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ABSTRACT

Gender Pay Gaps across STEM Fields of Study*

Gender pay gaps in earnings are well-documented in the literature. However, new factors contributing to women's lower earnings have emerged and remain under-researched. Educational choices are among them. We use a rich administrative dataset from Poland, a Central Eastern European country with high tertiary education enrolment and high female employment rates among young women, to study gender pay gaps among tertiary education graduates with degrees in different fields of study while paying particular attention to STEM fields graduates (science, technology, engineering, and mathematics). We find that already in the first year after graduation, women earn over 20% less than men. This gap widens over time. We also find significant variation across different STEM fields both in the size of the gender pay gap and in how it changes over time. The gap is largest among mathematics graduates, at over 25%; while it does not exceed 3% among chemical and Earth sciences graduates. As these differences narrow only slightly within the first four years of graduates' working careers, policymakers' efforts to increase the number of women earning STEM degrees may not be enough to achieve gender pay equality.

JEL Classification: J16, J24, J3, J71

Keywords: gender pay gap, higher education, labor market, STEM, field of study, Poland

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Introduction

Over the past few decades, women have made significant inroads into tertiary education, achieving higher enrolment rates than men in numerous regions across the globe. For example, in the OECD countries, the share of women aged between 25 and 34 with tertiary surpasses that of men in the same age bracket by 12.1. percentage points (pp). The gap is even wider in most Central and Eastern European (CEE) countries, where it exceeds 20 pp. Women have also gained more presence in fields of study dominated by men, especially business and STEM (i.e., science, technology, engineering, and mathematics) fields, although they remain underrepresented in computer science and mathematics (Bobbitt-Zeher 2007; Lundberg and Stearns 2019). Alas, despite the improvements in female educational attainment, women earn markedly less than men in most developed countries (OECD 2023). A growing body of research is investigating the role link between gender wage disparities among tertiary education graduates and gender differences in field of study choices (Bobbitt-Zeher 2007; Goldin et al. 2017; Joy 2000; Zhang 2008). Existing studies have demonstrated that men tend to enroll in fields of study, leading to higher wages. In contrast, women are over-represented in lower-paying fields, which is one of the factors contributing to differences in men's and women's average wages. For example, Shauman (2006) showed that in the US, gender differences in college majors explain 11–17% of the gender gap in the likelihood of employment in high-paying occupations. However, relatively little is known about the within-field gender wage gaps, net of other factors, and the differences in the magnitude of gender pay gaps across fields of study. This is a significant omission. The few existing studies suggest field of study might be a key factor explaining the gender gap in earnings among tertiary education graduates (Francesconi and Parey 2018).

This paper contributes to the literature by presenting a comprehensive picture of gender pay gaps among graduates across fields of studies, with a particular focus on STEM fields. We investigate the evolution of gender pay gaps in the initial years of graduates' working careers to identify the fields of study that benefit men and women the most, net of other factors. We do so by leveraging unique data from the Polish Graduate Tracking System (ELA), a linked administrative dataset designed specifically to track graduates' labor market outcomes. The data include monthly records capturing the first four years of the labor market trajectories of the full population of students who graduated from Polish higher education institutions in 2015. The panel structure of the data allows us to account partially for graduates' unobserved heterogeneity.

Our study focuses on Poland, a CEE country with an institutional context distinct from those of most countries studied in previous literature on gender wage disparities among tertiary graduates. First, the adjusted gender pay gap in Poland is much larger than the raw difference in the wages of men and women, which implies that there is a large unexplained gender wage gap. This is the case for most CEE countries, where women tend to be much better educated than men. Second, Poland stands out by simultaneously having traditional gender norms regarding childcare and family and relatively high female employment rates (especially among childless women). The prime-age female employment rates remain high despite the labor market's unfriendliness to women, including large gaps in childcare coverage, lack of working time flexibility and part-time work arrangements, limited public transportation, low wages, as well as social norms discouraging mothers' employment (Magda et al. 2020). Third, in Poland – again, like in many other CEE countries – higher education expanded rapidly after liberalization following the end of communist rule (Kwiek 2009). In the early 1990s, only 10% of secondary school leavers entered tertiary education, whereas, since the mid-2000s, about half of each year's upper secondary school graduating class has been pursuing higher education. These changes have had a clear gender pattern: not only have women been more likely to obtain tertiary qualifications, but they have also been increasingly moving away from women-dominated fields of education and toward STEM fields (OECD 2009, 2016). For instance, while in 2007, women accounted for 24% of new entrants in engineering programs, in 2014, their share reached 34% (OECD 2016). Furthermore, between 2016 and 2021, the number of women majoring in ICT increased by 38%, while the number of men majoring in ICT grew by 22% (Knapińska 2022).

Our results show that despite educational advances, university-educated women continue to face disadvantages in the labor market. We found that the gender pay gap is significantly larger among STEM graduates compared to non-STEM graduates. Furthermore, the scale of data at hand allowed us to demonstrate that the adjusted gender pay gaps vary widely across STEM fields. The disparities in labor market outcomes are particularly pronounced among mathematics graduates, whereas they are comparatively minor for chemical and Earth sciences graduates. These findings carry significant implications for policymaking, especially for formulating strategies to reduce gender labor market inequality by promoting female participation in STEM education.

Literature review

Gender wage inequality remains a field of active research (see Olivetti and Petrongolo 2016; Blau and Kahn 2017, for comprehensive literature reviews). Early studies suggested that differences in human capital factors such as educational attainment or work experience stood behind observed gender pay gaps (Goldin 2014). However, recent developments invalidated these claims. Women have largely bridged the gap with men in terms of education, and the gender disparity in job experience has also diminished. Despite that, gender wage differences persist, and the progress previously made in reducing these differences has stalled (Goldin 2014). One of the reasons behind the persistence of gender pay gaps is the gender differences in the choice of fields of study (Machin and Puhani 2003; Joy 2003) and the fact that the wage returns vary widely between these fields of study (Ceci et al. 2014; Zhang 2008; Gerber and Cheung 2008). Differences in average wages of men and women persist, as women tend to be overrepresented in fields where graduates consistently earn lower wages, while men tend to dominate higher-paying fields, with STEM being a notable example (Bobbitt-Zeher 2007; Joy 2000; Zhang 2008). However, less is known about whether men and women graduating from the same fields of study earn similar wages, net of other individual and workplace characteristics. Previous empirical work on gender pay gaps among graduates in various academic fields of study has not provided conclusive evidence regarding the existence and the potential sizes of these within-field gaps (Xu 2015). Ceci et al. (2014) reviewed studies on various aspects of women in academic careers. They discuss substantial variation in gender pay gaps across fields of study and over time. Joy (2003), Sánchez-Mangas and Sánchez-Marcos (2021), and Bobbit-Zeher (2007) also reported that gender wage gaps in specific fields of study remain even adjusting for several other covariates. In contrast, Albrecht et al. (2018) show that in Sweden, men and women graduating from Business or Economics have identical wages and earnings at the start of their careers.

