Department of Economics

Working Paper N315-22

The Dynamics of the Gender Earnings Gap for College Educated Workers: The Child Earnings Penalty, Job Mobility, and Field of Study

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Updated: 13/12/2022

Abstract

This paper explores gender wage dynamics using an administrative dataset covering Irish graduate earnings from 2010-2020. Our data allows us to look at a broad range of degrees and compare workers who are identical in important observable characteristics. We find that although male and female graduates have similar returns to study field immediately after graduation, a substantial gap soon emerges. This is particularly true when considering women with children and is driven by a 27 percent fall in earnings immediately after childbirth. We find no striking differences between fields of study; there is a substantial and persistent motherhood effect for all field groupings. We examine and dismiss the possibility that the gender difference in earnings dynamics is driven by job mobility; in fact, almost all of the difference is accounted for by changes within a job. Although there is a large and persistent reduction in hours of work after childbirth, this does not seem to explain all of the reduction in earnings.

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This paper uses Educational Longitudinal Database RMF and GUI RMF provided by the Central Statistics Office (CSO). Results are based on analysis of strictly controlled Research Microdata Files. The CSO does not take any responsibility for the views expressed or the outputs generated from this research We are grateful to Brian Stanley and Kieran Culhane for helpful discussions in relation to the ELD data and Bridget Hearne for assistance with the GUI data. We are also grateful to Judith Delaney, Alex Farnell, Bruno Morando and Irene Mosca for helpful comments on an earlier draft of this paper.

1. Introduction

Gender differences in earnings are particularly pronounced among top earners, a feature that is observed across many countries (OECD (2012)). Furthermore, there is evidence that this gap emerges over the career and is particularly pronounced for women with children. One possible explanation for the emerging earnings gap is that women and men choose different occupations, and those occupations have different lifetime earnings trajectories. However, Goldin (2014) finds that what happens within occupations is far more important than differences between them and that the effect of having children varies among graduates from different fields of study. She argues that the pay structures in some occupations entail a more serious penalty for non-flexible working schedules and time out than others. Given that field of study is a key determinant of occupation, the former has often been the focus of previous research. In this paper we use rich administrative data, covering earnings from 2010-2020 for a large sample of Irish graduates, to examine gender differences in earnings dynamics and returns to a broad range of fields of study. We consider the potential mechanisms underlying the observed dynamics, focusing on childbirth and related job mobility. In addition, we use a supplemental data set to look at changes in hours of work associated with childbirth.

Previous studies that have considered differences in returns to field by gender (Altonji (1993), Belfield et al. (2018)) have tended to find that gender differences in returns to major were relatively small. For example Belfield et al. (2018) estimate that the return to Business Studies (relative to the average worker) is 15.2 percent for women and 14.8 percent for men. Likewise Britton et al. (2022) report returns that "are extremely similar when split by gender." However, because such studies have tended to focus on returns at a single point in time after graduation or returns averaged over several years, these similarities may hide substantial variation in the dynamics of earnings returns by gender over workers' careers. In contrast, we estimate the return to field of study by gender in each year of workers' early careers. Consistent with previous work, we find no significant gender differences in returns across most fields of study immediately after graduation. However, this changes over time, so that ten years after graduating, the return is higher for males than for females across almost all fields of study. This is especially true of the fields of study with high returns, such as Maths & Statistics, IT, Engineering and Business & Law. It is even more true when comparing men to women with children. This has implications for the dynamics of the gender wage gap. For example, mothers who studied Business & Law in university see their earnings fall by about 28 percent below those of men with similar education and characteristics ten years after graduation, despite starting off with indistinguishable earnings.

Given the larger gender differences in returns observed for women with children, we then turn our attention to the wage penalty for motherhood. There is a growing body of research that use event studies to estimate the motherhood wage penalty by comparing the wage change for mothers and fathers in the years surrounding childbirth (Kleven, Landais, Posch, et al. (2019), Kleven, Landais and Sogaard (2019); Sieppi and Pehkonen (2019), de Quinto et al. (2021), Artmann et al. (2022); Rosenbaum (2021), Rabaté and Rellstab (2022) and Kleven (2022)). These studies typically find that while mothers experience a large, immediate and persistent reductions in earnings after childbirth, there is no evidence of similar changes for men. For instance Kleven, Landais, Posch, et al. (2019) estimate long-run child penalties in earnings ranging from 21 percent in Denmark to 61 percent in Germany. However, due primarily to data requirements, these studies have been restricted in their ability to examine variation in the motherhood penalty by workers' characteristics. Artmann et al. (2022) find that women with higher earnings capacities tend to experience lower earnings losses after childbirth; Rosenbaum (2021) finds large and significant penalties for all mothers although the penalties are slightly smaller for adopting mothers than those for biological mothers; and Li

(2022) finds that in the US, black women experience only half the child penalties experienced by white women.

A small number of recent studies have focused attention on the extent to which the penalty for college educated women differs by field of study (Goldin and Katz (2008), Goldin (2014), Butikofer et al. (2018), Albrecht et al. (2018), Artmann et al. (2022)). Albrecht et al. (2018) estimate a motherhood penalty of 15 log points ten years after first birth for those with a Business or Economics degree in Sweden. Butikofer et al. (2018) looks at the top 20 percent of earners in Norway amongst those who have completed a graduate degree in one of four professional areas (MBA, Law, Medicine and STEM) and find that the gender earnings gap for MBA and Law graduates is around 30 percent but substantially less for STEM graduates 10 years after childbirth. Artmann et al. (2022) look at a broad range of fields and find some heterogeneity across fields. For example, they report a long-term child penalty of 35.7 percent in Science and Mathematics and 51.1 percent in Health. However, they acknowledge that this pattern may be due to selection into fields and may not necessarily reflect the causal effect of different fields.

We extend the recent work by using the event study approach to examine earnings dynamics and the underlying mechanisms across a broad range of bachelor's degrees. In addition, our rich administrative data allows us to control for selection into different fields, along the lines of Britton et al. (2022). The Irish educational system is particularly useful in this respect, because of the fact that the HE options available to students are entirely dependent on their academic performance at second level. Our ability to control for prior academic performance allows us to control for selection into particular fields of study more completely than in many previous studies.

We find a substantial motherhood penalty of 27 percent overall. However, unlike other research that has tended to focus on high earners, when looking at graduates in general, we find no striking differences between fields of study; there is a substantial and persistent motherhood penalty for all field groupings.

To understand the underlying mechanisms, we examine the role of both labour mobility and hours of work following childbirth. Decomposing the gender difference in wage growth, we find that differences in job mobility explain very little of the gender wage divergence, with almost all the reduction in earnings reflecting changes within a job. Using a supplemental dataset that allows us to consider hours of work after childbirth suggests that about half of the earnings drop may be accounted for by persistent reductions in hours of work. Further reductions in the hour's component of the gender wage gap will require a reallocation of time within households, either through changing preferences or changing social norms.

Our findings highlight that a substantial penalty for childbirth exists for all types of graduates. This is particularly striking given that Irish graduates, both male and female, have a very strong attachment to the labour market. The penalty exists within all fields and even after controlling for a range of personal characteristics not usually available in administrative data. Our findings suggest that policies to tackle the gender wage gap need to be broad-based, rather than focussed on particular sectors.

2. Institutional Background

Ireland has one of the highest rates of higher education participation in Europe. In 2021, 58 per cent of 25–34-year-olds had a tertiary level qualification in Ireland, compared with an EU average of 41 per cent (CSO 2021)[1]. Furthermore, the gender gap in Higher Education participation in Ireland is the second lowest in Europe. For the EU-27, the gender difference in

[1] https://www.cso.ie/en/releasesandpublications/ep/p-eda/educationalattainmentthematicreport2021/

participation is 10 percentage points in favour of females, whereas in Ireland, the difference is just 6 percentage points, with 61 percent of females having a third level qualification, compared to 55 percent for males.

Higher education in Ireland is provided by a range of institutions comprising universities, Institutes of Technology (IoTs) and colleges of education. Almost all of these institutions are substantially funded by the State. There were ten universities in Ireland during the time period covered by our study, awarding degrees in most or all of the main fields of study. There were also fourteen IoTs, providing programmes in a slightly more limited range of largely technical study fields and to sub-degree as well as degree levels.[2] The colleges of education are small institutions largely devoted to teacher training.

Students typically enter second-level education at age 12 and five or six year later, sit a final set of state-wide exams called the Leaving Certificate (LC), usually in seven subjects. Although the minimum school leaving age is 16, 91.5 percent sit the LC.

