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IZA DP No. 15352

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ABSTRACT

Gender Differences in STEM Persistence after Graduation*

Much attention is focused on finding ways to encourage females to study STEM in school and college but what actually happens once women complete a STEM degree? We use the UK Quarterly Labour Force Survey to trace out gender differences in STEM persistence over the career. We find a continuous process whereby women are more likely to exit STEM than men. Among holders of STEM undergraduate degrees, women are more likely to obtain a non- STEM master's degree. Then, after entering the labour market, there is a gradual outflow of females during the first 15 years post-graduation so that females are about 20 percentage points less likely to work in STEM compared to their male counterparts. Conditional on leaving STEM, we find that females are more likely to enter the education and health sectors while males are more likely to enter the more lucrative business sector and that this can partly explain the gender pay gap for STEM graduates. Overall, our results suggest that policies that aim to increase the proportion of females studying STEM in school and college may have less effect than expected due to the lower attachment of females to STEM after graduation. Such policies may need to be augmented with efforts to tackle the greater propensity of females to exit STEM throughout the career.

JEL Classification: I23, I26, J16, J24, J31

Keywords: STEM, gender, STEM gender gap, labour market, gender pay gap

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1. Introduction

Women are underrepresented in Science, Technology, Engineering, and Mathematics (STEM) jobs and occupations. This gender gap in STEM has important implications for society and the economy as it is widely agreed that having an adequate supply of STEM graduates is important for both innovation and economic productivity (Peri et al. 2015). In addition, given the typically larger earnings of STEM workers, having more females working in STEM jobs may help to decrease the gender gap in earnings (Card and Payne, 2021).

Given the importance ascribed to increasing female representation in STEM, a large literature has tried to understand the reasons for gender differences in STEM uptake at both the high school and college level.[1] However, there is relatively little work analysing gender gaps in STEM conditional on studying a STEM field in college. While understanding why females are less likely to study STEM subjects in high school and college is crucial to increasing the supply of female STEM graduates, it is equally important to understand what happens to females who choose to study STEM in college: Are they less likely than male STEM graduates to work in STEM and how does this evolve over the life cycle? This is the question we seek to address in this paper. These issues are relevant to understanding the effect of college programs on the gender gap in earnings – if female STEM graduates do not work in STEM fields, then increasing the proportion of females studying STEM may have little impact on the gender earnings gap.

There are few studies examining STEM persistence after graduating from college. Recently, Jelks and Crain (2020) found, using US data, that over 25 percent of those with an undergraduate degree in STEM did not intend to remain in STEM by age 30. Also using US

[1] Many papers study the gender gap in preferences for studying STEM in college with potential factors including differences in comparative advantage in math and English (Speer, 2017; Delaney and Devereux, 2019), peer gender-composition (Brenoe and Zolitz, 2020; Schone et al., 2020), peer ability-composition (Balestra et al., 2020; Cools et al., 2019; Mouganie and Wang, 2020), math rank in high school cohort (Delaney and Devereux, 2021), and role models (Breda et al., 2020). See Kahn and Ginther (2018), McNally (2020), Cavaglia et al. (2020), and Delaney and Devereux (2021b) for reviews of this literature.

data, Hunt (2016) finds that women are relatively more likely to leave engineering fields rather than science and that this is mainly driven by women's dissatisfaction with promotion and pay opportunities. Jiang (2021) uses a unique dataset based on the first job that Purdue STEM undergraduates enter and finds that the reason more female STEM graduates exit STEM fields is because women tend to major in less math-intensive STEM fields for which there are many non-STEM jobs that constitute suitable matches.

Perhaps the closest paper to ours is Speer (2020) who uses US data to look at the gender gap in STEM across 6 different stages of the life cycle – from high school choices to college to mid-career. He finds that gender differences in STEM readiness prior to college and differences in persisting with a STEM major in college do not matter much for the overall gap. In contrast, the higher likelihood of males to choose STEM as their initial college major and for males to enter a STEM career upon entering the labour market together account for the majority of the overall gender gap in STEM. His paper highlights that it is important to look at different stages of the life cycle in order to get a complete picture of the gender gap in STEM. Other than studying a different country, our paper differs in that we focus specifically on graduates whose highest degree attainment is either a bachelor's or master's degree in STEM. First, we examine the gender gap in transitioning from an undergraduate degree in STEM to a master's degree in STEM. Then we examine how gender differences in working in STEM careers evolve over the first 25 years since college graduation for those whose highest degree is an undergraduate or master's degree in STEM.[2] We have information on graduation year so we can determine the exact point in the career when women leave STEM.

We also study how gender differences in working in STEM occupations relate to the gender gap in earnings. If the human capital acquired in STEM degrees is field-specific and

[2] In contrast, Speer (2020) focuses on differences in STEM persistence for STEM undergraduates at ages 30 and 45 and includes those with a post-graduate degree in any subject, some of whom have a postgraduate degree in a non-STEM subject and may be very unlikely to work in STEM. Altonji and Zhong (2021) find that the effect of field of post-graduate degree on post-graduate occupation is twice as large as the field of undergraduate degree.

not general, then the returns from studying a STEM degree will vary depending on the job in which the graduate is employed. Kinsler and Pavan (2015) find that science, engineering, and technology graduates who work in jobs unrelated to science, engineering, or technology earn 30 percent less than those working in related jobs. Thus, if female STEM graduates are less likely to work in STEM jobs, this may provide a partial explanation for the gender pay gap.

Also related to our work is the recent paper by Sloane, Hurst and Black (2020) that examines how field of study and subsequent occupational choices affect the gender gap in earnings over the past several decades in the US. Their study is not specifically focused on STEM graduates, and they examine gender differences in the mapping from college major to occupation across cohorts as opposed to looking at changes over the life cycle. We build on this by showing how gender gaps in STEM employment and earnings evolve over the life cycle.

We find that, conditional on pursuing a master's degree, female STEM graduates are 7 percentage points less likely to do their masters in STEM. The precise field of study of undergraduate degree can explain 40 percent of this gap but, even after controlling for high school and undergraduate achievement, female STEM graduates are still over 4 percentage points less likely to do their masters in STEM.

Gender differences in STEM persistence are also evident in the labour market. In the first year after graduation, the gender gap in STEM is about 10 percentage points; this slowly increases to about 25 percentage points 15 years after graduation. These gaps partly reflect college field of study (within STEM) – when we control for degree field, the immediate gap after graduation becomes very small but still increases to about 20 percentage points after 15 years. This highlights the importance of having detailed controls for field of study even within STEM. The gender gaps differ by STEM field of study. There are large immediate gaps for technology and math but not for the sciences or for engineering; however, after 15 years, the gender gap is 20+ percentage points in every STEM field except the life sciences. The gender gap in working in STEM is even larger for those with children. Also, the gender gap in whether the person works full time in STEM increases from a small immediate effect to 30 percentage points after 15 years.

We find that females who leave STEM jobs tend to switch to low paying sectors such as education and non-professional jobs while males who leave STEM tend to enter the more lucrative business sector. Finally, we see that the lower likelihood for females to work in high paying occupations can explain up to 50% of the gender gap in hourly pay for STEM graduates with the size of the effect increasing with labour market experience. Therefore, policies that help to attract women to high paying occupations may also help to mitigate the gender gap in earnings.

2. Institutional Background and Data

We use the UK Quarterly Labour Force Survey (QLFS) which is available from 1993 to 2021. The QLFS contains detailed information on field of study and the type of degree obtained. Since 1997 there is information available on approximately 1,300 unique fields of study which allows very precise allocation of STEM degrees. Prior to 1997, the fields were much broader and amounted to 87 unique fields. Therefore, we restrict our study to surveys from 1997 and later. A useful feature of the QLFS is that it has information on the age at graduation.[3] This allows us to precisely calculate the evolution of the STEM career from the point of graduation. Beginning in the last quarter of 2005 there is rich information on the number of General Certificate of Secondary Education (GCSE) exams obtained in high school and the quality of the undergraduate degree as measured by degree classification.[4] To

[3] This information is available from 2001 onwards. Prior to 2001, we use age left full-time education to assign the age at graduation.
[4] This measure has categories of first class honours, upper second class honours, lower second class honours, third class honours, and ordinary degree and is akin to having a measure of the Grade Point Average (GPA) for the degree.

determine whether a STEM graduate works in a STEM occupation or not, we use detailed 4-digit Standard Occupational Classification (SOC) codes. For those occupations classified as "senior executives" or "chief executives" we use information on industry sector to classify the worker as STEM or not. We limit the sample to those who are British and graduated with an undergraduate or master's degree between the ages of 20 and 26. This allows us to focus on a relatively homogenous group with little labour market experience before graduation. When we study earnings, we trim the top and bottom 0.5 percentile of gross weekly pay and hourly pay to avoid outliers and reduce measurement error and we convert to 2020 prices using the UK retail price index. Finally, we limit the sample to those who graduated between 1970 to 2020 and who are aged between 21 and 60 at the time of the survey.

We define STEM degrees in a similar way to Delaney and Devereux (2019) whereby we include all degrees in science, mathematics, technology and engineering, as well as including medical degrees such as physician, pharmacy, dentistry, etc. We follow the same criteria when constructing STEM occupations. Females are relatively more likely to enter medical degrees and so our estimates of gender gaps are likely lower than what we would find with a narrower definition of STEM that excludes medical degrees. Later, we show how robust our STEM definition is to the exclusion of medical degrees. We also show the effect of widening our STEM definition to include nursing degrees.

Table 1 below shows the gender differences in our main variables of interest for those with their highest degree in STEM.[5] There is substantial heterogeneity in gender gaps across the type of STEM degree with females being more likely to obtain a degree in the life sciences or a medical degree while males are more likely to obtain degrees in the hard sciences, math, technology, architecture, and engineering. The gender gap in graduating with a degree in engineering is largest with 5 percent of females having engineering as their highest degree

[5] Table A1 in the appendix shows the descriptive statistics for all graduates.

compared to 29 percent of males. Consistent with other studies (Delaney and Devereux, 2020), we find that females are more likely to graduate with an upper second-class honours degree (typically GPA between 3.3-3.9) but there is little gender gap in the proportion obtaining a first class honours degree (GPA of 4). Almost one fifth of the sample with STEM as their highest degree have a master's degree, highlighting the importance of looking beyond just undergraduate degrees. The most important gender difference for our analysis is the gap in working in STEM – we find that male STEM graduates are 20 percentage points more likely to work in STEM jobs compared to females. In contrast, female STEM graduates are more likely to work in health, education, and non-professional jobs. Unsurprisingly, we also see that females are much more likely to be out of the labour force. Both female and male STEM graduates earn substantially more than their non-STEM counterparts which suggests that increasing the proportion of females in STEM may decrease the gender pay gap. In the lower panel of Table 1, we see that STEM graduates with a master's degree are more likely that those with just an undergraduate degree to work in STEM jobs.

Table 1: Descriptive Analysis of STEM Graduates by Gender and Highest Degree

	Female		Male	
Undergraduate Degree	0.82	(0.38)	0.83	(0.38)
Master's Degree	0.18	(0.38)	0.17	(0.38)
Life Sciences	0.37	(0.48)	0.15	(0.35)
Hard Sciences	0.16	(0.37)	0.17	(0.38)
Medical Degrees	0.22	(0.41)	0.07	(0.26)
Math	0.07	(0.26)	0.08	(0.26)
Technology	0.05	(0.22)	0.14	(0.35)
Engineering	0.05	(0.23)	0.29	(0.46)
Architecture	0.07	(0.25)	0.10	(0.30)
First Class Degree	0.16	(0.37)	0.15	(0.36)
Upper Second Class Honours	0.54	(0.50)	0.45	(0.50)
Lower Second Class Honours	0.26	(0.44)	0.32	(0.47)
Third Class Honours/Pass	0.04	(0.18)	0.08	(0.27)
8+ GCSEs	0.87	(0.34)	0.77	(0.42)
5 to 7 GCSEs	0.12	(0.32)	0.20	(0.40)
Fewer than 4 GCSEs	0.02	(0.13)	0.03	(0.18)
Work in STEM (unconditional on working)	0.31	(0.46)	0.51	(0.50)
Work FT in STEM (unconditional on working)	0.22	(0.42)	0.50	(0.50)
Work in STEM (conditional on working)	0.36	(0.48)	0.56	(0.50)
Work in Health	0.10	(0.30)	0.01	(0.11)
Work in Education	0.08	(0.27)	0.03	(0.18)
Work in Business	0.14	(0.34)	0.16	(0.37)
Work in Low-Skill Sector	0.20	(0.40)	0.12	(0.33)
Work in Other Sector	0.13	(0.33)	0.12	(0.32)
Unemployed	0.02	(0.14)	0.02	(0.15)
Out of the Labour Force	0.11	(0.32)	0.05	(0.22)
Real Gross Weekly Pay 2020 prices	699.12	(403.54)	1001.74	(494.42)
Real Gross Hourly Pay 2020 prices	20.56	(10.40)	25.53	(12.24)
Age at First Child	31.41	(3.91)	32.72	(4.52)
Years Since Graduation First Child	9.32	(4.04)	10.51	(4.64)
Year of Graduation	1997.31	(11.35)	1994.00	(11.86)
Age	35.90	(10.01)	38.40	(10.43)
White	0.90	(0.31)	0.91	(0.29)
Observations	82730		147512	

	Undergraduate		Masters	
Life Sciences	0.24	(0.43)	0.18	(0.39)
Hard Sciences	0.16	(0.37)	0.20	(0.40)
Medical Degrees	0.13	(0.34)	0.09	(0.29)
Math	0.07	(0.26)	0.08	(0.27)
Technology	0.11	(0.31)	0.12	(0.33)
Engineering	0.20	(0.40)	0.24	(0.43)
Architecture	0.09	(0.28)	0.09	(0.29)
Work in STEM (conditional on working)	0.43	(0.50)	0.49	(0.50)
Work FT in STEM (unconditional on working)	0.39	(0.49)	0.45	(0.50)
Work in STEM	0.48	(0.50)	0.54	(0.50)
Work in Health	0.04	(0.20)	0.04	(0.19)
Work in Education	0.05	(0.21)	0.07	(0.25)
Work in Business	0.15	(0.36)	0.15	(0.36)
Work in Low-Skill Sector	0.16	(0.36)	0.10	(0.30)
Work in Other Sector	0.12	(0.33)	0.10	(0.30)
Unemployed	0.02	(0.15)	0.02	(0.15)
Out of the Labour Force	0.07	(0.26)	0.07	(0.26)
Real Gross Weekly Pay 2020 prices	887.71	(488.52)	924.74	(474.88)
Real Gross Hourly Pay 2020 prices	23.57	(11.92)	24.65	(11.59)
Observations	190131		40111	

Note: The sample years are 1997-2021 and the year of graduation is 1970-2020. The sample includes all graduates whose highest degree is a master's or bachelor's degree in STEM. The mean is shown and the standard deviation is in parentheses.

