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The labor market returns to 'first in family' university graduates

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ABSTRACT

We examine how first in family (FiF) graduates (those whose parents do not have university degrees) fare on the labor market in England. We find that among women, FiF graduates earn 7.4% less on average than graduate women whose parents have a university degree. For men, we do not find a FiF wage penalty. A decomposition of the wage difference between FiF and non-FiF graduates reveals that FiF men earn higher returns on their endowments than non-FiF men and thus compensate for their relative social disadvantage, while FiF women do not. We also show that a substantial share of the graduate gender wage gap is due to, on the one hand, women being more likely to be FiF than men and, on the other hand, that the FiF wage gap is gendered. We provide some context, offer explanations, and suggest implications of these findings.

JEL Classification Codes: I24, I26, J24

Keywords: socioeconomic gaps, intergenerational educational mobility, higher education, labor market returns, gender economics

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Elsőgenerációs diplomások a munkaerőpiacon

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ÖSSZEFOGLALÓ

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JEL: I24, I26, J24

Keywords: társadalmi egyenlőtlenségek, generációk közötti oktatási mobilitás, felsőoktatás, munkapiac, nemek közötti különbségek

1. Introduction

Previous literature on the returns to a university degree has presented convincing evidence that university degrees lead to significant labor market returns in terms of earnings and income compared to those without a degree (Card 1999; Blundell, Dearden, and Sianesi 2005; Dickson 2013; Oreopoulos and Petronijevic 2013). This had led policymakers to view university access as a key to social mobility and spurred a large literature on higher education and social mobility (Blanden and Machin 2004; Chetty et al. 2014; 2017; Britton et al. 2016). In the interest of improving access, universities across the world have introduced *affirmative action* policies to diversify the profile of their student intake and increase the participation of disadvantaged individuals who were traditionally less likely to attend university (Arcidiacono and Lovenheim 2016). As opposed to antidiscrimination measures in general, affirmative action involves explicit pro-active steps to erase differences between social groups (Holzer and Neumark 2000).

Most of the literature on affirmative action in higher education focuses on two main questions: who should such policies target, and whether affirmative action benefits those who gain admission (Bertrand, Hanna, and Mullainathan 2010). In England, affirmative action policy for higher education falls under the umbrella of a broader initiative called Widening Participation (WP) with the goal of increasing the rate of higher education participation by individuals from disadvantaged backgrounds (Gorard and Smith 2006). While some previous research has examined whether specific characteristics should be used as measures to widen participation (Adamecz-Völgyi, Henderson, and Shure 2020) or increase the enrolment of students from disadvantaged backgrounds for post-graduate courses (e.g. Wakeling and Kyriacou 2010), there is very little work looking at the relationship between markers of disadvantage, graduation, and labor market returns. Our first contribution is to fill this gap and document how 'first in family' (FiF) graduates, those whose (step) parents do not have a university degree, fare in the labor market in England. As FiF is a commonly used WP indicator by a range of universities (Henderson, Shure, and Adamecz-Völgyi 2020), we provide important evidence for university widening participation teams. These universities are not only interested in getting WP candidates 'through the door', but also in understanding how they fare at and beyond university. England is the ideal setting for this research thanks to its national, compulsory standardized examinations during school and centralized university admissions.

Our work also contributes to the extensive body of research that looks at the causes and evolution of the gender wage gap. A puzzling finding from this literature is that while on average, the gender wage gap is decreasing (Weichselbaumer and Winter-Ebmer 2005), it is still persistent at the top of the wage distribution or among the highly educated (Blau and Kahn 2017; Costa Dias, Elming, and Joyce 2016). De la Rica, Dolado, and Llorens (2008) and Albrecht, Bjorklund, and Vroman (2003) document for Spain and Sweden respectively that gender wage gap is higher at the top of the wage distribution even after controlling for education, industry and occupation, referring to this phenomenon as the *glass ceiling*. Based on their own research and a literature review, Francesconi and Parey (2018) discuss the role of human capital accumulation (educational attainment), choice of study, hours worked, parenthood, career interruptions and wage gain behind the graduate gender wage gap. To the best of our knowledge, no one has investigated the potential role of intergenerational educational mobility behind the graduate gender wage gap. The present paper aims to address this gap by looking at the heterogeneity of the gender wage gap by FiF status.

The existing evidence on how FiF individuals fare on the labor market is limited and contradictory. Manzoni and Streib (2019) show that there is a substantial gap in wages between first-generation and continuing-generation students (those whose parents have degrees) 10 years after graduation in the US. They find a similar raw 'generational' wage gap among men and women (11% and 9%, respectively). Controlling for race and motherhood decreases the gap to an insignificant 3% among women while controlling for these characteristics as well as for early educational attainment and labor market choices (industry, occupation, hours worked, and location) decreases the gap to an insignificant 4% among men. Simply comparing raw wages across FiF and non-FiF graduates in the 90's, Nunez and Cuccaro-Alamin (1998) find no difference in wages one year after graduation among those employed in the US. In this same period, Thomas and Zhang (2005) find a small FiF penalty shortly after graduation that increases to about 4% by the end of the fourth year on the labor market.

Whilst this paper uniquely focuses on labor market outcomes by FiF status in England, it builds on existing work that examines wage differences within groups of individuals who obtain university degrees (Chevalier and Conlon 2003; Britton, Shephard, and Vignoles 2015; Britton et al. 2016). Recently, research on returns to university in the UK has benefitted from the linkage of administrative schooling, higher education, and tax authority data. Britton et al. (2016) use the Longitudinal Education Outcomes (LEO) administrative data to examine heterogeneity in returns to university degrees by institution, subject, gender, and socioeconomic status. They find that graduates from higher-income households earn 25 percent more than their peers from low-income households, but that this earnings premium shrinks to 10 percent once institution and subject are included in their model. Belfield et al. (2018) use LEO data to differentiate between differences in earnings due to university courses and the differences between individuals on the same course. Most recently, Britton, Dearden, and Waltmann (2021) looked at the heterogeneity of returns to graduation by ethnicity and socio-economic status (SES). As the LEO data that they use has no information on parental income or education, they construct a measure of SES based on free school meal eligibility and a set of local area deprivation measures. They find that returns to graduation at age 30 vary little across SES-quintiles. While administrative data provides objective and accurate measures of earnings and large sample sizes, it does not include the same nuanced measures of socioeconomic status as cohort studies, including parental education.