Applications to Higher Education are made through a Central Applications Office (CAO) which processes entry to all Higher Education Institutions (HEIs) in Ireland. Each HEI offers a range of degrees in specific fields of study. Before students know the results from their LC, they rank ten degree-institution combinations (‘courses’) in order of their preferences on one CAO form. Once the LC results are available, the CAO converts LC grades into points, using the best six grades. Students are then offered their highest-ranked course from among those for which their points exceed the admission threshold. This threshold is determined by the number of available places and the points of those who apply for that course. Once a student has been offered a course, they cannot enter a lower ranked course even if they have sufficient points for that course. Some courses have additional subject requirements. For example, Engineering

[2] Since 2019, most IoTs have been involved in mergers and been awarded the status of a university. This development is not considered in our analysis as it is after the period that we study.

degrees typically have Science and Maths grade requirements. A small number of courses, including Medicine and Music, have additional assessments that are combined with the LC points to determine entry. However, for the most part, entry is determined by academic performance in the LC. While some students switch course after entering university, most continue with the course determined by the CAO application process.

There are two alternative entry routes for school leavers into college. For socioeconomically disadvantaged students, there is the Higher Education Access Route (HEAR) scheme and for students with disabilities there is the Disability Access Route to Education (DARE) scheme. Both schemes offer places on reduced LC points with extra post-entry support; 5-10 percent of places in each HEI are allocated to HEAR students and a similar proportion to DARE students. About half of the students on these schemes availed of the reduced LC point allowance.[3]

3. Data

The Educational Longitudinal Database (ELD) contains information on all those graduating from Irish HE institutions from 2010 to 2020. It matches individuals across a range of pseudonymised administrative sources, including education data, earnings data and data on benefit receipt. The match rate of individuals across these data sources is very high, accounting for more than 90% of all Irish HE graduates. Most of those who are not matched are assumed to have emigrated.[4]

Second-level education data includes information on school type, such as fee-paying status and whether the school is single-sex. Detailed school-area deprivation indices, which are

[3] http://accesscollege.ie/wp-content/uploads/2017/02/DH-Summary-Report_Final.pdf

[4] See https://www.cso.ie/en/releasesandpublications/ep/p-heo/highereducationoutcomes-graduationyears2010-2019/whatdograduatesdo/

constructed to have a mean of zero and standard deviation of 10, are also included. Information on LC points are taken directly from the State Examinations Commission and are therefore free of the measurement error typically associated with self-reported grades. As well as each student's LC points, we also know their ranking within their school. Information on Higher Education is collected centrally and contains information on institution, course, ISCED codes for field of study, year of graduation, graduation grade, age and gender. Detailed information on over 90 fields of study is recorded. We initially aggregate these into 24 broad fields of study to estimate the return to field of study. When looking at the mechanisms behind the observed earnings dynamics, we further aggregate these into three broad groups; Business & Law, STEM and Other. Similar groupings have been used in previous research.

The earnings and employment data used in this study are taken from tax authority records and include variables for total annual earnings, weeks worked and an employer identifier for each year after graduation up to 2020. This means that the data includes between one and ten years of post-graduation earnings data. Because it is a criminal offence to misreport to the tax authority, these data are largely free of measurement error in terms of both earnings and mobility between employers. Given the structure of our data, non-employment can be inferred from missing earnings records. Although we are unable to determine precisely whether these missing observations correspond to non-participation or are missing for other reasons such as migration, less than six percent of the person-year observations in our data are missing.

Data on benefit receipt comes from the government department responsible for its administration. We use these data to create an indicator variable for year of childbirth, using receipt of maternity benefits to indicate the birth of a child. In Ireland, all women who have paid the required social insurance contributions are entitled to maternity benefit. Russell et al. (2011) find very high take up of paid maternity benefit, with 95 percent of mothers with higher education taking paid maternity leave at the time of the pregnancy. [5] Consequently, our use of maternity benefits to identify childbirth for mothers is likely to capture almost all births in our data. In a later section of the paper, we also use receipt of paternity benefits for fathers to identify birth of a child for the men in our sample. Paid paternity leave was introduced in Ireland only in September 2016. Therefore, when looking specifically at fathers, we must restrict the analysis to those who graduated after 2015. In addition, in contrast to mothers, not all fathers claim paternity leave.[6]

Our data comprises a large random sample of the population data.[7] In our analysis, we restrict our sample to non-mature graduates of full-time courses with at least a Level 8 qualification, equivalent to an honours bachelor's degree. We focus on earnings histories from the first full year after graduation with the initial bachelor's degree. However, for those who go directly to Level 9 (master's) degrees, we ignore earnings during that year on the basis that these are likely to be casual earnings from non-graduate level jobs. The overall sample used in our analysis consists of 67,393 women and 51,308 men.

Summary statistics for the key variables are presented in Tables 1 and 2. We see from Table 1 that, on average, females perform better in the LC examination, while males are more likely to attend a fee-paying school. In addition, there is a slight difference in deprivation indices that indicates that males are more likely to attend secondary schools in more affluent areas. Table 2 provides the distribution of students by gender across broad fields of study. Business is the most popular field of study and both men and women are well represented in

[5] We find similar take up rates in the Growing up in Ireland Infant Cohort Wave 1 used in Section 4.2.
[6] Analysis by the Irish Central Statistics Office shows that in 2019, the take-up rate of paternity benefit was 60% that of maternity benefit.
https://www.cso.ie/en/releasesandpublications/er/eampb/employmentanalysisofmaternityandpaternitybenefits2016-2019/#:~:text=Maternity%20benefit%20was%20paid%20to,%2C%20(see%20figure%202).

[7] This reflects CSO guidelines in relation to data necessity and proportionality. Prior to the detailed analysis we engaged in an exploratory project with CSO and HEA to determine an appropriate sample.

this area. Men are overrepresented among Engineering and IT students, while women are overrepresented among students in Education, Nursing and Social Care.

While the administrative data in the ELD are unusually rich in the background variables provided and the sample size is large, these data contain no information on hours of work. To the extent that hours of work may change after childbirth, our administrative earnings data cannot capture this. Therefore, we also use data from the Growing Up in Ireland (GUI) Infant Cohort. This is a longitudinal study that began in 2008 (Wave 1) and collected data on over 10,000 9-month-olds and their families. Follow-up surveys were completed when the child was aged 3 years (Wave 2), 5 years (Wave 3), 7/8 years (Wave 4) and 9 years (Wave 5). Crucially, the 2008 survey also asked some retrospective questions on the mother's labour supply prior to the birth of the child. In particular, we can determine weekly hours of work – but not earnings – in the year prior to childbirth and in all subsequent waves. We use these data on hours of work to complement the earnings analysis from the administrative data.

4. Results

We begin by looking at the evolution of the gender wage gap post-graduation. To illustrate the raw earnings gap, we first regress log weekly earnings on calendar year, years since graduation and gender. The results are shown in Figure 1. The solid line shows that on average, male graduates earn 3.1 percent more than females immediately after graduation. However, this increases to 18.8 percent 10 years later. The dashed line on Figure 1 shows the wage gap after additionally controlling for field of study; this explains almost all of the gap at the beginning but explains little of the dynamics. After ten years, the gap is 18.8 percent without the field of study control and 17.1 percent with it. Given that 91 percent of the gender wage gap arises within field of study, the remainder of our analysis will focus on the gender gap within fields.

To control for selection into fields, we use a selection on observables approach similar to that used in Britton et al. (2022), regressing log weekly earnings on field of study plus controls for selection that include LC points, gender, fixed effects for university attended and calendar year, attendance at a disadvantaged or fee paying secondary school, a measure of local deprivation and the child's rank in their secondary school.[8] It is these adjusted earnings that we use throughout the remainder of the paper.

We begin our analysis of the within-field gender earnings gap by estimating the difference in the return to field of study between men and women. The results for the 24 study fields, with corresponding 95% confidence intervals, are shown in Figure 2. One year after graduation, we see that most of the differences are small in magnitude and very few are statistically significantly different from zero. In contrast, eight years after graduation, the return to field is consistently higher for males than for females, and in half of the cases these differences are statistically significantly different from zero. In the fields with high returns such as Maths/Stats, Engineering and Business, the return for males is of the order of 15-20 percentage points higher than for women and statistically significantly different from zero.

