers (ages 25-55) employed full-time and full-year whose earnings exceed the minimum wage in 2023. We drop individuals whose highest degree is a doctorate because the doctoral labor market is highly specialized. To estimate the hazard rate of being employed in the private sector, two independent datasets were selected based on occupation during the first observation period. The first dataset is comprised of individuals who were initially observed working full-time in the private sector. The second dataset consists of individuals who were initially observed as employed full-time. Both datasets are restricted to individuals aged 25 to 54 and utilize NSCG data from 2010—2019.[1]

Table 1 provides the descriptive statistics for the 2023 NSCG. The dataset includes individuals with bachelor's and master's degrees, with the age of samples restricted to 25-54. Without any restrictions, the simple wage gap ratio between men and women is observed to be 76%. Women have higher levels of education—36% of women have a master's degree compared with 30% of men and slightly more women have professional degrees than men. However, women are less likely to major in geoscience, engineering, economics math and computer science, and physical science (GEMP fields). Only 10% of women have GEMP

[1] We do not include the 2021 survey in the panel data set because that occurred during the COVID-19 pandemic. The longitudinal data set is not yet available for the 2023 NSCG.

majors compared to 30% of men. Men are more likely to be married and have younger children than women.

Figure 1 shows females as a percentage of males in the 2013, 2019, and 2023 NSCG surveys. In each survey year, women's salaries are roughly 75% of men's. The earnings gap is larger at 70% in 2023. As mentioned previously, women only one third as likely to major in GEMP fields but are 39% as likely to be employed in GEMP occupations. Women's employment in the private sector is 72% of men's but that gap has narrowed by nine percentage points in the last decade. Women are now almost equally likely to work in large employers defined as employer size greater than 1,000 employees, and women are 18% more likely to be working at small employers defined as employer size < 24 employees.

Figure 2 shows the distribution of full-time workers across employment sector in the 2023 NSCG. Women are more likely to be employed in K-12 education (18% compared to 6%), higher education (6% compared to 4%), non-profits (15% compared to 7%) and state and local government (10% compared to 8%). Figure 3 shows average salaries by employment sector. The private sector pays the highest salaries at over $120,000 per year, followed by the federal government and higher education. The K-12 education sector pays the least at just over $60,000 per year.

Figure 4 shows the gender salary gap in 2013 and 2023 by sector. The gender gap varies by sector, with larger gaps in the non-profit and private sectors. The gender salary gap narrowed in higher education and state and local government between 2013 and 2023. The gap grew substantially in the non-profit and federal government sectors. The gender salary gap in the private sector narrowed by about 3 percentage points in the past decade, but women still earn only 82% of men's salaries in the private sector—the second largest gap.

Table 2 shows the distribution by gender and age category a variety of labor force measures for high skilled individuals ages 25—54. The gender salary gap doubles when comparing the youngest and oldest workers. When women are in their 30s and 40s that are twice to three times as likely to be out of the labor force. Women are also significantly more likely to work part-time. There is no difference between men and women in the likelihood of working in a job that is closely related to their degree. Younger men are more likely to be working in a job unrelated to their degree, but this difference narrows with age. Younger and middle-aged women are more likely to change employers than men. While women are less likely to work in the private sector, the gap grows with age. Women work 2 to 4 hours less per week than men. There are no appreciable differences between men and women in job tenure.

Taken together, our results show a stable gender salary gap among prime-aged, full-time workers, significant salary differences across employment sector, and significant gender differences in academic majors and employment sectors. We next use a variety of methods to examine these gender differences.

3. Empirical Methods

The empirical methodology employed in this study aims to provide a comprehensive analysis of the gender wage structure and evaluate gender differences in job mobility. The analysis begins by estimating wage regressions that incorporate a range of variables including demographic characteristics, major of the highest degree, employment sector, and demographic characteristics including marriage and children. To further understand the factors contributing to the gender salary gap, a salary decomposition approach developed by Oaxaca (1973) is utilized. In addition, we use an approach developed by Gelbach (2016) that accounts for the sequence

sensitivity of including convariates. These approaches allow us to determine the factors that explain gender differences in salaries.

Given the significant gender differences in employment in the private sector, we use hazard models to estimate the likelihood of staying in the private sector and labor force. The duration of remaining in the private sector is estimated using the Cox proportional hazards model, which captures the instantaneous risk of leaving jobs in the private sector, the labor force, or changing employers at a given time (t). The hazard function ($h_i(t)$) is a function of the baseline hazard ($l_o(t)$) and covariates (x) included in equation 3.2.

$$h_i(t) = \lambda_0(t)exp(\beta_i x_{i1} + ...\beta_k x_{ik}) \quad (1)$$

The baseline hazard function is left unspecified and represents the hazard function for an individual with covariates equal to zero. The covariates included in equation (1) influence the scale of the hazard rate and are not time-dependent. The analysis also incorporates additional covariates related to demographic and employer characteristics and employment background to provide a comprehensive understanding of the factors influencing job retention and transitions among skilled women.

4. Estimates of the Gender Salary Gap

As shown previously, there is a persistent gender salary gap. To analyze the factors contributing to the gender salary gap, we conducted a regression analysis using the NSCG 2023 data for prime-aged, full-time workers in Table 3. Our first model includes controls for female, race, nativity experience and its square, job tenure and its square, and highest degree (bachelor's, master's or professional). The gender salary gap is -0.226 log points or about 25%. The second

column adds dummies for college major, and the coefficient on female drops by more than half. Adding occupation dummies does not change the coefficient, however, adding job sector reduces the female coefficient to -0.084 log points, reducing the gender gap to 8.8%. Employer size, marital status and children only reduce the female coefficient to -0.078. The final model in Table 3 includes interactions of female with marital status, children less than six years old, and older children ages 7—18. The female coefficient now represents single women without children, and it falls by half to -0.038. The coefficient on married female is -0.051 and the coefficient on female interacted with older children is -0.042, indicating a substantial marriage and child penalty. Surprisingly, the interaction term of female with young children is positive but not statistically significant. Appendix Table 1 shows the same estimates for the 2019 sample. The base gender salary gap is practically identical, but the model explains all but 3% of the gender wage gap.

Table 4 shows the estimated gender salary gap after splitting the sample into workers in the private sector and those in other employment sectors. The first model shows that the gender salary gap is 0.052 log points larger in the private sector than the other sectors, however, after controlling for majors, the gender gap only differs by 0.005 log points. After controlling for occupation there is no difference. The gap drops by 0.013 log points more in the not private sector after controlling for employer size. Once controls are added for marriage and children and the interaction terms, the gender gap in the non-private sector is half the size of that in the private sector. That said, the salary penalty associated with marriage and older children for women is remarkably similar in the private and non-private sectors.

To examine the overall contribution of covariates to the gender gap, we performed a Oaxaca decomposition after adding covariates for majors, occupations, job sector, employer size,

marriage and family, and marriage and family interaction terms. Figure 6 shows these results. Adding majors reduces the unexplained gap by half. The impact of job sector also reduces the unexplained gap, but the full model with interaction terms for marriage and children reduce the gap substantially. Clearly, a significant share of the gender gap is explained by the full model.

