Decoding the Gender Pay Gap: An Investigation of Gender Differences in Programmer Salaries

Abstract

This study uses the StackOverflow 2019 Developer Survey to investigate the causes of the gender pay gap between men and women working in the technology sector. Annual salaries of female and male programmers are evaluated using linear, fixed-effects and multilevel effects regressions of a skills-based human capital model. An Oaxaca-blinder decomposition identifies the explained versus unexplained portion of pay differentials. The set of models indicate differences in endowments cannot fully explain the pay gap, and that different valuations of these endowments by gender are at play. Particularly, the lower valuation of women's years of coding experience and the motherhood penalty remain as significant and important factors in determining the pay gap between male and female programmers.

Key Words: discrimination; gender pay gap; human capital model; Oaxaca-Blinder decomposition; StackOverflow

1 Introduction

Silicon Valley has a gender diversity problem – only 14% of US start-ups have a female CEO and almost half have no women in leadership or board roles (Silicon Valley Bank, 2020). Demand for programmers in the Valley has risen from 10,000 in 1980 and to 140,000 in 2015 (John & Carnoy, 2019). Female supply of STEM workers has not responded accordingly, and women occupy just 25% of jobs in computing and STEM fields (Ashcraft et al., 2016; Beede et al., 2013; Rivers, 2017; Zarrett et al., 2013). The technology sector suffers from a high female attrition rate (Gonzalez-Gonzalez et al., 2018; Judy, 2012), with women quitting twice as often as men (Hewlett et al., 2008).

What drives this lack of female representation? In his incendiary memo, Google employee James Damore cited biological differences as responsible for divergent skills and careers between the sexes (Varinsky, 2017). Unsupported by peer-reviewed evidence, this opinion perhaps better exemplifies the hostile environment and powerful male stereotypes which makes entering and remaining in the industry less likely (Ashcraft et al., 2016). Limiting factors include an absence of female role models, gender stereotypes or rigid demands on work-life balance (Beede et al., 2013). The pay gap between programmers may also stymy participation if women are paid less as well as heavily penalised for career interruptions and flexible working hours. There are two presiding arguments on the cause of pay differentials – the human capital approach (Mincer, 1974; Schultz, 1961) which treats the gap as 'explainable' through gender differences in career endowments and investments, versus the Oaxaca-Blinder approach (Blinder, 1973; Oaxaca, 1973) where the 'unexplained' portion of the gap arises when equal endowments are valued unequally if they belong to a man versus a woman.

Using the 2019 StackOverflow Developer Survey, this study employs both approaches to explain the gender pay gap between programmers. It finds significant premiums to years of coding experience, education in STEM fields and open source contributions versus significant penalties to a woman's accumulation of coding experience and to motherhood. The pay gap shrinks on addition of human capital variables, but a remainder of mean salary differences between men and women is unexplained. Human capital theory posits the pay gap arises from comparing 'apples' to 'oranges', that men and women receive unequal pay owing to unequal work. By controlling for differences in endowments, this study shows even comparing like-to-like, a woman's identical endowments are valued differently to a man's.

Why is this an important question? Developing technology is collaborative and influential for future innovation (Ashcraft et al., 2016). Research shows gender diversity in tech is associated with higher productivity (Vasilescu et al., 2014), more creativity (Ashcraft et al., 2016), faster problem solving (Ortu et al., 2017) and greater team cohesion (Catolino et al., 2019). By decoding the causes of the gender pay gap, this study seeks to understand the potential penalties female programmers face and makes a number of policy recommendations for encouraging the equal access and treatment of women in the technology industry.

1.1 Hypotheses

H 1. ***Experience:*** Years of professional coding experience indicate more accumulated skill, work productivity and granted responsibilities so have a significant positive effect on salary. The returns to experience are non-linear because as an individual matures, their skills become less relevant for the current labour market, especially if faced with quick-changing demand for new programming languages.

H 2. ***Education:*** Education is an investment in skills and a credible signal of ability so raises salary. STEM degrees develop specific skills to programmer roles so are likely valued higher by employers.

H 3. ***Occupation:*** Higher-skilled occupations have lower supply of qualified applicants and demand more responsibilities so are rewarded with wage premiums. This valuation effect is likely stronger for corporate jobs so academia receives a lesser premium.

H 4. ***Gender:*** Without controlling for endowments, women are expected to have lower wages than men. After controlling for human capital differences, the pay gap is expected to shrink, but persist as negative. Gender is expected to negatively interact with years of experience from gender-specific valuations of career endowments, and with dependents due to the motherhood penalty.

H 5. ***Discrimination:*** Human capital variables are expected to explain some proportion of pay gap as differences in endowments. The remainder is expected to come from different valuations of endowments, and at the disadvantage of women, not the favour of men.

2 Literature Review

A substantial body of literature reveals gender pay gaps in many fields including finance (Bertrand et al., 2010; Tharp et al., 2019), medicine (Jagsi et al., 2012), chemistry (Broyles, 2009) and software development (Dattero et al., 2005).

The human capital model, a cornerstone of neoclassical economics, argues renumeration fairly reflects the product of rational lifecycle decisions governing productivity-enhancing skills (Mincer, 1974; Schultz, 1961). To control for these differences, studies most commonly regress the natural logarithm of earnings as a function of schooling, experience, skills and other human capital indicators (Broyles, 2009; Suter & Miller, 1973; Weichselbaumer & Winter-Ebmer, 2005). In reality, the picture is more complicated than neo-classical assumptions entail. For each determinant of pay, there is conflicting evidence on how much is 'explained away' by endowments and how much comes from unequal market valuation of the same endowments by gender (Lips, 2013; Oaxaca, 1973).

Productivity is a significant determinant of the gender pay gap (Blau & Kahn, 2017; Cortés & Pan, 2019; Stanley et al., 1998; Weichselbaumer & Winter-Ebmer, 2005). Men more likely have continuous careers and work longer hours (Bertrand et al., 2010; Miyoshi, 2008; Topel, 1991). Women prioritise temporal flexibility in order to balance the share of time devoted to paid work and unpaid domestic duties (Gicheva, 2013), in contrast with men who prioritise compensation and bargain more aggressively over salary (Babcock & Laschever, 2003; Silveira et al., 2019). Goldin (2014) cites temporal flexibility as a core driver of wage differentials because higher-paying occupations disproportionately penalise part-time work and career interruptions. However, even after accounting for differences in career trajectories, a woman's experience is valued less. Using the US National Longitudinal Study of Youth, Duncan (1996) finds differences in work skills and efforts across genders do not fully explain gaps in earnings, and in an experimental setting, Steinpreis et al. (1999) find both men and women were more likely to hire a male applicant over a female one with an identical CV.

Women's distinct career patterns have been attributed to the dependency burden from children. Costa Dias et al. (2018) estimate the divergence in labour supply after a woman's first birth explains two-thirds of the gender pay gap 20 years later, and Adda et al. (2017) attribute the largest losses in female renumeration to fertility decisions. Sex differences in how parenthood is shared affects compensation because women are more likely to forgo higher pay in place of flexibility or child-care benefits, while fathers opt for higher paid jobs to support their family (Jagsi et al., 2012). From a cohort analysis of women from Germany, Britain and the United States, Gangl & Ziefle (2009) show mothers were more likely to work part-time hours in lesser prestige jobs with lower wages compared to women with no children. Scandinavian policies encourage the sharing of parenthood burdens, but such progress is by no means universal (Dribe & Stanfors, 2009; Petersen et al., 2014). In most societies, parenthood enforces the traditional division of domestic responsibilties, with mothers stereotyped as 'caregivers' and fathers as 'breadwinners' (Bear & Glick, 2017; Bertrand et al., 2015). Using a 30-year longitudinal study of individuals born in 1977, Gibb et al. (2014) find motherhood was associated with decreasing labour market participation but fatherhood resulted in no change or an increase in hours. Petersen et al. (2014) find fathers experience wage increases of 1-3% compared to non-fathers, and other studies report a 'marriage premium' for male wages (Hersch & Stratton, 2000).

'Unexplainable' gender biases are shown to be exacerbated for mothers (Correll et al., 2007). Budig & England (2001) find interruptions to work, reductions in experience, and shifts to part-time work only explain a third of the motherhood penalty, and the average employed mother experiences a per-child wage penalty of 5% even after controlling for human capital differences. Mothers are assumed to be less productive at work and less committed compared to unburdened workers (Benard & Correll, 2010; Budig & England, 2001). Cuddy et al. (2004) test this bias experimentally, finding participants were more likely to rate a consultant as less competent, less dependable and less authoritative if she was described as a mother or pregnant.