Given that these differences emerge over time, while the individuals are in their 20s and 30s, it is plausible that some of the divergence arises because of women having children. As noted earlier, we cannot identify fathers over the entire period, so we use all men as the comparator group. We compare the returns for all males to both women who have a child during the sample period ('women with children') (Figure 3) and women without children

[8] Like Britton et al. (2021), we find that Medicine, Maths/Stats, IT, Engineering and Business have high returns for both genders.

(Figure 4). We see that the emerging gender differential in returns to field by year eight is more pronounced for women with children.

To provide more information on the dynamics, we plot the evolution of returns over the entire eight years. For presentation purposes, we consider three groupings, Business & Law STEM and Others.[9] These groupings are large enough to allow for meaningful analysis. Business & Law and STEM account for almost half (48 percent) of all graduates, and with relatively even representation of both men and women. Similar groupings have been used in previous research (Goldin (2014), Butikofer et al. (2018), Albrecht et al. (2018), Britton et al. (2022)), although often focussing on high earners. We examine graduate earnings more broadly by considering graduates within these two groups, as well as all remaining graduates. The earnings gender gaps over the ten post-graduation years are presented in Figure 5. The first notable point is that the earnings gap is generally positive for both groupings. For women without children, the gender gap is relatively flat over the early career, with a gap of the order of 5 percent in Business & Law, 10 percent in STEM and 6 percent in Others. However, when comparing men to women with children, the gender gap increases markedly for all groups as workers' careers progress. Ten years after graduation, the earnings gap for women with children is 28.1 percent in Business & Law, 23 percent in STEM and 28.2 percent in Others.

Although the differences between women with and without children are striking, motherhood may not be the cause; women who have a child at some stage during the observation period may have different unobservable characteristics to those who do not. We now turn to whether the apparent child effect is causal. To do this, we follow the event-study approach adopted by others in this literature (Albrecht et al. (2018), Butikofer et al. (2018); Kleven, Landais and Sogaard (2019)). Under certain identifying conditions, this approach

[9] STEM is defined to include Biology, Information Technology, Engineering, Maths/Stats and Physical Sciences.

identifies the causal effect of childbirth by comparing earnings around the first post-graduation birth.

To carry out the event study we index all years relative to t = 0, this represents the time when a woman has her first (post-graduation) child, which may occur at any time between 2010 and 2020. Letting y_{ist} denote outcome for individual *i*, in calendar year *s* at event time *t*, we estimate the following event-study specification:

$$y_{ist} = \sum_{j \neq -1} \delta_j I[t = j] + \sum_k \beta_k I[k = YrsSinceGrad_{is}] + \sum_h \beta_h I[h = s] + \theta X_i + \varepsilon_{ist} \quad (2)$$

As noted earlier, the implied employment rate for the graduates in our data is very high. For this reason, participation effects are unlikely to be significant for earnings dynamics and so we focus on log weekly earnings among employees as our key outcome variable.[10]

We control for years since graduation and calendar year to model underlying life cycle and time trends. The additional controls, X_i, correspond to the remaining controls used in estimating the returns to field of study above and allow us to control for selection into field of study when estimating the child-penalty. The key parameters of interest are the δ_j, which give predicted earnings relative to the time of childbirth. In estimating the parameters, we omit the event time one year prior to childbirth; for example δ_1 estimates the percentage change in earnings in the year after childbirth relative to the year prior to childbirth. We can identify all the fixed effects in (2) because, conditional on years since graduation and calendar year, there is variation in event time driven by the age at which the woman has her first birth. The conditions needed for the estimated δ_j's to have a causal interpretation are discussed in Angelov et al. (2016) and include a smoothness condition similar to that required in the

[10] We have also conducted the analysis including zero earnings whenever the respondent has a missing earnings record. The inclusion of the zeros results in only a very small increase in the earnings change, which is to be expected given the very low non-participation rates among graduates in our data. This is consistent with Artmann et al. (2022), who also find a much smaller participation effect for college educated women than for other women.

Regression Discontinuity approach and a parallel trends assumption common in Difference-in-Difference estimation.

Figure 6 shows the resulting event study diagrams for all mothers, and separately for mothers in Business & Law, STEM and Others, where *t* runs from -9 to +6. Looking at the results for all mothers, the event study analysis shows a significant discontinuous drop in earnings of 26.8 percent in the year following first childbirth. Furthermore, earnings continue to fall, so that six years after the birth of the first child, women's earnings are 34.9 percent lower than in the year prior to birth. The fact that the most marked fall in earnings is in the year immediately after childbirth supports a causal interpretation of the effect of children on earnings.

Turning to our selected field groups, we see that the immediate fall in earnings in STEM is 23.0 percent, growing to 45.2 percent after six years, but this latter effect is imprecisely estimated. The immediate effect is slightly larger in Business & Law, at 30.2 percent, but the six-year effect of 46.5 percent is similar to that found in STEM. The results for Other graduates show an immediate effect of 26.2 percent and a six-year effect of 30.5 percent. While there are some differences in the patterns between fields, these differences are not particularly striking. However, there is clearly a substantial and persistent childbirth effect overall and in all field groupings.

In the event study literature, the motherhood wage penalty is calculated as the difference between mothers and fathers in the wage adjustment around childbirth. We note that at least some of this motherhood effect is the result of choices made by women. However, bearing in mind that these choices are arguably the result of societal constraints , we follow the literature in using the more common 'penalty' terminology. Because our data on parenthood relies on benefit receipt, the issue arises that paternity benefit was not introduced in Ireland until September 2016 and unlike maternity benefit, not all fathers claim it. This means that only men who have children after 2016 and claim paternity benefit will be recorded as fathers in our analysis. This raises the possibility of selection bias in estimating the wage change for fathers, although the direction of the bias is not clear *a priori* and we do control for many observable characteristics. The size of our sample of fathers is also smaller than that for mothers, implying increased standard errors.

The results are presented in Figure 7, which plots the event studies for mothers and fathers. In contrast to the large drop in earnings at childbirth for mothers, we find no evidence of a wage drop for fathers. The change is weekly earnings at time of first birth is almost zero. This implies a motherhood wage penalty of the order of 27.0 percent. Figure 8 reports the estimates for our field groupings. The motherhood wage penalty for Business & Law graduates is 25.0 percent, 23.2 percent for STEM graduates and 28.8 percent for Other graduates. These results show that the substantial and persistent childbirth effect we found for mothers, reported in Figure 6, are not found for fathers.

One possible explanation put forward in the literature for the large motherhood wage penalty concerns job-shopping (Manning & Swaffield, 2008). Topel and Ward (1992) found that in the US, one third of wage growth in the first ten years after labour market entry is due to job mobility. If childbirth alters job mobility for women and reduces the chances of women moving to better paying jobs, then this may feed into lower wage growth and explain the child penalty observed earlier. On the other hand, women may move to lower-paying jobs that are more family-friendly, which would also result in lower wage growth. To examine the role of job mobility in explaining the earnings changes associated with childbirth, we first estimate event studies, now using an indicator for changing employer as the outcome variable. The results, given in Figure 9, show that in the year following childbirth, women are 2.5 percentage points less likely to change employers than previously. When looking at our field groupings we see that job mobility declines in all fields of study following childbirth; by 5.1 percent in Business & Law, 4.0 percent in STEM and 1.5 percent for others.

Of course, the extent to which differences in job mobility translate into a gender pay gap depends not only on differences in the probability of moving but also on the associated premia for moving and staying. To examine this formally, we consider a decomposition similar to that used by Albrecht et al. (2018). For each gender (j=M,F) the average log earnings gain from year *t* to year *t*+1 can be written as

$$\Delta lnw^{j}{}_{t,t+1} = P^{j}\left[Switch_{t,t+1}\right] * \left[\Delta lnw^{j}{}_{t,t+1}|Switch_{t,t+1}\right] + P^{j}\left[Stay_{t,t+1}\right] * \left[\Delta lnw^{j}{}_{t,t+1}|Stay_{t,t+1}\right] \quad (3)$$

By adding and subtracting terms, we can write the difference in earnings growth between males and females as

$$\Delta lnw^{M}{}_{t,t+1} - \Delta lnw^{F}{}_{t,t+1} =$$

$$\left\{P^{M}\left[Stay_{t,t+1}\right] * \left[\left[\Delta lnw^{M}{}_{t,t+1}|Stay_{t,t+1}\right] - \left[\Delta lnw^{F}{}_{t,t+1}|Stay_{t,t+1}\right]\right]\right\}$$

$$+\left\{P^{M}\left[Switch_{t,t+1}\right] * \left[\left[\Delta lnw^{M}{}_{t,t+1}|Switch_{t,t+1}\right] - \left[\Delta lnw^{F}{}_{t,t+1}|Switch_{t,t+1}\right]\right]\right\}$$

$$+\left\{\begin{array}{c}\left[P^{M}\left[Switch_{t,t+1}\right] - P^{F}\left[Switch_{t,t+1}\right]\right] * \left[\Delta lnw^{F}{}_{t,t+1}|Switch_{t,t+1}\right] + \\ \left[P^{M}\left[Stay_{t,t+1}\right] - P^{F}\left[Stay_{t,t+1}\right]\right] * \left[\Delta lnw^{F}{}_{t,t+1}|Stay_{t,t+1}\right]\end{array}\right\} \quad (4)$$

The above expression decomposes the observed gender gap in earnings growth into a part due to differences in earnings gains for stayers (first term), a part due to differences for switchers (second term) and a part due to the difference in the employer mobility (third term). The results in Figure 10 show the above decomposition separately for women with children (left panel) and women without children (right panel), using all men as the comparator in both cases. As previously, we control for our selection variables here, so the results compare men and women with similar characteristics.