3. Persistence in STEM

3.1 Transition from STEM Undergraduate to Post-graduate Degree

Prior to, or shortly after entering the labour market, STEM graduates may switch out of STEM by pursuing post-graduate degrees in non-STEM fields. Information on both undergraduate degree and post-graduate degree is available in the data from 2012. We use this information to analyse whether, among persons who did their primary degree in STEM, females are more likely to switch to non-STEM subjects at this stage in the pipeline. While undergraduate degree holders can pursue both master's and PhD degrees, we focus on master's degrees only as they are much more common and typically are a requirement for entry to a PhD.[6]

Table 2 (Columns 1-3) shows that, among holders of a STEM primary degree, women are more likely than men to pursue a non-STEM master's degree. This is not just because they are more likely to do any master's degree. When we condition on graduating with a master's degree (columns 4-6), female STEM undergraduates are around 7 percentage points less likely to do a master's in STEM than their male counterparts. We also see that those with a first-class degree (the highest GPA category) in their undergraduate STEM degree are much more likely to do a masters in STEM. Interestingly, the type of STEM undergraduate degree can explain 35 percent of the gender gap in STEM persistence with life science and technology graduates being less likely to do their master's degree in STEM relative to graduates in the hard sciences. It is clear that, even at this initial stage of the STEM pipeline, females are relatively more likely to transition to non-STEM fields as the gender gap in doing a masters in STEM, conditional on doing a masters and having an undergraduate degree in STEM, is 4 percentage points.[7]

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[6] We also exclude PhDs from the analysis as, when we analyse how the gender gap evolves in the labour market for each year since graduation, we want to focus on those who have little pre-graduation labour market experience and so we limit the sample to those who obtained their highest degree between the ages of 20 and 26; many PhD graduates are much older upon graduation.

[7] Table 2 also shows that engineering and architecture graduates are less likely to do a master's degree in a non-STEM subject. Further analysis suggests that this may be because they are relatively narrowly focused, so more

Table 2: Gender Differences in Probability of Graduating with a Non-STEM Master's Degree
(persons who completed an undergraduate degree in STEM)

	Unconditional on Masters			Conditional on Masters		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Non-STEM Masters	Non-STEM Masters	Non-STEM Masters	Non-STEM Masters	Non-STEM Masters	Non-STEM Masters
Female	0.011***	0.010***	0.007***	0.062***	0.068***	0.044***
	(0.001)	(0.001)	(0.001)	(0.007)	(0.007)	(0.008)
Age	0.018***	0.018***	0.019***	0.039***	0.036***	0.034***
	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)	(0.006)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	-0.008***	-0.010***	-0.012***	-0.047***	-0.038***	-0.037***
	(0.002)	(0.002)	(0.002)	(0.012)	(0.012)	(0.012)
First Class Degree		-0.000	0.003		-0.148***	-0.142***
		(0.002)	(0.002)		(0.032)	(0.032)
Upper Second Class Honours		0.003	0.004***		-0.134***	-0.137***
		(0.002)	(0.002)		(0.031)	(0.031)
Lower Second Class Honours		0.001	0.002		-0.102***	-0.105***
		(0.002)	(0.002)		(0.032)	(0.032)
8+ GCSEs		0.021***	0.018***		-0.141**	-0.136**
		(0.002)	(0.002)		(0.056)	(0.056)
5 to 7 GCSEs		0.008***	0.006**		-0.111*	-0.112*
		(0.003)	(0.003)		(0.057)	(0.058)
Life Science			-0.003*			0.042***
			(0.002)			(0.010)
Medicine			-0.020***			0.008
			(0.002)			(0.017)
Math			-0.005**			-0.010
			(0.002)			(0.014)
Technology			-0.016***			0.043**
			(0.002)			(0.019)
Engineering			-0.017***			-0.059***
			(0.002)			(0.010)
Architecture			-0.021***			-0.030**
			(0.002)			(0.015)
Observations	80,986	80,986	80,986	10,134	10,134	10,134
R-squared	0.027	0.028	0.032	0.036	0.042	0.051

Note: Robust standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Age quadratic, survey year dummies, and year of graduation dummies included in all regressions. The excluded category for undergraduate degree class is scoring below lower second class, for number of GCSEs is fewer than 5 GCSES, and for type of undergraduate degree is a degree in hard sciences. Graduation cohorts included are 1970-2020. Survey years are 2012-2021.

likely to stay in the field when doing further study. The sign change for technology when we condition on doing a master's degree occurs because technology graduates are less likely to do a master's degree and, if they do one, it is less likely to be in STEM.

3.2 Persistence in STEM in the Labour Market

The previous section highlighted that gender differences in STEM persistence emerge directly after graduation for those STEM undergraduates who choose to remain in education and undertake a graduate degree. In this section, we look at the dynamics of STEM persistence over the life cycle for STEM graduates who are in the labour market. We focus on graduates whose highest degree is a master's or undergraduate degree in STEM and trace out the gender gap in working in STEM for each year since graduation. We study outcomes by years since graduation, defined as survey year minus graduation year. We use a linear probability model and regress whether or not the STEM graduate works in a STEM occupation for each value of years since the time of their graduation. The outcome variable is 1 if the graduate works in STEM and 0 if the graduate does not work in STEM or is not working.[8] The basic specification has the form:

$$y_t = \beta_{0t} + \beta_{1t}Female + \delta_t' X + u_t \tag{1}$$

where *y* is a binary variable denoting work in a STEM occupation, *Female* is a binary variable denoting female and *X* includes a set of controls including a dummy variable for whether the graduate is white or not, a quadratic in age, a dummy variable for whether the highest degree is a master's or undergraduate degree, and year of survey fixed effects. We run this regression for each year, *t*, since graduation and, so, estimate the coefficient on female for each length of time since graduation. The allows us to plot out the evolution of the gender gap in STEM for 25 years post-graduation. Throughout the analysis, we report robust standard errors.

Figure 1 shows that female STEM graduates are much less likely to work in STEM occupations than are males (the underlying coefficient estimates and standard errors are reported in Table A2 in the appendix). This finding emerges right after graduation with females

[8] Later in this section, we discuss the gender gap when we condition on being employed.

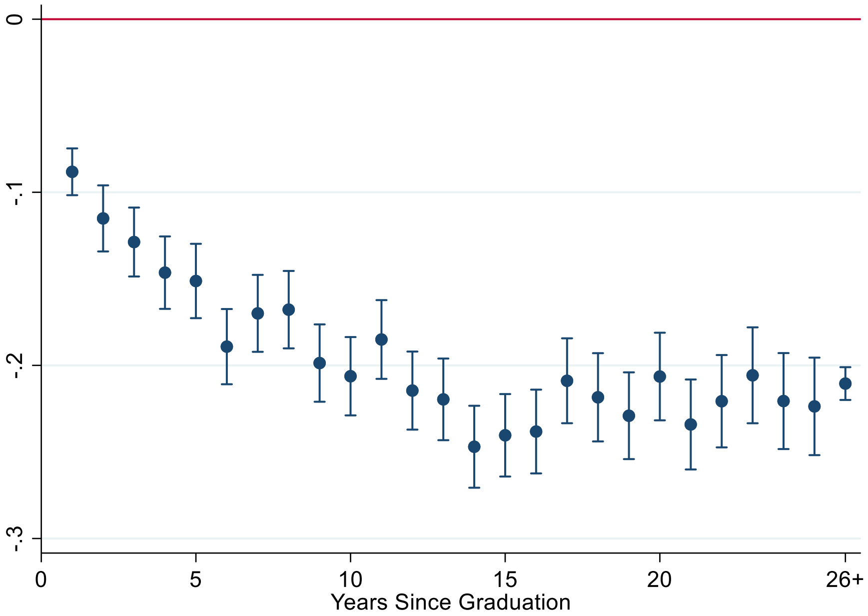
being about 10 percentage points less likely to work in STEM and this difference gradually increases for the next 9 years and then flattens out so that after about 10 years post-graduation, female STEM graduates are approximately 22 percentage points less likely to work in STEM. Clearly, even for STEM graduates, there is a large gender gap in working in STEM occupations.[9]

We cannot tell exactly why the gender gap increases rapidly over the first 10 years in the labour market and then flattens out. We show later that this is not likely due to cohort effects and, given we control for whether the individual has an undergraduate or master's degree in STEM, it is unlikely to be related to educational choices. However, the time-series for working in STEM mirrors that for marriage probabilities and for the probability of having a child in the family (both of which increase rapidly for about the first 10 years in the labour market and then stabilise). So, it is probable that these are important factors in determining the time pattern of the gender gap in STEM employment.[10] We investigate their role further in Section 4.

[9] In Appendix Figure A1 we show that this general pattern continues to appear if we include nursing in STEM or exclude medical degrees from STEM.

[10] Cech and Blair-Loy (2019) find using US data that 43 percent of female STEM professionals who work full-time leave STEM after the birth of the first child and that 23 percent of new fathers leave STEM after their first child.

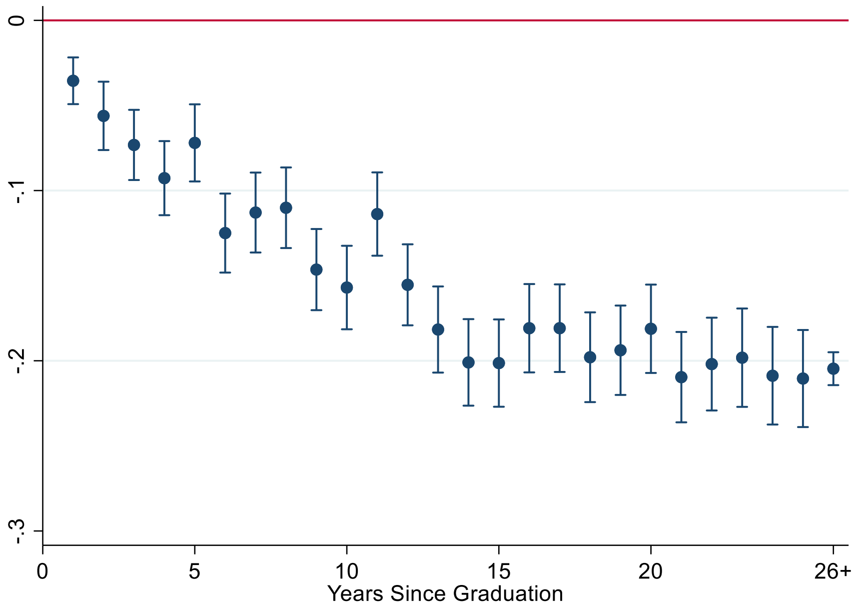
Figure 1: Gender Differences in Probability STEM Graduates Work in STEM



Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

We saw in Table 1 that females with STEM degrees were much more likely to be science graduates while males were more likely to obtain their STEM degree in math, technology, or engineering. Therefore, in Figure 2 we plot the persistence of working in STEM since entering the labour market from regressions that control for the type of STEM degree acquired (whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, or technology). We see that this attenuates the gender gap at all stages of the career, with the gender gap upon entering the labour market being about 4 percentage points and this gradually increases to about 20 percentage points after 14 years post-graduation. This suggests that certain STEM degrees such as science may offer the opportunity to work in a wider range of non-STEM careers while an engineering or math/technology degree may be more limiting in the type of occupations that are available to work in. We continue to control for the type of STEM degree acquired in the analysis in the rest of the paper.

Figure 2: Gender Differences in Probability STEM Graduates Work in STEM adding controls for STEM Specialisation



Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Robustness to Cohort Effects

While our strategy involves a separate regression for each value of years since graduation, we pool all graduation years together and run each regression controlling for year and age effects. A potential problem is that, since we have 40 graduation cohorts and our data only begin in 1997, the coefficients on early years after graduation will be predominantly identified from later graduation cohorts and the coefficients on later years after graduation will be predominantly identified from earlier graduation cohorts. If there are meaningful differences in the gender gap across graduation cohorts, this could imply that our coefficients for years since graduation are misleading. In order to test whether this is the case, we have run separate regressions by graduation cohort, using the same controls as in Figure 2 (so, including controls for field of specialisation in college). To increase precision, we group graduation cohorts into

5-and 10-year groups and group years since graduation into 3-year intervals.[11] Figure A2 shows the estimates for each set of graduation cohorts. While there is some variation across graduation cohorts, Figure A2 is very similar to our main estimates in Figure 2 with an initial gender gap of about 5 percentage points that gradually increases with years post-graduation. We conclude that it does not appear that our results are driven by cohort effects and, as in Figure 2, we continue to pool graduation cohorts in our subsequent analyses.

Robustness to Controls for Academic Achievement

From 2005 onwards, we have additional information about the degree class achieved and the number of GCSEs received in school. It is plausible that the differential choices made by women could partly reflect gender differences in academic achievement. Therefore, in Figure A3 in the appendix, we examine how the gender differences change when we estimate the model with and without these additional controls, restricting our sample to observations from 2005 onwards. Reassuringly, we find that the estimates for the gender gaps are very similar with and without these additional controls.[12]

Summary Findings for Average Gender Gap

Table A3 in the appendix summarizes how the average gender gap differs by specification, showing gender differences in working in STEM occupations, on average, for all years since graduation up to age 60. Column 1 shows the estimates without controlling for degree specialisation. We see that females are 19 percentage points less likely to work in STEM occupations. This gap falls to 15 percentage points after adding controls for field of study within STEM (column 2). This implies that over 20 percent of the gender gap in working in STEM is explained by field of study, highlighting the importance of having detailed

[11] We omit the earliest cohorts (1970-1974) and latest cohorts (2015-2020) due to the small number of years post-graduation that are available.
[12] It is possible that having information on the precise grade obtained in each GCSE subject would better capture differences in abilities.

information on subject of STEM degree when analysing gender gaps in STEM. Columns 3 and 4 show estimates for the 2005-2021 sample for which we have information on academic achievement. The estimates are similar in columns 3 and 4, showing that the addition of the academic achievement variables has very little impact. Therefore, in the remainder of the paper we focus on the larger 1997-2021 sample and exclude these achievement controls.