Education is another factor shown to be critical in determining pay (Altonji & Blank, 1999; Mincer, 1974), where investment in years of education accumulates skills and signals productivity (Spence, 1973; Stiglitz, 1975). Educational specialisations may explain some of the pay gap but evidence points to educational endowments being valued differently by gender: John & Carnoy (2019) find female programmers with bachelor's degrees earn lower wages than male programmers of the same age and education level.

Educational segregation entrenches occupational segregation (Blau & Kahn, 2017; Kunze, 2005). The clustering of women in relatively lower-paying jobs creates over-supply of female workers and puts downwards pressure on wages (Blau & Kahn, 2007). Even within occupations, women occupy lower paid jobs (Broyles, 2009; Dattero et al., 2005; Lips, 2013). Promotions affect men and women differently too. In a study of female IT workers, Brett & Stroh (1999) show women's careers are more likely to stagnate in midlevel positions, and Blau & Devaro (2007) show women are significantly less likely to be promoted even after controlling for human capital differences such as age, education and job performance. While (Booth et al., 2003) find women were equally likely to be promoted, they subsequently receive smaller wage premiums.

The literaure balances explainable determinants versus unexplainable remainders – some gaps are attributable to differences in human capital accumulation yet societal barriers to women's fair renumeration and participation in the workforce remain (Inglehart & Norris, 2003; Nsiah et al., 2013). The societal status-quo affects a woman's self-confidence in her own labour market value (Gonzalez-Gonzalez et al., 2018). Silveira et al. (2019) find 29.7% of women agree or strongly agree they are not as good as their peers, versus 17.3% of men. Psychology studies show the existence of small, and sometimes unconscious, gender bias results in stereotypes of traditional female roles at work and home. Women are expected to be more competent and warm than men (Phelan et al., 2008), and these different standards result in harsher evaluation of women who do engage in self-promotion or leadership roles (Phelan & Rudman, 2010; Rudman, 1998). Gender stereotypes lead to reduced workplace aspirations and stymied participation, ultimately damaging women's chances of being hired, paid or promoted at an equal rate to men (National Academies Press, 2007).

Related studies to this work include Silveira et al. (2019) who use the StackOverflow 2018 survey but to identify recruitment channels of women into the developer job market. Other papers use organic StackOverflow data generated from the question and answer platform to examine engagement (Vasilescu et al., 2013), reputation building (Bosu et al., 2013) and reward incentivisation (Berger et al., 2017). A body of studies address gender differences in the software community such as barriers to online participation (Ford et al., 2016; Vasilescu et al., 2014), lacking female representation (Ford et al., 2017), disengagement from open source communities (Qiu et al., 2019), speed of bug fixing from gender diverse teams (Ortu et al., 2017) and greater cohesion in development projects with female presence (Catolino et al., 2019). Regarding the pay gap in programming careers, Dattero et al. (2005) examine the differences in hourly salaries of female and male software developers, finding gender is a statistically and practically significant factor. Dattero & Galup (2004) find the choice of programming language differs by gender with a higher proportion of men in object-orientated languages such as Java and C++. This study augments the existing literature as the only study to investigate the gender pay gap using the StackOverflow survey of developers.

3 Methods

3.1 Data

The data is provided by the 2019 StackOverflow Developer Survey which contains responses on the demographics, backgrounds, and careers of 90,000 programmers from 183 countries. Repondants were recruited through StackOverlow (https://stackoverflow.com/) and participation was incentivised with a profile badge so likely samples the most active users within the community (Silveira et al., 2019). Reporting earnings was optional so individuals without salary information were removed, which didn't introduce selection bias because men and women have comparable rates of missing data. Salary was trimmed to exclude the 5% tails, and normalised with natural logarithms. Including only those in full-time employment ensures annual salary is a representative measure of renumeration, so part-time and unemployed individuals were excluded. This study uses just US respondants due to lacking complete observations in other countries. Non-binary individuals only made up 1.6% of the US sample so the investigation is regretably limited to two genders. The final sample includes 15,942 individuals.

3.2 Base Human Capital Model

The 'naive' gender pay gap is specified with a simple multiplicative model of annual salary (Y_i) on gender ($G_i = 1$ if female):

$$ln(Y_i) = \beta_0 + \beta_1 G_i + \epsilon_i \Leftrightarrow Y_i = \beta_0 e^{\beta_1 G_i + \epsilon_i} \tag{1}$$

The human capital model instructs a richer specification with a set of explanatory variables $\boldsymbol{X_i'}$ which control for differences in endowments. Determinants include non-linear years of experience (EX_i, $(EX_i)^2$), education level (E_i), and having dependents (D_i). Finally, working hours (W_i) are included as a control:

$$ln(Y_i) = \beta_0 + \beta_1 G_i + \boldsymbol{\beta' X_i'} + \epsilon_i \tag{2a}$$
$$ln(Y_i) = \beta_0 + \beta_1 G_i + \beta_2 EX_i + \beta_3 (EX_i)^2 + \beta_4 E_i + \beta_5 D_i + \beta_6 W_i + \epsilon_i \tag{2b}$$

To explain how endowments are valued differently by gender, interactions with a subset of variables $\boldsymbol{Z_i'}$ are included:

$$ln(Y_i) = \beta_0 + \beta_1 G_i + \boldsymbol{\beta' X_i'} + \boldsymbol{\gamma'}(G_i * \boldsymbol{Z_i'}) + \epsilon_i \tag{3a}$$
$$ln(Y_i) = \beta_0 + \beta_1 G_i + \boldsymbol{\beta' X_i'} + \gamma_1 (G_i * EX_i) + \gamma_2 (G_i * D_i) + \epsilon_i \tag{3b}$$

Equations (1 - 3a) are estimated using Ordinary Least Squares with robust standard errors.

3.3 Skills-Based Human Capital Model

An individual's skills contribute to their human capital. A set of additional explanatory variables are added including posession of a STEM degree, size of employer organisation and frequency of open source contributions. Survey respondents could select any number of 24 job roles, and of 28 used programming languages. Due to this complexity, two approaches are used to estimate the skill-based human capital model:

3.3.1 Approach 1: Aggregate Indicator Variables

Dummy variables were constructed for individual membership to seven aggregate job categories – Developer, Manager, Academic, Designer, Data Scientist, Business and Student. For the mapping of granular to aggregate job types, see Appendix A. These categories are neither mutually exclusive, nor exhaustive. The human capital model extended by aggregate job type (J_i) is:

$$ln(Y_i) = \beta_0 + \beta_1 G_i + \boldsymbol{\beta' X_i'} + \boldsymbol{\gamma'}(G_i * \boldsymbol{Z_i'}) + \sum_{J}^{7} \delta_J \times I(J_i = 1) + \epsilon_i \tag{4}$$

Equation (4) can be expanded to include interaction terms, e.g. female managers.

3.3.2 Approach 2: Granular Indicator Variables

The many combinations of job types and languages makes it infeasible to include dummies for every unique response. An alternative approach expands the nested responses into single rows, which creates a panel where each individual represents multiple data points. To control for this repetition, errors are clustered at the individual level. For an individual i with job type j and language l, the skills-based human capital model using granular job type and language fixed-effects is:

$$ln(Y_{ijl}) = \beta_0 + \beta_1 G_{ijl} + \boldsymbol{\beta' X'_{ijl}} + \boldsymbol{\gamma'}(G_i * \boldsymbol{Z'_{ijl}}) + \alpha_j + \alpha_l + \epsilon_{ijl} \tag{5}$$

Where α_j is the job fixed-effect, α_l the language fixed-effect and ϵ_{ijl} the idiosyncratic error term.