The top (solid) line in the left-hand panel shows a large and increasing earnings growth gap in favour of men when compared to women with children; men experience earnings growth that ranges from 4.6 to 8.4 percentage points higher than women. The remaining dashed lines show the components of this earnings growth gap. The dashed line for the stayers' component shows that male stayers experience higher earnings gains than females.[11] The fact that this line is so close to the top line shows that most of this earnings growth gap is driven by stayers. For example, eight years after graduation 84 percent of the total earnings growth gap between men and women is accounted for by differences in the earnings growth for stayers, 13.4 percent by the difference for switchers and 2.5 percent by the difference in mobility rates between men and women. The right-hand panel shows that the gender gap in earnings growth is much lower when comparing men to women without children, but the decomposition patterns are broadly similar. These results suggest that the gender difference in earnings growth is almost entirely explained by the fact that men experience higher earnings gains than women, particularly as 'stayers'; the gender differences in mobility shown in Figure 9 account for very little of the observed gap.

The results presented in Figure 11 repeat the above analysis separately for Business & Law , STEM graduates and all other graduates. The decomposition shows that, despite slightly different earnings growth rates, the drivers are similar in all fields; gender differences in earnings growth is almost entirely explained by the fact that male stayers experience higher earnings growth than female stayers. Although we find that women with children are less likely to change employers after childbirth, this is not a significant contribution to the diverging

[11] This is consistent with Doris et al. (2020), who examined the distribution of earnings changes in Ireland across all workers and found that male job stayers had significantly higher earnings growth than female job stayers.

earnings trends we observe in any field of study. This is similar to Albrecht et al. (2018), who find that differences in mobility explain almost none of the earnings growth gap observed in Business and Economics graduates in Sweden. Our results show that this is true of all undergraduates in Ireland.

5. The Role of Hours of Work

Prior research (Goldin (2014), Kleven, Landais and Sogaard (2019)) confirms that changes in hours of work contribute to the child penalty in the US and Denmark. While the administrative data allow us to carry out a detailed longitudinal analysis of the gender gap in earnings by field of study, these data contain no information on hours of work. We therefore turn to the GUI Infant Cohort data to supplement our earlier analysis. The timing of this dataset corresponds closely to that of the administrative data. Crucially, the GUI asks mothers and fathers to report their hours of work at the time of each survey wave; mothers are also asked to recall their hours of work before childbirth. By comparing hours before and after the birth, we can explore how changes in hours of work might explain the earnings patterns observed in the administrative data.

While the GUI does contain information on total household income, it does not separate this by family member so it cannot be used to examine the wage penalty. Although we can identify higher education graduates, no information is available on the selection variables used in our analysis of the administrative data.

For comparison with the administrative analysis, we restrict attention to first-time mothers with higher education who were working prior to childbirth. We carry out an event-study analysis of the effect of childbirth on hours of work, focussing on those who remained employed throughout. The results are shown in Figure 12, which also shows the hours of work of men in the four waves for which their hours are recorded. Mothers' hours of work fall from an average of 37.9 hours per week before childbirth to 33.0 hours in the year after childbirth, a 12.7 percent reduction. This reflects a substantial increase in part-time working (30 hours or less per week), from 17.4 percent before childbirth to 35.7 percent after childbirth. Although fathers' hours of work prior to childbirth are not recorded, fathers worked on average 43.1 hours in the year after childbirth. Only 4.7 percent of fathers were working part-time after the birth of the first child, so there cannot have been a similar response from the fathers. It is striking that the hours of work recorded for both men and women in the year after childbirth persist thereafter.[12]

Comparing the 12.7 percent hours reduction for GUI mothers to the 27.0 percent reduction in weekly earnings from the administrative data (Figure 6) provides a back-of-the-envelope estimate suggesting that about half of the earnings drop is accounted for by hours of work reductions. This is consistent with Kleven et al. (2019), who find that roughly equal proportions of the earnings penalty come from hours of work and the wage rate.

6. **Conclusion**

This paper examines the divergence in earnings between highly educated men and women in the ten years following graduation. Our results show that although female graduates start off with similar earnings to men, a substantial gap emerges early on in their careers. Differences in choice of field of study do not explain these earnings dynamics; we see substantial earnings gaps emerge even within narrow fields of study. This is especially true for women with

[12] The persistent reduction in hours was also evident for mother who had only one child during the sample period, indicating that this result is not due to the effect of having additional children.

children. For example, for graduates of Business & Law, the gender gap for women with children is zero upon graduation but grows to over 28 percent ten years after graduation. This is despite the fact that we control for a rich set of background variables, allowing us to compare men and women who are similar.

For this reason, a key focus of our paper is an exploration of the mechanisms generating the large gender gap for women with children. We carry out an event study around the time of first birth and show that women experience a significant penalty for childbirth; weekly earnings fall by 26.8 percent in the years immediately following the birth and remain low even eight years later. We find no evidence of such a drop for men. Comparing mothers to fathers, we estimate a motherhood penalty of 27 percent overall, 25 percent in Business & Law, 23.2 percent in STEM and 28.8 precent for other graduates

Possible explanations for these results include mothers reducing hours of work, mothers facing restricted job mobility and so prevented from availing of higher-paying jobs, mothers increasingly moving into lower-paying family-friendly jobs, mothers choosing different roles within jobs and discrimination. We first examine the job mobility issue and find that the wage dynamics are driven by job stayers and not job mobility. Turning to hours of work, we use a supplemental data set and find substantial hours reductions for mothers in the year after childbirth. This reduction is particularly associated with a move into part-time work. Our results suggest that hours of work may account for about half of the earnings reduction at childbirth for mothers.

To the extent that working from home and technological changes allow women to maintain their hours of work, recent changes in work practices have the potential to reduce the earnings penalty associated with childbirth. Further reductions in the gender wage gap may require a reallocation of time within households, either through changing preferences or changing social norms. However, a substantial proportion of the earnings gap does not appear to be related to hours of work. Further research on personnel practices within firms following childbirth is needed. Recent initiatives by many governments require large firms to publicly report a snapshot of their gender earnings pay gap. Our analysis suggests that reporting the gender gap in annual earnings changes for job-stayers would be equally important. This would help focus attention on the dynamic nature of the gender earnings gap.