The existing studies are limited not only in number but also in their methodology and scope. The existing studies are usually cross-sectional, based on small samples, rely on survey data, and study gender wage gaps at one point in time, often soon after graduation. The last point is particularly important. The rare studies investigating trends show noticeable changes in the gender pay gaps over time. Bertrand et al. (2010) showed that the earnings of male and female MBA graduates are quite similar at the beginning of their careers but diverge quickly after that, while Xu (2015) found that men's and women's earnings diverge substantially in the first ten years of their working careers, with female STEM graduates, in particular, facing a large wage disadvantage. Furthermore, previous studies tend to investigate very broad fields of study, often distinguishing only between STEM and non-STEM and overlooking the wide within-STEM variation. Third, most of the literature comes from the US. This is an important omission, as country-specific features (e.g., with respect to the degree of private financing of higher education) may not be gender-neutral (Francesconi and Parey 2018, Kirkeboen et al. 2016).

This paper addresses many of those shortcomings. Our study utilizes large-scale administrative data that are free of non-response or recall issues afflicting survey data, especially income-focused variables. Furthermore, the data at hand capture labor market outcomes in each of the first 48 months after graduation. This not only extends the scope of the analysis beyond the early stage of post-graduation trajectories and single-point measurement but improves the robustness of our statistical models thanks to the data's panel structure. Importantly, the unprecedented scale of our data allows us to disaggregate the STEM category and compare gender pay gaps across STEM fields. Finally, we provide novel evidence for a new country context, Poland, which blends high female educational attainment and labor market participation with conservative family norms.

Materials and methods

Dataset and sample selection

We utilize a comprehensive Polish administrative dataset that links records on graduates and their study programs with monthly data on individual labor market outcomes collected by the Polish Social Insurance Institution. The data at hand allow us to track graduates for full four years after graduation. The sample comprises graduates of master's programs (second-cycle or long-cycle studies) who completed their education in 2014.

We focus on graduates of master's programs, as in Poland, a bachelor's degree is usually seen as a transitional degree and not as a marker of a completed higher education[1].

There were over 170,000 individuals in the 2014 graduate cohort. As our focus is on pay inequality, we analyze working individuals only (that is, we analyze only records for months of employment, which constitute around 68.1% of all available person-month observations[2]). Among the graduates with employment records, 0.3% had missing data on one or more analytic variables and were thus removed from the sample. Furthermore, we eliminated observations with extremely high (top percentile), missing, or unrealistically low[3] monthly salaries (bottom one percentile). The final analytical sample consists of 5,304,124 observations of 148,904 graduates.

Measures

Our key measure captures gross income from employment[4] in a given month. It combines income received from all employers each month. The amounts have been inflation-adjusted and are expressed in 2014 Polish zlotys (PLN). The average monthly employment income in the pooled sample is PLN3,666.6 (SD=PLN2,015.4).

Gender and field of study are our key explanatory variables. Females comprise 68.7% of the individuals and 68.1% of the person-months in the sample. This gender imbalance results from the higher levels of participation in tertiary education among women than men. In Online Appendix 2, we demonstrate that the employment rates among male and female graduates are similar.

In our analysis, we distinguish between six STEM and six non-STEM fields of study. The STEM category includes the following fields: technology (mostly engineering), mathematics, and biological, chemical, Earth, and physical sciences. In our sample, 21.5% of graduates and 21.6% of person-months are in STEM fields. Our models include all 12 fields of study. However, for the sake of brevity and clarity, we only present the results for individual STEM fields and the two biggest non-STEM fields: humanities and social studies (29.5% of graduates) and economics and business (24.8% of graduates).

In our models (described in detail below), we control for a set of variables that may confound the relationships between gender, field of study, and employment income. The variables include two time-invariant variables: age at graduation (three categories)

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[1] Almost two-thirds of bachelor's degree holders enroll in a master's program within two years after graduation, and this trend is even more pronounced among science and mathematics graduates (Zając et al., 2018, 2019).

[2] We ran robustness check that included individuals with zero labour income. The overall conclusions did not change, and the results are available upon request.

[3] These records are likely to represent atypical payments: for example, payments for work for a small portion of a month, or compensation paid for unused leave after the end of employment.

[4] This includes income from both labor contracts and civil law contracts (a popular and widespread “substitute” for labor contracts). We should note we do not observe wages directly, but rather estimate wages based on social security contributions. The risk that this introduces any bias into our data is negligible, as these basic rates are different from workers' wages only for those who earn more than 30 times the average salary. The data from a large survey of employees (“Structure of Earnings survey”) include no such observations among young workers (under the age of 34).

and mode of study (full-time or part-time). Furthermore, we include a series of binary variables capturing various labor market statuses that might affect the salary received in a given month, such as being on maternity leave, being on parental leave, working under a civil law contract, being self-employed, or being unemployed. Finally, we also control for the number of children (zero, one, two, or more),[5] the economic sector (21 categories)[6], and the average salary in the *powiat* (NUTS-4 region) of residence. The last measure allows us to control for the geographical differentiation of the Polish labor market, changes in the local economy over time, and graduates' geographical mobility. Table 1 presents descriptive statistics for all analytic variables.
[Table 1 here]

Analytic approach

To investigate the gender pay gap, we draw on the longitudinal nature of our data and fit five mixed-effects linear regression models with a random intercept effect of graduates. First, we fit a base model without any controls (Model 1), which has the following form:

$$S_{gt} = \alpha + \beta_1 t + \beta_2 G_g + \beta_3 (t \times G_g) + u_g + e_{gt} \qquad (1)$$

Where the g and t subscript denote graduates and time points (number of months after graduation), respectively; S is salary; α is the model's grand intercept; G is a dummy for being female and t is a continuous time variable; β_1 *to* β_3 are coefficients to be estimated; u is an individual-level random effect (or random intercept) capturing unobserved effects assumed to be normally distributed and orthogonal to the model variables; and e is the usual individual-level regression error.

In Model 2, we introduce a set of control variables denoted by C (all but field of study and economic sector). In the next step (Model 3), we add variables controlling for the economic sector in which graduates work (denoted by E, captured by the NACE classification at the one-digit level). In Model 4, we add a set of binary variables capturing the field of study (biological sciences are the reference category).

Model 5 (formula 2) includes interaction terms between the field of study, gender, and the time since graduation. It has the following form:

$$S_{gt} = \alpha + \beta_1 t + \beta_2 G_g + \beta_3 F_g + \beta_4 (t \times G_g) + \beta_5 (F_g \times G_g) + \beta_6 (t \times SF_g) + \beta_7 (t \times G_g \times F_g) + \beta_8 C_{gt} + \beta_9 E_{gt} + u_g + e_{gt} \qquad (2)$$

Where $t \times G_g$ is the interaction between gender and time; $F \times G_g$ is the interaction between field of study and gender; $t \times F$ is the interaction between time and field of study; and $t \times G_g \times F_g$ is the focal interaction between time, gender, and field of study. To ease the

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[5] We also ran a sensitivity analysis without accounting for the number of children. The results remained the same.