We use a method developed by Gelbach (2016) to quantify the contribution of covariates to the explained portion of the gender gap. Gelbach (2016) argues that adding covariates one at a time creates sequence dependence and is not robust to the order that covariates are added to the model. The Gelbach decomposition allows us to fully calculate the share of the gender gap explained by various sets of covariates. Table 5 shows the base model and the full model for the entire sample and parses the share of gender gap that is explained by covariates for major, occupation, occupation match, job sector, employer size, family and family interacted with female. The results show that 74% of the overall gender gap is explained by the full model. Since women are more likely to obtain advanced degrees, including controls for highest degree reduces the overall gender gap by 12%. Majors contribute one-third and occupations contribute 13% to the explained portion of the gender gap. Family characteristics and interactions contribute about one quarter to the explained gap. Job sector contributes the most, 38%, to the explained gap. Appendix Table 2 presents the Gelbach decomposition for the 2019 salary gap. The shares of the gap explained by major and employment sector are very similar to the 2023 estimates.

Table 6 repeats this decomposition for the gender salary gap in the private sector and non-private sectors. The full model explains only 67% of the salary gap in the private sector, but the gender salary gap in private is somewhat lower than in the full sample at -0.181 log points or 20%. After controlling for all covariates, the gap falls to 4.4%. In the private sector, majors

contribute 29% to the explained gap followed by family characteristics at 24%. Unlike the full sample, occupations, and the relationship between occupation and highest degree combine to contribute over 20% to the explained gap. In the non-private sector, the salary gap is 0.129 log points or 13.8%. After controlling for all covariates, the gap falls to only 2%, and the full model explains 75% of the gender salary gap. Majors contribute much less compared to full sample, only 23%, to the explained gap. Occupation match, like degree, narrows the overall gender gap in the non-private sector. Family characteristics contribute over half (54%) of the explained gender gap in the non-private sector.

Given the growth in the gender gap with age that was shown in Table 2, we examine the gender wage gap for prime-aged workers by five-year increments of work experience over the past decade. The gender salary gap grows by 20 log points when comparing the lowest and highest years of experience. To probe this further, we split the sample by age. Young workers are ages 25—40 and older workers are ages 41—54. Table 7 shows the base and full model gender gap along with the Gelbach decomposition for young and older workers. Younger workers have a base gender gap of 0.207 log points or 23%, and older workers have a base gender gap of 0.267 log points or 31%. The covariates in the full model explain 77% of the gender salary gap for young workers, and the unexplained gap falls to only 2.7%. Both major and employment sector contribute roughly 37% each to the explained gap for younger workers. Family characteristics contribute 21% to the explained gender gap for younger workers. The gender gap is larger for older workers, but the covariates only explain 71% of the gap and the unexplained gap is higher at 6%. For older workers, major only contributes 25% to the explained gap and employment sector contributes 35%. In contrast, marriage and family

characteristics contribute 40% to the explained gap. These results suggest that family circumstances accrete over women's careers and contribute to their earnings disadvantage.

5. Sorting Into and Out of the Private Sector

Up to now, the analysis has shown that women are less likely to work in the private sector—the sector that pays the highest average wages. The question remains as to whether women are less likely to enter and/or more likely to leave the private sector. To explore the gender gap in working and remaining within the private sector we estimated pooled Ordinary Least Squares (OLS) and hazard models. Data from the 2010—2019 waves of the NSCG were utilized to construct a panel dataset, where individuals who were working full-time in the private sector in the first observation period were selected. The outcome variable of interest is the dummy variable of working in the private sector.

Estimation results are included in Table 8. In the first model that controls for race and ethnicity, citizenship status, educational degree, work experience, and tenure we see that women are 20 percentage points less likely to work in the private sector. Over half of this is explained by college major in the second model, which shows that women are 8.3 percentage points less likely to work in the private sector. Adding family characteristics and interaction terms reduces the gender gap in private sector employment to 6.4 percentage points, indicating that an additional part of the gap is explained by marital status and children. Surprisingly mothers with young children are 3 percentage points more likely to work in the private sector.

The gender gap in private sector employment could be driven by multiple factors. Women may be less likely to start in the private sector; alternatively, they may be more likely to leave or both. Ideally, we would have information that tracks the transition from highest degree

to employment in our data, but unfortunately that is not the case. Thus, we proxy starting in the private sector by estimating pooled OLS regressions for people first observed under the age of 30 in Table 9. As with the previous table, we see a significant gender gap in private sector employment of 17.4 percentage points. Adding major reduces the estimated effect of female employment in the private sector to 3.9 percentage points, a 77% reduction in the penalty. This suggests that much of the gender gap in private sector employment is explained by the pre-market choice of college major.

Next, we consider whether women are more likely to leave the private sector using Cox proportional hazard models. We limit the sample to prime-aged workers who are first observed as employed full-time in the private sector. Table 10 presents hazard ratios of the conditional likelihood of leaving employment in the private sector. Our analysis shows that in the model controlling for demographics and degrees, women are 2.4 times more likely to leave the private sector compared to men. Adding major reduces the hazard rate to 1.9 times as likely. The final model includes interaction terms with female, marital status and children. Married women are 1.4 times more likely to leave the private sector, and women with young children are 1.2 times more likely to leave. Nevertheless, single women with young children are 1.3 times more likely to leave private sector employment.

Previous research and our analysis in Table 2 shows that women are more likely to leave the labor force. We estimated the hazard model of leaving the labor force in Table 11 and found that in our base model that controls for demographics and degrees, women are 2.9 times more likely to leave. Surprisingly, controlling for employment sector only reduces the coefficient to 2.7 times as likely. After including female interacted with marital status, we find that marriage and children explain the entire likelihood of women leaving the labor force.

Finally, Table 12 examines gender differences in changing jobs. Women are 14% more likely to change jobs. However, after controlling for family characteristics the number falls to 6%. Interacting female with marital status and children shows that women with children are significantly less likely to change jobs, especially if they have young children (by about 16%). Unlike in previous models, marital status has no statistically significant impact on the likelihood that women change jobs.

6. Discussion and Conclusions

This paper examines the factors that explain the gender salary gap among prime-aged high skilled workers using several waves of the National Survey of College graduates. We find that college-educated women are less likely to major and have occupations in math-intensive fields such as geoscience, economics, engineering, math and computer science, and physical sciences. These majors and occupations pay better on average. We also find that women are 28% less likely to be employed in firms in the private/for-profit job sector. The raw gender salary gap is 25%. The data show that women sort out of higher paying majors before entering the job market and then sort out of the highest paying sector in the labor market.

Next, using a rich set of covariates including highest degree major, occupations, job sector, marital status, and family characteristics, we can explain 74% of the gender salary gap with only a 4% unexplained gap remaining. Similar to previous research, we find that major explains about one-third of the gender gap. Our analysis is the first to consider the impact of job sector on the gender salary gap. We find that job sector explains about 38% of the gender salary gap in part because women are 22 percentage points less likely to work in the private sector. We

also find that marital status and children contribute to 27% to the explained gap. Outside of the for-profit/private sector, marital status and children contribute 54% to the explained gap.

The gender salary gap grows over time. For younger workers, we found that major and job sector explain about 37% of the salary gap each with a lower impact of family characteristics at just over 20%. In contrast, major and employer type explain relatively less (25% and 35% respectively for older workers), while family characteristics explain double that amount 40%. Overall, the unexplained gap doubles for older workers at 6%. Taken together, these results make new contributions to the literature.

In previous studies, Sloane, Hurst, and Black (2021) find that occupational specialization explains 37% of the gender wage gap and undergraduate major explains 28%. Our results show that major explains 32% and job sector explains 38% of the salary gap. Occupation accounts for only 12.6% of the earnings gap in our models. The NSCG allows us to control for whether the major is closely or somewhat related to a person's occupation, a measure of occupational specialization. This occupation match explains only .6% of the salary gap. Thus, the relative importance of occupational specialization found in Sloane, Hurst, and Black (2021) is likely the result of omitting job sector from the analysis. Notably, we find that occupation and occupation match become more important (and majors less important) in the private sector, where the occupation variables explain 22% of the salary gap.