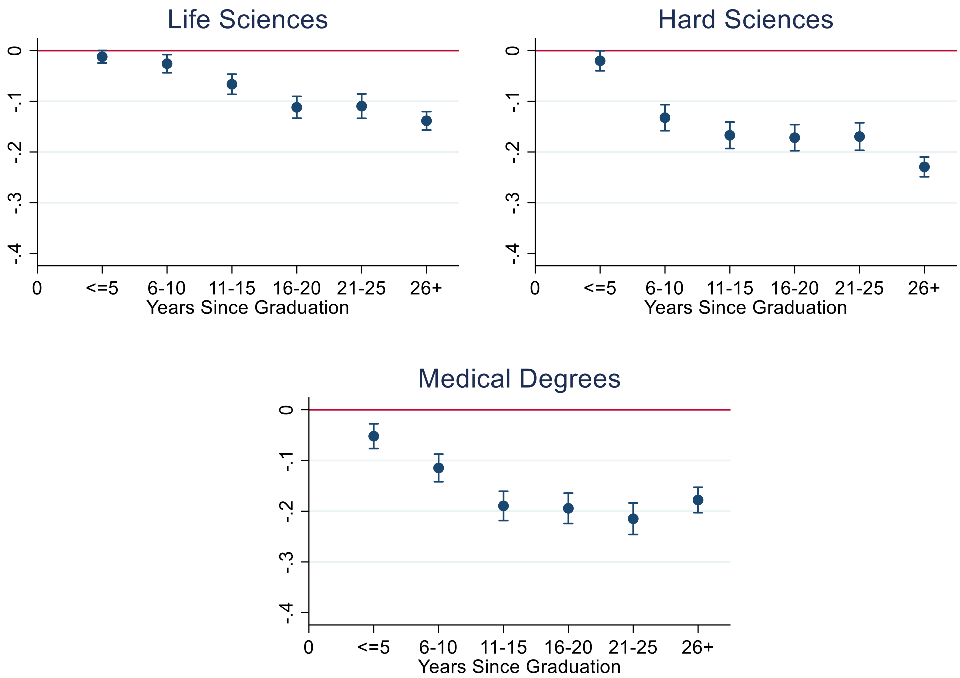
Table A3 also shows that technology graduates are 25 percentage points more likely to work in STEM relative to hard science graduates while life science graduates are 10 percentage points less likely than hard science graduates to work in STEM occupations. We also see that those graduates who achieved the highest degree class (first class honours) in their undergraduate degree are 10 percentage points more likely to work in STEM and the effect is quite linear for the other degree classifications. Similarly, graduates who obtained the highest number of GCSEs in high school are more likely to work in STEM jobs. This suggests that it is the highest quality graduates who are more likely to persist with STEM.

Persistence in STEM in the Labour Market by STEM Specialisation

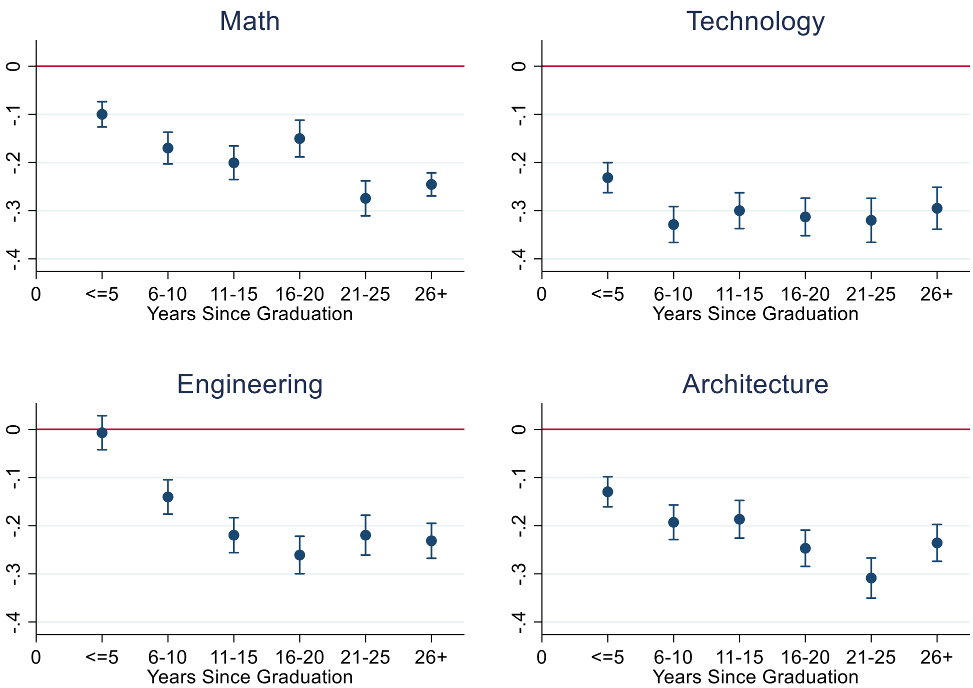
In the previous section, we noted the importance of controlling for type of STEM degree when analysing gender differences in STEM outcomes. In this section, we focus specifically on gender differences in STEM persistence by STEM specialisation. We group years since graduation into 5-year categories due to the lower sample sizes once we condition on field of study.

We see that there is substantial heterogeneity depending on the type of STEM degree studied. The upper panel of Figure 3 shows that, for life science graduates, there is very little gender difference in working in STEM for the first 10 years after graduation but that a gap opens up from about 16 years after graduation such that female life science graduates are about 10 percentage points less likely to work in STEM careers from this stage in their career. The gap for hard sciences is similar in that there is no gap at labour market entry, but a gender gap emerges after about 11 years post-graduation such that after this time females who graduated in hard sciences are almost 20 percentage points less likely to work in STEM. The effects for medical degree holders are similar to hard science graduates. For the more math-intensive fields such as engineering, math, architecture, and technology, the gender gap is much more salient with the gender gap in working in STEM being about 10 percentage points in the first 5 years of graduation for math and architecture graduates while the gap for technology graduates is over 20 percentage points in the first five years after graduation. These findings suggest that encouraging females to study science will be most successful at mitigating the gender gap in STEM careers as, relative to males, females who study engineering, math, or technology appear to be much more likely to leave STEM after graduation.

Figure 3: Gender Differences in Probability STEM Graduates Work in STEM by Field of Specialisation



Lower Panel



Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Persistence in STEM in the Labour Market Conditional on Employment

Up until now we have focused on gender differences in working in STEM unconditional on employment as we are interested in whether STEM graduates persist in working in STEM regardless of whether they stay in the labour market. In this section, we look at whether there are gender differences in working in STEM conditional on being in employment. This may particularly matter when looking at gender differences since it is well known that women are more likely to leave the labour force. As Appendix Figure A4 shows, this is also true for STEM graduates. However, Figure A5 in the appendix shows that we see a similar pattern to that in Figure 2 when looking at gender differences conditional on employment with the gender difference being small initially and then gradually increasing to approximately 20 percentage points after 20 years in the labour market. While the effect sizes are somewhat smaller, it is reassuring that our results hold whether we look at STEM persistence conditional or unconditional on employment.[13]

Persistence in STEM in the Labour Market by Full-Time Work Status

Focusing on working full-time in STEM may be particularly important in thinking about the effect on economic growth, innovation, and lifetime earnings. Recent work by Deming and Noray (2020) using job advertisement data found that many job vacancies in 2019 required skills that did not exist in 2007 and other skills that were prevalent in 2007 job adverts became obsolete by 2019. They also found that STEM jobs showed the largest change in skill requirements over the period. Thus, if females are more likely to work part-time, then it is likely that due to the ever-changing skill requirements of STEM jobs, they may ultimately leave STEM as they have less time to invest in learning these new skills if they are working part-

[13] In Figure A6 in the appendix we show estimates for gender differences in working in STEM conditional on employment by STEM specialisation. We find a very similar pattern to the estimates that are unconditional on employment.

time. Figure A7 in the appendix shows that, in the sample of employed STEM graduates, women are less likely to work full-time than men. To allow us to look at the gender gap in working in STEM abstracting from the greater tendency of females to work part-time, Figure A8 shows the gender gap in working in STEM for STEM graduates who are full-time workers. We see that, even conditioning on being in full-time employment, that there is quite a large gender gap in working in STEM, with females being almost 10 percentage points less likely to work in STEM at the beginning of the life cycle and this gap widens to almost 20 percentage points 25 years post-graduation.[14]

4. Heterogeneous Effects

In this section, we examine how our main findings differ across groups with emphasis on whether the findings differ between women with and without children, and for women with partners, between women whose partners have a STEM degree relative to women whose partners have a non-STEM degree.[15]

Children

It is well established that many females leave the labour force after having children and that this explains some of the gender gap in pay (Kleven et al., 2019). In this section, we examine how this contributes to the higher likelihood of females to leave STEM.

In the data, we have information on the number of children and whether the respondent works part-time or full-time. In Figure 4, we see that the presence of children has disparate

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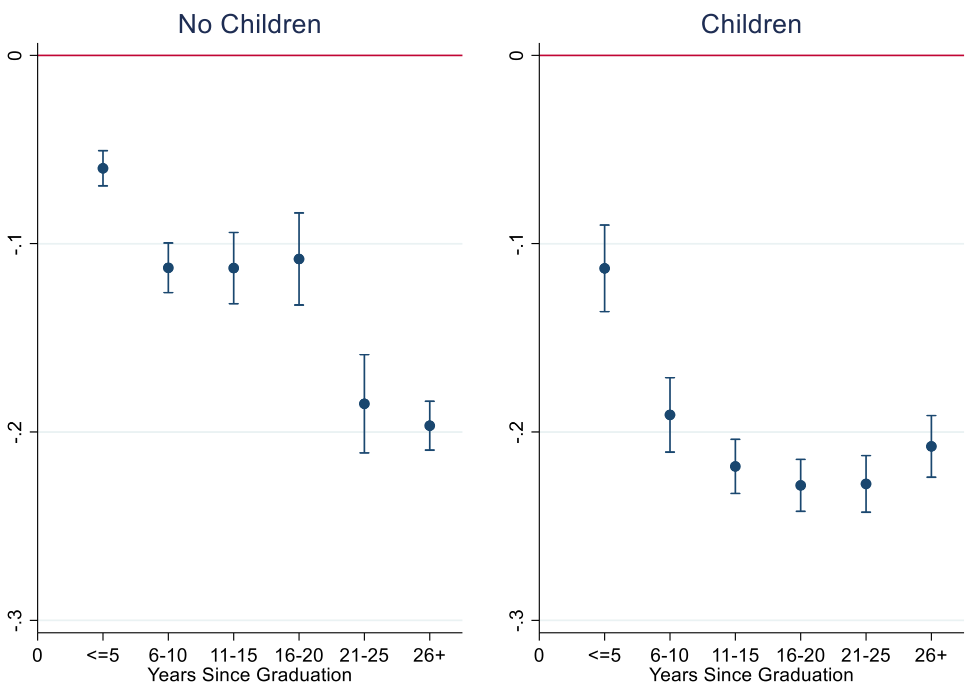
[14] Figure A9 in the paper shows the gender gap in working full time in STEM for STEM graduates unconditional on being employed. As expected, the gap is much larger.

[15] There is also information available for the winter quarter from 2014 onwards on the occupation of the parent who was the main wage earner when the respondent was aged 14 years old. We have used this variable to create social class categories based on whether the parent worked in an unskilled, semi-skilled, or professional occupation and found that there was no clear pattern in how the gender gap in working in STEM varied across these categories. We also found that there was little difference based on whether the main parental wage earner worked in a STEM occupation or not.

effects on the gender gap in remaining in STEM employment. The left figure shows that for those without children the gap is about 5 percentage points initially and that this increases slightly to just over 10 percentage points up to 20 years after graduation and then becomes a 20 percentage point gender gap. In contrast, comparing men and women with children, we see that the initial gap is over 10 percentage points but this increases to 20 percentage points after 5 years in the labour market and increases slightly over the remainder of the career. Figure A10 in the appendix shows that the results are similar if we condition on employment.[16]

Figure 4: Gender Differences in Probability STEM Graduates Work in STEM



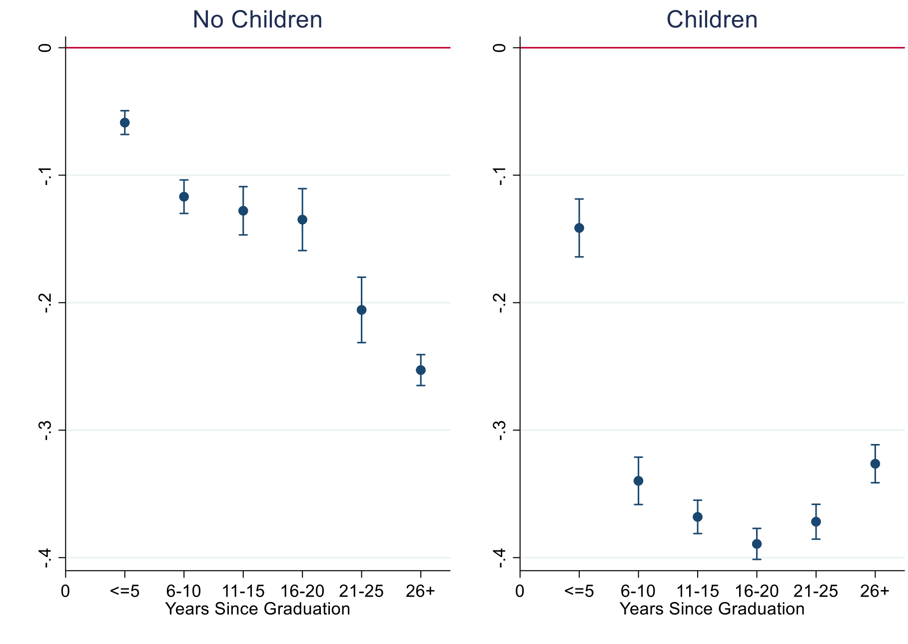
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Given the likelihood that females switch to part-time employment after having children, in Figure 5 we study the gender gap in working full-time in STEM for those with and without

[16] We have also analysed whether the gender gap in working in STEM differs for married/cohabiting individuals versus non-partnered individuals and found that the overall gaps are smaller but the pattern is similar to that for children versus no children.

children. While the gender gap in working full-time in STEM is very similar to the overall gap in working in STEM in Figure 4, the right-hand figure shows that, for those with children, females are over 30 percentage points less likely to work full-time in STEM and this gap increases in absolute value to 40 percentage points between 16 and 20 years after graduating. We find a similar pattern if we condition on being in employment (see Figure A11 in the appendix). This highlights the difficulty of retaining female STEM graduates in full-time STEM employment. Given the fast-changing nature of STEM jobs, in engineering and technology in particular, it may be difficult for females to remain up to date with the requisite skills if they are only working part-time. Clearly, finding ways to keep females working full-time in STEM is paramount to reap the full benefits to increased female participation in STEM in terms of innovation and decreasing the gender pay gap.