Previous work on the labor market outcomes of graduates from disadvantaged backgrounds in the UK has been limited and relied on older cohorts. Bukodi and Goldthorpe (2011) examine the relationship between social class and labor market outcomes across three British cohort studies (born 1946, 1958, and 1970) and find that graduates from a salariat background are 20-30% more likely to stay in the salariat than their peers from disadvantaged backgrounds who also acquire a university degree. Crawford and Vignoles (2014) examine the differences in earnings between university graduates from advantaged and disadvantaged backgrounds and find that graduates who attended private school go on to earn seven percent more than their peers who attended state school almost four years after completing university. These differences also hold for university graduates from advantaged and disadvantaged backgrounds in the same occupation, indicating that this gap is not driven by university course choice. Other studies from the UK have affirmed this difference in earnings attributed to private schooling (Green et al. 2012; Dolton and Vignoles 2000). In a related measure of labor market returns, Macmillan, Tyler, and Vignoles (2015) find that graduates from disadvantaged backgrounds are less likely to end up in 'top jobs' than their advantaged peers. Bratti, Naylor, and Smith (2005) use the British Cohort Study (BCS), a cohort born in 1970, to examine how labor market returns to an undergraduate degree in the UK vary by socioeconomic status.

Henderson, Shure, and Adamecz-Völgyi (2020) provide the first descriptive evidence on FiF individuals in England. They find that FiF individuals are more likely to choose certain university subjects, including Economics and Law, than their non-FiF peers at university. They also find that FiF individuals are slightly more likely to take 'high earning' subjects (based on the classification from Walker and Zhu (2011)), but that this difference is only significant at the 10 percent significance level and they have not looked at any gender differences. Our work extends this by explicitly examining the difference between the labor market outcomes of FiF and non-FiF male and female graduates at age 25/26.

The main empirical section of this paper is divided into three parts. First, we compare the probability of employment, hours worked, and the annual and hourly wages of FiF and non-FiF graduates. This allows us to explore whether FiF graduates have different labor market outcomes than their graduate peers whose parents are graduates. We probe the relationships uncovered in this analysis using regression techniques and Blinder-Oaxaca (BO) decompositions. We use linked survey-administrative data on a sample of young people born in 1989/90 in England. While being FiF is not random, we exploit rich data on the observed pre-university characteristics of young people, including detailed childhood measures of family background and prior educational attainment. Furthermore, the data allow us to look at how university and employment choices and general adult life circumstances contribute to wage differences between FiF and non-FiF graduates.

As we find that the FiF wage gap is gendered, the second part of the paper looks at the graduate gender wage gap directly and shows that it is heterogeneous by FiF status. Third, we estimate the returns to graduation for the entire group of individuals who had the *potential* to go to university based on their secondary school attainment. This allows us to probe our earlier findings and disentangle the effect of an individual's graduation from an individual's family background.

Our results show that controlling for a rich set of pre-university individual characteristics, most importantly, for early educational attainment as a proxy for cognitive abilities, FiF graduate women face a 7.4% wage penalty in term of log hourly wages compared to their female peers who match their parents with a university degree. This association is stable across several robustness checks, including entropy balancing and propensity score matching. We find no evidence of this penalty for male FiF university graduates. In fact, we find that conditional on pre-university characteristics, male FiF graduates earn more on average than non-FiF male graduates, although this relationship is not stable across all robustness checks. We find no evidence of any meaningful FiF disadvantage for men or women in terms of the probability of employment or hours worked.

Turning to the potential channels of these differences in terms of university and employment choices, post-university life circumstances, and adult non-cognitive skills, we find that controlling for these characteristics somewhat attenuates the negative FiF hourly wage gap among women. We conduct a Blinder-Oaxaca decomposition of the FiF versus non-FiF graduate gaps to see how much of the gap comes from the different distributions of individual characteristics (*endowments*) between the two groups, and how much of it remains *unexplained* (i.e. comes from the different returns FiF and non-FiF graduates have to these characteristics).

We find that the theoretical FiF wage gap that emerges due to the different endowments of FiF and non-FiF graduates is similarly negative for men and women. However, FiF men compensate about two-thirds of this endowment gap by showing different returns to these characteristics. For women, on the other hand, different endowments explain two-thirds of the FiF penalty and they show no signs of compensation through differential returns. We propose that as potential FiF women are more likely to graduate than potential FiF men, men are more selected not just in their observed but probably also in their unobserved characteristics, which could explain why men compensate some of their social disadvantage but women do not.

Looking at the graduate gender wage gap, we find that it is more than two-times as large among FiF graduates as among non-FiF graduates. This result is intuitive, as earlier we show a FiF wage penalty among graduate women but not among men. We propose that women being more likely to be FiF than men as well as the female FiF wage penalty might offer an explanation as to why the graduate gender wage gap in early career is persistent over time (Blau and Kahn 2017; Costa Dias, Elming, and Joyce 2016).

Lastly, we find that the average returns to graduation in terms of hourly wage are insignificant and close to zero for both genders at age 25. However, these models also reveal that the association between being a potential FiF and wages are significantly positive among men and significantly negative among women. Thus, the gendered FiF-wage relationships that we see on the sample of graduates are not exclusive to graduates. It is clear though that the negative female FiF wage gap is the consequence of the large negative effect of having non-graduate parents in general and not the consequence of the returns to graduation being smaller among women with non-graduate parents. This implies that the intergenerational transmission of labor market advantage via parental education is gendered and not exclusive to graduates.

The rest of this paper proceeds as follows. We present the data in Section 2 and our empirical approach in Section 3. We compare the labor market outcomes of FiF and non-FiF graduates in Section 4. In Section 5, we look at the heterogeneity of the graduate gender wage gap by FiF status. We estimate the general returns to graduation for the population of individuals who had the potential to go to university in order to disentangle the effect of obtaining a degree from the effect of having parents without a university degree in Section 6. In Section 7 we offer some discussion before concluding.

2. Data

We use Next Steps (formerly the Longitudinal Study of Young People in England, LSYPE), which follows a cohort of children born in 1989/1990. Next Steps began in 2004 when the sample members were aged 13/14 and comprises eight waves of data until age 25/26.[1] This cohort of young people can be linked with the National Pupil Database (NPD), administrative data on all pupils attending schools in England, allowing us to access their national school exam results.