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Table 1: Summary Statistics by Gender

	Gender		
	Female	Male	Total
Leaving Cert Points			
Mean	425.17	418.45	422.27
Standard deviation	(88.84)	(91.76)	(90.17)
Deis			
Mean	0.10	0.11	0.11
Standard deviation	(0.30)	(0.32)	(0.31)
Attended a Fee paying Secondary School			
Mean	0.10	0.15	0.12
Standard deviation	(0.30)	(0.36)	(0.33)
Secondary School Electoral District HP relative index score 2011			
Mean	3.06	4.18	3.55
Standard deviation	(13.40)	(13.25)	(13.34)
Rank in High School Class			
Mean	55.36	55.25	55.31
Standard deviation	(27.29)	(27.39)	(27.33)
Number of non-missing values	67,393	51,308	118,701

Table 2: Numbers and Percent in Each Field of Study by Gender and Total

	Gender		
	Female	Male	Total
Agriculture and Fisheries	493	1,134	1,627
	0.7%	2.2%	1.4%
Architecture and Town Planning	421	786	1,207
	0.6%	1.5%	1.0%
Biology and Environment Science and other science	5,090	3,292	8,382
	7.6%	6.4%	7.1%
Business and Administrative studies	11,106	12,443	23,549
	16.5%	24.3%	19.8%
Services	1,823	1,647	3,470
	2.7%	3.2%	2.9%
Information and Computers	850	3,872	4,722
	1.3%	7.5%	4.0%
Creative Arts and Design	4,001	2,665	6,666
	5.9%	5.2%	5.6%
Education	6,016	1,842	7,858
	8.9%	3.6%	6.6%
Engineering/Manufacturing and Building/Civil	1,466	7,428	8,894
	2.2%	14.5%	7.5%
Literature and Linguistics	1,274	614	1,888
	1.9%	1.2%	1.6%
Humanities excl languages	9,041	5,112	14,153
	13.4%	10.0%	11.9%
Languages	1,207	376	1,583
	1.8%	0.7%	1.3%
Law	2,490	1,747	4,237
	3.7%	3.4%	3.6%
Journalism and Library	454	272	726
	0.7%	0.5%	0.6%
Maths/Statistics	399	892	1,291
	0.6%	1.7%	1.1%
Medicine/Dental Studies	1,150	801	1,951
	1.7%	1.6%	1.6%
Nursing/Midwifery	5,728	367	6,095
	8.5%	0.7%	5.1%

Physical Sciences	1,741	1,809	3,550
	2.6%	3.5%	3.0%
Psychology	1,223	445	1,668
	1.8%	0.9%	1.4%
Other Social Science	3,077	2,029	5,106
	4.6%	4.0%	4.3%
Pharmacy/Pharmaceutical Science	537	253	790
	0.8%	0.5%	0.7%
Other medical	3,002	1,045	4,047
	4.5%	2.0%	3.4%
Veterinary	124	72	196
	0.2%	0.1%	0.2%
Social work/care	4,680	365	5,045
	6.9%	0.7%	4.3%
Total	67,393	51,308	118,701
	56.8%	43.2%	100.0%

Figure 1: Proportionate Difference in Male and Female Earnings in the Years After Graduation

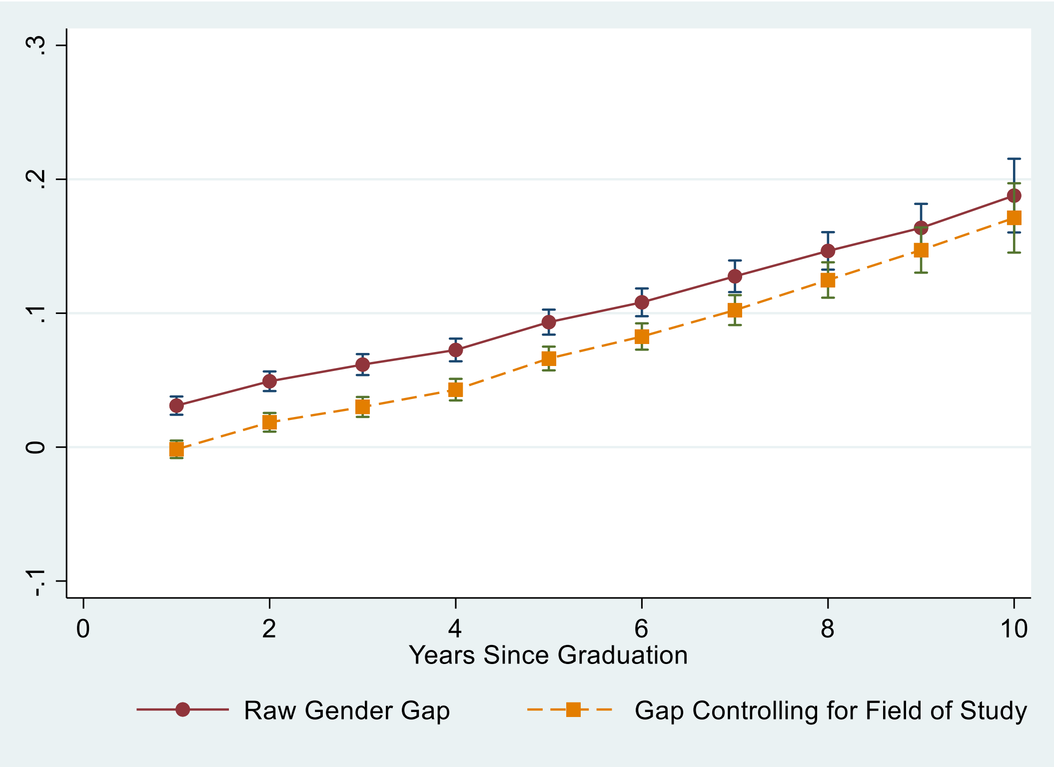
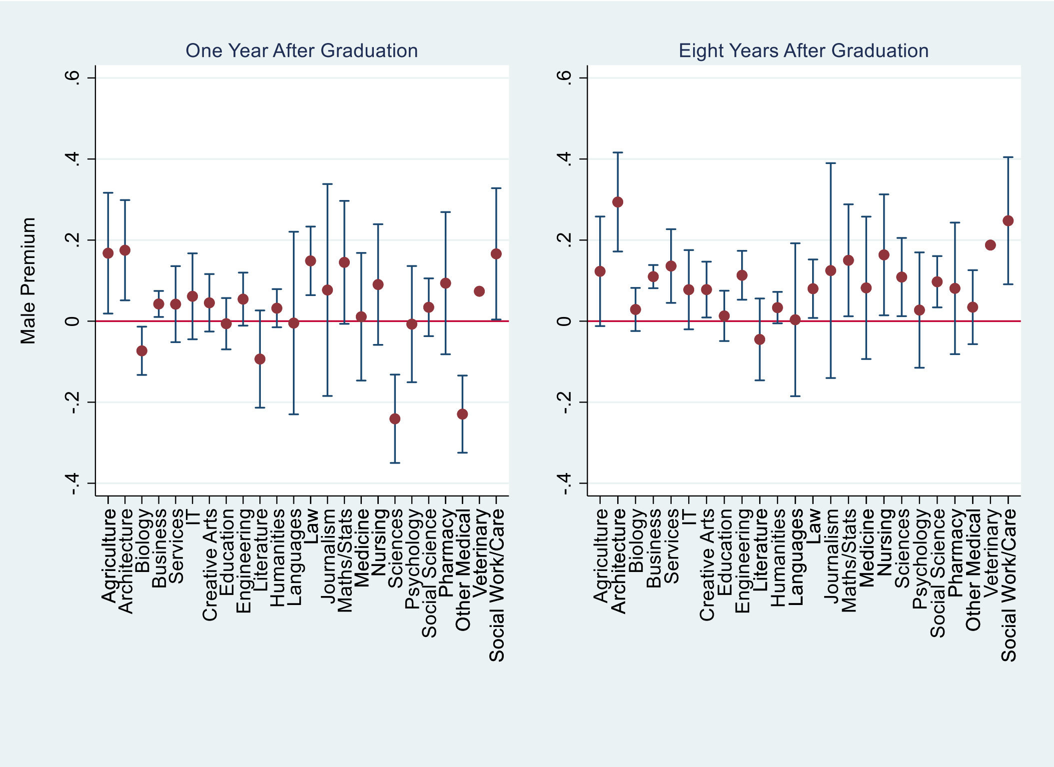


Figure 2: Gender Differences in Returns to Field of Study Comparing All Men to All Women, One Year and Eigh Years After Graduation



Note: the error bars on Veterinary are omitted because they are so large as to distort the graph

Figure 3: Gender Differences in the Returns to Field of Study Comparing All Men to Women with Children, One Year and Eight Years After Graduation