Figure 5: Gender Differences in Probability STEM Graduates Work in STEM Full-Time



Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

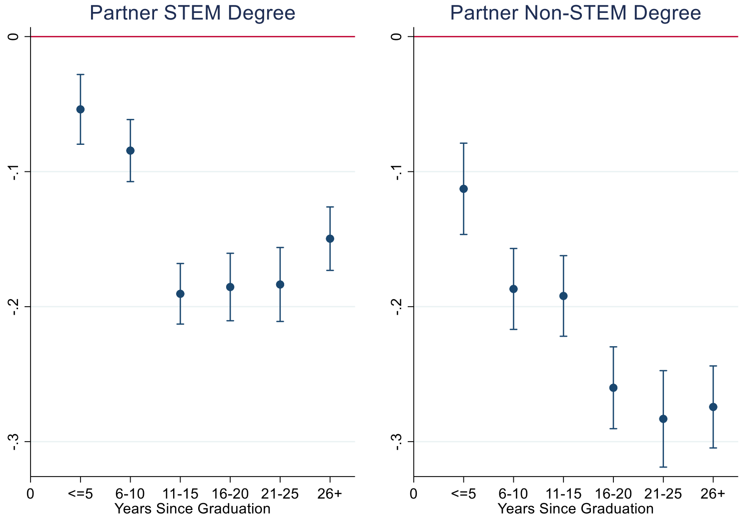
In Table A4 we show the overall gender difference (looking over the whole career) in working in STEM by whether the person has children. Columns 1 and 2 of Table A4 show that the gender gap in working in STEM is almost twice as large for the sample with children than for the sample without children – females with children are 21 percentage points less likely to work in STEM compared to the gap of 11 percentage points for those without children. In columns 3 and 4, we see the gender gap in working full-time in STEM (working part-time in STEM or not working are set to 0). The gender gap in working full-time in STEM for the sample without children is 13 percentage points, similar to the gap in working in STEM. However, we see that the gender gap in working full-time in STEM for the sample with children is much larger in magnitude with females that have children being 35 percentage points less likely to work full-time in STEM compared to their male counterparts.[17]

By Partner STEM Status

In Figure 6 we show the gender difference in the probability of working in STEM over the life cycle for STEM graduates whose partner has a highest degree in STEM (left hand side of the graph) and for STEM graduates with a partner with a highest degree in a non-STEM subject. The sample is restricted so that only people who have a spouse or cohabiting partner are included. If married, partners are spouses; otherwise, they are cohabitating partners. We find that the gender gap in working in STEM is larger in the sample of STEM graduates who are partnered with a non-STEM degree graduate compared to that in the sample of STEM graduates whose partner has a highest degree in STEM.

[17] In Table A5, we show the effect of age and number of children. We find that females with at least 2 children between the ages of 5 and 9 are 20 percentage points less likely to work in STEM relative to men who have at least 2 children between ages 5 and 9. The difference is even more pronounced if we look at whether the person works full-time in STEM with females being 34 percentage points less likely to work full-time in STEM if they have at least 2 children aged 5 to 9 compared to their male counterparts.

Figure 6: Gender Differences in Probability STEM Graduates Work in STEM by Partner STEM Educational Attainment



Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020. The sample is restricted to heterosexual couples.

5. Where Do People Move to if they Leave STEM?

In the previous section, we found that, conditional on obtaining their highest degree in a STEM field, females are less likely to work in STEM. We now turn our attention to the sectors that graduates who leave STEM switch into and whether there are systematic differences by gender. We categorize the non-STEM sectors as health, education, business, low-skilled (or non-professional), or "other" sector. The other sector contains occupations not included in health, education, business, or non-professional occupations and includes occupations such as journalists, police officers, and career advisers.

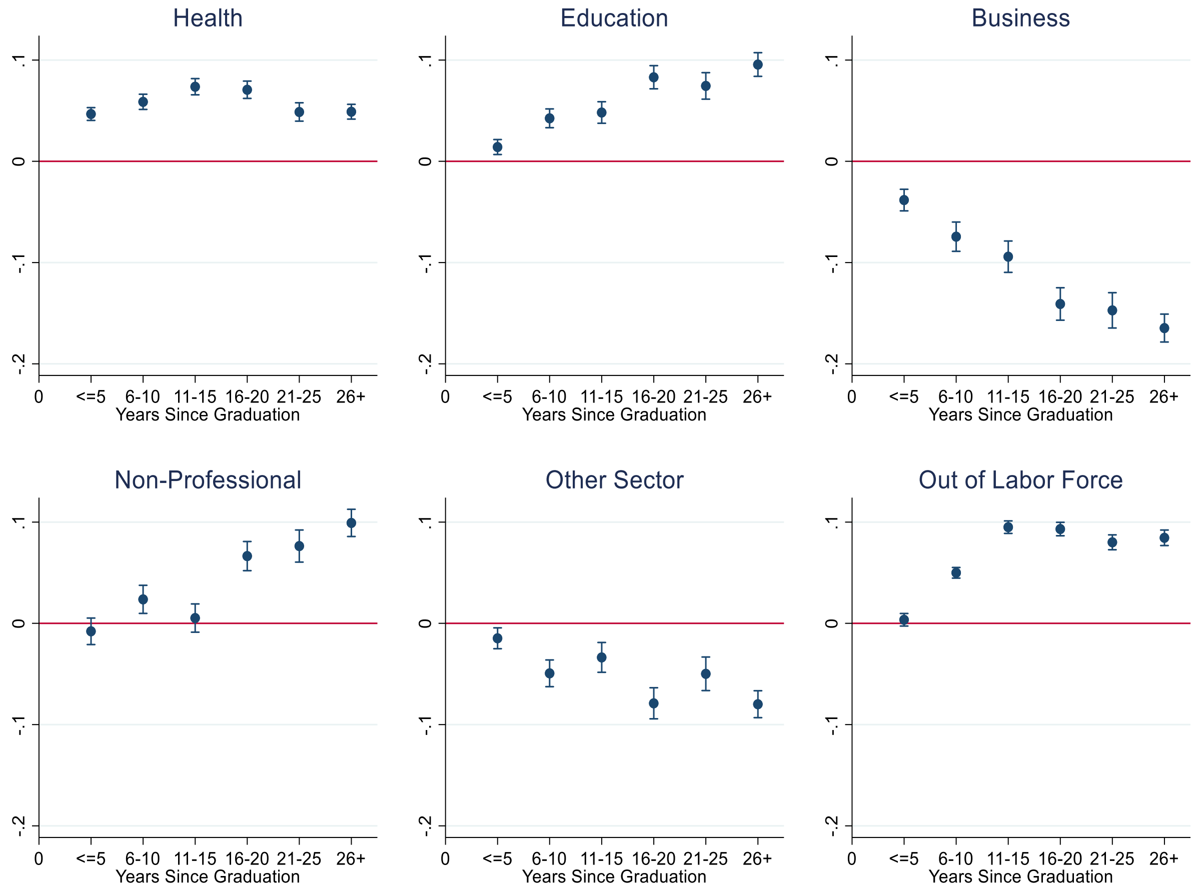
Figure 7 shows that females are much more likely to switch to work in the education and health sectors while men are more likely to work in business and other sectors. But there are interesting dynamics across the life cycle and by sector. Upon entering their career, females are approximately 5 percentage points more likely to work in the health sector and this remains consistent for the entire career. Interestingly, there is little gender difference in working in the low-skilled (non-professional) sector until 15 years after graduating when we see that females are almost 10 percentage points more likely to work in the non-professional sector. The latter may be due to females switching to secretarial and administrative jobs, which are less demanding and have more regular hours, after having a child (on average, individuals working in the non-professional sector work about 7 hours less per week than those working in STEM (34 versus 41)). In addition, Deming and Noray (2020) found that business jobs had high rates of skill change, but that education and health had the lowest rate of skill obsolescence, consistent with our finding that females are more likely to switch to education, health, and non-professional sectors – those sectors with the lowest required skill upkeep.

The average real hourly pay (for any graduate) for working in the business sector is £27, for working in the health sector is £19, for working in education sector is £22, for working in the low-skilled sector is £14 and for working in the other sector is £21.[18] It is clear that females are switching to the lowest-paying sectors while men who switch out of STEM are more likely to work in the business sector – the highest paying sector. This is consistent with the pay penalty from leaving STEM being larger for women than for men.[19]

[18] The average real gross weekly pay (for any undergraduate/master's graduate) for working in the business sector is £1022, for working in the health sector is £646, for working in the education sector is £742, for working in the low skilled sector is £460 and for working in the other sector is £796**.**

[19] In Appendix Table A6, we show that women who do not work in STEM suffer an hourly pay penalty that is 7 percentage points larger than for men.

Figure 7: Gender Differences in Probability STEM Graduates Work in Different Sectors (conditional on not working in STEM)



Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome for working in each sector is conditional on not working in STEM and controls include an age quadratic, indicators for white, for whether the highest degree is undergraduate or masters, indicators for STEM specialisation, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

6. Effect of Persistence in STEM on the Gender Pay Gap

Given that STEM jobs are typically higher paying, and females are less likely to work in STEM, in this section, we look at the effect of occupation on the gender gap in log pay for STEM graduates.

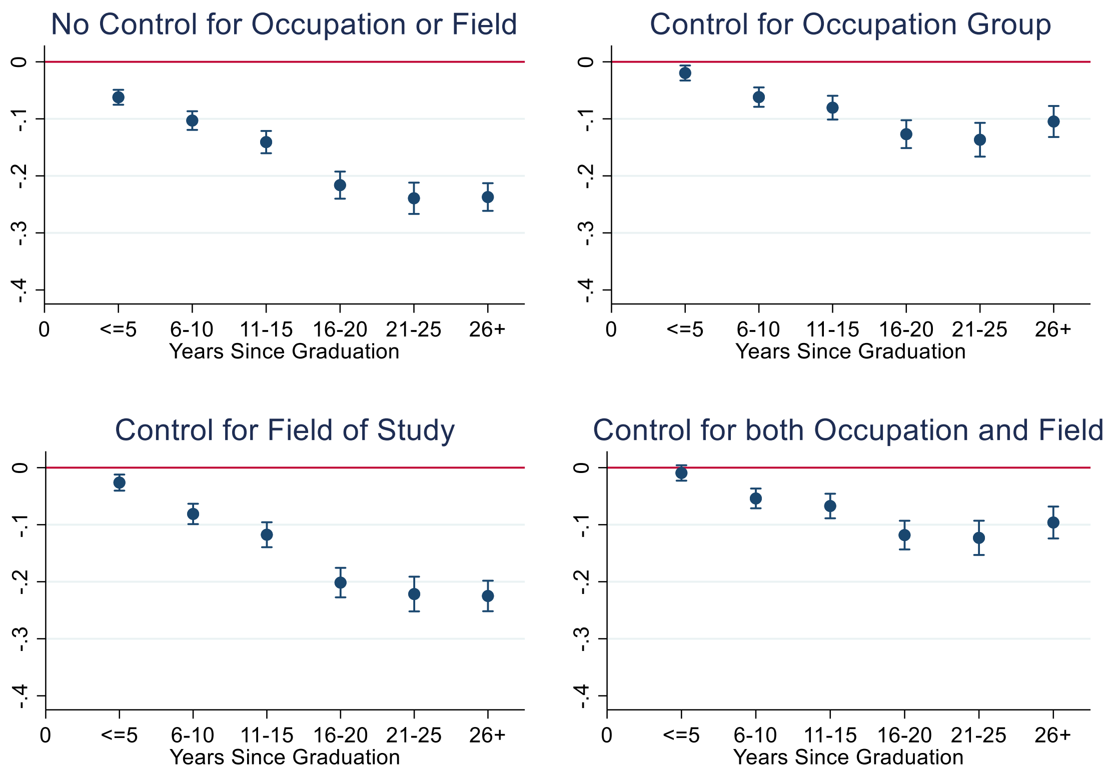
Figure 8 shows how the gender gap in pay evolves over the career. The outcome variable is log gross weekly pay (or log hourly pay) and the basic specification has the form:

$$y_t = \beta_{0t} + \beta_{1t}Female + \delta_t'X + u_t \tag{2}$$

where y is log gross weekly pay (or log hourly pay), *Female* is a binary variable denoting female and X includes a set of controls including a dummy variable for whether the graduate is white or not, a quadratic in age, a dummy for whether the highest degree is undergraduate or master's, year of survey fixed effects, and indicators for field of STEM specialisation. We run this regression for each year, t, since graduation and, so, estimate the coefficient on female for each length of time since graduation. The allows us to plot out the evolution of the gender earnings gap for 25 years post-graduation. When looking at how working in specific occupations affects the gender gap in earnings, we add controls for 3-digit SOC groups.

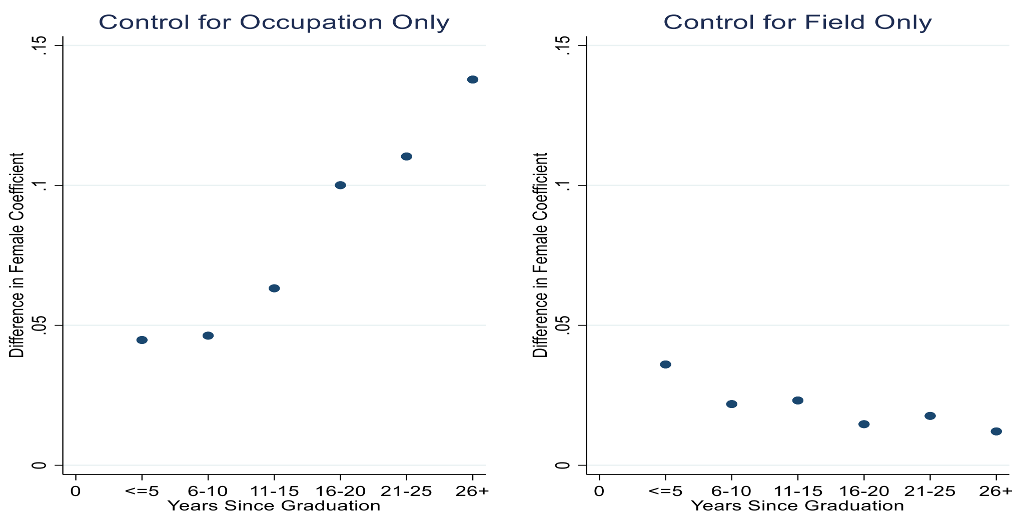
The results for log hourly pay are in Figure 8a. We find that controlling for occupation has a meaningful impact on the gender earnings gap at all phases of the lifecycle. For example, the addition of occupation controls reduces the gender gap for log hourly pay at 6-10 years post-graduation from 10 to 6 percentage points and from 14 to 8 percentage points at 11-15 years post-graduation. The effect of occupational controls is even larger at later years in the career with the gender gap in log hourly pay reducing from 24 percentage points to 13 percentage points between 21 and 25 years after graduation. Figure 8b shows that the impact of the occupational controls on log hourly pay is increasing over much of the life cycle. The effect is constant at 5 percentage points for the first 10 years post-graduation but then increases linearly such that the effect of the occupational controls 26 years post-graduation is 14 percentage points. Interestingly, the effect of field of study is much smaller at roughly 3 percentage points and this remains constant over time.