Respondents of the Next Steps study were selected to be representative of young people in England using a stratified random sample of state and independent schools, with disproportionate sampling for deprived schools, i.e. those in the top quintile of schools in terms of the share of pupils eligible to Free School Meals (Department for Education 2011).[2] In deprived schools, students of minority ethnic backgrounds were over-sampled to provide a sufficient number of observations for analysis (Centre for Longitudinal Studies 2018). Design weights were constructed to take care of the oversampling of deprived schools and ethnic minority students within deprived schools using inverse probability weighting such that "*the school selection probabilities and the pupil selection probabilities ensured that within a deprivation stratum, all pupils within an ethnic group had an equal chance of selection*" (Department for Education 2011).

Starting from Wave 1, attrition weights are published, estimated by stratum, to take care of the initial school-level non-compliance as well as individual attrition from the study. The weighting procedure differs by school type (independent vs. state schools) and takes into account both school-level and individual-level information. The final models to predict the probability of individual non-response differ in each wave, and the estimated probabilities are carried across waves as the study progresses.

Schools are the primary sampling units of Next Steps, then pupils within schools. The two-stage sampling design presents a possible clustering effect due to school-specific

[1] The timing of this cohort means that the young people were affected by New Labour education policy, which promoted diversity and flexibility in the 14-16 curriculum and introduced capped tuition fees in higher education before this cohort attended university. Despite universities being allowed to choose their fee amount, almost all UK institutions chose to charge the full £3,000 per annum fee (Wyness 2010). In addition to this policy change, the Next Steps cohort also faced some administrative changes in loan and grant entitlement, which ultimately did not result in an overall change to access to finances, rather changes in the application process (see Wyness (2010) for additional information). It is worth noting that most students do not have to pay their fees in advance of study and they can take out a government endorsed student loan for the full value of the fees and a contribution to the costs of living. These are 'income-contingent' student loans which mean that graduates only start to repay the loans when they are earning over a certain income threshold, which reduces some of the risk involved in higher education study.

[2] In the beginning of the study, 54 independent and 646 state-maintained schools were chosen, but almost half of the independent schools (especially those in inner-London) and a fifth of state schools decided not to participate. The first wave thus started with a 21,000-observation issued sample of 13/14-year-old pupils in 28 independent and 646 maintained schools with an average response rate of 74%, resulting in a 15,770-observation initial sample. In Wave 4, a 600-participant ethnic boost sample were added to the study, selected from the schools that were chosen at the beginning but did not cooperate in Wave 1 (Centre for Longitudinal Studies 2018).

unobserved random shocks. We account for the potential within-school correlation of the error terms via the application of clustered robust standard errors as suggested by Abadie et al. (2017). In the first four waves both young people and their parents were interviewed, and the information content of all variables on family background and parental education that we use in this paper was reported directly by the parents. From Wave 5, only young people were interviewed.

In terms of information on employment, wages and university graduation, we use the Next Steps age 25/26 data which covers 7,707 young people, 49% of the actual sample of the first wave. All results that we present in this paper are weighted by the final weights that are constructed by the data provider to take care of initial oversampling of disadvantaged schools and ethnic minority students, school non-compliance, the Wave 4 ethnic boost, and attrition across all waves. In order to avoid dropping cases with missing or unknown information on background variables, we take the first available response over the first four waves. We take care of any remaining item non-response of explanatory variables using missing flags. As a robustness check, we reproduce our main results with mean imputation of the missing values in Table C3 in Appendix C.

We are looking at four outcome variables: employment, log annual wage, hours worked, and log hourly wage. Out of the 7,683 observations having data on employment, 81% worked in 2015 when the data were collected (Table 1). From the wage models, we exclude observations with outlier values on annual wage, hours worked, and hourly wage according to the following criteria. We exclude those whose annual wage is less than 50 GBP (14 observations) or more than 1,000,000 GBP (six observations), those who reported working less than one hour per week (nine observations) or more than 80 hours per week (10 observations), and those earning less than one GBP per hour (nine observations) or more than 200 GBP per hour (seven observations). We provide a robustness check to our main results (Model 4 in Table 3) in Table C2 in Appendix C to show that this step does not change our results. After this step, we are left with a total sample of 5,213 observations having data on hourly wages. As we do not observe wage data for everybody, as a robustness check we replicate our main results with controlling for the inverse Mills ratio of the probability of employment and reporting wage conditional on employment estimated in a Heckman-style selection equation in Table C6 in Appendix C. Although data on wages are self-reported in Next Steps, comparisons with recent estimates of the returns to university graduation using administrative tax return data (Belfield et al. 2018) are very similar to the estimates obtained using Next Steps, which gives us confidence in the quality of the wage data (Table C1 in Appendix C).[3]

In our sample, 27% of young people have graduated from university. The most comparable statistics capturing the share of graduates in this cohort comes from the Annual Population Survey (APS) and gives a higher estimate, 39.6% (Office For National Statistics 2019). There are however significant differences between the two samples and the two definitions. The APS samples everyone who lived in England in 2015 and is aged 25/26, while Next Steps includes only those who have lived in England since age 13/14. The APS graduation rate also takes all types of Level 4 degrees into account, while in Next Steps we only look at BA/BSc and higher university degrees (and thus exclude Level 4 specifications below university degree level).

Out of university graduates, 68% are first in family (FiF) (Table 1), i.e. none of their (step) parents have earned a university degree (BA, BSc or above).[4] Note that the share of FiF among graduates would be 45% in Next Steps if we used the same definition of parental graduation as the UK Higher Education Statistical Agency (HESA) that considers parents as graduates not only if they hold university degrees but also if they hold below-degree level higher education diplomas or certificates. We have chosen the definition of FiF in this paper to stay in line with WP policy.

Table 1: Descriptive statistics

	Total sample			Men			Women			Gender gap
	Obs	Mean	SE	Obs	Mean	SE	Obs	Mean	SE	(women –men)
Employed	7,683	0.81	0.01	3,417	0.84	0.01	4,266	0.78	0.01	-6 pp
Annual wage	5,374	22413	377	2,381	24,901	617	2,993	19834	417	-20%
Hours worked per week	6,196	37.99	0.18	2,870	40.28	0.25	3,326	35.41	0.25	-4.9
Hourly wage	5,213	11.20	0.15	2,328	11.70	0.22	2,885	10.69	0.22	-9%
Parents have no degree	7,664	0.84	0.00	3,403	0.83	0.01	4,261	0.84	0.01	1 pp
Graduated	7,707	0.27	0.01	3,426	0.25	0.01	4,281	0.28	0.01	3 pp
FiF	7,664	0.18	0.00	3,403	0.16	0.01	4,261	0.20	0.01	4 pp
FiF among the graduated	2,689	0.68	0.01	1,155	0.64	0.02	1,534	0.71	0.01	7 pp

Obs refers to the number of non-missing observations. Total number of unweighted observations: 7,707. Weighted using Wave 8 weights.