3.4 Multilevel Effects Model

The large number of groups with small sample sizes makes the fixed-effects model vulnerable to estimation bias. Accordingly, a multilevel model is fitted with random intercepts for job type (j) and used languages (l):

$$ln(Y_{ijl}) = \overbrace{\beta_0 + \beta_1 G_{ijl} + \boldsymbol{\beta' X'_{ijl}} + \boldsymbol{\gamma'}(G_i * \boldsymbol{Z'_{ijl}})}^{\text{fixed part}} + \overbrace{u_j + u_l + \epsilon_{ijl}}^{\text{random part}} \tag{6a}$$

$$u_j \sim N(0, \sigma^2_{u_j}) \tag{6b}$$

$$u_l \sim N(0, \sigma^2_{u_l}) \tag{6c}$$

$$\epsilon_{ijl} \sim N(0, \sigma^2_{\epsilon}) \tag{6d}$$

3.5 Chow Test

Chow (1960) advises an alternative to including a gender dummy, where the model is fitted for gender subsamples, then compared to a full sample pooled regression. This allows all subgroup coefficients to vary such that $\beta_M \neq \beta_W$:

$$ln(Y_M) = \beta_0 + \boldsymbol{\beta'_M X'_M} + \sum_{J}^{7} \delta_{JM} \times I(J_M = 1) + \epsilon_M, \forall M \in n_M \tag{7a}$$

$$ln(Y_W) = \beta_0 + \boldsymbol{\beta'_W X'_W} + \sum_{J}^{7} \delta_{JW} \times I(J_W = 1) + \epsilon_W, \forall W \in n_W \tag{7b}$$

$$ln(Y_i) = \beta_0 + \boldsymbol{\beta' X'_i} + \sum_{J}^{7} \delta_J \times I(J_i = 1) + \epsilon_i, \forall i \in (n_M + n_W) \tag{7c}$$

The Chow test compares the residuals from fitted model on all n samples with k parameters, and the summed residuals from the subsamples with n_M men and n_W women. A rejection of the null implies the two gender regressions are not equal.

The Chow test statistic is:

$$F = \frac{(RRSS - URSS)/(k+1)}{URSS/(n_M + n_W - 2k)} \sim F(k+1, n_M + n_W - 2k)$$

3.6 Oaxaca-Blinder Decomposition

An Oaxaca-Blinder decomposition is used to clarify the explainability of the pay gap (Oaxaca, 1973). Following the notation of Hlavac (2018), the mean outcome difference between men (M) and women (W) is:

$$\Delta\bar{Y} = \bar{Y}_M - \bar{Y}_W \tag{8}$$

The mean outcome of gender $G \in \{M, F\}$ depends on a set of explanatory variables $\boldsymbol{\bar{X}_G}$ multiplied by coefficient estimates $\boldsymbol{\hat{\beta}_G}$. Rewriting (8):

$$\Delta\bar{Y} = \boldsymbol{\bar{X}_M}\boldsymbol{\hat{\beta}_M} - \boldsymbol{\bar{X}_W}\boldsymbol{\hat{\beta}_W} \tag{9}$$

Threefold-Decomposition: Equation (9) can be decomposed into three terms: (1) endowments: differences in explanatory variables, (2) coefficients: differences in magnitude of regression coefficients, and (3) interactions: the combined effect of endowments and coefficients:

$$\Delta\bar{Y} = \underbrace{(\boldsymbol{\bar{X}_M} - \boldsymbol{\bar{X}_W})'\boldsymbol{\hat{\beta}_W})}_{\text{endowments}} + \underbrace{\boldsymbol{\bar{X}'_W}(\boldsymbol{\hat{\beta}_M} - \boldsymbol{\hat{\beta}_W})}_{\text{coefficients}} + \underbrace{(\boldsymbol{\bar{X}_M} - \boldsymbol{\bar{X}_W})'(\boldsymbol{\hat{\beta}_M} - \boldsymbol{\hat{\beta}_W})}_{\text{interactions}} \tag{10}$$

Twofold-Decomposition: A twofold decomposition partions $\Delta\bar{Y}$ into a portion explained by gender differences in explanatory variables and a remainder of unexplained variation which is commonly treated as evidence of discrimination. The computation is relative to a baseline coefficient vector $\boldsymbol{\hat{\beta}_R}$:

$$\Delta\bar{Y} = \underbrace{(\boldsymbol{\bar{X}_M} - \boldsymbol{\bar{X}_W})'\boldsymbol{\hat{\beta}_R})}_{\text{explained}} + \underbrace{\boldsymbol{\bar{X}'_M}(\boldsymbol{\hat{\beta}_M} - \boldsymbol{\hat{\beta}_R})}_{\text{unexplained M}} + \underbrace{\boldsymbol{\bar{X}'_W}(\boldsymbol{\hat{\beta}_R} - \boldsymbol{\hat{\beta}_W})}_{\text{unexplained W}} \tag{11}$$

The threefold and twofold decompositions are estimated with Ordinary Least Squares regressions of real salary (USD) on a set of explanatory variables, and standard errors are based on 1000 bootstrapped samples.

4 Results

4.1 Descriptive Statistics

Table (1) reports summary statistics, with t-tests and chi-square tests of equality across genders. Trimmed compensation is preferred due to the presence of outliers in the original measure. Men have higher average salaries than women ($\mu_M = \$121,000, \mu_W = \$106,000, p = 0.001$), though the untrimmed difference is larger, suggesting a higher density of men in the upper ends of the salary distribution. Men are significantly older ($\mu_M = 33.7$ years, $\mu_W = 31.8$ years, $p = 0.001$), have more years of professional coding experience ($\mu_M = 10.0$ years, $\mu_W = 6.61$ years, $p = 0.001$), work marginally longer hours ($\mu_M = 42.7$ hours/week, $\mu_W = 41.5$ hours/week, $p = 0.001$), and are less likely to have dependents ($\mu_M = 57.8\%, \mu_W = 75.7\%, p = 0.001$). Additionally, men are more likely to work at large organisations and make frequent open source contributions. Conversely, women are more educated than men with a higher proportion of graduate and bachelor's degrees but these are less likely to be in STEM. For jobs and skills, the proportion of managers is balanced across genders, but men on average have more job roles and use more languages.

Table 1: Summary Statistics for US Sample of Programmers

	Man (n=14302)	**Woman (n=1640)**	**P-Value**
ConvertedComp			
Mean (SD)	$262,000 (466000)	$190,000 (356000)	0.001
Median [Min, Max]	$115,000 [0.00, 2e+06]	$100,000 [0.00, 2e+06]	
Missing	2168 (15.2%)	277 (16.9%)	
TrimmedComp			
Mean (SD)	$121,000 (65,800)	$106,000 (54,400)	0.001
Median [Min, Max]	$108,000 [6,250, 630,000]	$95,700 [6,200, 600,000]	
Missing	3354 (23.5%)	371 (22.6%)	
Age			
Mean (SD)	33.7 (9.23)	31.8 (8.11)	0.001
Median [Min, Max]	32.0 [1.00, 99.0]	30.0 [18.0, 67.0]	
Missing	937 (6.6%)	114 (7.0%)	
YearsCodePro			
Mean (SD)	10.0 (8.58)	6.61 (6.67)	0.001
Median [Min, Max]	7.00 [1.00, 50.0]	4.00 [1.00, 43.0]	
Missing	367 (2.6%)	62 (3.8%)	
WorkWeekHrs			
Mean (SD)	42.7 (7.21)	41.5 (5.65)	0.001
Median [Min, Max]	40.0 [1.00, 168]	40.0 [7.00, 90.0]	
Missing	1158 (8.1%)	182 (11.1%)	
Dependents			
No	8264 (57.8%)	1242 (75.7%)	0.001
Yes	5767 (40.3%)	366 (22.3%)	
Missing	271 (1.9%)	32 (2.0%)	
EdLevel			
Bachelors Degree	8325 (58.2%)	989 (60.3%)	0.001
Graduate Degree	3195 (22.3%)	442 (27.0%)	
Less than BA	2700 (18.9%)	196 (12.0%)	
Missing	82 (0.6%)	13 (0.8%)	
OrgSize			
Large (1000)	6066 (42.4%)	622 (37.9%)	0.013
Medium (1000)	3656 (25.6%)	443 (27.0%)	
Small (100)	2440 (17.1%)	297 (18.1%)	
Missing	2140 (15.0%)	278 (17.0%)	
STEM			
Mean (SD)	0.789 (0.408)	0.623 (0.485)	0.001
Median [Min, Max]	1.00 [0.00, 1.00]	1.00 [0.00, 1.00]	
OpenSourcer			
Never	5002 (35.0%)	823 (50.2%)	0.001
Rarely	4299 (30.1%)	483 (29.5%)	
Often	5001 (35.0%)	334 (20.4%)	
Manager			
Mean (SD)	0.0171 (0.130)	0.0226 (0.149)	0.156
Median [Min, Max]	0.00 [0.00, 1.00]	0.00 [0.00, 1.00]	
NumRoles			
Mean (SD)	3.05 (2.38)	2.24 (1.73)	0.001
Median [Min, Max]	2.00 [1.00, 24.0]	2.00 [1.00, 12.0]	
Missing	264 (1.8%)	41 (2.5%)	
NumLang			
Mean (SD)	5.27 (2.41)	4.48 (2.09)	0.001
Median [Min, Max]	5.00 [1.00, 26.0]	4.00 [1.00, 16.0]	
Missing	60 (0.4%)	14 (0.9%)	