Figure 8a: Gender Gap in Log Hourly Pay



Note: Each point represents the female coefficient from the regression in (2) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include age quadratic, indicators for white and for whether highest degree is undergraduate or master, and survey year fixed effects. Occupation group refers to 3-digit SOC groupings interacted with indicators for year in which SOC classification was used. Field of study refers to whether the STEM degree is in life science, hard science, medical degree, engineering, math, technology, or architecture. The sample years are 2005-2021 and the year of graduation is 1970-2020.

Figure 8b: Difference in Gender Gap in Log Hourly Pay with Addition of Controls



Note: Each point represents the difference in female coefficients from the regression in (2) with the addition of occupational controls (left hand side) and separately with the addition of field of study controls (right hand side).

Figure A12a in the appendix shows the effect of occupation and STEM specialisation on log weekly pay. Perhaps, unsurprisingly, we see much larger effects of controlling for occupation on log weekly pay, particularly many years after graduation when females may decide to work fewer hours. The addition of occupation controls reduces the gender gap from 23 percentage points to 16 percentage points at 6-10 years post-graduation but reduces the gap from 51 percentage points to 29 percentage points after 25 years post-graduation. This implies that occupation is particularly important for the gender pay gap – even for STEM graduates.[20] Figure A12b shows that the effect of the occupational controls on the gender pay gap increases steeply across years since graduation.

7. Implications for Policy

Do our findings have implications for policy?[21] There are no easy answers to this question. If individuals are making well-informed decisions given their skills and preferences, then gender disparities do not imply inefficiency. There is much evidence that preferences over fundamental characteristics of occupations differ by gender with a robust finding that females tend to choose occupations that are oriented towards working with people, while males tend towards occupations that involve working with things (Kuhn and Wolter, 2020). Also, research suggests that women may be particularly influenced by non-pecuniary characteristics of occupations such as job flexibility (Zafar, 2013; Wiswall and Zafar, 2018; Angelov et al., 2019). So, differential occupational choices by gender may be efficient and imply no role for policy.

[20] Table A7 in the appendix shows detailed regression estimates for log hourly and weekly pay when we pool across years since graduation. On average, adding occupational controls reduces the gender gap in log hourly pay from 0.13 to 0.07 and reduces the gender gap in log weekly pay from 0.32 to 0.23.

[21] This section draws heavily from Delaney and Devereux (2021b).

However, there are reasons why this benign scenario may be unrealistic. First, as we are studying STEM graduates and conditioning on field of study, there is unlikely to be any meaningful gap in average skill levels by gender. Also, by completing a STEM degree and, in many cases, starting their careers working in STEM, the women we study have displayed both an aptitude for STEM and an interest in pursuing a STEM career. As such, it may be socially wasteful that they are much more likely than men to subsequently move away from STEM occupations.

Second, differences in preferences across occupations by gender may not be due to fundamental characteristics of occupations but rather from cultural factors arising from their gender mix. For example, women may be reluctant to build a career in computer science because it is male-dominated and is considered to have a male-ethos and be unfriendly (and possibly discriminatory) towards women. Additionally, female role models such as managers may be scarce in male-dominated occupations such as computer science and engineering and this may also make the environment less friendly to women.

Overall, if the gender gaps result in part from gender stereotypes, discrimination, and work environments that are unfriendly to females, it may be that outcomes are suboptimal and policy interventions are justifiable. There also may be virtuous cycles if attracting more women to remain in STEM occupations influences the decisions of other women through role model type effects. Certainly, given the higher salaries in STEM occupations, female STEM graduates appear to be leaving money on the table with their occupational choices.

8. Conclusions

Increasingly, government policies aim to encourage females to study STEM degrees in school and in college. This is based on the presumption that female STEM graduates will go on to work in STEM careers and thus help to contribute towards technological innovation and also to mitigate the gender pay gap as STEM workers earn higher wages. In this paper, we find that such policies may have lower returns than expected due to the tendency for female STEM graduates to leave STEM at early stages of their career.[22] This begins in the educational system -- we find that, conditional on pursuing a master's degree, females are 7 percentage points less likely to do their masters in STEM. The precise field of study of undergraduate degree can explain 35 percent of this gap but even after controlling for high school and undergraduate achievement, female STEM graduates are still over 4 percentage points less likely to do their masters in STEM.

Gender differences in STEM persistence are also evident in the labour market. In the first year after graduation, the gender gap in STEM is about 10 percentage points; this slowly increases to about 25 percentage points 15 years after graduation. These gaps partly reflect college field of study (within STEM) – when we control for degree field, the immediate gap after graduation becomes very small but still increases to about 20 percentage points after 15 years. This highlights the importance of having detailed controls for field of study even within STEM. The gender gaps differ by STEM field of study. There are large immediate gaps for technology and math but not for the sciences or for engineering; however, after 20 years, the gender gap is 20+ percentage points in every STEM field except the sciences. The gender gap in working in STEM is even larger for those with children. Also, the gender gap in whether the person works full-time in STEM increases from a small immediate effect to 30 percentage points after 15 years.

We also find that females who leave STEM jobs tend to switch to low paying sectors such as education and non-professional jobs while males who leave STEM tend to enter the

[22] It is also worth pointing out that the cost of providing a STEM degree in college is much larger than the cost of providing other programs. The American Institutes for Research (2013) found that, in the US in 2009, the full cost of an engineering degree, in terms of education and related spending per undergraduate completion at a 4-year college, was almost double that of the average field. The cost for sciences and technology was also above average while the cost of providing a degree in math was below average.

more lucrative business sector. Finally, we see that the lower likelihood for females to work in high paying occupations can explain up to 50% of the gender gap in hourly pay for STEM graduates with the size of the effect increasing with labour market experience. Therefore, policies that help to attract women to high paying occupations may also help to mitigate the gender gap in earnings.

Our findings suggest that policies that aim to increase the proportion of females studying STEM in high school and college may have lower effects than expected due to the lower attachment of females to STEM after graduation. The results also caution against providing affirmative action policies such as gender points that give females an advantage in college admissions to STEM programs if some female STEM graduates (and most likely those at the margin) are not likely to work in STEM. On the other hand, if the reason females are leaving STEM jobs is due to lack of females in their jobs or discrimination, then increasing the supply of female graduates may help to prevent the flow of female graduates out of STEM jobs.

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Appendix Tables

Table A1: Descriptive Analysis of All Graduates by Gender and Degree

	Female		Male	
Undergraduate Degree	0.88	(0.33)	0.85	(0.36)
Master's Degree	0.12	(0.33)	0.15	(0.36)
Life Sciences	0.11	(0.32)	0.08	(0.27)
Hard Sciences	0.05	(0.22)	0.09	(0.29)
Medical Degrees	0.07	(0.25)	0.04	(0.19)
Math	0.02	(0.15)	0.04	(0.20)
Technology	0.02	(0.13)	0.08	(0.26)
Engineering	0.02	(0.13)	0.16	(0.36)
Architecture	0.02	(0.14)	0.05	(0.23)
First Class Degree	0.13	(0.33)	0.13	(0.34)
Upper Second Class Honours	0.56	(0.50)	0.49	(0.50)
Lower Second Class Honours	0.28	(0.45)	0.32	(0.47)
Third Class Honours/Pass	0.03	(0.16)	0.06	(0.23)
8+ GCSEs	0.81	(0.39)	0.76	(0.43)
5 to 7 GCSEs	0.16	(0.37)	0.20	(0.40)
Fewer than 4 GCSEs	0.03	(0.16)	0.04	(0.19)
Work in STEM (unconditional on working)	0.12	(0.33)	0.31	(0.46)
Work FT in STEM (unconditional on working)	0.09	(0.28)	0.31	(0.46)
Work in STEM (conditional on working)	0.14	(0.35)	0.34	(0.47)
Work in Health	0.07	(0.26)	0.01	(0.11)
Work in Education	0.16	(0.36)	0.06	(0.23)
Work in Business	0.19	(0.39)	0.25	(0.43)
Work in Low-Skill Sector	0.24	(0.43)	0.16	(0.36)
Work in Other Sector	0.20	(0.40)	0.18	(0.38)
Unemployed	0.02	(0.15)	0.03	(0.17)
Out of the Labour Force	0.11	(0.31)	0.05	(0.22)
Real Gross Weekly Pay 2020 prices	662.45	(389.26)	957.93	(503.69)
Real Gross Hourly Pay 2020 prices	19.66	(10.01)	24.55	(12.48)
Age at First Child	31.29	(4.00)	32.76	(4.54)
Years Since Graduation First Child	9.27	(4.11)	10.61	(4.66)
Year of Graduation	1996.77	(11.34)	1994.40	(11.87)
Age	35.93	(9.89)	37.75	(10.37)
White	0.91	(0.29)	0.91	(0.28)
Observations	357562		352930	

	Undergraduate		Masters	
Life Sciences	0.10	(0.30)	0.09	(0.29)
Hard Sciences	0.07	(0.25)	0.10	(0.29)
Medical Degrees	0.05	(0.22)	0.05	(0.21)
Math	0.03	(0.17)	0.04	(0.19)
Technology	0.04	(0.21)	0.06	(0.24)
Engineering	0.08	(0.27)	0.12	(0.32)
Architecture	0.04	(0.19)	0.04	(0.21)
Work in STEM (conditional on working)	0.21	(0.40)	0.29	(0.45)
Work FT in STEM (unconditional on working)	0.19	(0.39)	0.26	(0.44)
Work in STEM	0.23	(0.42)	0.32	(0.47)
Work in Health	0.04	(0.21)	0.03	(0.18)
Work in Education	0.10	(0.31)	0.13	(0.33)
Work in Business	0.22	(0.42)	0.21	(0.41)
Work in Low-Skill Sector	0.21	(0.41)	0.12	(0.32)
Work in Other Sector	0.19	(0.39)	0.19	(0.39)
Unemployed	0.03	(0.16)	0.02	(0.15)
Out of the Labour Force	0.08	(0.27)	0.08	(0.26)
Real Gross Weekly Pay 2020 prices	794.33	(469.99)	894.90	(482.90)
Real Gross Hourly Pay 2020 prices	21.74	(11.50)	24.17	(11.73)
Observations	612752		97740	

Note: The sample years are 1997-2021 and the year of graduation is 1970-2020. The sample includes all graduates whose highest degree is a master's or bachelor's degree. The mean is shown and the standard deviation is in parentheses.

Table A2: Coefficient and Standard Error Estimates Underlying Figures 1 and 2

	Figure 1 Estimates			**Figure 2 Estimates**			
Years Since Graduation	Female Coefficient	Standard Error	R-squared	Female Coefficient	Standard Error	R-squared	Observations
1	-0.089***	-0.007	0.078	-0.035***	-0.007	0.16	15,406
2	-0.115***	-0.01	0.073	-0.056***	-0.01	0.149	9,355
3	-0.129***	-0.01	0.07	-0.073***	-0.011	0.152	8,968
4	-0.146***	-0.011	0.069	-0.093***	-0.011	0.158	8,413
5	-0.151***	-0.011	0.072	-0.072***	-0.012	0.167	8,014
6	-0.189***	-0.011	0.075	-0.125***	-0.012	0.16	7,827
7	-0.170***	-0.011	0.072	-0.113***	-0.012	0.164	7,661
8	-0.168***	-0.011	0.075	-0.110***	-0.012	0.167	7,539
9	-0.199***	-0.011	0.073	-0.146***	-0.012	0.142	7,482
10	-0.206***	-0.012	0.073	-0.157***	-0.013	0.149	7,333
11	-0.185***	-0.012	0.069	-0.114***	-0.012	0.149	7,469
12	-0.214***	-0.012	0.087	-0.155***	-0.012	0.173	7,381
13	-0.220***	-0.012	0.072	-0.182***	-0.013	0.145	6,937
14	-0.246***	-0.012	0.083	-0.201***	-0.013	0.153	6,817
15	-0.240***	0.000	0.073	-0.201***	-0.013	0.139	6,801
16	-0.237***	-0.012	0.088	-0.181***	-0.013	0.153	6,494
17	-0.209***	-0.013	0.057	-0.181***	-0.013	0.139	6,536
18	-0.218***	-0.013	0.062	-0.198***	-0.013	0.123	6,239
19	-0.229***	-0.013	0.077	-0.194***	-0.013	0.14	6,174
20	-0.207***	-0.013	0.062	-0.181***	-0.013	0.144	6,338
21	-0.234***	-0.013	0.074	-0.210***	-0.014	0.159	5,895
22	-0.220***	-0.014	0.073	-0.202***	-0.014	0.168	5,604
23	-0.206***	-0.014	0.062	-0.198***	-0.015	0.13	5,356
24	-0.221***	-0.014	0.065	-0.209***	-0.015	0.132	5,241
25	-0.224***	-0.014	0.07	-0.210***	-0.015	0.159	5,082
26	-0.204***	-0.005	0.052	-0.205***	-0.005	0.117	45,805

Note: Robust standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Survey year dummies and year of graduation dummies included in all regressions. Sample conditional on highest degree being an undergraduate or master's degree in STEM. Figure 2 estimates include controls for field of study. The sample years are 1997-2021 and the year of graduation is 1970-2020. The outcome is not conditional on employment.