[6] Economic sectors are categorized according to the statistical classification of economic activities in the European Community (NACE).

interpretation of the models, we present and discuss their results as marginal effects and partial predictions computed with values of other predictors fixed at their means.

Results

Growth in the gender wage gap among graduates

Figure 1 compares the average salaries of female and male graduates in consecutive months after graduation. In the first year, the average monthly gap between men and women is 22.9% of the average male salary. The gap expands to 25.0% of the average male salary in the fourth year after graduation.

[Figure 1 here]

To go beyond the descriptive results and investigate the mechanisms underlying the observed gender wage gap, we turn to multivariable models. First, we compare the results from the four models summarized in Table 2. They all include a dummy variable capturing being female, time since graduation (in months), and an interaction term between the time since graduation and gender to capture the longitudinal trend of wage growth, which is likely different for men and women. The models differ in the set of control variables used to adjust the results, which allows us to evaluate the importance of subsequently introduced controls. The full results are presented in Table A1 in the Online Appendix.

As we introduce first the demographic control variables, then the economic sector, and finally the field of study, we observe that the initial gender gap in salaries decreases (the coefficient for being female shrank by 12%, from PLN550.5 in Model 1 to PLN487.1 in Model 2, PLN433.8 in Model 3, and to PLN370 in Model 4, which is 33% less than the gap in Model 1). Thus, the gap in the wages earned by male and female graduates arises already at the beginning of their working careers and is large and statistically significant even after adjusting for all controls and the field of study (in Model 4).

Moreover, while there is a clear growth trend in wages over time, the growth rate is lower among female workers, as the estimated coefficients associated with the *Female x t* interaction term in Models 1 to 4 demonstrate. The estimated gap in the rate of wage growth narrows with the introduction of new variables from 18.97 in Model 1 to 8.07 in Model 4. However, the results show that even if all control variables, sectoral segregation, and detailed information on the field of study are accounted for, a large gender wage gap remains among graduates, and it continues to grow over time.

[Table 2 here]

Gender wage gaps within fields of study

The final step in our analysis entails introducing interaction terms between time, gender, and field of study. The aim is to capture the differences in employment income and employment income growth trends among males and females who completed studies in the same field of study. This allows us to investigate whether the gender pay gaps differ across fields of study.

Figure 2 shows the adjusted gender pay gap among graduates in a given field of study, expressed as a percent of the average salary of men with degrees in that field. The adjusted gender pay gap is calculated using marginal predictions based on the results from Model 5. Full sets of the estimated parameters are available in Table A2 in Online Appendix 1. The results reveal significant variation across different STEM fields both in the size of the gender pay gap and in how it changes over time. Initially, the gap is widest among mathematics and engineering graduates, at 27.2% and 26.2%, respectively. However, the gender pay differences in these fields diverge over time. Within four years, the gender pay gap among engineering graduates narrows slightly to 23.9%, while it expands among mathematics graduates to 31.4%. The biggest changes over time can be observed among physical sciences graduates. The pay gap among these graduates is modest at first, at 13.9%, but it expands to 24.4% over the next four years.

In contrast, the gender pay gaps among graduates with degrees in other STEM fields are much smaller than those observed among mathematics or technology graduates. Among chemical and Earth sciences graduates, the gender pay gap is around 3% upon entry into the labor market. The gap grows steadily over time, to 12.3% and 7.9%, respectively. The gap among graduates of biological graduates is similarly small. Its initial magnitude is 12.6%, but it declines to 10.8% at the end of the fourth year.

Figure 2 also presents data for the two largest non-STEM fields: humanities and social studies, and economics and business. The gender wage gap among humanities and social studies graduates is quite stable over the four years we observe, at a level below 10%, which is on par with the results for graduates of biological, chemical, and Earth sciences. By contrast, female economics and business graduates enter the labor market with wages that are 13.7% lower than those of their male counterparts, and this gap grows over time. The observed gap is thus higher than among graduates of biological, chemical, and Earth sciences but not as high as among graduates of mathematics or technology.
[Figure 2 here]

Additionally, Figure 3 illustrates the relationship between the adjusted gender pay gap and other characteristics of the fields of study in the final month of the observation. The left panel presents the relationship between the gender pay gap and the share of men among graduates of a particular field. STEM fields form two groups. The first group, clustered in the bottom-left corner, comprises fields with a lower share of men and a smaller gender pay gap, that is, with values similar to those observed among humanities and social sciences graduates. The second group is made up of fields with a higher share of men and a larger gender pay gap (physical sciences, mathematics, technology).

The middle and the right panels display the relationship between the adjusted gender pay gap and the average predicted salaries of women and men, respectively. They show a similar pattern: i.e., fields with higher salaries tend to have a larger adjusted gender pay gap.

[Figure 3 here]

Discussion

This study utilized longitudinal administrative data linking information on higher education attainment with social security records in Poland to investigate gender wage gaps among tertiary education graduates. We found that raw pay gaps can be observed as soon as graduates enter the labor market. In the first year, women earn, on average, 22.9% less than men. Over the next four years, the gap increases to 25.0%. Our results corroborate previous findings, suggesting that the field of study is an important factor contributing to gender differences in earnings. Similarly to Triventi (2013) and Goldin et al. (2017), we found evidence of women storing into less lucrative fields of study.

Moreover, we contribute to the relatively small body of research focused on the moderating role of field of study (e.g., Francesconi and Parey 2018) by studying differences in gender pay gaps across STEM fields and comparing them to major non-STEM fields. We find that the gender pay gaps vary markedly depending on the field of study. The adjusted gender pay gap is the largest among mathematics graduates, at 27.2% upon labor market entry, and it continues to grow to reach over 31% after four years. In contrast, the gender pay gap among graduates of chemical and Earth sciences is much smaller than that in mathematics, at around 3% upon labor market entry. We also observe a link between field-of-study feminization and the magnitude of the gender pay gaps. The adjusted gender pay gaps are much larger in male-dominated STEM fields. At the same time, these fields tend to lead to higher wages for both men and women.

Our study of university graduates has limitations that need to be acknowledged. On the one hand, focusing on more homogeneous groups of workers – e.g., young graduates with degrees in a particular field of study – may provide more convincing evidence of wage differences. On the other hand, this may introduce an additional element of selection, not only into employment but also into a particular workplace. Given that women still lag behind men in enrolling in STEM fields (despite considerable progress) and may drop out from certain fields more often than men (Pedersen and Nielsen 2023), women with degrees in these fields are likely to be a positively selected group relative to men. Thus, our study likely understates the extent of pay discrimination.