4.2 Linear Models

Table (2) presents the base human capital model. Following the rejection of the studentised Breusch-Pagan test for homoskedasticity (see Appendix B-4.5.1), all standard errors are robust. The simple multiplicative model shows women earn 86% of male salary. The low R^2 suggests gender alone is insignificant to explain the determinants of salary. Specifications (2) and (3) add additional explanatory human capital variables. Years of professional coding and its square are highly significant with positive but decreasing returns to experience. Education has a significant effect on salary, with bachelor's degrees and graduate degrees equivalent to approximately two and four years of additional experience. The pay gap falls to 96.4% on the addition of these variables. Specification (4) includes interactions with years of experience and dependents. Each additional year of experience is worth less for women than men, but dependents *a priori* has no significant interaction with gender (p=0.120). Gender becomes positive, but the significant contribution from years of experience combined with the negative penalty on female experience explains this sign change. The increase in R^2 across these specifications suggests the expanded models explain more of the variation in pay across individuals.

Table 2: Base Human Capital Model

	Dependent variable:			
	LogSalary			
	(1)	(2)	(3)	(4)
GenderWoman	-0.122^{***}	-0.025^{*}	-0.036^{***}	0.041^{**}
	(0.014)	(0.013)	(0.013)	(0.019)
YearsCodePro		0.055^{***}	0.054^{***}	0.056^{***}
		(0.001)	(0.002)	(0.002)
I(YearsCodePro^2)		-0.001^{***}	-0.001^{***}	-0.001^{***}
		(0.00004)	(0.00005)	(0.00005)
DependentsYes			-0.006	-0.003
			(0.009)	(0.009)
EdLevelBachelors Degree			0.132^{***}	0.133^{***}
			(0.011)	(0.011)
EdLevelGraduate Degree			0.228^{***}	0.229^{***}
			(0.013)	(0.013)
WorkWeekHrs			0.006^{***}	0.006^{***}
			(0.001)	(0.001)
GenderWoman:YearsCodePro				-0.010^{***}
				(0.002)
GenderWoman:DependentsYes				-0.050
				(0.032)
Constant	11.588^{***}	11.232^{***}	10.864^{***}	10.854^{***}
	(0.005)	(0.009)	(0.037)	(0.037)
Observations	12,217	12,177	11,968	11,968
R^2	0.006	0.184	0.214	0.217
Adjusted R^2	0.006	0.184	0.214	0.216
Residual Std. Error	0.480	0.434	0.426	0.425
F Statistic	73.217^{***}	916.878^{***}	466.306^{***}	367.383^{***}

Note: Robust SE, *p<0.1; **p<0.05; ***p<0.01

Table (3) presents the skill-based human capital model. Specification (1) includes the main effects, demonstrating significant reductions in salary from smaller organisation size, and significant additions from open-source contributions and STEM degrees. Aggregate occupational indicators demonstrate job type is a significant determinant of salary for academics and business-side employees who are on average paid less, and for managers, developers and data scientists who are paid more. Specification (2) includes the interactions on gender, where a woman receives a significant negative penalty for years of experience but is significantly higher compensated if she is a manager. The significance and magnitude of most coefficients is comparable across specifications with and without fixed-effects, but the pay gap is larger in Specification (3). In Specification (4), years of experience and dependents have a highly significant and negative interaction with gender. The increase in R^2 across the set of specifications implies added variables explain a greater proportion of variance in salary.

4.3 Mutltilevel Model

The multilevel results are consistent with the fixed-effect model (Table 4): years of experience, higher education, working at a large firm, open sourcing, and STEM degrees have positive and significant contributions to salary. The coefficients on gender interactions with years of experience and dependents are negative and significant, confirming that later-stage career women are paid less than their male and early-stage career female counterparts.

Table 3: Skills-Based Human Capital Model

	Dependent variable:			
	LogSalary			
	(1)	(2)	(3)	(4)
GenderWoman	−0.004	0.068***	−0.027***	0.044***
	(0.014)	(0.020)	(0.004)	(0.006)
YearsCodePro	0.051***	0.052***	0.050***	0.050***
	(0.002)	(0.002)	(0.0004)	(0.0004)
I(YearsCodePro^2)	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00005)	(0.00005)	(0.00001)	(0.00001)
DependentsYes	−0.014	−0.012	0.008***	0.010***
	(0.009)	(0.009)	(0.002)	(0.002)
EdLevelBachelors Degree	0.092***	0.093***	0.060***	0.060***
	(0.012)	(0.012)	(0.003)	(0.003)
EdLevelGraduate Degree	0.185***	0.186***	0.141***	0.141***
	(0.014)	(0.014)	(0.003)	(0.003)
WorkWeekHrs	0.006***	0.006***	0.007***	0.007***
	(0.001)	(0.001)	(0.0002)	(0.0002)
OrgSizeMedium (<1000)	−0.110***	−0.110***	−0.097***	−0.097***
	(0.009)	(0.009)	(0.002)	(0.002)
OrgSizeSmall (<100)	−0.147***	−0.146***	−0.122***	−0.121***
	(0.010)	(0.010)	(0.003)	(0.003)
OpenSourcerOften	0.134***	0.133***	0.076***	0.075***
	(0.010)	(0.010)	(0.002)	(0.002)
OpenSourcerRarely	0.067***	0.067***	0.047***	0.046***
	(0.010)	(0.010)	(0.002)	(0.002)
STEMYes	0.056***	0.057***	0.047***	0.048***
	(0.010)	(0.010)	(0.003)	(0.003)
Developer	0.071***	0.070***		
	(0.009)	(0.009)		
Manager	0.364***	0.341***		
	(0.038)	(0.041)		
Academic	−0.253***	−0.250***		
	(0.081)	(0.081)		
Designer	0.010	0.017		
	(0.175)	(0.176)		
Data_Scientist	0.161***	0.157***		
	(0.044)	(0.044)		
Business	−0.151***	−0.149***		
	(0.041)	(0.041)		
Student	0.167	0.173		
	(0.848)	(0.848)		
GenderWoman:YearsCodePro		−0.010***		−0.008***
		(0.002)		(0.001)
GenderWoman:DependentsYes		−0.042		−0.051***
		(0.033)		(0.010)
GenderWoman:Manager		0.213**		
		(0.107)		
Constant	10.879***	10.869***	10.700***	10.696***
	(0.042)	(0.042)	(0.020)	(0.020)
Developer FE	No	No	Yes	Yes
Language FE	No	No	Yes	Yes
Observations	10,419	10,419	165,622	165,622
R^2	0.257	0.259	0.279	0.280
Adjusted R^2	0.256	0.258	0.279	0.280
Residual Std. Error	0.406	0.406	0.402	0.401
F Statistic	189.488***	165.501***	1,032.523***	1,006.299***