Table A3: Gender Differences in Probability STEM Graduates Work in STEM (unconditional on employment)

VARIABLES	(1) Work in STEM	(2) Work in STEM	(3) Work in STEM	(4) Work in STEM
Female	-0.189***	-0.151***	-0.139***	-0.143***
	(0.002)	(0.002)	(0.003)	(0.003)
Age	0.066***	0.048***	0.048***	0.049***
	(0.001)	(0.001)	(0.002)	(0.002)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
White	-0.002	0.045***	0.033***	0.027***
	(0.004)	(0.003)	(0.005)	(0.005)
Master's Degree	0.028***	0.041***	0.048***	0.040***
	(0.003)	(0.003)	(0.005)	(0.005)
Life Sciences		-0.079***	-0.100***	-0.100***
		(0.003)	(0.004)	(0.004)
Medicine		0.308***	0.193***	0.185***
		(0.004)	(0.006)	(0.006)
Math		-0.062***	-0.123***	-0.128***
		(0.004)	(0.005)	(0.005)
Technology		0.240***	0.253***	0.251***
		(0.004)	(0.005)	(0.005)
Engineering		0.173***	0.178***	0.174***
		(0.003)	(0.005)	(0.005)
Architecture		0.162***	0.150***	0.150***
		(0.004)	(0.006)	(0.006)
First Class Degree				0.099***
				(0.006)
Upper Second Class Honours				0.045***
				(0.006)
Lower Second Class Honours				0.032***
				(0.006)
8+ GCSEs				0.054***
				(0.008)
5 to 7 GCSEs				0.038***
				(0.008)
Observations	228,167	228,167	123,731	123,731
R-squared	0.064	0.139	0.143	0.146

Note: Robust standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Survey year dummies and year of graduation dummies included in all regressions. Sample conditional on highest degree being an undergraduate or master's degree in STEM. The excluded category for undergraduate degree class is scoring below lower second class, for number of GCSEs is less than 5 GCSES, and for type of degree is a degree in hard science. Graduation cohorts included are 1970-2020. Survey years for columns 1 and 2 is 1997-2021 and for columns 3 and 4 is 2005-2021.

Table A4: Gender Differences in Probability STEM Graduates Work in STEM by whether have Children

	Work in STEM		**Work Full-Time in STEM**	
	(1)	(2)	(3)	(4)
VARIABLES	No Children	Children	No Children	Children
Female	-0.111***	-0.211***	-0.126***	-0.349***
	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.051***	0.052***	0.055***	0.036***
	(0.001)	(0.002)	(0.001)	(0.002)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
White	0.045***	0.036***	0.044***	0.022***
	(0.005)	(0.005)	(0.005)	(0.005)
Master’s	0.049***	0.032***	0.048***	0.027***
	(0.004)	(0.004)	(0.004)	(0.004)
Life Sciences	-0.093***	-0.050***	-0.093***	-0.032***
	(0.004)	(0.005)	(0.004)	(0.005)
Medicine	0.270***	0.359***	0.211***	0.212***
	(0.005)	(0.006)	(0.005)	(0.005)
Math	-0.061***	-0.053***	-0.055***	-0.036***
	(0.006)	(0.006)	(0.006)	(0.006)
Technology	0.247***	0.232***	0.238***	0.226***
	(0.005)	(0.006)	(0.005)	(0.006)
Engineering	0.175***	0.177***	0.174***	0.167***
	(0.005)	(0.005)	(0.005)	(0.005)
Architecture	0.149***	0.184***	0.139***	0.167***
	(0.006)	(0.007)	(0.006)	(0.006)
Observations	121,707	92,448	121,707	92,448
R-squared	0.133	0.157	0.133	0.210

Note: Robust standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Survey year dummies and year of graduation dummies included in all regressions. Sample conditional on highest degree being an undergraduate or master’s degree in STEM. The excluded category for field of degree is a degree in hard sciences. The sample years are 1997-2021 and the year of graduation is 1970-2020. The outcome is not conditional on employment.

Table A5: Gender Differences in Probability STEM Graduates Work in STEM by Number and Age of Children

VARIABLES	(1) Work in STEM	(2) Work in STEM	(3) Work FT in STEM	(4) Work FT in STEM
Female	-0.120***	-0.124***	-0.137***	-0.146***
	(0.003)	(0.003)	(0.003)	(0.003)
Age	0.053***	0.053***	0.052***	0.052***
	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
White	0.042***	0.042***	0.035***	0.035***
	(0.003)	(0.003)	(0.003)	(0.003)
Master’s	0.042***	0.042***	0.039***	0.039***
	(0.003)	(0.003)	(0.003)	(0.003)
Life Sciences	-0.076***	-0.076***	-0.070***	-0.070***
	(0.003)	(0.003)	(0.003)	(0.003)
Medicine	0.312***	0.311***	0.212***	0.211***
	(0.004)	(0.004)	(0.004)	(0.004)
Math	-0.059***	-0.059***	-0.048***	-0.049***
	(0.004)	(0.004)	(0.004)	(0.004)
Technology	0.239***	0.239***	0.232***	0.232***
	(0.004)	(0.004)	(0.004)	(0.004)
Engineering	0.174***	0.174***	0.170***	0.170***
	(0.003)	(0.003)	(0.003)	(0.003)
Architecture	0.163***	0.163***	0.150***	0.150***
	(0.004)	(0.004)	(0.004)	(0.004)
1 Child under 2 years old		0.006		0.004
		(0.005)		(0.005)
>=2 Children under 2 years old		-0.026		-0.023
		(0.021)		(0.021)
1 Child under 2 # Female		-0.032***		-0.102***
		(0.007)		(0.006)
>=2 Children under 2 # Female		-0.051		-0.140***
		(0.033)		(0.030)
1 Child 2- 4 years old		-0.006		-0.005
		(0.004)		(0.004)
>=2 Children 2-4 years old		0.005		-0.000
		(0.010)		(0.010)
1 Child 2-4 years old # Female		-0.054***		-0.141***
		(0.007)		(0.006)
>=2 Children 2-4 years old # Female		-0.085***		-0.232***
		(0.016)		(0.014)
1 Child 5 - 9 years old		0.001		0.001
		(0.004)		(0.004)
>=2 Children 5 - 9 years old		-0.022***		-0.017***
		(0.006)		(0.006)
1 Child 5 - 9 years old # Female		-0.034***		-0.111***
		(0.007)		(0.006)
>=2 Children 5 - 9 years old # Female		-0.079***		-0.197***
		(0.009)		(0.008)

1 Child 10 - 15 years old		-0.009**		0.005
		(0.004)		(0.005)
>=2 Children 10 - 15 years old		-0.014**		0.005
		(0.006)		(0.006)
1 Child 10 - 15 years old # Female		-0.065***		-0.128***
		(0.007)		(0.006)
>=2 Children 10 - 15 years old # Female		-0.085***		-0.188***
		(0.009)		(0.008)
1 Child under 16 years old	0.002		0.009**	
	(0.004)		(0.004)	
2 Children under 16 years old	0.000		0.007*	
	(0.004)		(0.004)	
3 Children under 16 years old	-0.023***		-0.014**	
	(0.006)		(0.006)	
>=4 Children under 16 years old	-0.060***		-0.043***	
	(0.013)		(0.014)	
1 Child under 16 years old # Female	-0.075***		-0.162***	
	(0.006)		(0.005)	
2 Children under 16 years old # Female	-0.091***		-0.247***	
	(0.005)		(0.005)	
3 Children under 16 years old # Female	-0.117***		-0.277***	
	(0.010)		(0.008)	
>=4 Children under 16 years old # Female	-0.109***		-0.255***	
	(0.021)		(0.018)	
Observations	214,155	214,155	214,155	214,155
R-squared	0.142	0.142	0.166	0.166

Note: Robust standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Survey year dummies and year of graduation dummies included in all regressions. Sample conditional on highest degree being an undergraduate or master's degree in STEM. The excluded category for field of degree is a degree in hard sciences. The sample years are 1997-2021 and the year of graduation is 1970-2020. The outcome is not conditional on employment.

Table A6: Gender Differences in Pay Penalty for Leaving STEM

	Log Hourly Pay		Log Weekly Pay	
	(1)	(2)	(3)	(4)
VARIABLES	Female	Male	Female	Male
Age	0.093***	0.095***	0.068***	0.115***
	(0.004)	(0.003)	(0.005)	(0.003)
Age Squared	-0.001***	-0.001***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
White	0.009	0.081***	0.014	0.087***
	(0.011)	(0.009)	(0.016)	(0.010)
Master's Degree	0.092***	0.094***	0.099***	0.081***
	(0.008)	(0.006)	(0.011)	(0.007)
Life Sciences	-0.041***	-0.076***	-0.062***	-0.070***
	(0.009)	(0.008)	(0.013)	(0.009)
Medicine	0.155***	0.140***	0.109***	0.199***
	(0.010)	(0.011)	(0.014)	(0.013)
Math	0.202***	0.133***	0.183***	0.111***
	(0.015)	(0.010)	(0.020)	(0.012)
Technology	0.043**	0.061***	0.043*	0.043***
	(0.017)	(0.009)	(0.023)	(0.009)
Engineering	0.109***	0.067***	0.170***	0.083***
	(0.016)	(0.007)	(0.021)	(0.008)
Architecture	-0.027*	0.000	-0.054***	0.011
	(0.015)	(0.009)	(0.020)	(0.010)
Work in Non-STEM Job	-0.172***	-0.104***	-0.253***	-0.128***
	(0.007)	(0.005)	(0.009)	(0.006)
Observations	18,915	34,402	18,915	34,402
R-squared	0.264	0.284	0.129	0.285

Note: Robust standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Survey year dummies and year of graduation dummies included in all regressions. Sample conditional on highest degree being an undergraduate or master's degree in STEM. The excluded category for field of degree is a degree in hard sciences. The sample years are 1997-2021 and the year of graduation is 1970-2020.

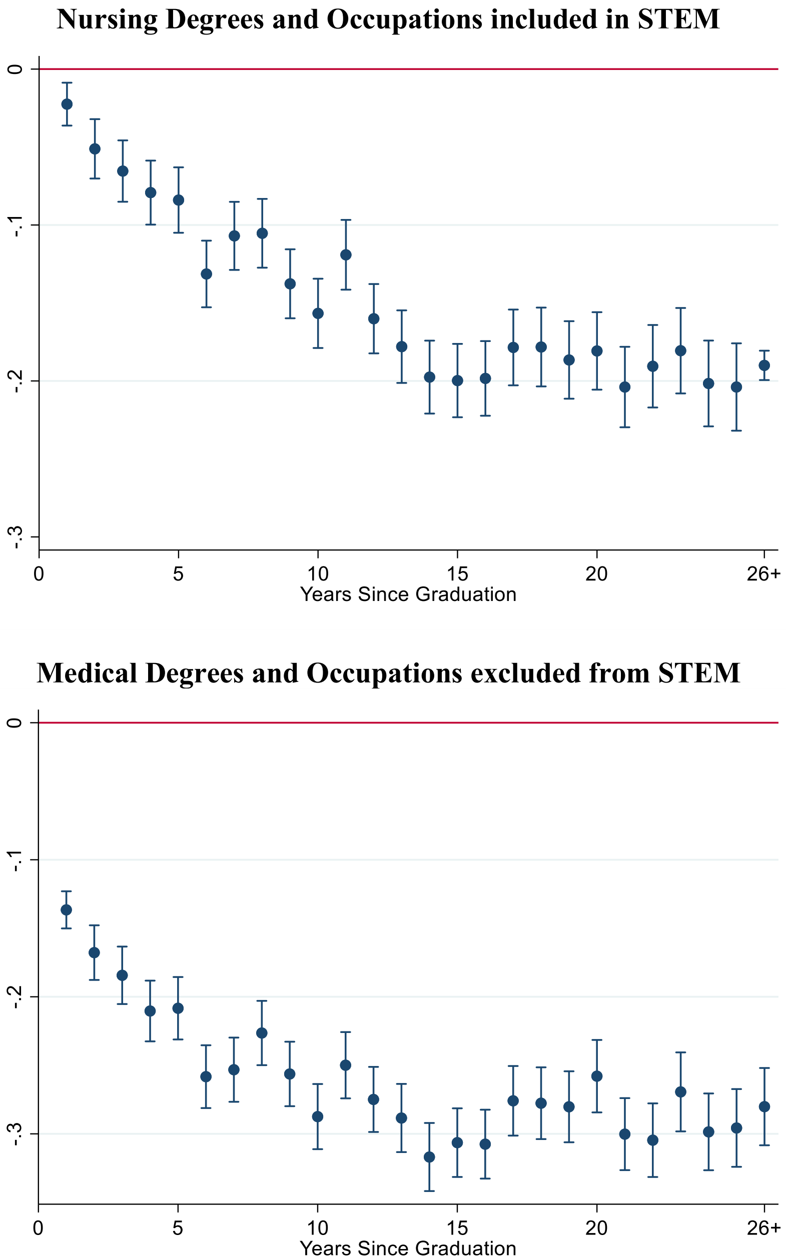
Table A7: Gender Gap in Log Weekly and Hourly Pay

VARIABLES	(1) Log hourly pay	(2) Log hourly pay	(3) Log hourly pay	(4) Log hourly pay	(5) Log weekly pay	(6) Log weekly pay	(7) Log weekly pay	(8) Log weekly pay
Female	-0.153***	-0.080***	-0.131***	-0.071***	-0.346***	-0.236***	-0.318***	-0.226***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)
Age	0.099***	0.070***	0.096***	0.070***	0.104***	0.062***	0.100***	0.063***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Age Squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.027***	0.028***	0.053***	0.035***	0.029***	0.023***	0.054***	0.028***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)	(0.008)
Master's Degree	0.100***	0.068***	0.098***	0.065***	0.097***	0.056***	0.094***	0.053***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
Life Sciences			-0.075***	-0.034***			-0.088***	-0.036***
			(0.006)	(0.006)			(0.008)	(0.007)
Medicine			0.175***	0.089***			0.178***	0.078***
			(0.007)	(0.009)			(0.010)	(0.012)
Math			0.143***	0.069***			0.111***	0.038***
			(0.009)	(0.008)			(0.010)	(0.009)
Technology			0.082***	0.004			0.064***	-0.014
			(0.008)	(0.008)			(0.009)	(0.009)
Engineering			0.099***	0.047***			0.122***	0.055***
			(0.006)	(0.006)			(0.007)	(0.007)
Architecture			0.012	-0.007			0.013	-0.009
			(0.008)	(0.008)			(0.009)	(0.009)
Control for 3-digit SOC	No	Yes	No	Yes	No	Yes	No	Yes
Observations	53,317	53,317	53,317	53,317	53,317	53,317	53,317	53,317
R-squared	0.258	0.432	0.284	0.437	0.235	0.447	0.256	0.450