[3] Following Belfield et al. (2018) as closely as possible, we estimated returns to graduation using a sample of individuals having at least five A*-C GCSE examinations in Next Steps, using log annual wages measured at age 25/26 as the dependent variable and controlling for the same background characteristics and prior school achievements as Belfield et al. (2018), separately for men and women. While there are some inherent differences in the data and the setup between Belfield et al. (2018) and Next Steps, we have received quite similar returns to graduation estimates (subsection C1: in Appendix C).

[4] Information on parental education is missing for 43 observations in the sample. We provide a robustness check to this problem in subsection C5: in Appendix C.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Women are six percentage points less likely to work, and if they do, they work about five hours less per week than men (Table 1). The raw gender wage gap is 20% in annual wages and 9% in hourly wages. Women are three percentage points more likely to be graduated, and among graduates, seven percentage points more likely to be FiF.

Interestingly, while among those whose parents are graduates (not-potential FiF), women are 1 percentage points less likely to graduate than men, among the potential FiF (i.e. whose parents are not graduates) women are 4 percentage points more likely to graduate than men (Table 2). Thus, it is only true among the potential FiF that women are more likely to graduate than men.

Comparing the means of the four labor market outcomes (Table 2), FiF graduates are about as likely to be employed as graduates whose parents are also graduates (89% and 87%, respectively), but they are a lot more likely to be employed than non-graduate individuals whose parents are not graduates (89% vs. 77%). In terms of annual and hourly wages, graduates whose parents are also graduated earn the most, both on average and among each gender (Table 2). Interestingly, they work the most hours per week as well. Among university graduates, FiF graduates earn on average 14% less annually and 9% less hourly than non-FiF university graduates. The raw FiF wage penalty is higher for women than for men: 17% vs. 10% per annum and 15% vs. 2% per hour.

Looking at the gender difference in the two potential FiF groups, we see no meaningful gender gap in the probability of employment and in hours worked (Table 2). There is however a gender gap in annual (-15%) and hourly wages (-8%). Interestingly, in hourly wages, there is only a gender gap in the FiF group (14%).

Table 2: Descriptive statistics by groups

	Total			Men			Women			Gender gap (women –men)
Group	Obs	Mean	SE of Mean	Obs	Mean	SE of Mean	Obs	Mean	SE of Mean	
Graduation										
Not potential FiF (at least one parent is graduate)	1,490	0.52	0.01	706	0.53	0.02	784	0.51	0.02	-1 pp
Potential FiF (neither parent is graduate)	6,174	0.22	0.01	2,697	0.20	0.01	3,477	0.24	0.01	4 pp
Employment										
Downward mobile	667	0.86	0.02	317	0.88	0.02	350	0.83	0.02	-5 pp
Matching parental non-graduation	4,302	0.77	0.01	1,930	0.81	0.01	2,372	0.72	0.01	-9 pp
FiF	1,853	0.89	0.01	759	0.88	0.01	1,094	0.89	0.01	1 pp
Matching parental graduation	818	0.87	0.01	388	0.87	0.02	430	0.87	0.02	0 pp
FiF gap: FiF- Matching parental graduation (pp)		1.4			0.7			1.9		
Annual wage										
Downward mobile	476	25,759	2,010	222	27,920	3552	254	23,550	1,824	-16%
Matching parental non-graduation	2,789	20,095	458	1,265	23,176	761	1,524	16,646	441	-28%
FiF	1,447	24,464	555	583	26,742	923	864	22,604	658	-15%
Matching parental graduation	635	28,558	1,407	298	29,646	1933	337	27,376	2,056	-8%
FiF gap: FiF- Matching parental graduation (%)		-14%			-10%			-17%		
Hours worked										
Downward mobile	552	39.46	0.54	270	41.11	0.75	282	37.57	0.74	-3.5
Matching parental non-graduation	3,321	37.04	0.25	1,598	40.21	0.34	1,723	33.08	0.34	-7.1
FiF	1,606	39.08	0.31	664	39.80	0.46	942	38.48	0.43	-1.3
Matching parental graduation	689	40.62	0.45	324	40.88	0.66	365	40.35	0.61	-0.5
FiF gap: FiF- Matching parental graduation (hours per week)		-1.5			-1.1			-1.9		
Hourly wage										
Downward mobile	459	12.05	0.63	216	11.57	0.51	243	12.54	1.17	8%
Matching parental non-graduation	2,699	10.41	0.20	1,237	11.02	0.30	1,462	9.71	0.27	-12%
FiF	1,414	12.10	0.26	574	13.08	0.46	840	11.28	0.27	-14%
Matching parental graduation	616	13.32	0.54	289	13.29	0.44	327	13.34	1.03	0%
FiF gap: FiF- Matching parental graduation (%)		-9%			-2%			-15%		

Total number of unweighted observations: 7,707. Weighted using Wave 8 weights. Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

3. Empirical approach

Throughout this analysis, we look at the relationship between intergenerational educational mobility and four outcome variables at age 25/26: the probability of employment, log annual wage, hours worked, and log hourly wage. Employment is a binary variable indicating whether the individual is employed or not. Hours worked is continuous variable indicating how many hours one works during a usual work week. Log wages are continuous variables capturing the natural logarithm of self-assessed gross annual and hourly wages. Naturally, we only observe wages only for those who were working at the time of the data collection and reported wage data. As mentioned before, on average, 81% of the sample work and 82% of those employed report wage data (Table 1). In Table C6 in Appendix C, we provide a robustness check to investigate any potential estimation bias due to selection to employment and reporting a wage.

We are using observational data and cannot exploit a random or natural experiment to identify the causal effects of being FiF on labor market outcomes. We do not claim that our findings are causal; instead, we aim to decrease the selection bias by using a rich set of control variables, including prior educational attainment to control for ability and compulsory school progression to get closer to the causal impacts of intergenerational educational mobility on labor market outcomes. As robustness checks, we explore quasi-experimental methods, entropy balancing and propensity score matching techniques.

This paper looks at FiF graduates from three angles. First, we look at differences in the labor market outcomes of FiF and non-FiF university graduates. Second, we look at whether the graduate gender wage gap is heterogeneous by FiF status. Third, we estimate returns to graduation among those who could have been able to go to university based on their secondary school achievements.