Note: Robust SE, *p<0.1; **p<0.05; ***p<0.01

Table 4: Multi-Level Model

	Dependent variable:	
	LogSalary	
	(1)	(2)
GenderWoman	-0.027^{***}	0.044^{***}
	(0.004)	(0.006)
YearsCodePro	0.050^{***}	0.050^{***}
	(0.0004)	(0.0004)
I(YearsCodePro^2)	-0.001^{***}	-0.001^{***}
	(0.00001)	(0.00001)
DependentsYes	0.008^{***}	0.010^{***}
	(0.002)	(0.002)
EdLevelBachelors Degree	0.060^{***}	0.060^{***}
	(0.003)	(0.003)
EdLevelGraduate Degree	0.141^{***}	0.141^{***}
	(0.003)	(0.003)
WorkWeekHrs	0.007^{***}	0.007^{***}
	(0.0001)	(0.0001)
OrgSizeMedium (<1000)	-0.097^{***}	-0.097^{***}
	(0.002)	(0.002)
OrgSizeSmall (<100)	-0.121^{***}	-0.121^{***}
	(0.003)	(0.003)
OpenSourcerOften	0.076^{***}	0.075^{***}
	(0.002)	(0.002)
OpenSourcerRarely	0.047^{***}	0.046^{***}
	(0.003)	(0.003)
STEMYes	0.047^{***}	0.048^{***}
	(0.003)	(0.003)
GenderWoman:YearsCodePro		-0.008^{***}
		(0.001)
GenderWoman:DependentsYes		-0.051^{***}
		(0.010)
Constant	10.892^{***}	10.887^{***}
	(0.028)	(0.028)
Random Effects		
σ^2	0.16	0.16
τ_{00} UsedLang	0.00	0.00
DevType	0.01	0.01
ICC	0.10	0.10
N UsedLang	28	28
DevType	24	24
Observations	165,622	165,622
Log Likelihood	-84,124.600	-83,995.040
Akaike Inf. Crit.	168,281.200	168,026.100
Bayesian Inf. Crit.	168,441.500	168,206.400

Note: Robust SE, *p<0.1; **p<0.05; ***p<0.01

4.4 Chow Test

The Chow test F-statistic is 3.47 which exceeds the critical value at the 99% confidence interval. In Table (5) the constant term is larger for men than women suggesting a higher base salary. Years of experience, bachelor's degrees and open source contributions are valued more highly for men than women. Conversely, STEM degrees are more highly valued for women, and women face a lower reduction in salary from working at medium or small organisations relative to large organisations. In aggregate job categories, female academics are paid less compared to men, but female managers are paid more. The R^2 for the male regression is higher than for females (0.266 v.s. 0.171) suggesting the human capital variables included in this model explain a higher proportion of male salary.

Table 5: Chow-Test Model

	Dependent variable:		
	LogSalary		
	man	woman	pooled
	(1)	(2)	(3)
YearsCodePro	0.053***	0.038***	0.051***
	(0.002)	(0.006)	(0.002)
I(YearsCodePro^2)	−0.001***	−0.001***	−0.001***
	(0.00005)	(0.0002)	(0.00005)
DependentsYes	−0.012	−0.047	−0.014
	(0.009)	(0.032)	(0.009)
EdLevelBachelors Degree	0.094***	0.085	0.092***
	(0.012)	(0.053)	(0.012)
EdLevelGraduate Degree	0.186***	0.185***	0.184***
	(0.014)	(0.057)	(0.014)
WorkWeekHrs	0.005***	0.009***	0.006***
	(0.001)	(0.003)	(0.001)
OrgSizeMedium (<1000)	−0.118***	−0.044	−0.110***
	(0.010)	(0.030)	(0.009)
OrgSizeSmall (<100)	−0.148***	−0.123***	−0.147***
	(0.011)	(0.032)	(0.010)
OpenSourcerOften	0.137***	0.079**	0.134***
	(0.010)	(0.038)	(0.010)
OpenSourcerRarely	0.063***	0.092***	0.067***
	(0.010)	(0.028)	(0.010)
STEMYes	0.055***	0.067**	0.056***
	(0.011)	(0.027)	(0.010)
Developer	0.068***	0.086***	0.071***
	(0.009)	(0.027)	(0.009)
Manager	0.342***	0.565***	0.364***
	(0.041)	(0.102)	(0.038)
Academic	−0.183**	−0.530***	−0.253***
	(0.089)	(0.154)	(0.081)
Designer	0.032	0.019	0.009
	(0.236)	(0.202)	(0.175)
Data_Scientist	0.160***	0.134**	0.160***
	(0.055)	(0.065)	(0.044)
Business	−0.131***	−0.199**	−0.151***
	(0.048)	(0.083)	(0.041)
Constant	10.883***	10.796***	10.878***
	(0.043)	(0.143)	(0.042)
Observations	9,338	1,081	10,419
R^2	0.266	0.171	0.257
Adjusted R^2	0.265	0.158	0.256
Residual Std. Error	0.404	0.415	0.406
F Statistic	198.608***	12.920***	211.788***

Note: Robust SE, *p<0.1; **p<0.05; ***p<0.01
Student excluded as no observations for woman sample

4.5 Oaxaca-Blinder Decompositions

The mean annual salary is \$123,932 for men and \$109,337 for women, with a difference of \$14,585. Endowments explain 47.8% of the gap, coefficients 14.8% and interactions 37.4%.

Table 6: Threefold Oaxaca Blinder Decomposition Results in USD

	coeff	pct	se
Endowments	6977.696	47.8%	1504.225
Coefficients	2157.110	14.8%	1738.487
Interaction	5450.489	37.4%	1517.453

Figure (1) shows years of professional coding has a significant effect on endowments ($p<0.000$), reinforcing the finding that part of the pay gap is explained by women possessing on average 3.5 years less experience than men. Male and female years of experience have significantly different coefficients, where the payoff for an additional year of coding experience is \$459 greater for men. Dependents also has a significant coefficient effect ($p = 0.047$). Despite no differences in endowments, fathers earn \$7,435 more on average than mothers.

Figure 1: Endowments, coefficients and intercepts of gender wage differentials

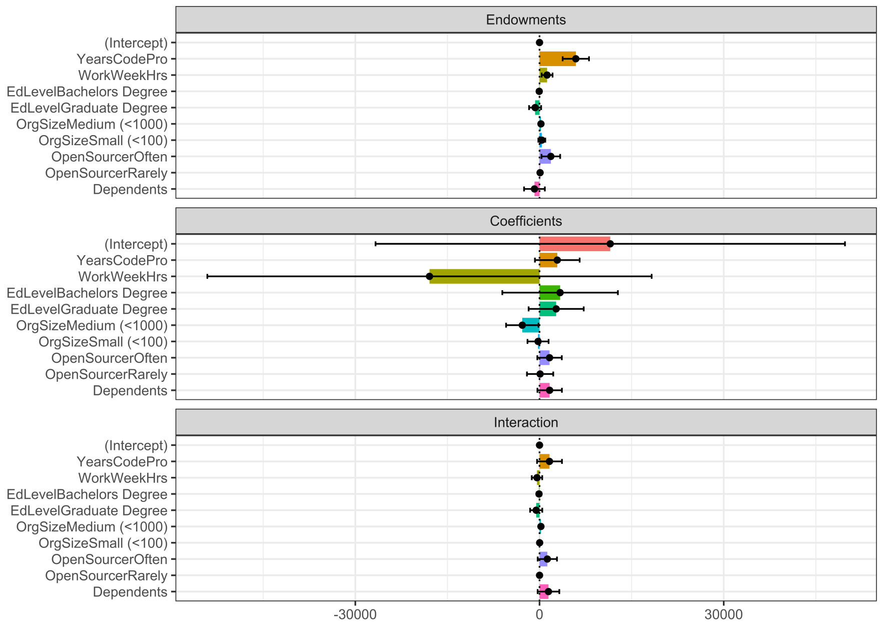


Table (7) shows the twofold decomposition with differently weighted reference coefficients. Using $W \in \{0, 1\}$ assumes only one group faces labour market discrimination. This assumption is strong, especially considering the undervaluation of one group is often associated with overvaluation of the other (Cotton, 1988). Instead, Reimers et al. (1983) proposes an equal weighting between groups ($W = 0.5$), Cotton (1988) proposes scaling by the proportion of individuals in each group ($W = 0.9$), and Neumark (1988) proposes using the pooled regression coefficients excluding either group indicator variable ($W \in \{-1, -2\}$). The imbalance between male and female samples makes a Cotton (1988) weighting most appropriate. Assuming the regression equation does not suffer from omitted variable bias, this weighting implies \$11,283 of the wage gap is explained, while the remaining \$3,259 is unexplained and may be indicative of labour market discrimination. Of the unexplained differences, \$669 arise in favour of men and \$2,590 from discrimination against women. Figure (2) show years of experience, graduate-level eduation, open source contributions and dependents are significant in determining the unexplained differences betwen men and women. As Figure (3) demonstrates, these unexplained pay differentials are skewed towards discrimination against women. Table (8) gives point estimates of key variables.