Given the importance of job sector in explaining the gender salary gap, we examine whether women sort into and sort out of the private sector and the labor force using hazard analysis. Pooled OLS models show that women are 20 percentage points less likely to work in the private sector, and that major explains over half of that gap. Marital status and children explain another 2.5 percentage points of the gender gap in employment in the private sector. As

a proxy for starting a job in the private sector, we limited the sample to women under the age of 30 and found a 17 percentage point gap that was explained mostly by college major. Taken together, our results suggest women are less likely to pursue majors that are good matches with the private sector.

Next, we considered whether women who were first observed working in the private sector leave it. We found that women were 2.4 times more likely to leave the private sector compared with men. Major explains part of that decision, but family is more salient. Single women are 1.3 times more likely to leave the private sector while married women are 1.4 times more likely and women with young children are 1.2 times more likely to leave the private sector. Our analysis also found that women were close the 3 times more likely to leave the labor force than men. However, this is entirely explained by marital status and presence of young children.

Several potential explanations exist for job sector sorting. Our results on the private sector and family characteristics are most consistent with a "greedy jobs" explanation Coser (1974) and Goldin (2006). Despite the pay premium associated with the private sector, women are less likely to pursue majors that are good matches with private sector jobs, making them less likely to work in the private sector. Conditional on being first observed in the private sector, women are most likely to leave it. Our analysis shows that the private sector demands higher working hours (43.12 hours) compared to the non-private sector (41.64 hours). Coupled with family considerations and the lack of flexibility, women may be more likely to leave.

In addition, the private sector is made up of profit maximizing firms that compete for market share. The competitive nature of the firm may create a competitive work environment. Niederle & Vesterlund (200y) propose that women may avoid competition, leading them to sort into sectors with less competition. Additionally, there is evidence that firms employing women

are more profitable, but do not share rents equitably with female employees (Hellerstein et al. (2002)).

The gender composition within a workplace also influences sorting and retention patterns. Studies by Card et al. (2016), Lordan & Pischke (2022), Bayard et al. (2003) suggest that factors such as women's preference to work with other women and occupational segregation contribute to sorting outcomes. Faberman, Mueller, and Şahin (2026) have shown that women are more likely to work in higher-amenity occupations. To the extent that the non-private sector offers more amenities, this may explain part of the gender gap. For example, women in our sample are more likely to work in the K-12 education sector where most employees have long summer breaks but relatively lower salaries.

A recent paper by Blair and Posmanick (2023) showed that the gender salary gap stagnated after the introduction of the Family and Medical Leave Act and paid family leave. Previous research from Sweden also showed that generous family leave policies in that country reduced wage growth and promotion (Albrecht, Bjorklund and Vroman 2003). Future research will examine whether state family leave policies were associated with gender differences in employment in the private sector and the likelihood of leaving the private sector. In addition, future research will examine whether family leave laws exacerbated the marriage and child penalties we observe in our data. Finally, examining whether there are gender differences in wage growth that contribute to the widening gender salary gap with age is warranted.

References

Albrecht, J., Bjorklund, A., and Vroman, S. 2003. Is there a glass ceiling in Sweden? *Journal of Labor Economics*, 21(1), 145–177.

Altonji, Joseph G., John Eric Humphries, Yagmur Yuksel, and Ling Zhong. 2025. Decomposing Trends in the Gender Gap for Highly Educated Workers. NBER Working paper 34133.

Bayard, K., Hellerstein, J., Neumark, D., & Troske, K. 2003. New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data. *Journal of Labor Economics*, 21(4), 887–922.

Bertrand, M., Goldin, C., & Katz, L. F. 2010. Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. *American Economic Journal: Applied Economics*, 2(3).

Binder, Ariel J., Amanda Eng, Kendall Houghton, and Andrew Foote. 2025. Variation in the Gender Pay Gap across a Diverse Sample of Postsecondary Graduates. Working paper.

Blair, P. Q. and Posmanick, B. 2023. Why Did Gender Wage Convergence in the United States Stall? NBER Working paper 30821.

Blau, F. D. & Kahn, L. M. 2017. The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, 55(3), 789–865.

Card, D., Cardoso, A. R., & Kline, P. 2016. Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women. *The Quarterly Journal of Economics*, 131(2), 633–686.

Ceci, S. J., Ginther, D. K., Kahn, S., & Williams, W. M. 2014. Women in Academic Science: A Changing Landscape. *Psychological Science in the Public Interest*, 15(3), 75–141.

Cortes, P. & Pan, J. 2017. Cross-Country Evidence on the Relationship between Overwork and Skilled Women's Job Choices. *American Economic Review*, 107(5), 105–109.

Cortés, Patricia, and Jessica Pan. 2023. Children and the Remaining Gender Gaps in the Labor Market. *Journal of Economic Literature* 61 (4): 1359–1409.

Coser, L. A. 1974. Greedy Institutions; Patterns of Undivided Commitment. Free Press.

Delaney, Judith M., and Paul J. Devereux. 2022. Gender Differences in STEM Persistence after Graduation. IZA Discussion Paper.

Faberman, R. Jason, Andreas I. Mueller, and Ayşegül Şahin. 2026. Job Search, Job Amenities and the Gender Pay Gap. NBER Working Paper 34877.

Gelbach, Jonah. 2016. When Do Covariates Matter? And Which Ones? And How Much? *Journal of Labor Economics* 34(2).

Goldin, C. 2006. The quiet revolution that transformed women's employment, education, and family. *American Economic Review*, 96(2), 1–21.

Goldin, C. 2014. A Grand Gender Convergence: Its Last Chapter. *American Economic Review*, 104(4), 1091–1119.

Goldin, C. and Katz, L. F. 2011. The Cost of Workplace Flexibility for High-Powered Professionals. *The ANNALS of the American Academy of Political and Social Science*, 638(1), 45–67.

Goldin, C. and Katz, L. F. 2016. A Most Egalitarian Profession: Pharmacy and the Evolution of a Family-Friendly Occupation. *Journal of Labor Economics*, 34(3), 705–746.

Goldin, C., Kerr, S. P., Olivetti, C., and Barth, E. 2017. The Expanding Gender Earnings Gap: Evidence from the LEHD-2000 Census. *American Economic Review*, 107(5), 110–114.

Hellerstein, J. K., Neumark, D., & Troske, K. R. 2002. Market Forces and Sex Discrimination. *The Journal of Human Resources*, 37(2), 353–380.

Humphries, John Eric, Juanna Schrøter Joensen, and Gregory F. Veramendi. 2024. "The Gender Wage Gap: Skills, Sorting, and Returns." Working paper.

Hurst, Kiley. 2024. U.S. Women are Outpacing Men in College Completion, Including in Every Major Racial and Ethnic Group. Available online at https://www.pewresearch.org/?p=192631.

Imberman, Scott A., Michael F. Lovenheim, Patrick Massey, Kevin M. Stange, and Rodney J. Andrews. 2026. "The Contribution of College Majors to Gender and Racial Earnings Differences." NBER Working Paper 34726.

Kahn, Shulamit and Donna K. Ginther. 2018. Women and Science, Technology, Engineering and Mathematics (STEM): Are Differences in Education and Careers due to Stereotypes, Interests or Family? In *The Oxford Handbook on the Economics of Women*, ed. Susan L. Averett, Laura M. Argys, and Saul D. Hoffman. New York: Oxford University Press.