3.1. Comparing the labor market outcomes of FiF and non-FiF graduates

We start by examining whether being first in family influence the probability of employment, hours worked, and wages among graduates, conditional on pre-university individual characteristics. Note that being FiF, i.e., parental education, could theoretically have already affected some of these characteristics well before going to university (such as test scores at age 11 and 16) and thus they might be *bad controls* (Angrist and Pischke, 2009). This would most likely cause a downward bias in terms of the magnitude of the estimated FiF coefficients. To address these concerns, we differentiate between *control variables* and *potential channels* of the effects of being FiF on labor market outcomes based on the timing of observation. Individual characteristics observed before university participation are considered as controls and they are included in our main model in subsection 0, while variables observed after going to university are considered as channels and added to the model in subsection 4.2.

We estimate the following linear regression models:

$$y_i = a_1 + b_1{*}FiF_i + c_1{*}X_i + u_{1i} \quad (1)$$

where

y_i	is one of the four outcome variables;
FiF_i	is a binary variable taking the value '1' when neither of the individual's (step) parents have a university degree;
X_i	is a vector of pre-university individual characteristics; and
u_{1i}	is an error term, robust and clustered by sampling schools.

In the first model, we do not include any control variables besides FiF (Model 1). In Model 2, we control for whether the individual belongs to the boost sample. Then, following the empirical strategy of Blundell, Dearden, and Sianesi (2005) and Belfield et al. (2018), we control for demographic and family background characteristics (individuals' age measured in months, ethnicity, fixed effects (FE) for the region of school at age 13/14, whether individuals were born in the UK, and mother's and father's age, mother's and father's social class, and the number of siblings, all measured when individuals aged 13/14, and lastly, for free school meal (FSM) eligibility in age 15/16), as well as whether individual *i* belongs to the sample boost added to the survey in Wave 4, in Model 3.[5] Lastly, we extend the model with Key Stage 2 exam score quintiles[6], measured at age 11, in math and reading as a proxy for cognitive abilities, and with capped linear GCSE (Key Stage 4) score[7] quintiles measured at age 16 to control for educational progression in compulsory schooling in Model 4. We include the quintiles of test scores instead of their continuous values because it allows us to include a

[5] As a further specification, we aimed at estimating a further type of model that included sampling school fixed effects (FE). However, the number of observations did not allow the inclusion of 647 school indicator variables.

[6] English schools monitor the attainment of children throughout compulsory education by means of national examinations called Key Stages. These exams are taken at age 7 (Key Stage 1), 11 (Key Stage 2) in primary school, and 14 (Key Stage 3), 16 (Key Stage 4/General Certificate of Secondary Education/GCSE) in secondary school. At age 18 students take A-level examinations (Key Stage 5) or equivalent vocational qualifications, which are generally seen as a prerequisite for participation in higher education (although other routes are possible) (Anders and Henderson 2019). The subjects which comprised key stages from September 2014 are: Maths, English, science, history, geography, art and design, physical education, music, languages (Key Stage 2 and Key Stage 3), computing, design and technology, citizenship education (Key Stage 3) (Roberts 2018).

[7] Capped linear GCSE scores are capped to the best eight subjects studied and the grades translated into a linear score where the worst grade, G, is allocated 16 points and thereafter each grade improvement is worth six additional points. This variable was derived by the Department for Education and is commonly used as a measure of attainment at age 16.

missing category for the proportion of our dataset that did not have the successful link to administrative education data. To make sure that not missing values (or the categorization) drive our results, we provide a robustness check in Table C3 in Appendix C where we use the scores themselves and apply mean imputation (and a separate missing dummy) for the missing values. We consider Model 4 as our main model. First, we control for the missing values of the explanatory variables using missing flags as mentioned above, except in the case if first in family. The number of missing values of FiF among graduates is eight among men and 10 among women in the total sample of graduates and six and nine, respectively, among those reporting hourly wage. We drop these observations and provide a robustness check showing that not dropping these observations lead our results. In particular, we re-estimate our main results allocating either 0 or 1 to all individuals with missing FiF and show that our results stay similar in Table C5 in Appendix C. We provide a robustness check where we employ mean imputation for the missing values of the key control variables in Table C3 Appendix C. The descriptive statistics of all variables in the models are shown in
Table A1 in Appendix A.

We provide three further robustness checks to these main results in Appendix C. First, we apply two quasi-experimental evaluation methods in subsection C4: entropy balancing and propensity score matching. These results confirm that the negative FiF wage gap is robust among women; however, the positive FiF wage gap among men is not (Table C4).

Second, as mentioned before, we do not observe wage data for all individuals. We aim at controlling for selection to employment and reporting wage using a selection model (Heckman, 1979) in Table C6 in Appendix C. While we have to rely on the same control variables that we used before (i.e., no exclusion restriction), we believe that the fact that these models are estimated on the full sample, we still exploit additional information. These results again confirm that the negative FiF wage gap in hourly wages is robust among women; however, the positive FiF wage gap among men is not.

Finally, we apply two methods to look at the potential channels of the estimated relationship between FiF and labor market outcomes. First, we extend the main model (Model 4) with a set of university and post-university variables using the same regression framework in subsection 4.1. Second, we decompose the raw FiF gaps using a Blinder-Oaxaca decomposition (Blinder 1973; Oaxaca 1973) and estimate the share of the gap originating from the different distribution of individual characteristics (*endowments*) across FiF and non-FiF graduates in subsection 4.2. This method reveals how large of a share of the gap is the consequence of the different endowments of FiF and non-FiF graduates, and how large of a share remains unexplained. We apply common coefficients estimated from a pooled regression (Neumark 1988); thus, the estimated coefficient of the unexplained gap is identical to the coefficient of FiF in a regression model that pools together the data of the two groups and controls for FiF as well as the same control variables (as Model 5 in Table 4). In other words, the unexplained gap in the pooled Oaxaca model is the gap that still remains after controlling for all control variables. The value added of the method compared to a regression is that it shows how large is the relative contribution of each endowment to the raw gap as well as how the returns to these characteristics differ across the two groups in one step.

3.2. The heterogeneity of the graduate gender wage gap by FiF status

Next, we turn to looking at the graduate gender wage gap and investigate whether it differs between FiF and non-FiF graduates in Section 5. We start by estimating similar equations as previously described, but we pool the data of men and women and control for gender, FiF, and the interaction of FiF and gender. Next, we apply a Blinder-Oaxaca decomposition again, but while previously we decomposed the FiF gaps separately among male and female graduates, this time we decompose the gender gaps separately among FiF and non-FiF graduates.