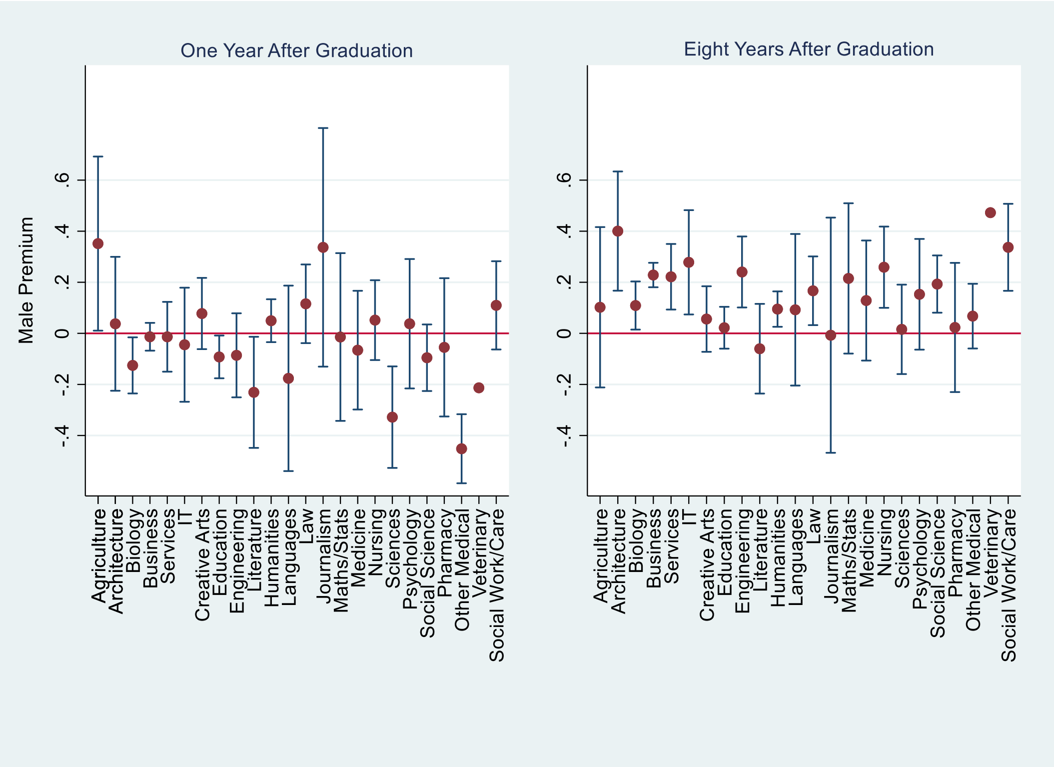


Figure 4: Gender Differences in the Returns to Field of Study Comparing All Men to Women Without Children, One Year and Eight Years After Graduation

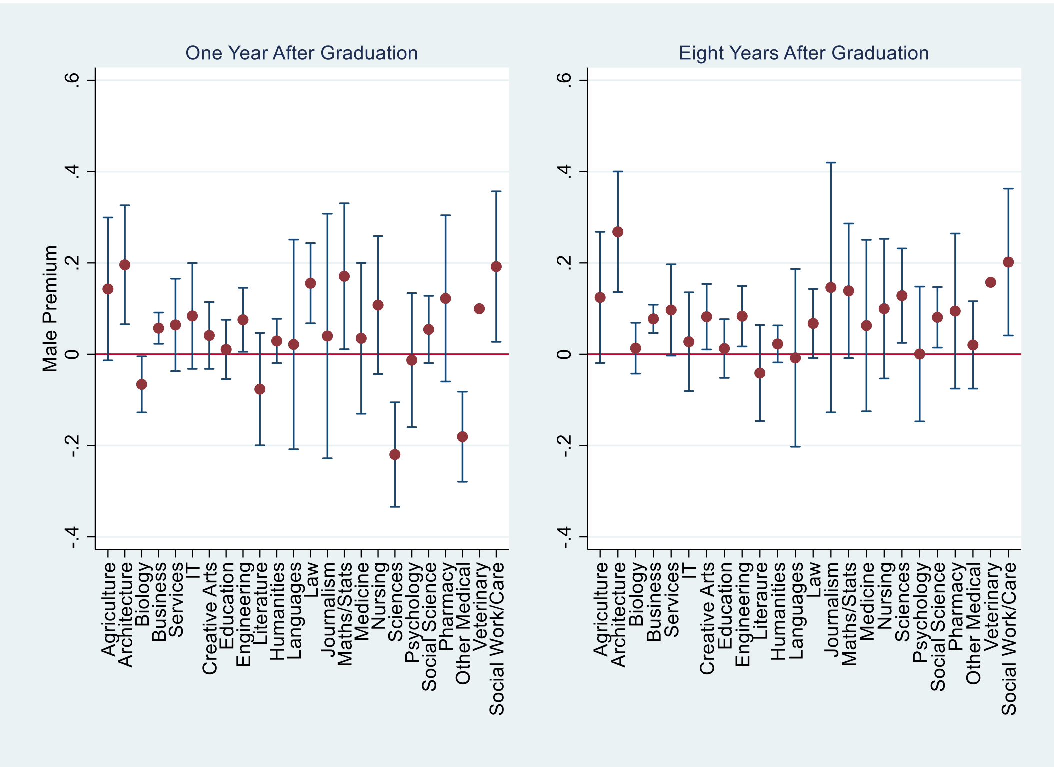


Figure 5: Gender Differences in Earnings in the Years After Graduation by Field of Study and for Women With and Without Children

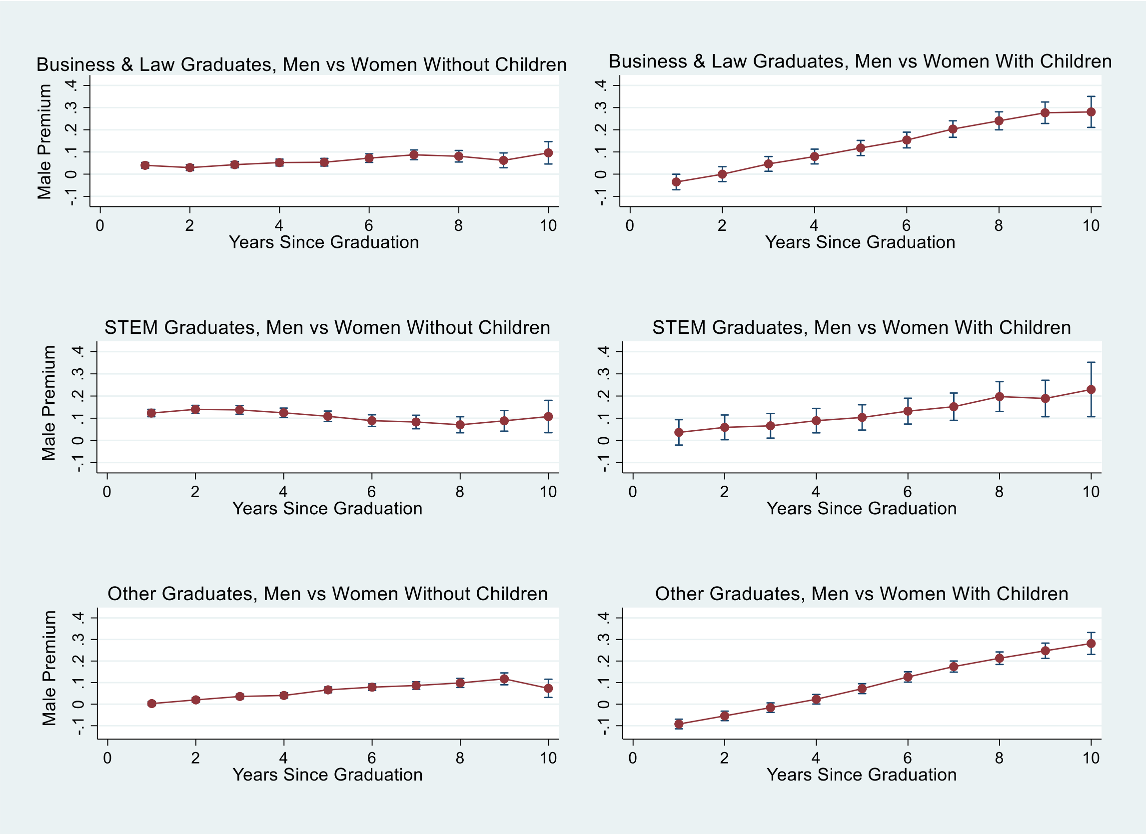


Figure 6: Earnings Changes after Childbirth for All Mothers and by Field of Study