Furthermore, we cannot measure returns to fields of study among men and women nor attribute all the observed pay gaps to the field of study, as such analyses require identification strategies and instruments not available to us due to data limitations. For example, we do not have access to detailed information on educational capital, such as final grades. However, previous research suggests such factors might have a limited impact on graduate labor market outcomes in Poland (Piróg 2016). Consequently, we are also limited in our capacity to investigate thoroughly the mechanisms underlying differences between fields of study. For example, while we controlled for important factors such as economic sector or local labor market conditions, we did not have access to data on occupation or the number of hours worked. This prevented us from testing the role of gender occupational sorting (women taking up lower-paid jobs that offer them more working time flexibility needed to combine work and family life), a plausible explanation of the observed gaps. However, despite not being able to fully explain the mechanisms, this study provides clear evidence of gender labor market inequality. Wage differences, regardless of the underlying mechanisms, result in gender wealth gaps, lower retirement savings for women, and less financial freedom. Differences in hours worked among men and women are unlikely to contribute to the observed gender pay gaps as the incidence of part-time employment is low in Poland (2.3% among tertiary educated men and 4.9% among women, respectively).

Our findings offer important lessons for higher education policy. Given the observed actions to draw more women into male-dominated fields of study, and STEM fields in particular, policymakers must consider the labor market outcomes. First of all, gender differences in wages – which, as we show, are already present and large at the beginning of graduates' working careers – may hamper any efforts to boost female enrolment in STEM fields. Women may avoid pursuing math- and technology-intensive careers if they offer high earnings to men but lower compensation to women. Wide gender pay gaps might be perceived as a signal of unfriendliness to women and discourage them from investing in education in these areas. There is also a risk channeling more women into STEM fields without tackling the within-field differences will entrench or even exacerbate gender inequality. For example, our results suggest different paths for female and male graduates of mathematics, resulting in differential labor market outcomes. Increasing the number of women graduating in the field does not have to grant women more access to the more lucrative and currently male-dominated paths. Furthermore, existing literature on occupational segregation (e.g., Levanon et al. 2009; Mandel 2013) suggests that increasing the share of women might even lead to worse labor market outcomes of certain pathways, increasing the gender pay gap among mathematics graduates.

The policy approaches to tackling the problem of gender inequality in tertiary education should not be restricted to supporting women in male-dominated fields of study and encouraging them to enter these fields. Other factors may influence women's educational and occupational decisions and limit their career opportunities: e.g., gender and social norms in technology fields that are unfriendly to women; motherhood-related career breaks with little father involvement; the unequal burden of domestic work that tends to limit women's labor supply; and the unfriendliness of the labor market to parents' demands for temporal flexibility. Further research is needed to understand better the pathways of school-to-work transitions among men and women, how they depend on fields of study, and the underlying causes of the documented gender heterogeneity. We would also benefit from more investigations of the nature of gender segregation in technology-intensive fields. Finally, future studies should rely on large samples, allowing disaggregation of the STEM category. Our results corroborate previous studies (Light and Rama 2019, Zając et al., 2023), suggesting that we should not discuss STEM fields as a single entity, as is often done, given that the labor market outcomes of graduates with degrees in different STEM fields are very heterogeneous.

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Tables

Table 1. Descriptive statistics.

	Mean/ % (Standard deviation)
Gross salary (in 2014 PLN)	3666.6 (2015.4)
Key predictors	
Gender	
Female	68.1
Male	31.9
Field of study (STEM vs non-STEM)	
non-STEM	78.4
STEM	21.6
Field of study	
Biological sciences	1.7
Chemical sciences	0.7
Physical sciences	0.2
Mathematics	1.0
Earth sciences	1.2
Technology	16.8
Economics & business	24.8
Humanities & social studies	29.5
Medical and health sciences	10.4
Agricultural sciences	3.2
Law	9.4
Arts	1.2
Covariates	
Age at graduation	
24 or less	37.5
25-29 years	46.4
30 or more	16.1
Part-time studies	49.1
Parental leave	0.9
Maternity leave	5.8
Number of children	
No children	89.7
1 child	9.9
2 or more children	0.4
Economic sector of employment	
Agriculture, forestry and fishing	0.6
Mining and quarrying	0.4
Manufacturing	11.3
Electricity, gas, steam and air conditioning supply	0.5
Water supply; sewerage, waste management and remediation activities	0.6
Construction	3.4
Wholesale and retail trade; repair of motor vehicles and motorcycles	11.2
Transportation and storage	2.9
Accommodation and food service activities	1.3
Information and communication	5.4
Financial and insurance activities	4.8

Real estate activities	1.1
Professional, scientific and technical activities	10.8
Administrative and support service activities	3.2
Public administration and defence; compulsory social security	10.2
Education	10.7
Human health and social work activities	10
Arts, entertainment and recreation	1.5
Other service activities	2.1
Activities of extraterritorial organisations and bodies	0.0
Not specified	8.0
Civil law contract	9.3
Self-employed	3.1
Unemployed	0.5
Average salary in the area of residence (in 2014 PLN)	4097.1 (778.0)
Number of observations	5,304,124

Notes: Own calculations.

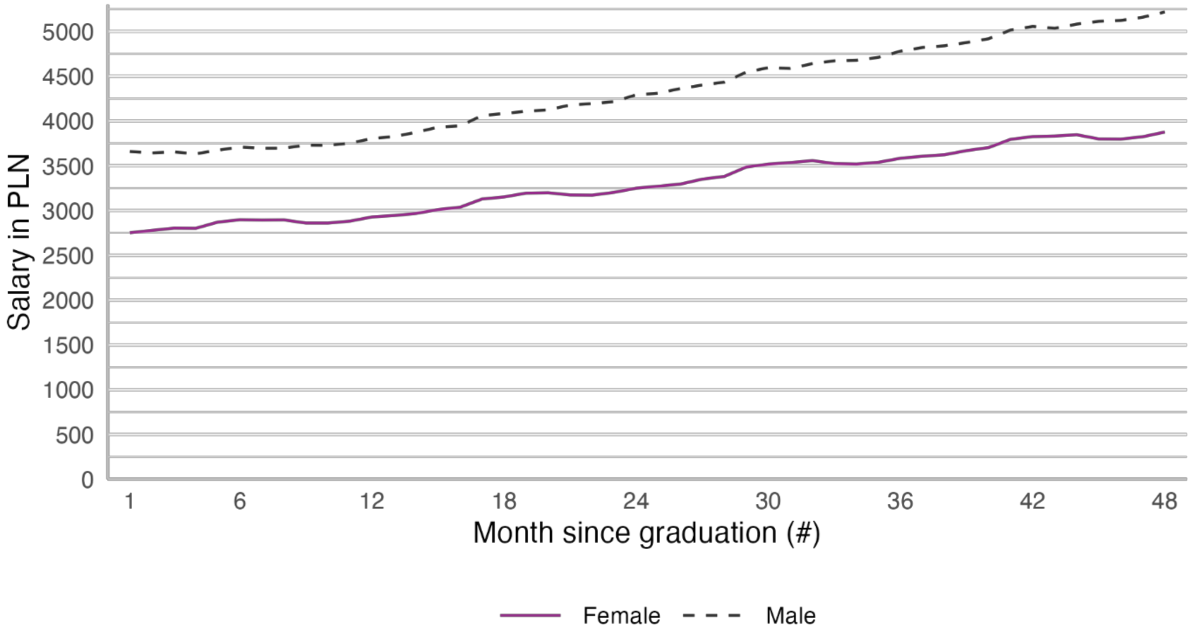
Table 2. Abridged results (coefficients) from random-effects models of salaries.