Lordan, G. and Pischke, J.-S. 2022. Does Rosie Like Riveting? Male and Female Occupational Choices. *Economica*, 89(353), 110–130.

Niederle, M. & Vesterlund, L. 2007. Do women shy away from competition? Do men compete too much? *Quarterly Journal of Economics*, 122(3): 1067-1101.

Rosenball, Riccarda, Tobias Eibinger, Jörn Kleinert, and Ismir Mulalic. 2026. Hidden in Plain Sight: Occupational Structure and the Gender Wage Gap. Working paper.

Sloane, Carolyn M., Erik G. Hurst, and Dan A. Black. 2021. College Majors, Occupations, and the Gender Wage Gap. *Journal of Economic Perspectives* 35 (4): 223–48.

Sorkin, I. 2017. The Role of Firms in Gender Earnings Inequality: Evidence from the United States. *American Economic Review*, 107(5), 384–387.

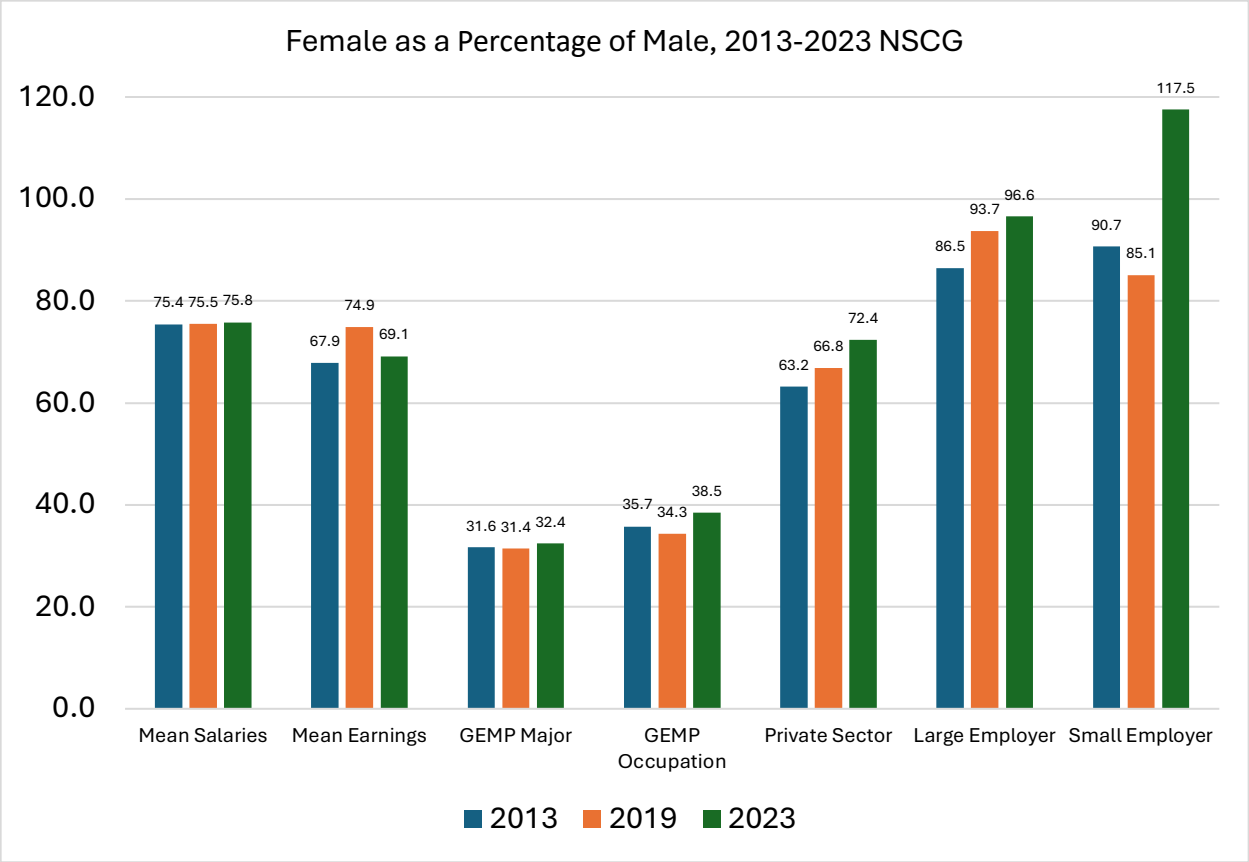


Figure 1: Female as Percentage of Male in Salaries and Representation, for full-time prime-aged workers. Source: National Survey of College Graduates, 2013,2019,2023.

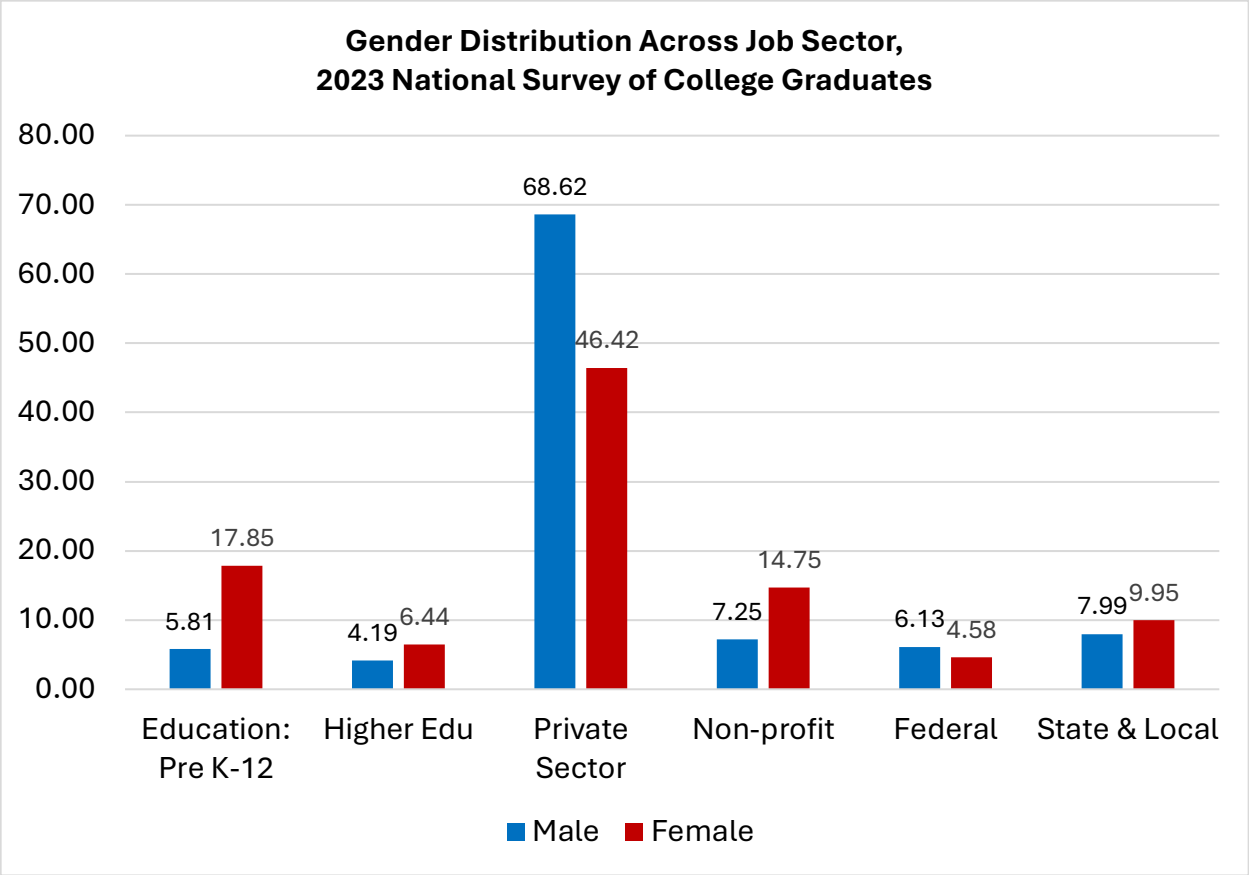


Figure 2 : Gender Distribution Across Job Sector, for full-time prime-aged workers. Source: National Survey of College Graduates, 2023