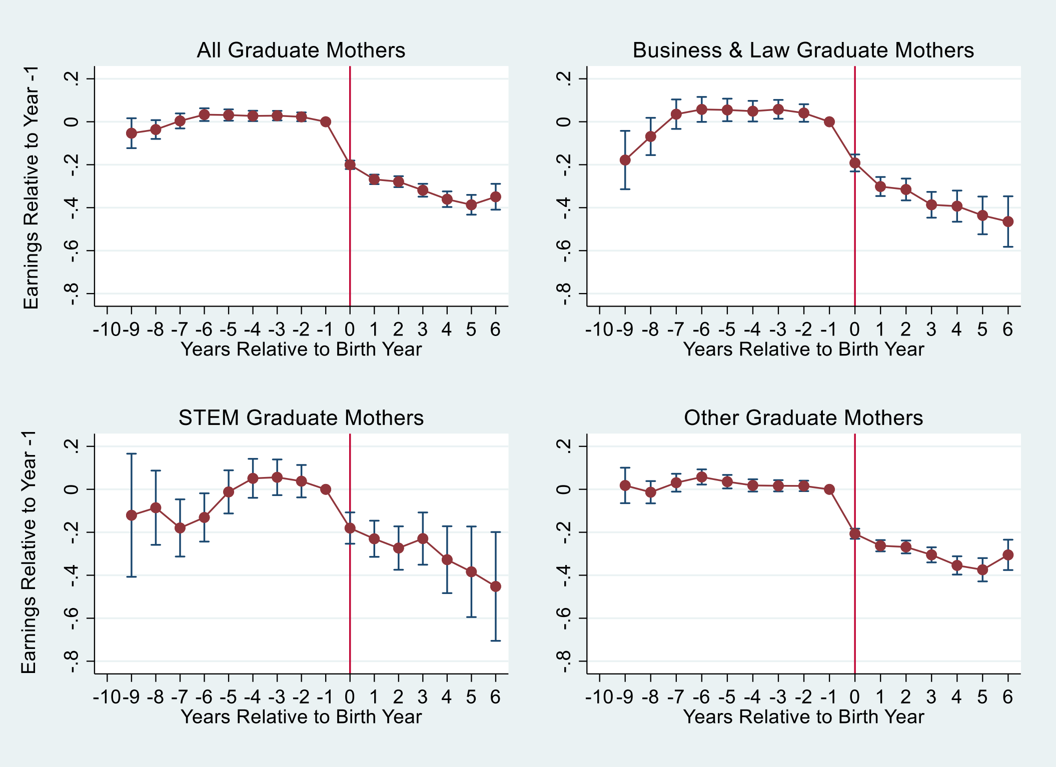


Figure 7: Earnings Changes after Childbirth for Mothers and Fathers

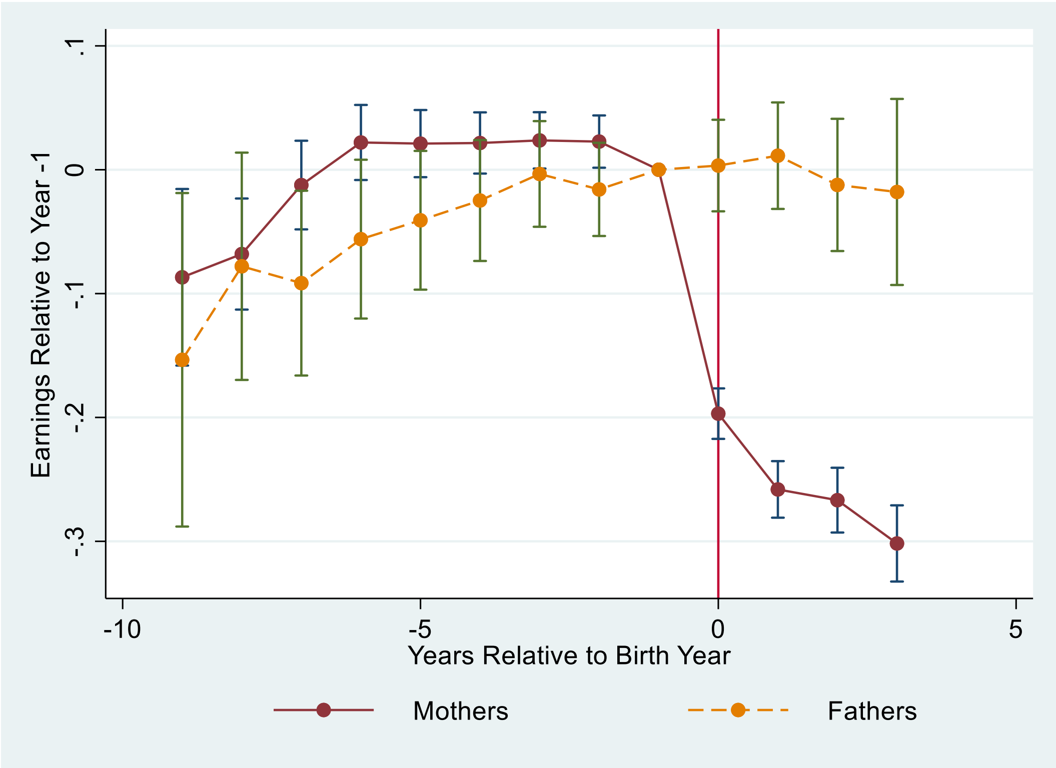


Figure 8: Earnings Changes after Childbirth for Mothers and Fathers by Field of Study

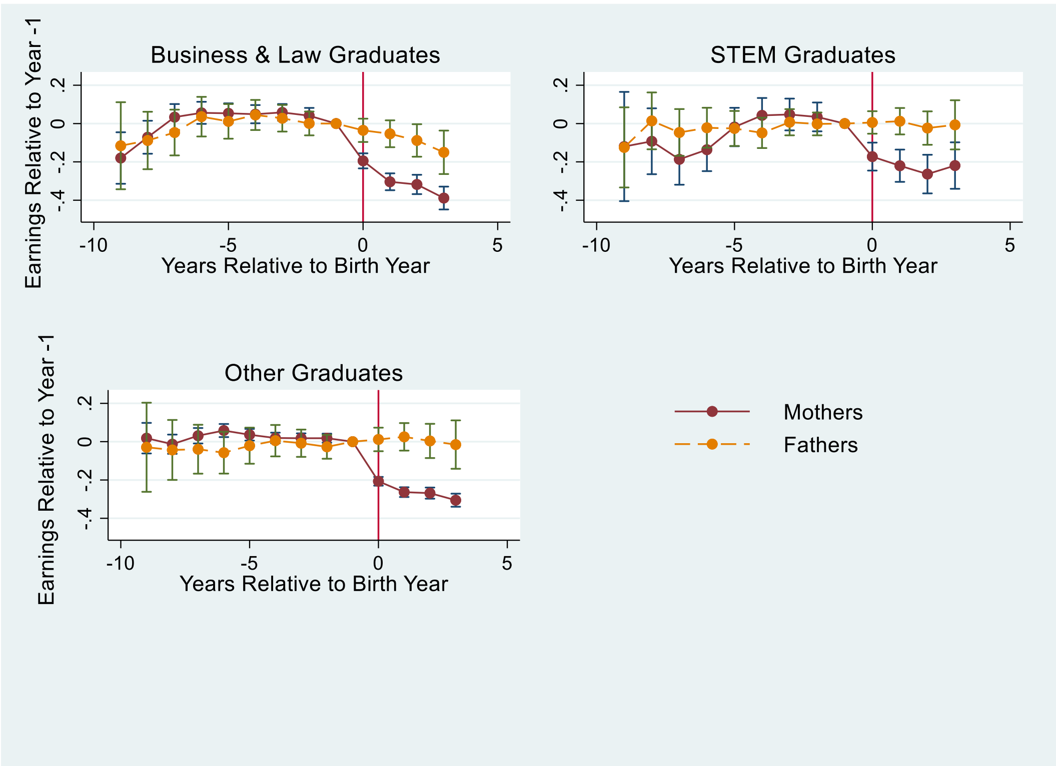


Figure 9: Changes in Job Mobility after Childbirth for All Mothers and by Field of Study