3.3. Estimating returns to graduation

In Section 6, we estimate the returns to graduation for a subsample of Next Steps (including those who did and did not go to university) and look at whether they are heterogeneous by parental graduation. We follow Belfield et al. (2018) and construct a subsample of those who could theoretically have gone to university, i.e. achieved high-enough grades at the GCSE exams at age 16 (at least five A*-C GCSEs). This would have enabled them to pursue A-levels, and therefore university, and should assuage some concerns about the comparability of the control group. We then estimate the following wage models separately by gender:

$$\text{wage}_i = a_2 + b_2{*}\text{graduate}_i + c_2{*}X_i + u_{2i} \qquad (2)$$

where

wage_i is log hourly wages,

graduate_i is a binary variable capturing whether individual *i* is a university graduate;

X_i is a vector of individual characteristics, which in some models includes:

$\text{parents\_nodegree}_i$ is a binary variable capturing whether individual *i's* parents do not have university degrees;

FiF_i is the interaction of ‘parents_nodegree’ and ‘graduate’;

u_{2i} is an error term, robust and clustered by sampling schools.

We estimate equation (2) using ordinary least squares and sequentially introduce our control variables as before. In Model 1, we do not control for any other characteristics than the variables of interest, ‘$graduate_i$’. In Model 2, we add whether the individual belongs to the sample boost added to the survey in Wave 4, along with demographic and family background characteristics (age in months, mother’s and father’s social class, region at age 13/14, ethnicity). In Model 3, we add pre-university educational attainment (GCSE and A-level raw scores) as well as indicator variables for A-level subjects (Math, Sciences, Social science, Humanities, Arts, Languages and Other), whether attended Level 3 studies, whether obtained vocational qualifications, and whether attended independent secondary school at age 13/14. In Model 4, we add potential FiF (i.e. parents without a university degree, non-graduates) and in Model 5 we add the interaction term of potential FiF and whether or not the individual obtained a university degree. This allows us to disentangle the effects of an individual’s own graduation from their parents’ educational attainment.

4. The FiF gap in labor market outcomes

Main results and robustness checks**Error! Not a valid bookmark self-reference.** This relationship is significant at the 10 percent significance level.

Table 3: The FiF gap in labor market outcomes (Model 4)

	(1) Employed Men	(2) Employed Women	(3) Log annual wage Men	(4) Log annual wage Women	(5) Hours worked Men	(6) Hours worked Women	(7) Log hourly wage Men	(8) Log hourly wage Women
FiF	0.026	0.003	0.044	-0.059	-1.129	0.523	0.075**	-0.077*
	(0.031)	(0.024)	(0.042)	(0.044)	(0.781)	(0.688)	(0.037)	(0.040)
Constant	0.996	0.894	8.466***	8.154***	14.832	51.895**	1.981	0.637
	(0.827)	(0.674)	(1.309)	(1.147)	(28.594)	(23.415)	(1.206)	(0.899)
No. of unweighted observations	1,147	1,524	863	1,167	863	1,167	863	1,167
R-squared	0.086	0.076	0.218	0.186	0.144	0.139	0.186	0.140

Sample of university graduates. Weighted using Wave 8 weights. Robust standard errors clustered by school in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers’ and fathers’ age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are controlled for using missing flags. Interpretation of the estimated coefficients: Employment: All coefficients are interpreted as one-hundredths of a percentage point, i.e. 100 times the coefficients are interpreted as percentage points. Hours worked: number of hours per week. Log annual and hourly wage: coefficients are in log points and may be transformed to percentages through the following transformation: $100*(e^{beta} – 1)$, where beta is the estimated coefficient.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

We provide several robustness checks to these results in Appendix C. We get very similar results when we do not exclude the outlier values of wages and hours worked (Table C2), when we use mean imputation to handle the missing values of the control variables instead of missing flags (Table C3), and when we assign all missing values of FiF to be either 0 or 1 (Table C5). Applying entropy-balanced weights and propensity score matching (Table C4) shows that the negative FiF wage gap is robust among women; however, the positive FiF wage gap among men is not. Controlling for the probability of employment and reporting wage again confirms that the negative FiF wage gap in hourly wages is robust among women but the positive FiF wage gap among men is not (Table C6).

4.1. Potential channels of FiF hourly wage differences

In Table 4, we extend our main wage model (Model 4 in Table 3) to look at whether adding further control variables to the model changes the magnitude of the estimated FiF gap on the sample of graduates. The goal here is to identify variables that may be driving the FiF gap. We include measures on the details of university degree (university quality, subject choice), the details of employment and finding a job, fertility and living conditions, and non-cognitive skills. We think about these measures as potential channels of the effects of being FiF on wages, and we are interested in whether they attenuate the FiF gap. Note that any of these variables, just as some of the earlier control variables that we used in the main model, could be *bad controls* (Angrist and Pischke 2008) in the sense that they could already be the consequence of parental education. Model 1 in in Table 4 is our previous main model (i.e. the same as Model 4 in Table 3), which we include as a point of comparison.

One potential source of the female FiF penalty could be if FiF graduates study at lower quality institutions or do degrees in lower return subjects. Thus, in Model 2, we add variables on the details of the university degree of individuals, on top of the variables used in the main model. These are:

- Having an MA/MSc degree (as opposed to a BA/BSc);

- University course in seven categories: Medicine; Sciences; Engineering, tech, architecture; Law and business; Social sciences, humanities, languages; Education; Other;
- Attending a Russell Group university[8] (a group of 24 research intensive universities, often used as a measure of elite university);
- Having a student loan;
- Working while at university at age 19/20 in wave 7 as a career step or for other reasons.

Second, it also may be that they choose different occupations, work in different industries, have different preference about jobs, or they have less social capital that would help them to find good jobs, than non-FiF graduates. In Model 3, we add variables on the details of employment on top of the variables used in the previous model:

- Preference for a high-paying job at age 13/14;
- Finding job through social network;
- Whether qualification was needed to get current job;
- Working more than 45 hours a week;
- Working part-time;
- Occupation (1-digit Standard Occupational Classification (SOC) code);
- Industry (1-digit Standard Industrial Classification (SIC) code);
- Living in London;
- Employment tenure in month;
- Firm size (small, medium, large).