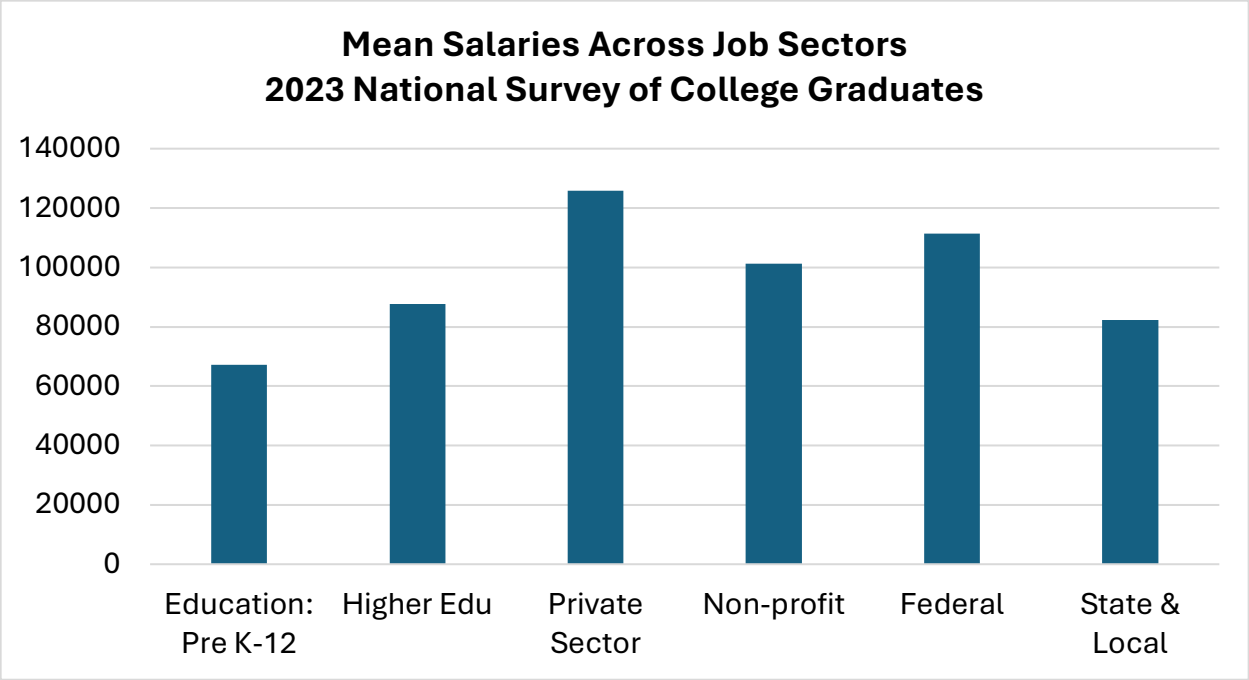


Figure 3: Mean Salaries Across Job Sectors for full-time prime-aged workers (weighted). Source: National Survey of College Graduates, 2023

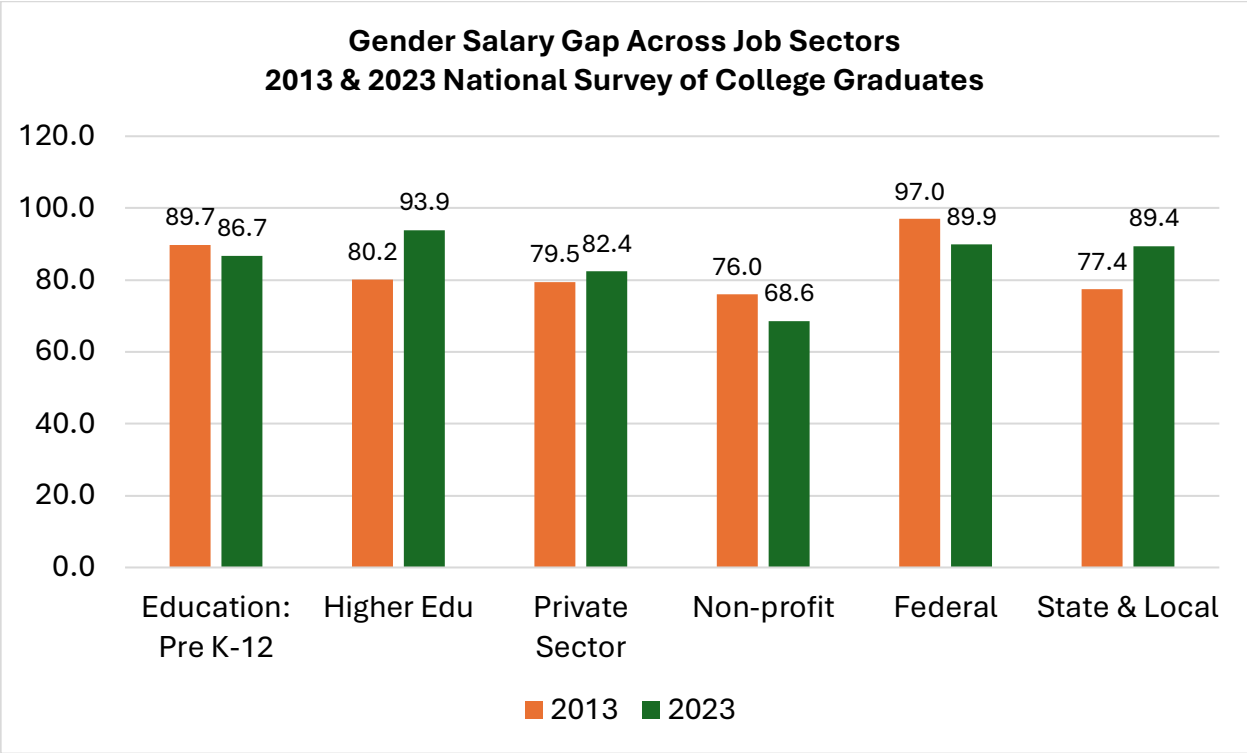


Figure 4: Gender Salary Gap Across Job Sector, for full-time prime-aged workers. Source: National Survey of College Graduates, 2013, 2023