Table 7: Twofold Oaxaca Blinder Decomposition Results in USD

	Explained		**Unexplained**		**Unexplained(M)**		**Unexplained(W)**	
Weight	coef	se	coef	se	coef	se	coef	se
0.0	8090.42	1580.81	6451.85	2613.90	6451.85	2613.90	0.00	0.00
1.0	11652.53	834.20	2889.74	1755.49	0.00	0.00	2889.74	1755.49
0.5	9871.47	999.63	4670.80	2087.81	3225.93	1306.95	1444.87	877.75
0.9	11282.95	1445.47	3259.32	2494.16	669.40	2342.70	2589.92	182.14
-1.0	11540.62	819.57	3001.65	1713.93	311.43	178.00	2690.22	1536.27
-2.0	11416.16	820.37	3126.11	1786.54	0.00	0.00	3126.11	1786.54

Table 8: Point estimates of unexplained differentials for men and women

	Weight	coef(unexplained M)	coef(unexplained W)
YearsCodePro	0.9	468.89	2594.42
Dependents	0.9	322.41	1479.37
OpenSourcerOften	0.9	301.75	1465.31
EdLevelGraduate Degree	0.9	224.78	2430.52

Figure 2: Explained and unexplained portions of gender wage differentials

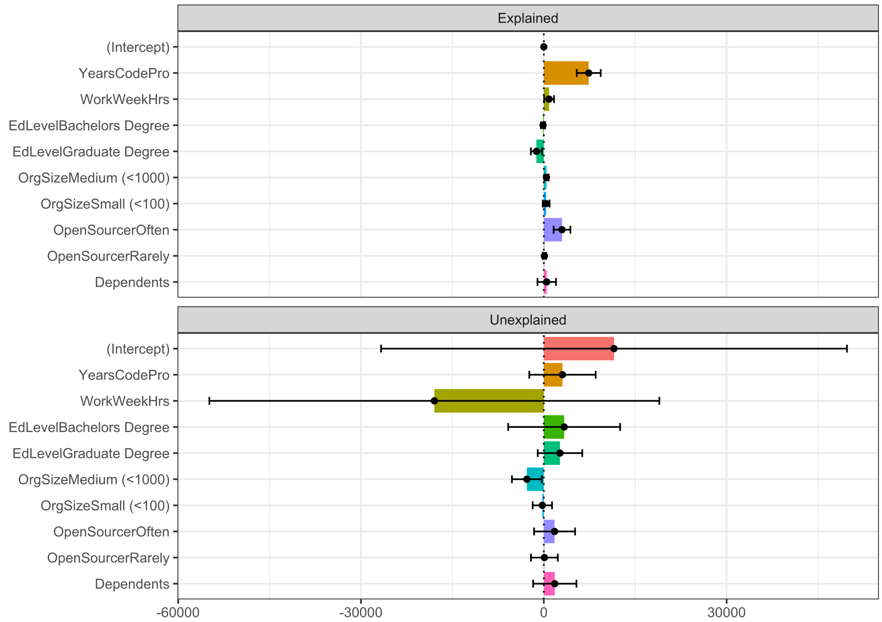
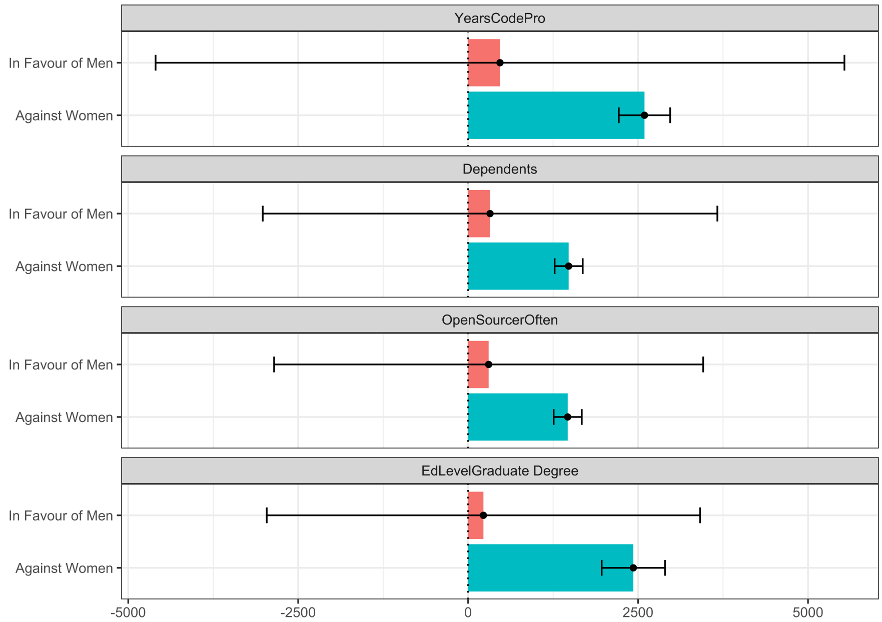


Figure 3: Key variables in unexplained gender wage differentials



4.6 Robustness Checks

To confirm findings, three robustness checks are conducted. Firstly, influential outliers are removed based on Cook's Distance (Williams, 1987), which measures the change in estimated regression coefficients when the ith case is deleted:

$$\begin{aligned} D_i &= \frac{(\hat{\beta} - \hat{\beta}_i)^T \boldsymbol{X^T X} (\hat{\beta} - \hat{\beta}_i)}{\rho \hat{\sigma}^2} \\ &= \frac{e_i^2}{\rho \hat{\sigma}^2} \left[\frac{h_{ii}}{(1 - h_{ii})^2} \right] \end{aligned}$$

Distance D_i depends on the size of residual e_i and leverage value h_{ii}. If either are large and D_i exceeds a threshold of $T = 4/N$, the ith case is considered influential. Table (9) show the significant of explanatory variables is consistent and the coefficients are in most cases larger when outliers are dropped. An exception is in the interaction between gender and dependents which remains significant in Specification (4) but is lower in magnitude.

Secondly, to test assumptions on error structure, robust standard errors are compared to robust errors clustered at the individual level. Table (10) shows the significance and magnitude of coefficients is consistent across error assumptions, with the exception of the interaction between gender and dependents.

Finally, upsampling is used to counteract sample imbalace. Table (11) confirms the significance and magnitude of coefficients is consistent across specifications, suggesting class imbalance does not significantly impact interpretation of the results.

Table 9: Robustness Check: Outliers

	Dependent variable:			
	LogSalary			
	default	rm outliers	default	rm outliers
	(1)	(2)	(3)	(4)
GenderWoman	0.068***	0.087***	0.044***	0.058***
	(0.019)	(0.018)	(0.006)	(0.005)
YearsCodePro	0.052***	0.056***	0.050***	0.055***
	(0.002)	(0.001)	(0.0004)	(0.0003)
I(YearsCodePro^2)	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00004)	(0.00004)	(0.00001)	(0.00001)
DependentsYes	−0.012	−0.023***	0.010***	−0.004**
	(0.009)	(0.008)	(0.002)	(0.002)
EdLevelBachelors Degree	0.093***	0.099***	0.060***	0.079***
	(0.011)	(0.010)	(0.003)	(0.002)
EdLevelGraduate Degree	0.186***	0.191***	0.141***	0.153***
	(0.013)	(0.011)	(0.003)	(0.003)
WorkWeekHrs	0.006***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.0001)	(0.0001)
OrgSizeMedium (<1000)	−0.110***	−0.111***	−0.097***	−0.085***
	(0.009)	(0.008)	(0.002)	(0.002)
OrgSizeSmall (<100)	−0.146***	−0.145***	−0.121***	−0.111***
	(0.011)	(0.009)	(0.003)	(0.002)
OpenSourcerOften	0.133***	0.134***	0.075***	0.095***
	(0.010)	(0.008)	(0.002)	(0.002)
OpenSourcerRarely	0.067***	0.069***	0.046***	0.047***
	(0.010)	(0.008)	(0.003)	(0.002)
STEMYes	0.057***	0.061***	0.048***	0.037***
	(0.010)	(0.009)	(0.003)	(0.002)
Developer	0.070***	0.062***		
	(0.009)	(0.008)		
Manager	0.341***	0.305***		
	(0.037)	(0.038)		
Academic	−0.250***	−0.253***		
	(0.059)	(0.081)		
Designer	0.017	0.016		
	(0.129)	(0.241)		
Data_Scientist	0.157***	0.200***		
	(0.042)	(0.042)		
Business	−0.149***	−0.154***		
	(0.042)	(0.043)		
Student	0.173			
	(0.287)			
GenderWoman:YearsCodePro	−0.010***	−0.011***	−0.008***	−0.010***
	(0.002)	(0.002)	(0.001)	(0.001)
GenderWoman:DependentsYes	−0.042	−0.022	−0.051***	−0.028***
	(0.033)	(0.031)	(0.010)	(0.008)
GenderWoman:Manager	0.213*	0.235		
	(0.119)	(0.201)		
Constant	10.869***	10.785***	10.696***	10.660***
	(0.030)	(0.028)	(0.016)	(0.015)
Developer FE	No	No	Yes	Yes
Language FE	No	No	Yes	Yes
Observations	10,419	9,952	165,622	156,421
R^2	0.259	0.331	0.280	0.384
Adjusted R^2	0.258	0.330	0.280	0.383
Residual Std. Error	0.406	0.340	0.401	0.319
F Statistic	165.501***	233.883***	1,006.299***	1,520.065***