Another potential explanation for why we observe a FiF penalty for women may be that FiF women might be more likely to have children earlier than their non-FiF graduate peers. If they have already taken time out of the labor market to have children, they may face a child penalty, which might explain part of the FiF penalty. Similarly, they might also make different living and mating choices. Thus, in Model 4, we add variables on their amily and living circumstances at age 25/26 on top of the variables used in the previous model:

- Having a partner: defined as a partner living in the same household;
- Living with parents;
- Having children (binary).

[8] See https://russellgroup.ac.uk/about/ for more detail.

Lastly, it may be that FiF graduates have different non-cognitive skills than their non-FiF graduate peers, which leads to lower labor market outcomes. Thus, we test this hypothesis by adding non-cognitive measures measured at age 25/26 in Model 5 including:

- Locus of control: the extent to which participants believe that they have control over events in their lives; derived using a 4-item scale based on (Lefcourt 1991);
- Trust: how trusting individuals would say themselves in other people on a scale from 0 to 10;
- Risk-taking: how willing individuals are to take risks on a scale from 0 to 10; and
- Patience: how patient individuals believe themselves on a scale from 0 to 10.

Table 4 shows the main estimated coefficients on FiF in the five models (while the detailed version of the table including the estimated coefficients on all control variables is reported in Table O2 and Table O3 in the Online Appendix). The descriptive statistics of the channels are reported in Table A2 in Appendix A. For men, the estimated significant, positive effects survive through all five models, and the magnitude of the estimated coefficients stay similar. For women, adding information on the university degree slightly decreases the originally estimated coefficient from -0.077 to -0.059; adding the details of employment has no effect on the magnitude of the coefficient (-0.054), while adding information on family circumstances again cause a small decrease (-0.051). Lastly, adding variables on non-cognitive skills produces a coefficient of -0.047. While this effect is not significant, its magnitude is not different in a statistical sense from the one estimated in Model 1 (two-sided t-test p-value= 0.5725).

Table 4: The FiF gap in log hourly wages: potential channels

	Model 1	Model 2	Model 3	Model 4	Model 5
		Men			
FiF	0.075**	0.075**	0.099***	0.106***	0.100***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Constant	1.981	2.222*	1.812	1.753	1.596
	(1.206)	(1.213)	(1.123)	(1.114)	(1.127)
Observations	863	863	863	863	863
R-squared	0.186	0.213	0.377	0.386	0.394
		Women			
FiF	-0.077*	-0.059	-0.054	-0.051	-0.047
	(0.040)	(0.038)	(0.036)	(0.036)	(0.035)
Constant	0.637	0.418	1.008	0.917	1.057
	(0.899)	(0.905)	(0.820)	(0.821)	(0.822)

Observations	1,167	1,167	1,167	1,167	1,167
R-squared	0.140	0.202	0.348	0.353	0.363
Control variables					
Sample boost	yes	yes	yes	yes	yes
Demographics and family background	yes	yes	yes	yes	yes
Early educational attainment	yes	yes	yes	yes	yes
Educational progression	yes	yes	yes	yes	yes
Details of HE degree		yes	yes	yes	yes
Details of employment and finding a job			yes	yes	yes
Family and living conditions				yes	yes
Non-cognitive skills					yes

Sample of university graduates. Linear regression models estimated by OLS, weighted using Wave 8 weights. Robust standard errors clustered by sampling school are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); region at age 13; whether born in the UK; mothers' and fathers' age, mothers' and fathers' social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. Details of HE degree: having an MA degree; course (7 categories: Medicine; Sciences; Engineering, tech, architecture; Law and business; Social sciences, humanities, languages; Education; other); going to a Russell Group university, having student loan; working while at university. Details of employment and finding a job: industry, occupation, preference for a high-paying job at age 13, finding job through social network, whether qualification was needed to get current job, working more than 45 hours a week; occupation (1-digit SOC); industry (1 digit SIC), living in London, firm size, employment tenure. Family and living conditions: having children; living with parents; having a partner. Non-cognitive skills: locus of control; preference for risk; patience; trust. The missing values of control variables are controlled for using missing flags.

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4.2. Blinder-Oaxaca decomposition of the FiF gap

The Blinder-Oaxaca decomposition separates the FiF wage gap into an *explained* part that is the consequence of FiF and non-FiF graduates having different individual characteristics (*endowments*) and an *unexplained* part that consists of the different returns they have to these characteristics. In all decompositions presented below, we control for the same variables as in Model 5 in Table 4 in the previous section. As we have seen in Table 2, the raw FiF gap is negative in terms of log annual and hourly wages, both for women and men. Testing the raw gap formally reveals that for men, the gap in log hourly wages is small and insignificant (0.043, Table 5). The difference in the endowments between FiF and non-FiF graduates would suggest a larger wage penalty on FiF graduate men, 0.143; however, almost 70% of this difference (0.100) is counterbalanced by the different returns FiF male graduates have to those characteristics (unexplained gap). Note that the unexplained gap coefficient is the same as the coefficient on FiF in Model 5 in

Table 4 4; thus, this is the statistical relationship between FiF and log hourly wages after controlling for the same characteristics. In the case of women, endowments explain 0.086 out of the 0.133 raw gap in log hourly wages, and the role of returns to those characteristics (the unexplained gap) is insignificant (0.047, just as the coefficient of FiF in Model 5 in Table 4).

As mentioned before, the value added of the BO decomposition compared to simple regression models is that it allows to look at the relative contribution of each endowment to the endowment gap, as well as to look at which characteristics might bring higher or lower returns to FiF graduates than to non-FiF graduates. In terms of endowments, the detailed results in Table B2 in Appendix B show that it contributes towards FiF graduates earning less that they are less likely to work in a job where their highest degree is needed and they are also less likely to work for large firms than non-FiF graduates for both genders. For men, relative family disadvantage (FSM eligibility) also contributes to the endowment gap, as well as whether they live with their parents. For women, being less likely to make it to the highest quintile of math test scores at age 11, being less likely to go to a Russell Group university, being more likely to choose Education as a university course and being more likely to have a child than non-FiF graduate women contributes to the female FiF endowment gap.

In terms of the returns to these characteristics, both FiF men and women seem to earn relatively less if they are White than non-FiF graduates, while FiF men are able to compensate some of the gap if they were born in the UK, choose Engineering as a university subject, or have a student loan. For women, it contributes toward the FiF penalty (i.e., offers lower returns to FiF women than to non-FiF women) if they studied Social science, humanities or languages, had high reading test scores in age 11, or found their job through their social network.