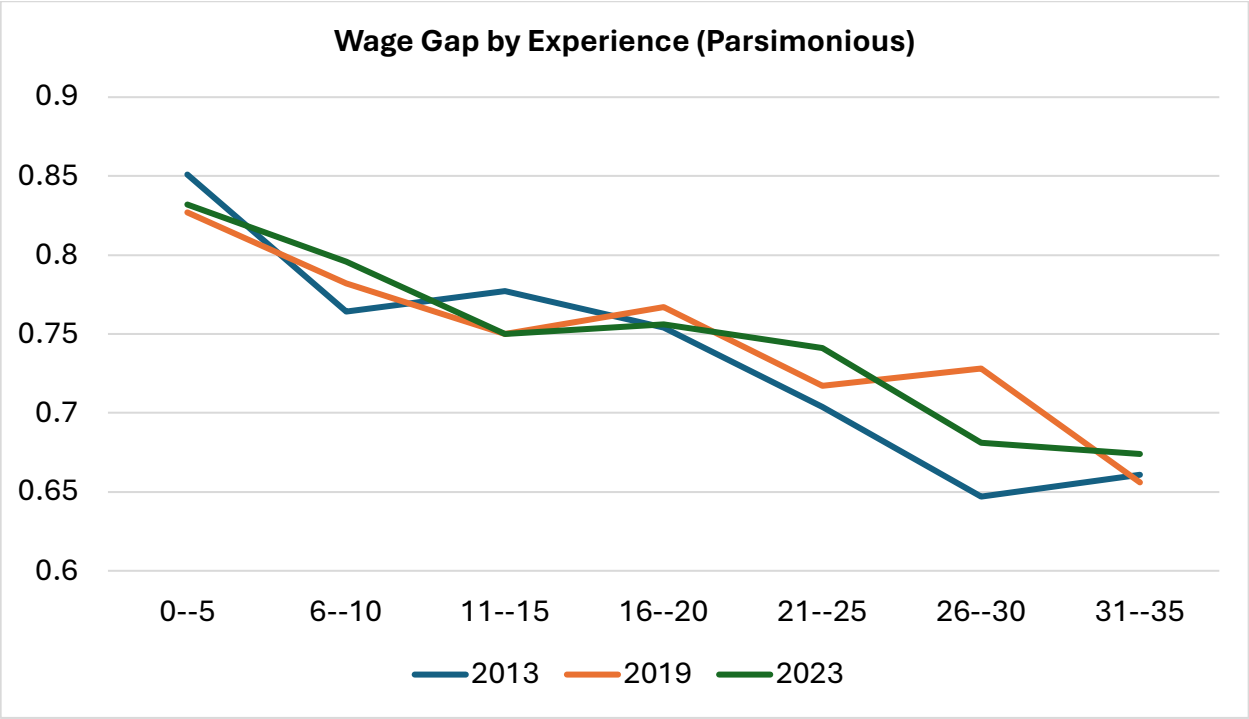


Figure 3: Wage Gap by Experience, Base Model for full-time prime-aged workers. Source: National Survey of College Graduates, 2013, 2023

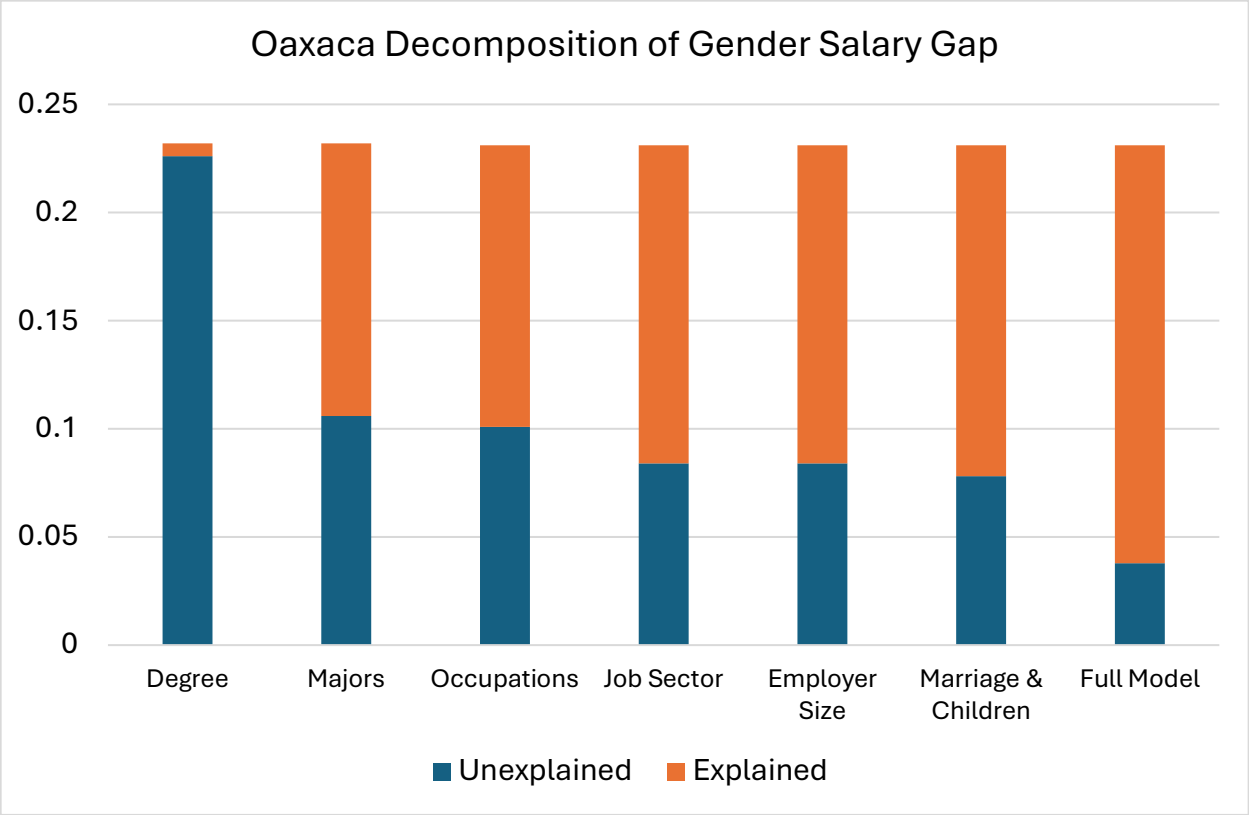


Figure 6: Oaxaca Decomposition of Gender Salary Gap for full-time prime-aged workers. Source: National Survey of College Graduates, 2023

Table 1: Analysis Sample: Prime Aged Workers
2023 National Survey of College Graduates

	Male	Female
Salary Annualized	124980.04	94731.51
Age	39.10	38.79
Experience	13.92	13.31
Tenure	6.01	5.91
Race/ethnicity		
Asian	12.39%	11.51%
Black	6.83%	9.47%
Hispanic	11.31%	12.13%
White	66.44%	63.76%
Other Race	0.07%	0.09%
Foreign Born	6.97%	4.28%
Type of Certificate or Degree, Highest Degree		
Bachelor's	64.55%	58.01%
Masters	29.61%	35.54%
Professional	5.84%	6.45%
Field of study for highest degree minor group		
Computer and information sciences	10.16%	2.34%
Mathematics and statistics	1.73%	0.97%
Agricultural and food sciences	0.48%	0.58%
Biological sciences	2.93%	3.39%
Environmental life sciences	0.77%	0.46%
Chemistry, except biochemistry	0.61%	0.48%
Earth, atmospheric and ocean sciences	0.69%	0.29%
Physics and astronomy	0.54%	0.15%
Other physical sciences	0.03%	0.04%
Economics	2.69%	0.94%
Political and related sciences	2.29%	1.63%
Psychology	2.16%	6.09%
Sociology and anthropology	1.56%	1.88%
Other social sciences	0.83%	1.05%
Aerospace, aeronautical and astronautical engineering	0.53%	0.08%
Chemical engineering	0.76%	0.27%
Civil and architectural engineering	1.70%	0.45%
Electrical and computer engineering	5.45%	0.85%
Industrial engineering	0.89%	0.25%
Mechanical engineering	3.39%	0.36%
Other engineering	1.77%	0.63%
Health	6.86%	16.14%