	Model 1 (No controls)	Model 2 (C)	Model 3 (C + E)	Model 4 (C + E + Fxt)
Female	-550.50***	-487.10***	-433.80***	-370.00***
t	50.97***	48.22***	47.83***	47.00***
Female x t	-18.97***	-12.81***	-12.60***	-8.07***
C	N	Y	Y	Y
E	N	N	Y	Y
F x t	N	N	N	Y

Notes: Data from the ELA 2019 dataset. C: a set of control variables (age at graduation, full-time/part-time study; labor market status; number of children, local wages). E: economic sector. t: month since graduation. F: field of study. F x t: interaction between field of study and month since graduation. Based on the model results presented in Online Appendix 1 Table A1. Statistical significance: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

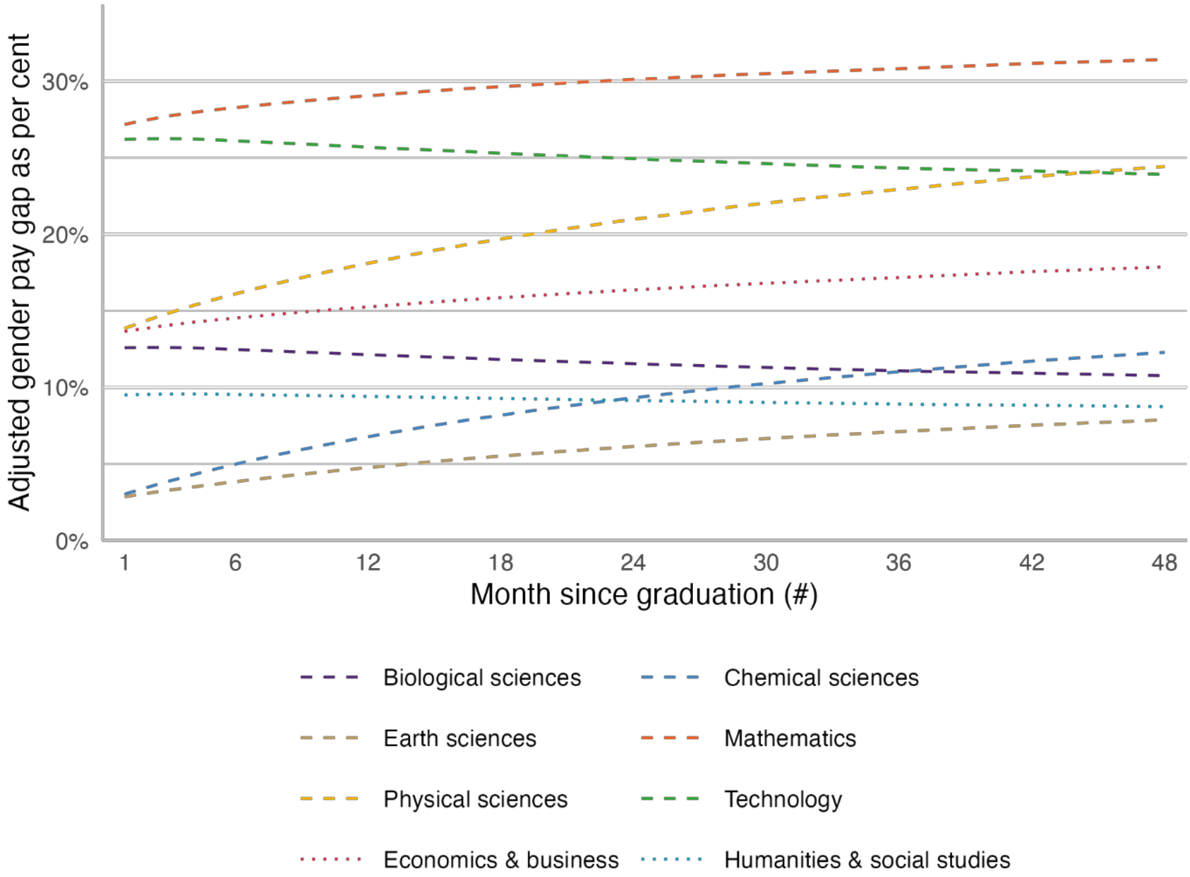
Figures

Figure 1. Gross monthly salaries in PLN, by gender and time since graduation, all fields of study.