Note: Robust standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Survey year dummies and year of graduation dummies included in all regressions. Sample conditional on highest degree being an undergraduate or master's degree in STEM. The 3-digit SOC groupings are interacted with indicators for year in which SOC classification was used. The excluded category for field of degree is a degree in hard sciences. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Appendix Figures

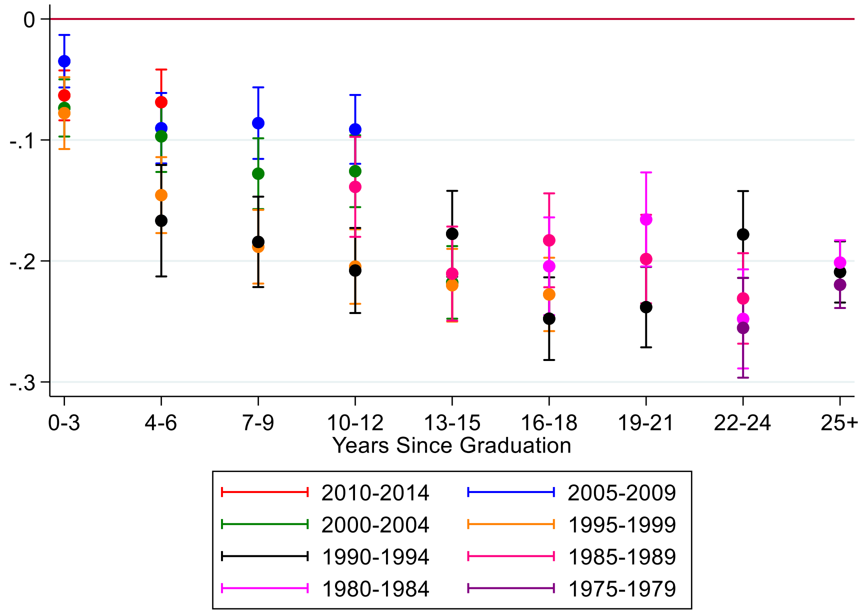
Figure A1: Gender Differences in Probability STEM Graduates Work in STEM



Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include age quadratic, indicators for white and for whether highest degree is undergraduate or master's, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

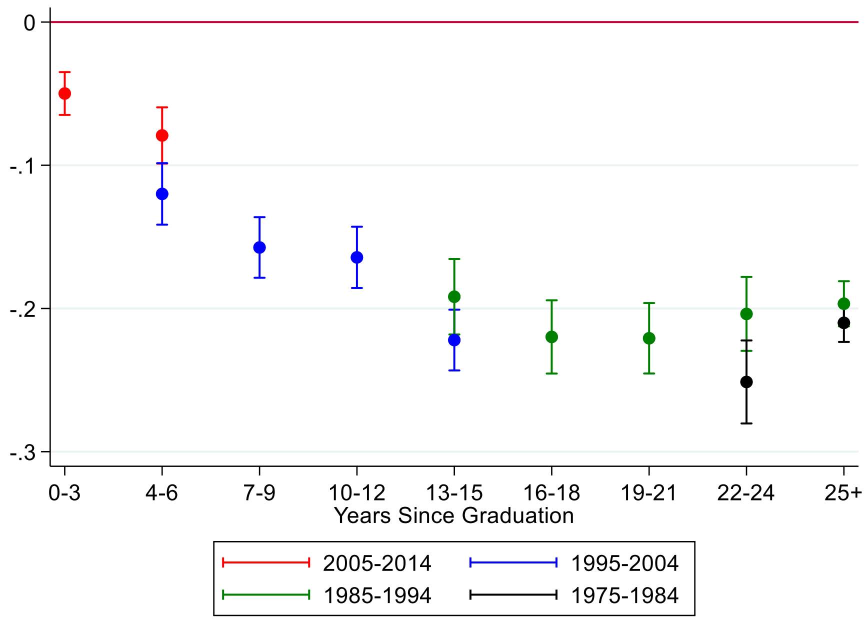
Figure A2: Gender Differences in Probability STEM Graduates Work in STEM by 5-Year and 10-year Graduation Cohorts

5-Year Graduation Cohorts



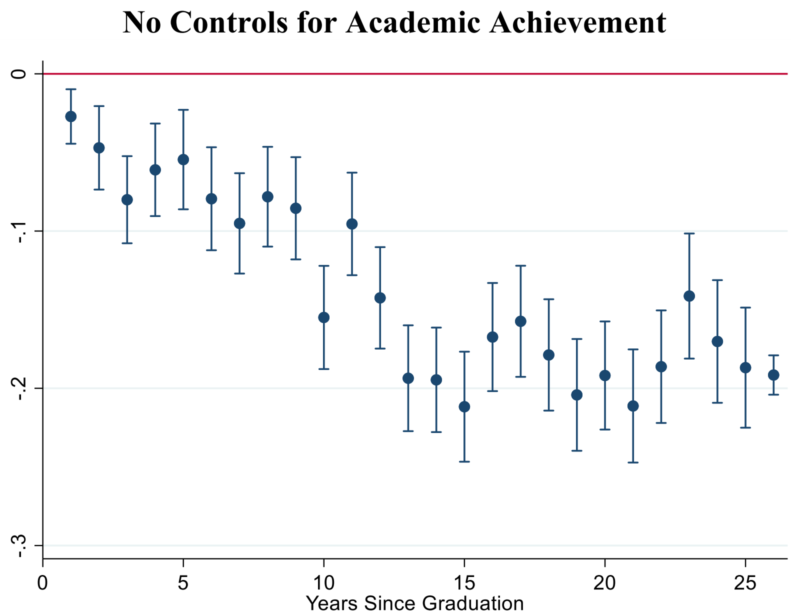
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the regression is done separately for each group of 5-year graduation cohorts.

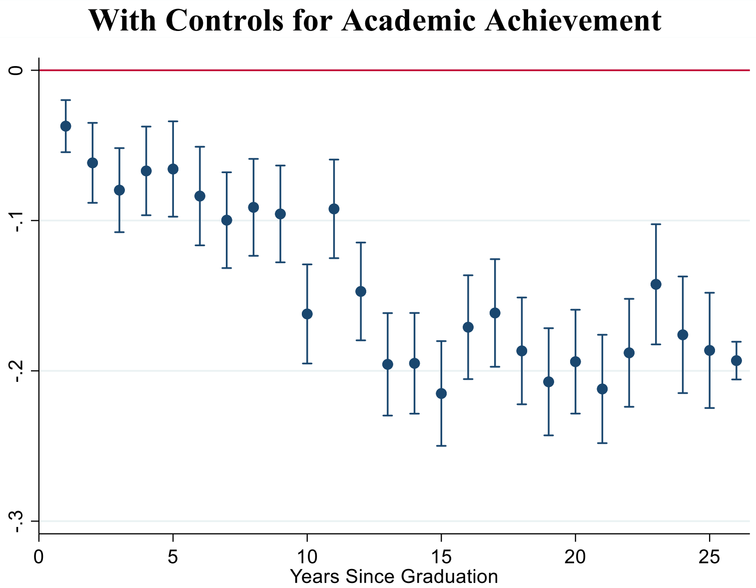
10-Year Graduation Cohorts



Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the regression is done separately for each group of 10-year graduation cohorts.

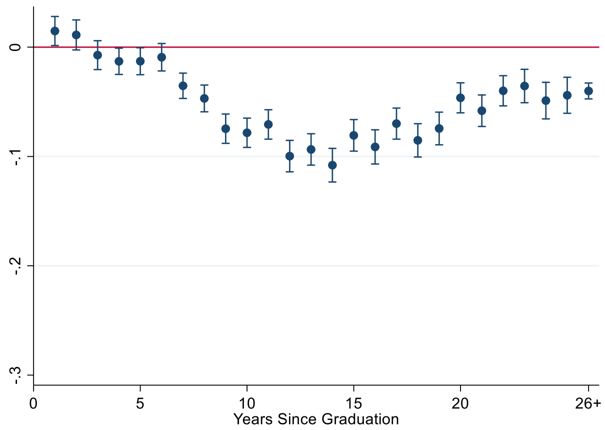
Figure A3: Gender Differences in Probability STEM Graduates Work in STEM





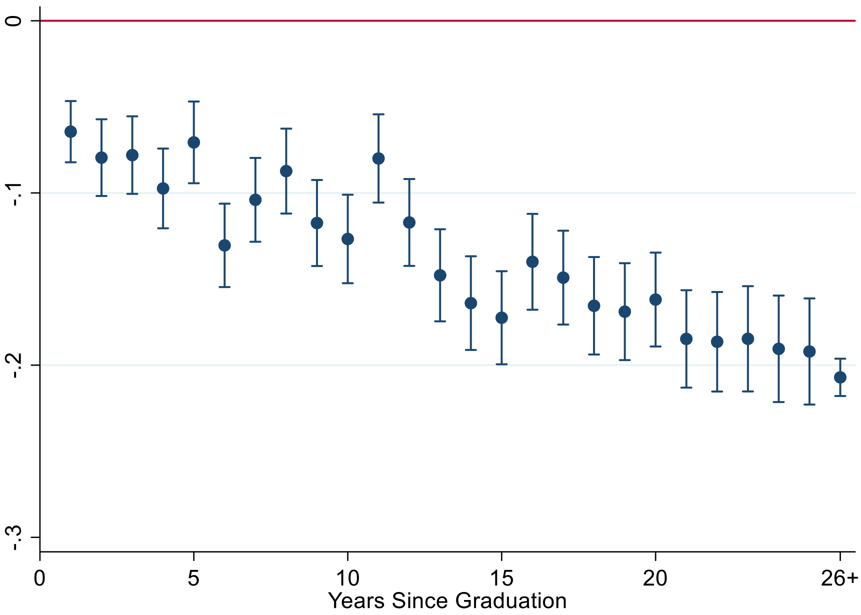
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, or technology, and survey year fixed effects. Controls for academic achievement in the lower panel include controls for number of GCSEs and degree classification. The sample years are 2005-2021 and the year of graduation is 1970-2020.

Figure A4: Gender Differences in Probability STEM Graduates are in Employment



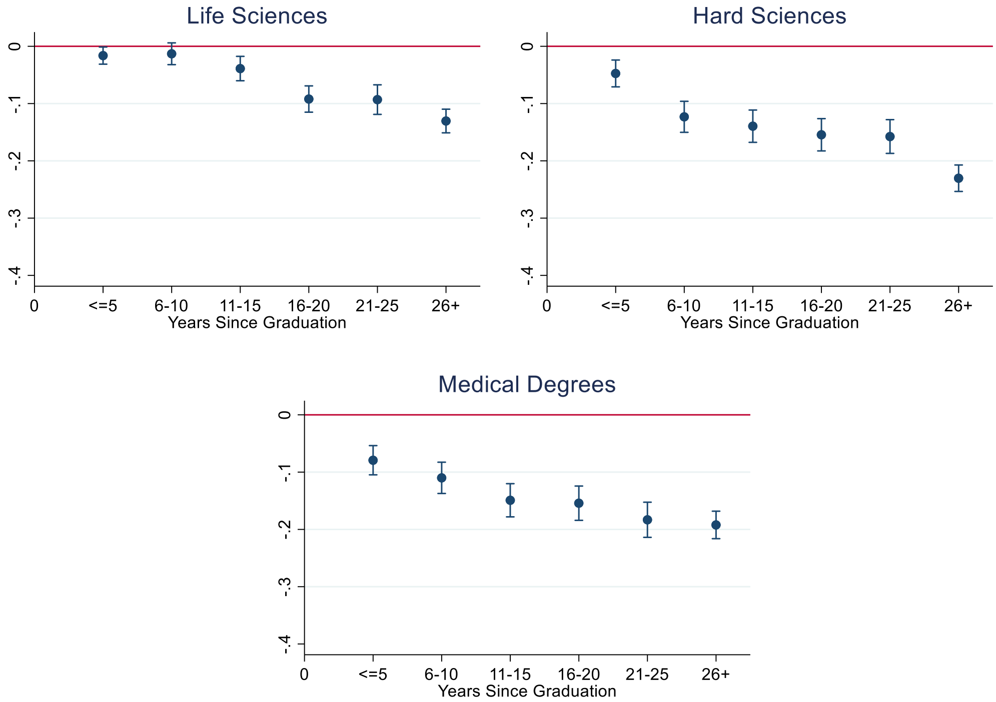
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. Controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A5: Gender Differences in Probability STEM Graduates Work in STEM (Conditional on Employment)

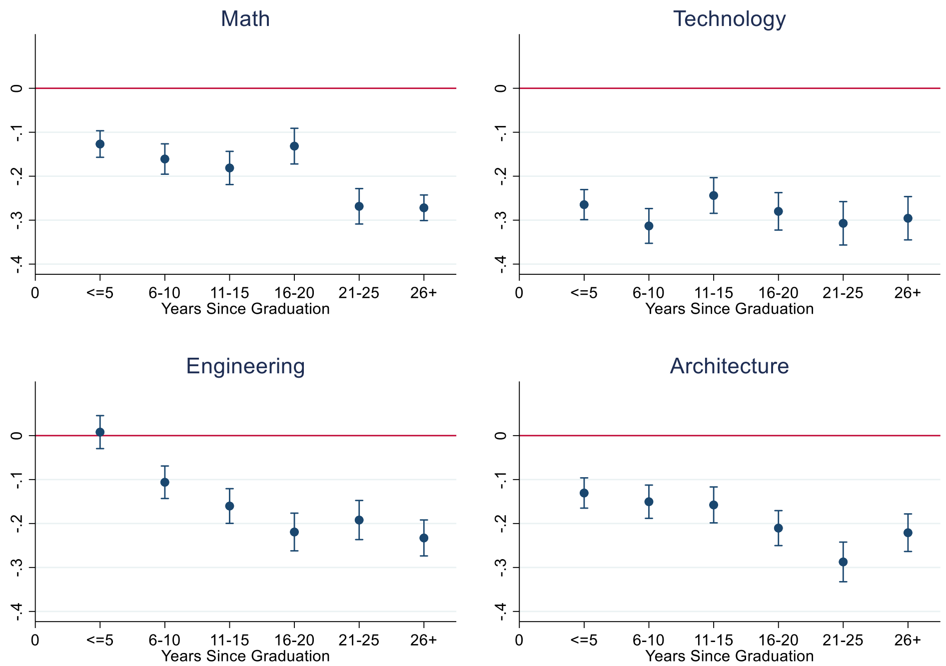


Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is conditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A6: Gender Differences in Probability STEM Graduates Work in STEM by Field of Specialisation (Conditional on Employment)