	Male	Female
Science and Mathematics Teacher Education	0.92%	1.05%
Technology and Technical Fields	1.64%	0.32%
Other S and E related fields	1.09%	0.93%
Management and administration fields	21.44%	17.46%
Education, except science and math teacher education	3.74%	12.45%
Social service and related fields	1.41%	3.73%
Sales and marketing fields	2.33%	2.45%
Art and Humanities Fields	6.18%	9.23%
Other Non-S and E fields	12.43%	13.04%
Gemp Major	34.60%	10.41%
Gemp Occupation	36.57%	13.06%
Job Sector		
K-12 Education	5.81%	17.85%
Higher Education	4.19%	6.44%
Private	68.62%	46.42%
Non-Profit	7.25%	14.75%
Federal Government	6.13%	4.58%
State Government	7.99%	9.95%
Work Closely Related	54.03%	57.27%
Work Somewhat Related	28.48%	26.38%
11-24 employees	3.78%	4.34%
25-99 employees	9.58%	10.06%
100-499 employees	15.32%	18.10%
500-999 employees	6.75%	9.12%
Married	67.54%	58.74%
Young Child (age6)	23.37%	16.40%
Older Child (age 6-18)	36.35%	35.84%

Notes: Weighted percentages from 2023 National Survey of College Graduates. Prime aged, full-time workers ages 25—55.

Table 2: Analysis Sample by Age Group
2023 National Survey of College Graduates

	Age Group (in 5-year intervals)					
	25-30	31-35	36-40	41-45	46-50	50-54
Mean Salary						
Male	82,650	104,106	120,177	125,185	139,778	147,324
Female	66,070	78,553	88,542	89,786	99,319	89,894
Female Share	80%	75.5%	73.7%	71.7%	71%	61%
Not in Labor Force						
Male	5.78	3.41	4.01	3.62	3.86	6.86
Female	11.08	12.02	10.74	12.29	11.16	14.89
Full-time, Full year						
Male	93.13	92.37	95.08	93.17	94.36	94.44
Female	87.64	87.12	84.39	83.93	84.55	86.17
Part-time						
Male	5.90	5.85	3.33	4.76	4.30	3.30
Female	9.75	9.61	12.84	12.83	10.79	10.67
Part-year						
Male	2.14	2.54	2.34	2.74	2.03	2.89
Female	3.56	4.55	4.62	5.27	6.01	5.44
Work unrelated to degree						
Male	14.71	19.82	20.52	15.34	15.18	16.18
Female	12.13	15.72	16.01	13.47	15.08	15.67
Work closely related to degree						
Male	49.88	50.87	48.12	49.63	50.29	46.97
Female	49.18	48.30	48.77	48.69	49.34	45.95
Changed Employer						
Male	26.63	25.72	20.01	17.85	12.07	14.24
Female	29.78	22.62	19.83	13.04	15.47	13.62
Private Sector						
Male	60.95	66.96	64.75	58.94	64.07	57.83
Female	39.32	39.84	40.15	35.53	35.63	35.12
Principal Job Hours Worked						
Male	42.025	42.828	43.71	43.459	44.058	44.498
Female	40.387	40.342	39.384	39.835	40.949	41.002
Job Tenure						
Male	2.785	3.719	4.948	6.803	8.083	10.238
Female	2.652	3.935	4.77	6.988	8.227	9.867

Notes: Weighted percentages from 2023 National Survey of College Graduates. Prime aged, full-time workers ages 25—55.

Table 3 : OLS Wage Regressions for Prime-Aged Workers, 2023 NSCG

VARIABLES	Degree	Majors	Occupations	Sector	Size	Family	Full Model
Female	-0.226***	-0.106***	-0.101***	-0.084***	-0.084***	-0.078***	-0.038***
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]	[0.007]
Female x Married							-0.051***
							[0.009]
Female x Young Child							0.017
							[0.010]
Female x Older Child							-0.042***
							[0.009]
Race	y	y	y	y	y	y	y
Foreign Born	y	y	y	y	y	y	y
Experience	y	y	y	y	y	y	y
Degree	y	y	y	y	y	y	y
Major		y	y	y	y	y	y
Occupation			y	y	y	y	y
Sector				y	y	y	y
Employer Size					y	y	y
Family						y	y
Family Interaction							y
Observations	42,474	42,474	42,474	42,474	42,474	42,474	42,474
R-squared	0.185	0.293	0.333	0.385	0.399	0.406	0.407

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05.

Table 4: OLS Wage Regressions for Prime-Aged Workers, 2023 NSCG

VARIABLES	Degree	Majors	Occupations	Job Sector	Size	Family	Full Model
Private Sector							
Female Private	-0.181***	-0.090***	-0.085***		-0.087***	-0.082***	-0.044***
	[0.006]	[0.006]	[0.006]		[0.006]	[0.006]	[0.009]
Female x Married							-0.048***
							[0.012]
Female x Young Child							0.022
							[0.014]
Female x Old Child							-0.053***
							[0.013]
Observations	26,090	26,090	26,090		26,090	26,090	26,090
R-squared	0.188	0.262	0.310		0.323	0.330	0.331
Non-Private Sector							
Female Non-Private	-0.129***	-0.085***	-0.086***	-0.077***	-0.074***	-0.067***	-0.021*
	[0.007]	[0.007]	[0.007]	[0.007]	[0.006]	[0.006]	[0.010]
Female x Married							-0.048***
							[0.014]
Female x Young Child							-0.004
							[0.015]
Female x Old Child							-0.050***
							[0.014]
Observations	16,384	16,384	16,384	16,384	16,384	16,384	16,384
R-squared	0.192	0.283	0.322	0.365	0.380	0.389	0.390
Race	y	y	y	y	y	y	y
Foreign Born	y	y	y	y	y	y	y
Experience	y	y	y	y	y	y	y
Degree	y	y	y	y	y	y	y
Major		y	y	y	y	y	y
Occupation			y	y	y	y	y
Sector				y	y	y	y
Employer Size					y	y	y
Family						y	y
Family Interaction							y

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 5: Gelbach Decomposition for Prime-Aged Workers, 2023 NSCG

VARIABLES	Base	Full Model	Explained	Percent Explained
Female Gap	-0.226***	-0.038***	-0.167***	73.9%
	[0.001]	[0.007]	[0.006]	
Degree			0.021***	-12.6%
			[0.001]	
Majors			-0.054***	32.3%
			[0.003]	
Occupations			-0.021***	12.6%
			[0.002]	
Occupation Match			-0.001	0.6%
			[0.001]	
Job Sector			-0.063***	37.7%
			[0.002]	
Employer Size			-0.005***	3.0%
			[0.001]	
Family			-0.006***	3.6%
			[0.001]	
Family Interactions			-0.039***	23.4%
			[0.005]	
Observations	42,474	42,474	42,474	

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 6: Gelbach Decomposition for Prime-Aged Workers, 2023 NSCG