Note: Robust SE, *p<0.1; **p<0.05; ***p<0.01

Table 10: Robustness Check: Clustered Errors

	Dependent variable:			
	LogSalary			
	robust	cluster	robust	cluster
	(1)	(2)	(3)	(4)
GenderWoman	0.068***	0.068***	0.044***	0.044
	(0.020)	(0.020)	(0.006)	(0.029)
YearsCodePro	0.052***	0.052***	0.050***	0.050***
	(0.002)	(0.002)	(0.0004)	(0.003)
I(YearsCodePro^2)	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00005)	(0.00005)	(0.00001)	(0.0001)
DependentsYes	−0.012	−0.012	0.010***	0.010
	(0.009)	(0.009)	(0.002)	(0.015)
EdLevelBachelors Degree	0.093***	0.093***	0.060***	0.060***
	(0.012)	(0.012)	(0.003)	(0.019)
EdLevelGraduate Degree	0.186***	0.186***	0.141***	0.141***
	(0.014)	(0.014)	(0.003)	(0.021)
WorkWeekHrs	0.006***	0.006***	0.007***	0.007***
	(0.001)	(0.001)	(0.0002)	(0.002)
OrgSizeMedium (<1000)	−0.110***	−0.110***	−0.097***	−0.097***
	(0.009)	(0.009)	(0.002)	(0.014)
OrgSizeSmall (<100)	−0.146***	−0.146***	−0.121***	−0.121***
	(0.010)	(0.010)	(0.003)	(0.017)
OpenSourcerOften	0.133***	0.133***	0.075***	0.075***
	(0.010)	(0.010)	(0.002)	(0.015)
OpenSourcerRarely	0.067***	0.067***	0.046***	0.046***
	(0.010)	(0.010)	(0.002)	(0.014)
STEMYes	0.057***	0.057***	0.048***	0.048***
	(0.010)	(0.010)	(0.003)	(0.017)
Developer	0.070***	0.070***		
	(0.009)	(0.009)		
Manager	0.341***	0.341***		
	(0.041)	(0.041)		
Academic	−0.250***	−0.250***		
	(0.081)	(0.081)		
Designer	0.017	0.017		
	(0.176)	(0.176)		
Data_Scientist	0.157***	0.157***		
	(0.044)	(0.044)		
Business	−0.149***	−0.149***		
	(0.041)	(0.041)		
Student	0.173	0.173		
	(0.848)	(0.848)		
GenderWoman:YearsCodePro	−0.010***	−0.010***	−0.008***	−0.008***
	(0.002)	(0.002)	(0.001)	(0.003)
GenderWoman:DependentsYes	−0.042	−0.042	−0.051***	−0.051
	(0.033)	(0.033)	(0.010)	(0.049)
GenderWoman:Manager	0.213**	0.213**		
	(0.107)	(0.107)		
Constant	10.869***	10.869***	10.696***	10.696***
	(0.042)	(0.042)	(0.020)	(0.077)
Developer FE	No	No	Yes	Yes
Language FE	No	No	Yes	Yes
Observations	10,419	10,419	165,622	165,622
R^2	0.259	0.259	0.280	0.280
Adjusted R^2	0.258	0.258	0.280	0.280
Residual Std. Error	0.406	0.406	0.401	0.401
F Statistic	165.501***	165.501***	1,006.299***	1,006.299***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: Robustness Check: Upsampling

	Dependent variable:			
	LogSalary			
	default	upsampled	default	upsampled
	(1)	(2)	(3)	(4)
GenderWoman	0.068***	0.076***	0.044***	0.039***
	(0.020)	(0.010)	(0.006)	(0.006)
YearsCodePro	0.052***	0.050***	0.050***	0.049***
	(0.002)	(0.001)	(0.0004)	(0.0004)
I(YearsCodePro^2)	−0.001***	−0.001***	−0.001***	−0.001***
	(0.00005)	(0.00004)	(0.00001)	(0.00001)
DependentsYes	−0.012	−0.008	0.010***	0.013***
	(0.009)	(0.009)	(0.002)	(0.002)
EdLevelBachelors Degree	0.093***	0.089***	0.060***	0.067***
	(0.012)	(0.010)	(0.003)	(0.003)
EdLevelGraduate Degree	0.186***	0.184***	0.141***	0.144***
	(0.014)	(0.011)	(0.003)	(0.003)
WorkWeekHrs	0.006***	0.007***	0.007***	0.009***
	(0.001)	(0.001)	(0.0002)	(0.0002)
OrgSizeMedium (<1000)	−0.110***	−0.083***	−0.097***	−0.089***
	(0.009)	(0.007)	(0.002)	(0.002)
OrgSizeSmall (<100)	−0.146***	−0.142***	−0.121***	−0.132***
	(0.010)	(0.008)	(0.003)	(0.003)
OpenSourcerOften	0.133***	0.121***	0.075***	0.054***
	(0.010)	(0.008)	(0.002)	(0.002)
OpenSourcerRarely	0.067***	0.085***	0.046***	0.060***
	(0.010)	(0.007)	(0.002)	(0.002)
STEMYes	0.057***	0.070***	0.048***	0.043***
	(0.010)	(0.007)	(0.003)	(0.003)
Developer	0.070***	0.082***		
	(0.009)	(0.006)		
Manager	0.341***	0.340***		
	(0.041)	(0.041)		
Academic	−0.250***	−0.358***		
	(0.081)	(0.051)		
Designer	0.017	0.060		
	(0.176)	(0.072)		
Data_Scientist	0.157***	0.165***		
	(0.044)	(0.022)		
Business	−0.149***	−0.210***		
	(0.041)	(0.025)		
Student	0.173	0.186		
	(0.848)	(0.841)		
GenderWoman:YearsCodePro	−0.010***	−0.010***	−0.008***	−0.008***
	(0.002)	(0.001)	(0.001)	(0.001)
GenderWoman:DependentsYes	−0.042	−0.052***	−0.051***	−0.043***
	(0.033)	(0.014)	(0.010)	(0.010)
GenderWoman:Manager	0.213**	0.285***		
	(0.107)	(0.052)		
Constant	10.869***	10.802***	10.696***	10.598***
	(0.042)	(0.034)	(0.020)	(0.020)
Developer FE	No	No	Yes	Yes
Language FE	No	No	Yes	Yes
Observations	10,419	18,697	165,622	310,511
R^2	0.259	0.232	0.280	0.258
Adjusted R^2	0.258	0.231	0.280	0.258
Residual Std. Error	0.406	0.408	0.401	0.408
F Statistic	165.501***	255.733***	1,006.299***	1,686.210***

Note: Robust SE, *p<0.1; **p<0.05; ***p<0.01

5 Discussion

This study implements a carefully considered statistical design to explain gender pay differentials between programmers, returning a number of key findings. Experience is highly influential in determining salary and exhibits decreasing marginal returns, in line with H1 predictions and a Mincerian wage relationship (Mincer, 1974). Education is important in deciding the market rate of an individual's productivity, satisfying H2. The value of a bachelor's degree and a graduate degree is equal to two and four years of additional experience, respectively. Degrees in STEM have a wage premium of 5.7%. Larger organisation size and more frequent open-source contributions are also associated with wage premiums. As predicted under H3, wages are higher for highly-skilled occupations of managers, data scientists and developers, but academics and business-facing roles face a wage reduction. Female managers enjoy significant wage premiums in line with findings from Blau & Kahn (2007) and Lyness & Judiesch (2001). The addition of granular job types and programming languages explains additional variation in salary between individuals in the sample, increasing the model R^2 by approximately 2%.