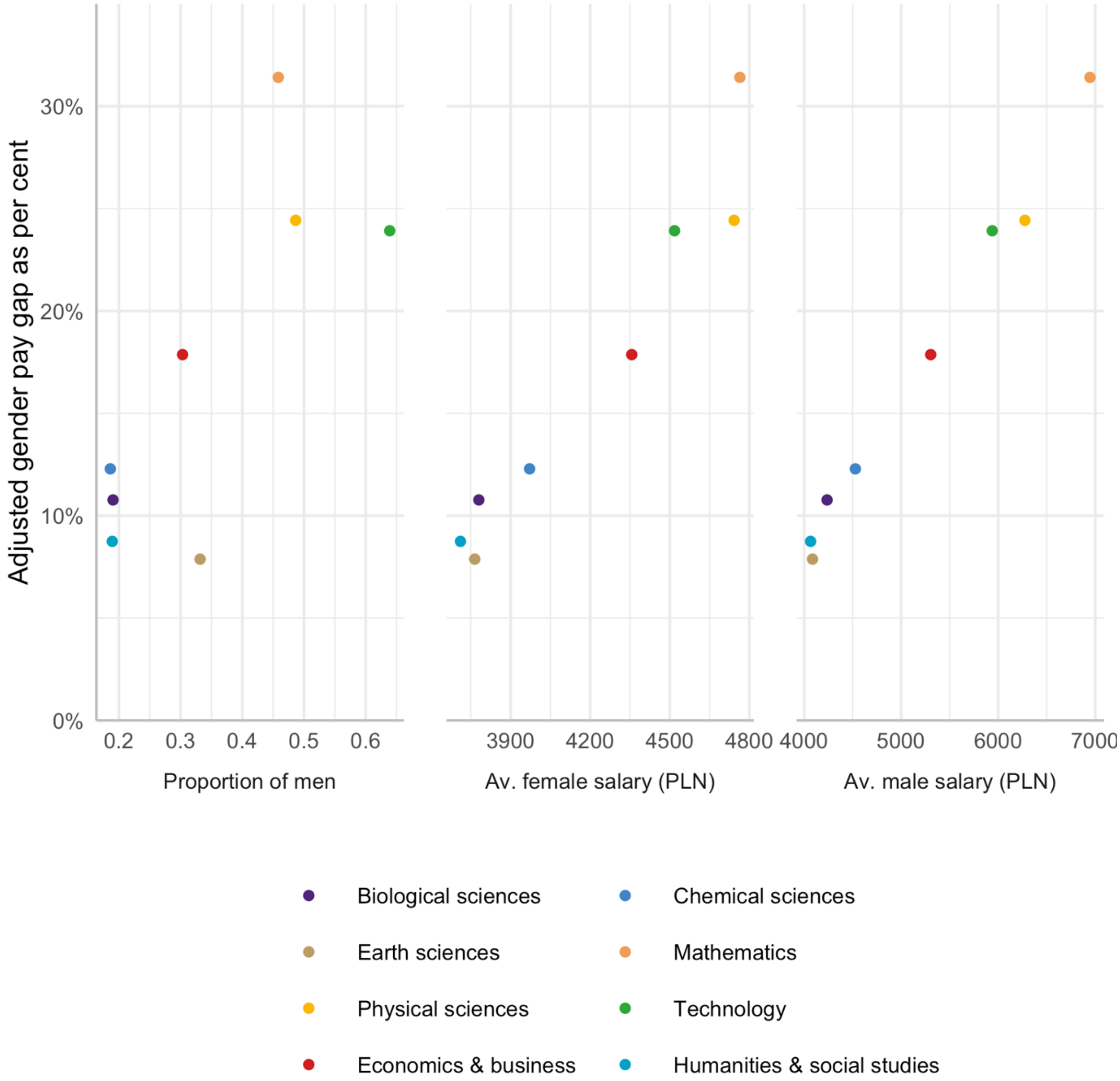
Notes: Own calculations, data on salaries in 2014 prices.

Figure 2. Adjusted gender pay gap as per cent of the average salary of male graduates with a degree in the same field, by field of study and time since graduation.



Notes: Data from the ELA 2019 dataset. Based on Model 5. Only selected fields are presented. Complete model results are presented in Online Appendix 1 Table A2.

Figure 3. Adjusted gender pay gap as per cent of the average male graduate with a degree in the same field at the end of the fourth year after graduation, the proportion of men among graduates, average predicted salary among women, and average predicted salary among men, by field of study.



Notes: Data from the ELA 2019 dataset. Based on Model 5. Only selected fields are presented. Complete model results are presented in Online Appendix 1 Table A2.

Online Appendix 1

Table A1. Model coefficients from regression models of salaries – models 1 to 4.

	Model 1 (No controls)	Model 2 (C)	Model 3 (C + E)	Model 4 (C + E + Fxt)
Month since graduation	50.97***	48.22***	47.83***	47.00***
Female	-550.5***	-487.1***	-433.8***	-370.0***
Female # Month since graduation	-18.97***	-12.81***	-12.60***	-8.07***
Age at graduation (ref: 24 or less)				
25-29 years		276.8***	273.1***	227.1***
30 or more		1032.3***	1056.6***	1045.2***
Parental leave		-322.5***	-289.9***	-292.6***
Maternity leave		-353.8***	-334.2***	-339.1***
Number of children (ref: No children)				
1 child		-783.4***	-772.6***	-773.4***
2 or more children		-1509.5***	-1491.4***	-1483.5***
Part-time studies		-102.7***	-88.84***	-47.30***
Civil law contract		-116.3***	-111.2***	-118.2***
Self-employed		67.18***	70.98***	39.96***
Unemployed		-749.2***	-745.5***	-748.1***
Average earnings in the place of residence		0.146***	0.145***	0.143***
Economic sector (ref: Agriculture, forestry and fishing)				
Mining and quarrying			-178.5***	-329.8***
Manufacturing			-196.4***	-250.4***
Electricity, gas, steam and air conditioning supply			154.9***	63.92**
Water supply; sewerage, waste management and remediation activities			-302.1***	-359.9***
Construction			-359.6***	-423.7***
Wholesale and retail trade; repair of motor vehicles and motorcycles			-367.6***	-407.9***
Transportation and storage			-448.5***	-491.8***
Accommodation and food service activities			-730.6***	-771.8***
Information and communication			-52.38**	-110.1***
Financial and insurance activities			-130.8***	-169.8***
Real estate activities			-326.4***	-367.6***
Professional, scientific and technical activities			-411.9***	-452.8***
Administrative and support service activities			-448.5***	-486.6***

Public administration and defense; compulsory social security			-473.1***	-486.2***
Education			-551.1***	-538.9***
Human health and social work activities			-491.9***	-509.6***
Arts, entertainment and recreation			-538.8***	-551.9***
Other service activities			-615.8***	-638.3***
Activities of extraterritorial organisations and bodies			295.4***	294.6***
Not specified			-464.7***	-498.2***
Field of study (ref: biological sciences)				
Chemical sciences				-7.310
Physical sciences				651.0***
Mathematics				831.6***
Earth sciences				4.807
Technology				748.7***
Economics & business				739.6***
Humanities & social studies				413.8***
Medical and health sciences				269.1***
Agricultural sciences				163.6***
Law				307.0***
Arts				118.4*
Field of study # Month since graduation				
Chemical sciences # Month since graduation				4.589***
Physical sciences # Month since graduation				15.13***
Mathematics # Month since graduation				16.63***
Earth sciences # Month since graduation				-2.223***
Technology # Month since graduation				9.635***
Economics & business # Month since graduation				-1.340***
Humanities & social studies # Month since graduation				-10.69***
Medical and health sciences # Month since graduation				3.984***
Agricultural sciences # Month since graduation				-0.952**
Law # Month since graduation				-8.448***
Arts # Month since graduation				-10.77***
Constant	2893.3***	2113.2***	2462.9***	1970.4***
Random intercept variance	2673100.2***	2478929.4***	2365223.1***	2256731.0***
Variance of level 1 residuals	6.991***	6.975***	6.974***	6.970***

Observations	5304124	5304124	5304124	5304124

Notes: Data from the ELA 2019 dataset. E: economic sector. S: STEM vs non-STEM variable. t: month since graduation. S x t: interaction between the STEM vs non-STEM variable and month since graduation. F: field of study. F x t: interaction between field of study and month since graduation. Statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2. Model coefficients from regression models of salaries – model 5