	Private				Non-Private			
VARIABLES	Base	Full Model	Explained	Percent Explained	Base	Full Model	Explained	Percent Explained
Female Gap	-0.181***	-0.044***	-0.122***	67.4%	-0.129***	-0.021*	-0.097***	75.2%
	[0.006]	[0.009]	[0.008]		[0.007]	[0.010]	[0.009]	
Degree			0.016***	-8.8%			0.012***	-12.4%
			[0.002]				[0.002]	
Majors			-0.053***	29.3%			-0.022***	22.7%
			[0.003]				[0.003]	
Occupations			-0.025***	13.8%			-0.013***	13.4%
			[0.003]				[0.003]	
Occupation Match			-0.014***	7.7%			0.005***	-5.2%
			[0.001]				[0.001]	
Job Sector							-0.018***	18.6%
							[0.002]	
Employer Size			-0.003***	1.7%			-0.009***	9.3%
			[0.001]				[0.001]	
Family			-0.006***	3.3%			-0.008***	8.2%
			[0.001]				[0.001]	
Family Interactions			-0.037***	20.4%			-0.044***	45.4%
							[0.007]	
Observations	26,090	26,090	26,090		16,384	16,384	16,384	

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 7: Gelbach Decomposition for Prime-Aged Workers by Age, 2023 NSCG

	Young				Older			
VARIABLES	Base Model	Full Model	Explained	Percent Explained	Base	Full	Explained	Percent Explained
Female	-0.207***	-0.027***	-0.159***	76.8%	-0.267***	-0.060***	-0.190***	71.2%
	[0.005]	[0.007]	[0.006]		[0.009]	[0.017]	[0.016]	
Degree			0.022***	-13.8%			0.018***	-9.5%
			[0.002]				[0.003]	
Major			-0.060***	37.7%			-0.047***	24.7%
			[0.003]				[0.004]	
Occupation			-0.024***	15.1%			-0.012***	6.3%
			[0.003]				[0.003]	
Occupation Match			-0.001	0.6%			-0.001	0.5%
			[0.001]				[0.002]	
Job Sector			-0.059***	37.1%			-0.066***	34.7%
			[0.002]				[0.004]	
Employer Size			-0.004***	2.5%			-0.006***	3.2%
			[0.001]				[0.001]	
Family			-0.003***	1.9%			-0.020***	10.5%
			[0.001]				[0.002]	
Family Interaction			-0.030***	18.9%			-0.056***	29.5%
			[0.005]				[0.013]	
Observations	29,374	29,374	29,374		13,100	13,100	13,100	

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 8 : Pooled OLS Model of Working in Private Sector, 2010-2019 NSCG

VARIABLES	Degree	Major	Family	Full Model
Female	-0.203***	-0.083***	-0.082***	-0.064***
	[0.003]	[0.003]	[0.003]	[0.005]
Female x Married				-0.015*
				[0.007]
Female x Kids				-0.020***
				[0.003]
Female x Young Child				0.031***
				[0.009]
Race	y	y	y	y
Foreign Born	y	y	y	y
Experience/Tenure	y	y	y	y
Degree	y	y	y	y
Year	y	y	y	y
Major		y	y	y
Family			y	y
Interaction				y
Observations	88,427	88,427	88,427	88,427
R-squared	0.098	0.210	0.211	0.211

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 9 : Pooled OLS Model of Private Under 30, 2010-2019 NSCG

VARIABLES	Degree	Major	Family	Full model
Female	-0.174***	-0.039***	-0.039***	-0.040***
	[0.006]	[0.006]	[0.006]	[0.008]
Female x Married				0.017
				[0.012]
Female x Kids				-0.032
				[0.017]
Female x Young Children				0.01
				[0.029]
Race	y	y	y	y
Foreign Born	y	y	y	y
Experience/Tenure	y	y	y	y
Degree	y	y	y	y
Major		y	y	y
Family			y	y
Family Interaction				y
Observations	25938	25938	25938	25938
R-squared	0.075	0.204	0.204	0.204

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 10: Hazard Model of Leaving Private, 2010-2019 NSCG

VARIABLES	Degree	Major	Family	Interaction
Female	2.436***	1.852***	1.715***	1.285***
	[0.073]	[0.061]	[0.057]	[0.065]
Female x Married				1.440***
				[0.104]
Female x Kids				1.012
				[0.040]
Female x Young Children				1.239**
				[0.098]
Race	y	y	y	y
Forborn	y	y	y	y
Degree	y	y	y	y
Major		y	y	y
Employer Size			y	y
Family			y	y
Family Interaction				y
Observations	98482	98482	98482	98482

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 11: Hazard Model of Leaving Labor Force, 2010-2019 NSCG

VARIABLES	Degree	Major	Private	Family	Interaction
Female	2.907***	2.530***	2.684***	2.559***	0.97
	[0.276]	[0.268]	[0.285]	[0.277]	[0.172]
Female x Married					2.766***
					[0.643]
Female x Kids					0.944
					[0.118]
Female x Young Children					2.581***
					[0.617]
Race	y	y	y	y	y
Foreign Born	y	y	y	y	y
Degree	y	y	y	y	y
Major		y	y	y	y
Private			y	y	y
Size				y	y
Family				y	y
Family Interaction					y
First Private					y
Observations	161528	161528	161528	161528	161528

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Table 12: Hazard Model of Changing Jobs, 2010-2019 NSCG

VARIABLES	Degree	Major	Family	Interaction	First Private
Female	1.144***	1.103***	1.062***	1.155***	1.232***
	[0.015]	[0.015]	[0.015]	[0.025]	[0.031]
Female x Married				0.992	0.997
				[0.030]	[0.031]
Female x Kids				0.945**	0.944**
				[0.017]	[0.017]
Female x Young Children				0.839***	0.842***
				[0.030]	[0.030]
First Time Private					0.938***
					[0.013]
Race	y	y	y	y	y
Foreign Born	y	y	y	y	y
Degree	y	y	y	y	y
Major		y	y	y	y
Private			y	y	y
Size			y	y	y
Family			y	y	y
Interaction				y	y
First Private					y
Observations	136250	136250	136250	136250	136250

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Appendix

Appendix Table 1: OLS Wage Regression for Prime-Aged Worker, 2019 NSCG

VARIABLES	Degree	Majors	Occupation	Sector	Size	Family	Full Model
Female	-0.225***	-0.109***	-0.106***	-0.086***	-0.085***	-0.079***	-0.031***
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]	[0.007]
Female x Married							-0.055***
							[0.009]
Female x Young Child							0.010
							[0.010]
Female x Old Child							-0.058***
							[0.009]
Race	y	y	y	y	y	y	y
Forborn	y	y	y	y	y	y	y
Experience	y	y	y	y	y	y	y
Degree	y	y	y	y	y	y	y
Major		y	y	y	y	y	y
Occupation			y	y	y	y	y
Sector				y	y	y	y
Employer Size					y	y	y
Family						y	y
Family Interaction							y
Observations	40,513	40,513	40,513	40,513	40,513	40,513	40,513
R-squared	0.216	0.324	0.365	0.416	0.429	0.434	0.436

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05

Appendix Table 2: Gelbach Decomposition for Prime-Aged Worker, NSCG 2019

VARIABLES	Base	Full Model	Explained	Percent Explained
Female Gap	-0.225***	-0.030***	-0.171***	76.0%
	[0.005]	[0.007]	[0.006]	
Degree			0.023***	-13.5%
			[0.001]	
Majors			-0.055***	32.2%
			[0.003]	
Occupations			-0.014***	-8.2%
			[0.002]	
Occupation Match			-0.001	0.6%
			[0.001]	
Job Sector			-0.067***	39.2%
			[0.002]	
Employer Size			-0.005***	2.9%
			[0.001]	
Family			-0.005***	2.9%
			[0.001]	
Family Interactions			-0.047***	27.5%
			[0.005]	
Observations	40,513	40,513	40,513	

Notes: Robust standard errors in brackets. *** p<0.001, ** p<0.01, * p<0.05