Controlling for these human capital factors shrinks the unexplained gender pay gap from 11.5% to 2.7%, consistent with the pattern predicted by H4 and found across the literature (Dattero et al., 2005; Tharp et al., 2019). The Chow test shows the R^2 for men was higher than women, suggesting the human capital model better explains the dependencies of income for men, a similar result as Suter & Miller (1973). Adding interactions on women's years of experience and dependents switches the pay gap in favour of women, but coefficients on these interactions are significant and negative. Thus, a woman programmer is paid more than a man in her early-career but penalties amass with experience, especially if she decides to have children. The differential valuation of the same endowments is indicative of burdens from career interruptions and motherhood (Budig & England, 2001; Costa Dias et al., 2018). The results of the Oaxaca-Blinder decomposition confirm H5: \$11,283 of the mean pay gap between men and women is explained, while \$2,590 is unexplained for women and may signify discrimination. As DesRoches et al. (2010) describe, this difference might seem inconsequential given the average man and woman earn a six-figure annual salary. However, over a 40-year career, these unexplained differences result in a woman earning nearly \$100,000 less than a similar male, without accounting for compound interest or investments. The threefold decomposition reveals that each year of additional experience is valued \$459 less for women, and that fathers earn \$7,435 more on average than mothers. These findings suggest only part of the gender pay gap can be explained by differences in endowments, and the remainder originates in the differential valuation of the same endowments. Proponents of the human capital model argue men and women receive unequal pay owing to unequal work, but the findings of this study suggest even equal work is valued unequally by gender.

The findings of this study are subject to some limitations. Pay gap studies are particularly sensitive to the sample used and the technique deployed (Weichselbaumer & Winter-Ebmer, 2005). A number of robustness checks confirm the effect of explanatory variables. The exception is the interaction between gender and dependents which remains in the anticipated negative direction but falls in significance so careful interpretation of this effect is required. The choice of annual salary as the outcome variable may exacerbate the estimated pay gap and some economists prefer hourly wages instead (Blau & Kahn, 2007). Annual salary may conversely underestimate the true gap because it excludes bonuses and stock options, which have been shown to boost the salary of men more than women (Geddes & Heywood, 2003; Lips, 2013). The pay gap may also be an underestimate because a large driver of pay differentials comes from women working part-time hours (Goldin, 2014), especially if they are mothers (Allard & Janes, 2008), so leaving out part-time workers obscures some of the story (Lips, 2013). The inclusion of working hours may explain the fall in significance on the gender and dependents interaction in some specifications.

The sample also has limitations. As Tharp et al. (2019) suggest, the coefficients of the women-only Chow regression should be interpreted cautiously due to small cross-tabulations. However, a robustness check using upsampling confirms the main findings are robust to sample imbalance. The sample represents only a snapshot in time and is therefore limited in comparison to longitudinal studies which better account for individual-specific idiosyncrasy so permit more accurate estimates of gendered career trajectories (Gibb et al., 2014; Green, 1990). Weichselbaumer & Winter-Ebmer (2005) find the pay gap has shifted from 65% in the 1960s to 35% in the 1990s, and likely continues to shift. Cohort effects could be significant, especially in the programmer industry which is relatively young (Tharp et al., 2019). Other threats to external validity come from representativeness. Those in the StackOverflow community who volunteered responses may have different innate characteristics to the population of programmers at large. The sample also only contains men and women from the United States so cannot comment on the discrimination faced by programmers of different countries or gender identities. Despite this limitation, the 2019 United National Development Programme Report finds that women in 150 countries are paid less than men, indicating universal pay gaps worldwide (United Nations Development Program, 2019).

The assumptions of frameworks can be questioned. On one hand, the Oaxaca-Blinder model assumes that unexplained differences are attributable to discrimination, but only if the model does not suffer from omitted variable bias (Tharp et al., 2019). Due to the relatively low R^2, particularly for women, the Oaxaca-Blinder decomposition may overstate the influence of discrimination. On the other hand, as Lips (2013) argues, the human capital model assumes gender neutrality of the inputs such that women and men are evaluated on a 'level-playing field', but this idealised benchmark of fairness is rare in reality so the pay gap in this study may underestimate discrimination. Accordingly, Lips (2013) advocates for an acknowledgement that the socialisation of gender renders any input non-neutral and reflective of a discriminatory system beginning at birth. Take education as an example – the choice of school subjects, college degree or career path cannot be considered a free, rational choice when stereotypes guide boys' and girls' decisions (Leaper et al., 2007; White & White, 2006). A study by O'Dea et al. (2018) shows girls are attuned to gender stereotypes, making them less likely to pursue traditionally male-dominated STEM fields, while Sukhai & Mohler (2016) show 'Imposter Syndrome' disproportionately affects female STEM graduate students, preventing them from internalising their worth and accomplishments (Jackson & Heath, 2014). As Lips (2013) elucidates, this psyche is unsurprising given girls are 13% less likely to be told by a teacher and 19% by a parent that they'd be well-suited to a degree in computer science. Working hours are another example where the assumption of free-choice is weak. A study by Özbilgin et al. (2011) confirms that work-life choices reflect a deeper entrenchment of traditional parenting and domestic roles, indicative of a societal power relationship. The key question arises, is it fair to assume controlling for human capital endowments like education and career choices 'explains away' the gender pay gap? A more productive understanding requires the examination of pre-market gender stereotypes and pervasive social conditioning for male and female workers in society, not just their treatment in the labour market.

6 Policy Recommendations and Conclusions

This study investigates the determinants of programmers' pay, finding significant premiums to years of coding experience, education in STEM fields and open source contributions versus significant penalties to a woman's accumulation of coding experience and to motherhood. A number of policy recommendations arise to alleviate gendered penalties for female programmers, increase diversity and improve the current market equilibrium. Firstly, pre-market factors are important, education policies should focus on attracting more female talent into computer science and STEM fields. Secondly, to retain this talent, corporations must commit to more diverse hiring policies and to making the work environment of the technology sector more amenable to women with STEM qualifications. Thirdly, work flexibility is a key determinant of women's labour market participation, so greater efforts can be made in granting women the flexibility to juggle both domestic and professional commitments. Particularly, offering substitutes to domestic responsibilities through better childcare provision can mitigate the reduction in hours and career interruptions. The Scandinavian model has appeal, where mandatory paternity leave compels a more equal share of parenthood between fathers and mothers. Finally, open source communities lack diversity, and poor representation causes disengagement. Encouraging more women into these communities will thus encourage more to follow, benefitting the women themselves and the wider community.

For any of the prior recommendations to have effect, a change in attitudes is a necessary prerequisite to tackle the perpetuation of stereotypes which bolster the dominance of men in tech, and limit women from reaching top-level positions. By identifying the implicit and often invisible biases which encode the gender pay gap, educators, corporations and policy-makers have a role to play in ensuring that a programmer's equal endowments are judged and paid fairly irrespective of gender.

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A Mapping Table for Constructed Variables

Var	**Levels**	**Original Levels**
	Less than BA	`I never completed any formal education', `Primary/elementary school', `Secondary school (e.g. American high school, German Realschule or Gymnasium, etc.)',`Some college/university study without earning a degree'
EdLevel	Bachelors Degree	`Bachelor's degree (BA, BS, B.Eng., etc.)'
	Graduate Degree	`Master's degree (MA, MS, M.Eng., MBA, etc.)', `Other doctoral degree (Ph.D, Ed.D., etc.)', `Professional degree (JD, MD, etc.)'
STEM	1	`Computer science, computer engineering, or software engineering', `Another engineering discipline (ex. civil, electrical, mechanical)', `Information systems, information technology, or system administration', `A natural science (ex. biology, chemistry, physics)', `Mathematics or statistics', `A health science (ex. nursing, pharmacy, radiology)'
Developer	1	`Back-End Dev', `Mobile Dev', `Application Dev', `Full-Stack Dev', `Desktop Dev', `Game Dev', `Front-End Dev', `QA Dev'
Manager	1	`Senior Exec', `Engineering Manager', `Product Manager'
Academic	1	`Educator', `Academic', `Scientist'
Designer	1	`Designer'
Data Scientist	1	`Data Scientist or Machine Learning Specialist'
Business	1	`Marketing or Sales Professional', `Data or Business Analyst'
Student	1	`Student'