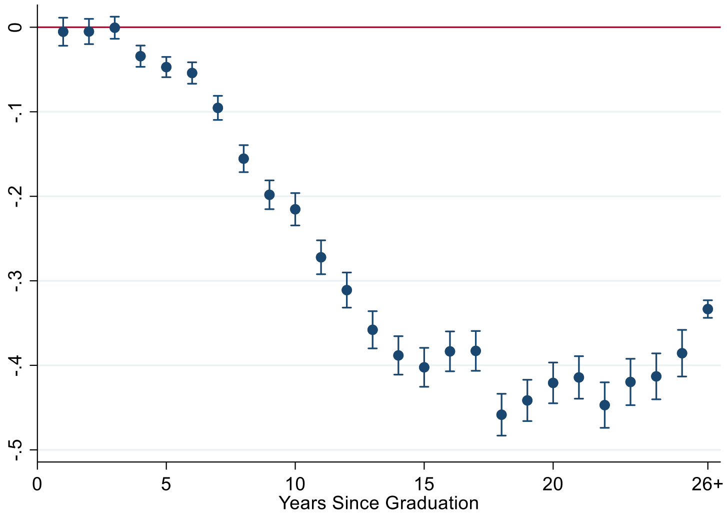


Lower Panel



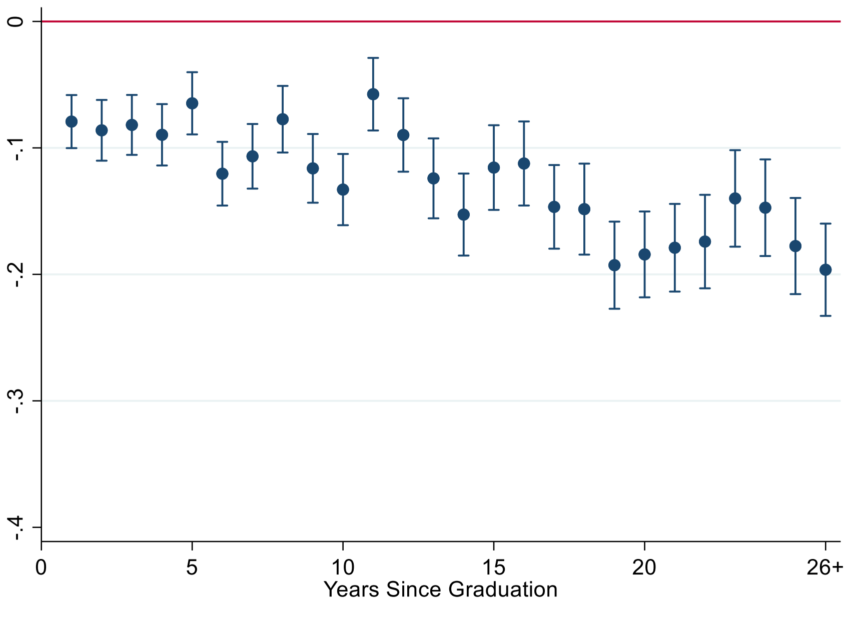
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is conditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A7: Gender Differences in Probability STEM Graduates are in Full-Time Employment (Conditional on Employment)



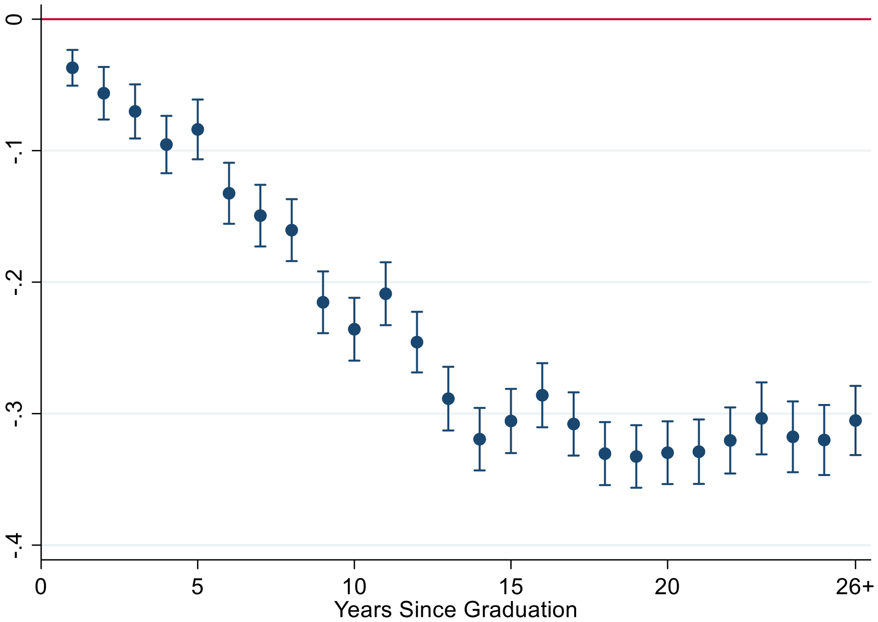
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is conditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A8: Gender Differences in Probability that STEM Graduate Full-Time Workers Work in STEM



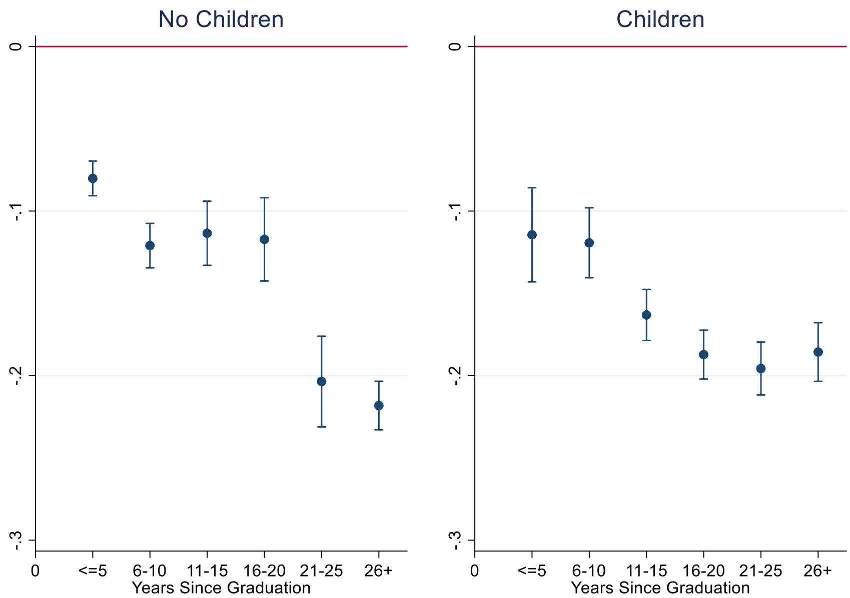
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is conditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A9: Gender Differences in Probability STEM Graduates Work Full-Time in STEM



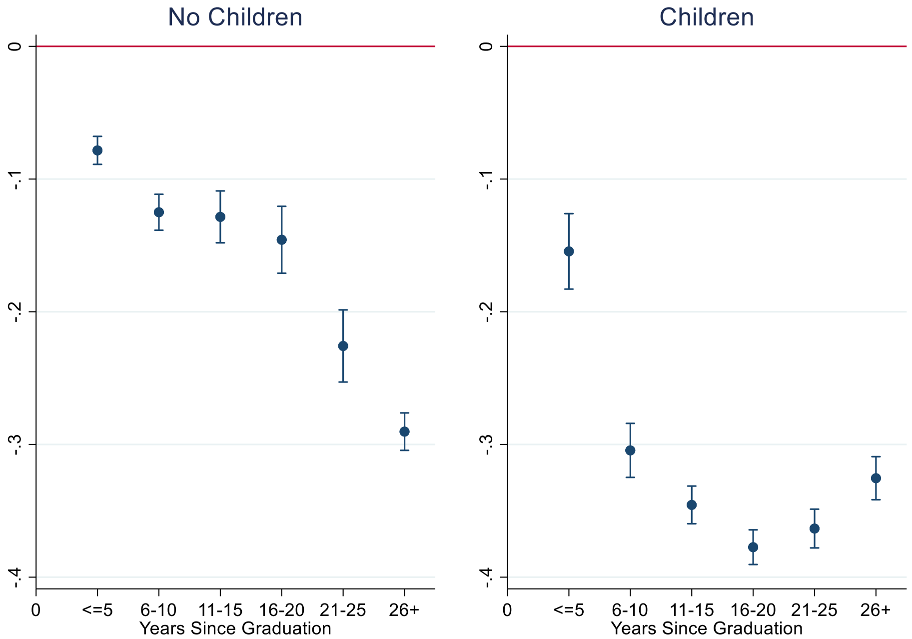
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A10: Gender Differences in Probability STEM Graduates Work in STEM (Conditional on Employment)



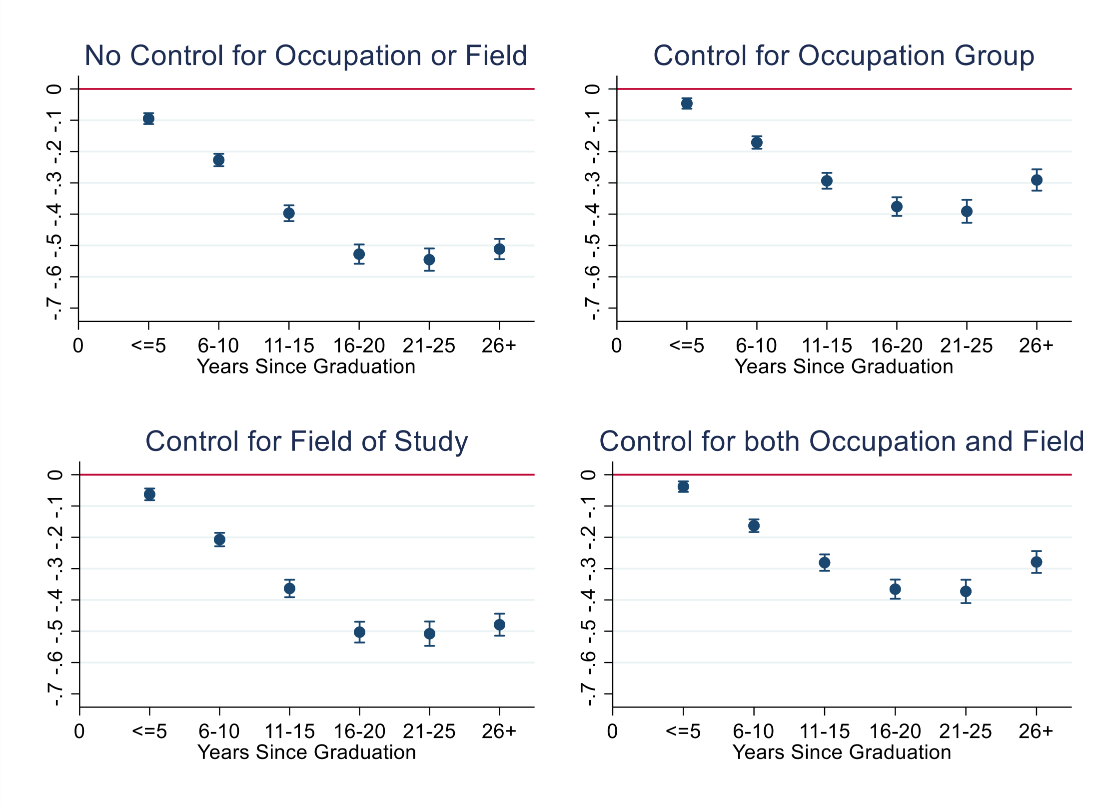
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is conditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A11: Gender Differences in Probability STEM Graduates Work in STEM Full-Time (Conditional on Employment)



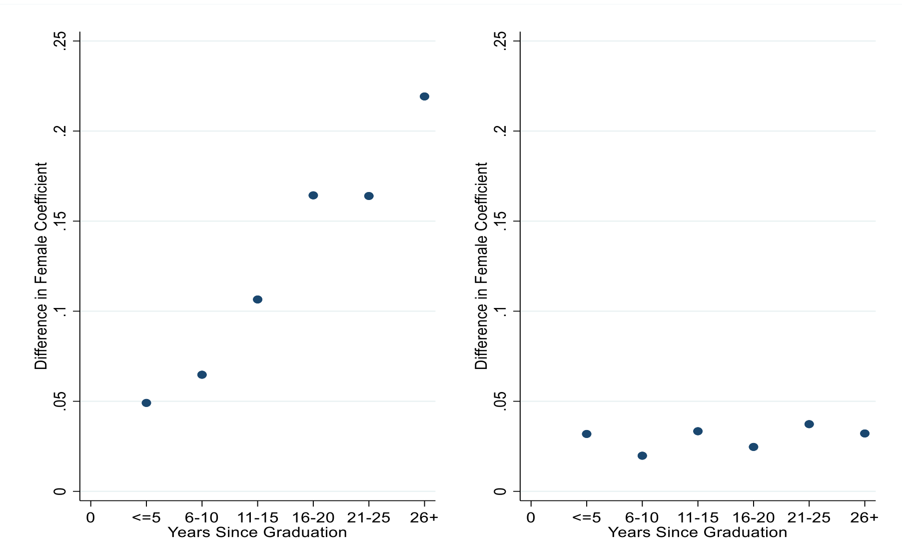
Note: Each point represents the female coefficient from the regression in (1) and the upper and lower bars represent the 95% confidence interval. The outcome is conditional on employment and controls include an age quadratic, indicators for white and for whether the highest degree is undergraduate or master's, indicators for whether the degree is in life sciences, hard sciences, medical, engineering, architecture, math, and technology, and survey year fixed effects. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A12a: Gender Gap in Log Weekly Pay



Note: Each point represents the female coefficient from the regression in (2) and the upper and lower bars represent the 95% confidence interval. The outcome is unconditional on employment and controls include age quadratic, indicators for white and for whether highest degree is undergraduate or master's, and survey year fixed effects. Occupation group refers to 3-digit SOC groupings interacted with indicators for year in which SOC classification was used. Field of study refers to whether the STEM degree is in life science, hard science, medical degree, engineering, math, technology, or architecture. The sample years are 1997-2021 and the year of graduation is 1970-2020.

Figure A12b: Difference in Gender Gap in Log Weekly Pay with Addition of Controls



Note: Each point represents the difference in female coefficients from the regression in (2) with the addition of occupational controls (left hand side) and separately with the addition of field of study controls (right hand side).