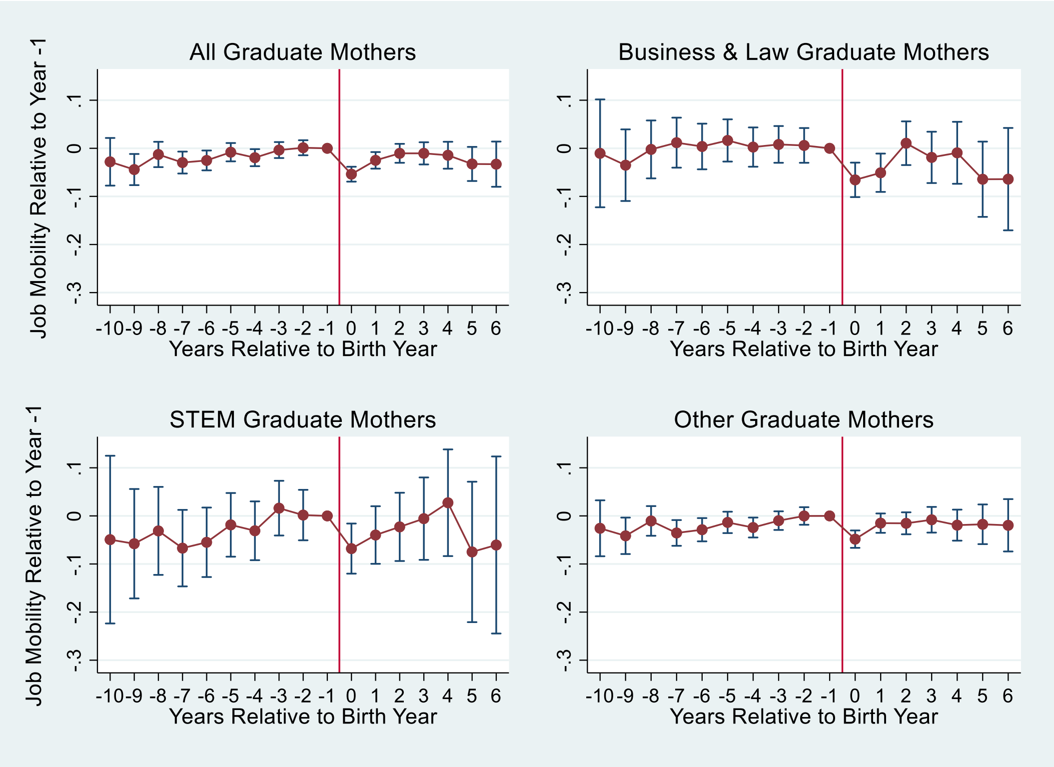


Figure 10: Decomposition of the Gender Difference in Earnings Growth for Women With and Without Children

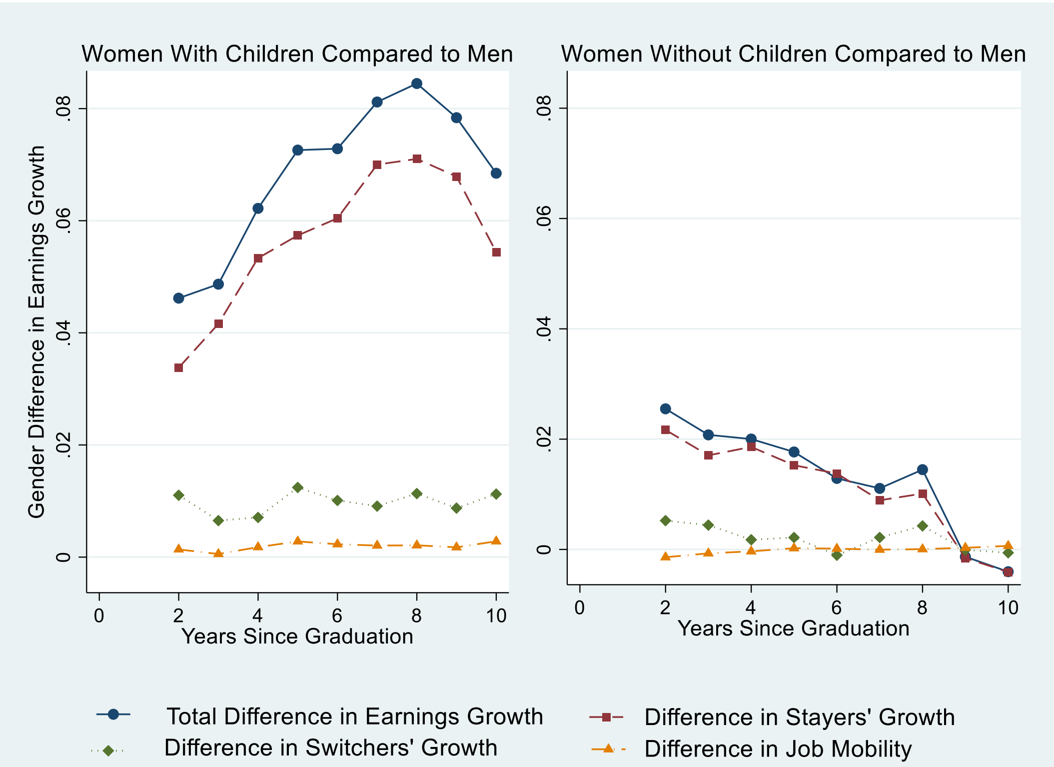


Figure 11: Decomposition of the Gender Difference in Earnings Growth by Field of Study and for Women With and Without Children

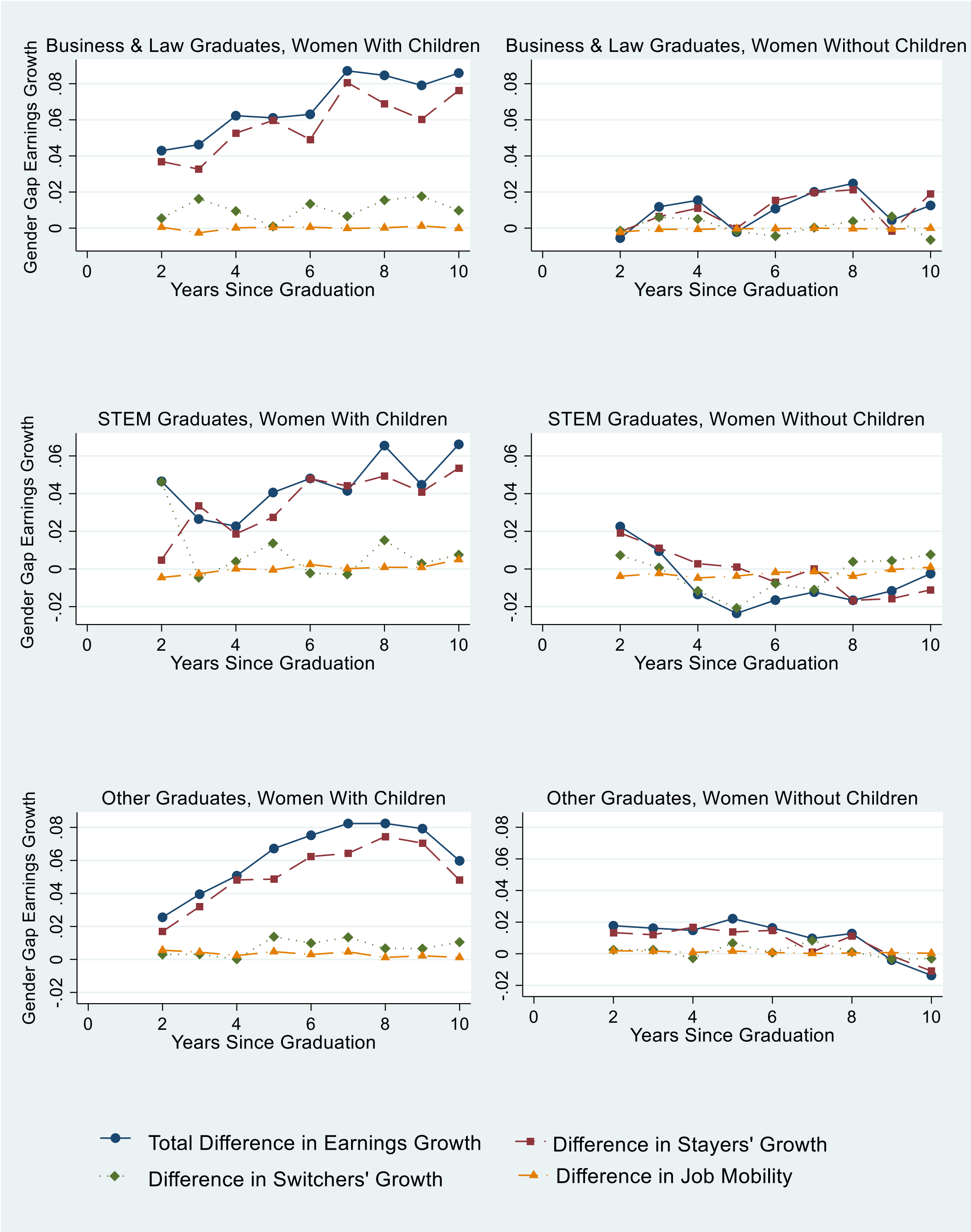


Figure 12: Changes in Hours of Work After Childbirth for Mothers and Fathers