	Model 5 C + E + F x t x G
Month since graduation	43.23***
Female	-290.5***
Female # Month since graduation	-3.453***
Age at graduation (ref: 24 or less)	
25-29 years	225.5***
30 or more	1040.7***
Parental leave	-291.9***
Maternity leave	-338.2***
Number of children (ref: No children)	
1 child	-772.9***
2 or more children	-1483.5***
Part-time	-68.53***
Civil law contract	-118.2***
Self-employed	36.66***
Unemployed	-748.2***
Average earnings in the place of residence	0.144***
Economic sector (ref: Agriculture, forestry and fishing)	
Mining and quarrying	-349.1***
Manufacturing	-250.4***
Electricity, gas, steam and air conditioning supply	61.39**
Water supply; sewerage, waste management and remediation activities	-354.9***
Construction	-424.4***
Wholesale and retail trade; repair of motor vehicles and motorcycles	-406.9***
Transportation and storage	-489.5***
Accommodation and food service activities	-771.0***
Information and communication	-113.3***
Financial and insurance activities	-169.8***
Real estate activities	-366.2***
Professional, scientific and technical activities	-452.2***
Administrative and support service activities	-486.3***
Public administration and defense; compulsory social security	-478.5***
Education	-541.8***
Human health and social work activities	-510.9***
Arts, entertainment and recreation	-549.8***
Other service activities	-637.8***
Activities of extraterritorial organisations and bodies	288.5***
Not specified	-497.6***
Field of study (ref: biological sciences)	
Chemical sciences	-204.7
Physical sciences	739.1***

Mathematics	1230.2***
Earth sciences	-140.1
Technology	1003.4***
Economics & business	855.9***
Humanities & social studies	396.5***
Medical and health sciences	-98.78
Agricultural sciences	376.5***
Law	220.7**
Arts	-112.6
Field of study # Month since graduation	
Chemical sciences # Month since graduation	10.34***
Physical sciences # Month since graduation	27.09***
Mathematics # Month since graduation	30.82***
Earth sciences # Month since graduation	-0.203
Technology # Month since graduation	14.55***
Economics & business # Month since graduation	4.420***
Humanities & social studies # Month since graduation	-11.80***
Medical and health sciences # Month since graduation	9.374***
Agricultural sciences # Month since graduation	0.704
Law # Month since graduation	-6.768***
Arts # Month since graduation	-7.378***
Female # Field of study	
Female # Chemical sciences	236.1
Female # Physical sciences	-115.6
Female # Mathematics	-661.1***
Female # Earth sciences	233.2*
Female # Technology	-576.1***
Female # Economics & business	-134.8
Female # Humanities & social studies	33.95
Female # Medical and health sciences	511.6***
Female # Agricultural sciences	-298.8***
Female # Law	153.4
Female # Arts	339.4**
Female # Field of study # Month since graduation	
Female # Chemical sciences # Month since graduation	-7.005***
Female # Physical sciences # Month since graduation	-20.02***
Female # Mathematics # Month since graduation	-22.18***
Female # Earth sciences # Month since graduation	-2.060
Female # Technology # Month since graduation	-8.084***

Female # Economics & business # Month since graduation	-7.432***
Female # Humanities & social studies # Month since graduation	1.389
Female # Medical and health sciences # Month since graduation	-6.757***
Female # Agricultural sciences # Month since graduation	-1.350
Female # Law # Month since graduation	-1.714*
Female # Arts # Month since graduation	-4.097***
Constant	1905.8***
Random intercept variance	2229337.1***
Variance of level 1 residuals	1131697.8***
Observations	5304124

Notes: Data from the ELA 2019 dataset. E: economic sector. t: month since graduation. F: field of study. F x t X G: interaction between field of study, month since graduation, and gender.
Statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Online Appendix 2 Employment rates by gender

To investigate gender differences in employment rates among graduates, we fit a mixed-effects logistic regression model with a random intercept effect of graduates, which has the following form:

$$ln\left(\frac{P(emp_{ti}=1)}{1-P(emp_{ti}=1)}\right) = \alpha + \beta_1 t + \beta_2 G_i + \beta_3(t \times G_i) + \beta_4 C + u_i$$

where $empt_{ij}$ is a binary variable indicating employment at time t for graduate *i*. *G* is a dummy for female, and *t* is a continuous time variable; *t x G* is the interaction of these variables; *C* is a set of control variables; β_1 *to* β_3 are coefficients to be estimated; *u* is an individual-level random effect (or random intercept) capturing unobserved effects assumed to be normally distributed and orthogonal to the model variables.

Next, we assess the gender gap in employment rates across fields of study. We do so by replacing the two-way interaction term *t x G* with a three-way interaction term *t x G x F*, where F represents field of study. Table B1 presents results from both models.

To ease the interpretation of the models, we present and discuss their results as marginal predictions (predicted probabilities) computed with values of other predictors fixed at their means. Figure B1 presents adjusted employment rates among all graduates by gender. The employment rate for men is higher than for women, but the gap is rather small and stable over time. Figure B2 presents selected predictions based on the second model. It shows the gender employment gap (difference between the employment rate for men and women divided by the rate for men) for the fields of study in scope. Technology is the only field for which we observe a markedly lower employment rate among women. However, even this gap shrinks over time – from nearly 15% in the first month after graduation to below 5% at the end of the observation period. For most other fields, the gap is small or negative, suggesting that women are more likely than men in their field to be employed. Most of the gaps reduce over time. Mathematical sciences are the only exception.

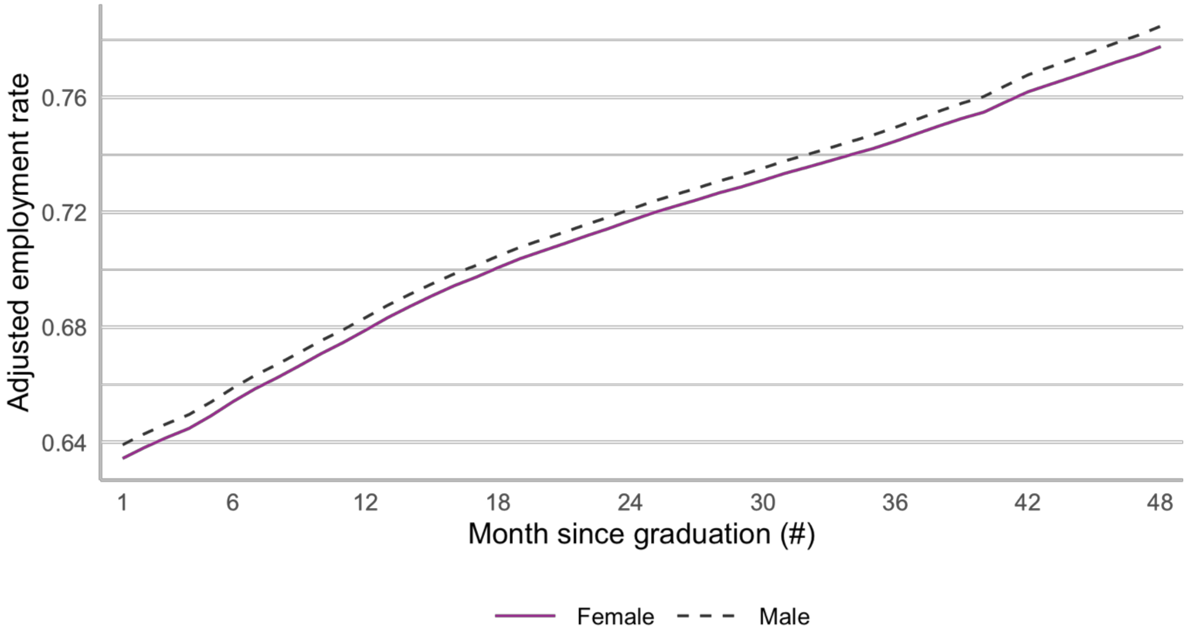
Table B1. Estimated coefficients from logistic regression models, dependent variable: employment.

	Model B1	Model B2
Female	-0.06**	0.56**
Month since graduation	0.09***	0.12***
Female # Month since graduation	-0.00***	0.00
Field of study (ref: biological sciences)		
Chemical sciences	0.28*	0.11
Physical sciences	-0.02	0.98***
Mathematics	2.20***	3.33***
Earth sciences	0.94***	1.28***
Technology	2.56***	4.38***
Economics & business	2.49***	3.85***
Humanities & social studies	1.31***	2.46***
Medical and health sciences	2.22***	2.40***
Agricultural sciences	0.92***	1.74***
Law	1.00***	1.58***
Arts	-0.94***	-0.05
Female # Field of study		
Female # Chemical sciences		0.01
Female # Physical sciences		-0.06
Female # Mathematics		-0.64*
Female # Earth sciences		-0.10
Female # Technology		-2.30***
Female # Economics & business		-0.27
Female # Humanities & social studies		-0.57**
Female # Medical and health sciences		0.76***
Female # Agricultural sciences		-0.73***
Female # Law		0.06
Female # Arts		-0.33
Field of study # Month since graduation		
Chemical sciences # Month since graduation		-0.01***
Physical sciences # Month since graduation		-0.03***
Mathematics # Month since graduation		-0.05***
Earth sciences # Month since graduation		0.00
Technology # Month since graduation		-0.04***
Economics & business # Month since graduation		-0.05***
Humanities & social studies # Month since graduation		-0.02***
Medical and health sciences # Month since graduation		-0.02***
Agricultural sciences # Month since graduation		-0.01***
Law # Month since graduation		-0.01***
Arts # Month since graduation		-0.02***
Female # Field of study # Month since graduation		
Female # Chemical sciences # Month since graduation		0.03***
Female # Physical sciences # Month since graduation		-0.01*
Female # Mathematics # Month since graduation		0.05***
Female # Earth sciences # Month since graduation		-0.01***
Female # Technology # Month since graduation		0.03***
Female # Economics & business # Month since graduation		-0.01**
Female # Humanities & social studies # Month since		-0.01***

graduation		
Female # Medical and health sciences # Month since graduation		-0.02^{***}
Female # Agricultural sciences # Month since graduation		0.00^{*}
Female # Law # Month since graduation		-0.01^{***}
Female # Arts # Month since graduation		-0.01
Age at graduation (ref: 24 or less)		
25-29 years	0.45^{***}	0.45^{***}
30 or more	2.46^{***}	2.43^{***}
Part-time studies	1.81^{***}	1.79^{***}
Civil law contract	-2.10^{***}	-2.11^{***}
Self-employed	-3.75^{***}	-3.73^{***}
Average earnings in the place of residence	-0.00^{***}	-0.00^{***}
Constant	2.38^{***}	1.18^{***}
Random intercept variance	21.95^{***}	22.00^{***}
Observations	7970688	

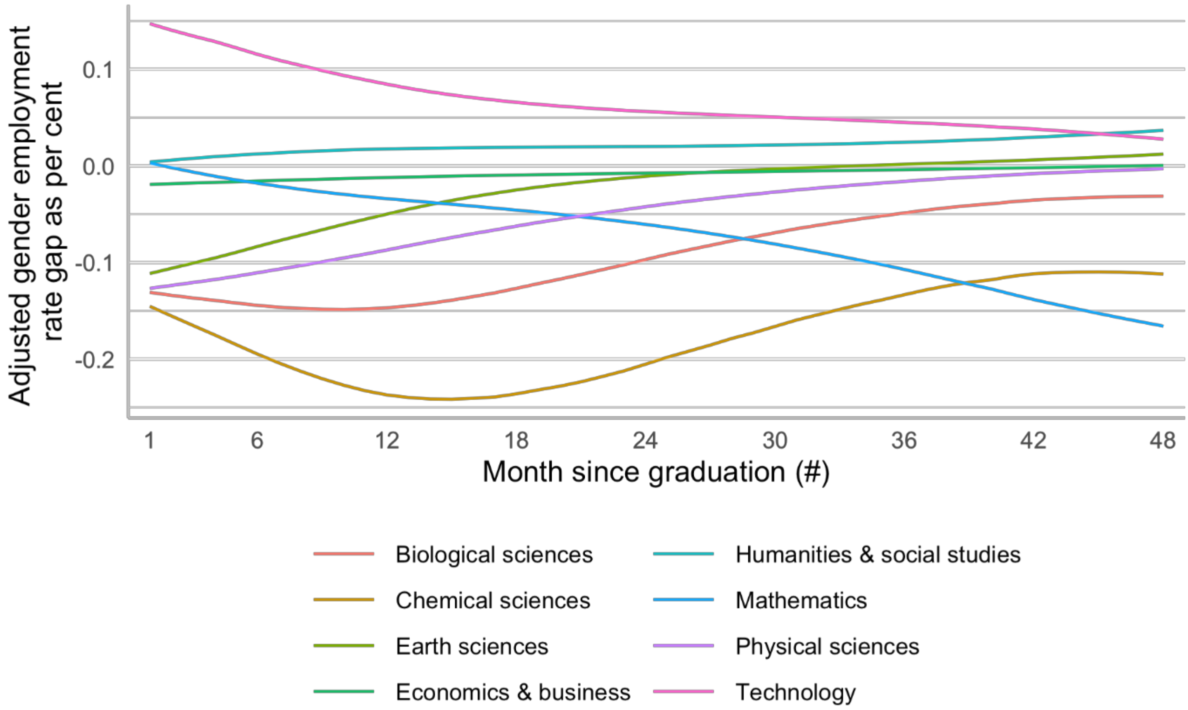
Notes: Data from the ELA 2019 dataset. Statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure B1. Adjusted employment rates by gender.



Notes: Data from the ELA 2019 dataset. Adjusted employment rates (predicted probabilities) based on Model B1 in Table B1.

Figure B2. Adjusted gender employment gap by field of study.



Notes: Data from the ELA 2019 dataset. Gender employment gaps (difference between the employment rate for men and women divided by the rate for men) calculated from predicted probabilities based on Model B2 in Table B1. Only selected fields are presented.