Even though we see some differential returns between men and women, we cannot entirely explain why men compensate their FiF disadvantage while women do not. We propose that as potential FiF women are more likely to graduate than potential FiF men while among not-potential FiF young people there is no such gender difference (Table 2), men are more selected not just in their observed but probably also in their unobserved characteristics, which could explain why men compensate some of their social disadvantages but women do not. Solving this puzzle entirely, however, remains open to future research.

Table 5: Blinder-Oaxaca decomposition of labor market outcomes of graduate men and women by FiF status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employed	Employed	Log annual wage	Log annual wage	Hours worked	Hours worked	Log hourly wage	Log hourly wage
	Women	Men	Women	Men	Women	Men	Women	Men
Non-FiF	0.875***	0.872***	10.088***	10.154***	40.907***	41.931***	2.457***	2.494***
	(0.018)	(0.019)	(0.031)	(0.032)	(0.586)	(0.588)	(0.027)	(0.027)
FiF	0.894***	0.879***	9.907***	10.064***	39.154***	40.338***	2.324***	2.451***
	(0.011)	(0.014)	(0.020)	(0.025)	(0.379)	(0.450)	(0.015)	(0.021)
FiF gap	-0.019	-0.007	0.181***	0.090**	1.752**	1.593**	0.133***	0.043
	(0.021)	(0.023)	(0.037)	(0.041)	(0.698)	(0.740)	(0.031)	(0.034)
Explained	-0.016	0.014	0.152***	0.169***	2.266***	0.980	0.086***	0.143***
	(0.015)	(0.020)	(0.033)	(0.038)	(0.646)	(0.690)	(0.026)	(0.031)
Unexplained	-0.003	-0.021	0.029	-0.079**	-0.514	0.613	0.047	-0.100***
	(0.023)	(0.027)	(0.034)	(0.037)	(0.481)	(0.574)	(0.031)	(0.034)
Observations	1,524	1,147	1,167	863	1,167	863	1,167	863

Sample of university graduates. Weighted using Wave 8 weights. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); region at age 13; whether born in the UK; mothers' and fathers' age, mothers' and fathers' social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. Details of HE degree: having an MA degree; course (7 categories: Medicine; Sciences; Engineering, tech, architecture; Law and business; Social sciences, humanities, languages; Education; other); going to a Russell Group university, having student loan; working while at university. Details of employment and finding a job: industry, occupation, preference for a high-paying job at age 13, finding job through social network, whether qualification was needed to get current job, working more than 45 hours a week; occupation (1-digit SOC); industry (1 digit SIC), living in London, firm size, employment tenure. Family and living conditions: having children; living with parents; having a partner. Non-cognitive skills: locus of control; preference for risk; patience; trust. The missing values of control variables are controlled for using missing flags.

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5. The graduate gender gap in labor market outcomes

We have previously showed that among graduates, there is a (raw) gender gap in hourly wages among FiF graduates, but there is no gender wage gap among graduates of graduate parents (Table 2). In this section we investigate this phenomenon in more depth. First, we estimate the same Mincer-type wage models as in subsection 0, but pool the data of men and women and control for gender. These results are presented in Table 6 and show that the graduate gender wage gap conditional on pre-university control variables is 0.115 in log annual and 0.088 in log hourly wages. Both of these gaps are statistically significant at the one percent significance level. Decomposing the gender gap by adding the interaction term of FiF and gender to the models confirms that most of the conditional graduate gender wage gap is indeed among FiF graduates. In terms of log hourly wages, the interaction term is -0.068 (statistically significant at the 10 percent level). This result, along with our earlier findings that FiF women are the more likely to graduate than FiF men and they face a FiF penalty in the labor market while men do not, might explain why the gender wage gap is decreasing on average but not among graduates (Blau and Kahn 2017; Costa Dias, Elming, and Joyce 2016).

Table 6: The gender-FiF gap in log annual and hourly wages (Model 4, genders pooled)

	Log annual wage			Log hourly wage		
	(1)	(2)	(3)	(4)	(5)	(6)
FiF		-0.008	0.030		-0.003	0.032
		(0.031)	(0.039)		(0.028)	(0.033)
Female	-0.115***	-0.117***	-0.067*	-0.085***	-0.088***	-0.042
	(0.026)	(0.026)	(0.040)	(0.021)	(0.021)	(0.034)
Female*FiF			-0.073			-0.068*
			(0.047)			(0.040)
Constant	8.077***	8.424***	8.437***	1.074	1.412*	1.424*
	(0.882)	(0.884)	(0.887)	(0.751)	(0.743)	(0.745)
No. of unweighted observations	2,045	2,030	2,030	2,045	2,030	2,030
R-squared	0.183	0.182	0.183	0.137	0.136	0.137

Sample of university graduates. Weighted using Wave 8 weights. Robust standard errors clustered by school in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers' and fathers' age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

5.1. Blinder-Oaxaca decomposition of the gender gap

Next, we repeat the BO exercise separately for FiF and non-FiF graduates, but this time we decompose the gender gap in Table 7. As we have seen before, the raw gender gap among non-FiF graduates is small and insignificant (0.037), while large and significant (0.127) among FiF graduates. More than half of this gap among FiF graduates, 0.073, is explained by the different endowments of FiF women as compared to FiF men. Interestingly, the unexplained gap, i.e. the statistical association between gender and log hourly wage after controlling for these characteristics, which is usually referred to as the upper bound of labor market discrimination, is about the same for non-FiF and FiF graduates (0.052 and 0.054).

Table 7: Blinder-Oaxaca decomposition of labor market outcomes of non-FiF and FiF graduates, by gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employed	Employed	Log annual wage	Log annual wage	Hours worked	Hours worked	Log hourly wage	Log hourly wage
	Non-FiF	FiF	Non-FiF	FiF	Non-FiF	FiF	Non-FiF	FiF
Men	0.872***	0.879***	10.154***	10.064***	41.931***	40.338***	2.494***	2.451***
	(0.019)	(0.014)	(0.032)	(0.025)	(0.588)	(0.450)	(0.027)	(0.021)
Women	0.875***	0.894***	10.088***	9.907***	40.907***	39.154***	2.457***	2.324***
	(0.018)	(0.011)	(0.031)	(0.020)	(0.586)	(0.379)	(0.027)	(0.015)
Raw gender gap	-0.003	-0.014	0.066	0.157***	1.025	1.184**	0.037	0.127***
	(0.026)	(0.017)	(0.045)	(0.032)	(0.830)	(0.588)	(0.038)	(0.026)
Explained	0.016	0.010	-0.004	0.079***	0.798	0.250	-0.015	0.073***
	(0.017)	(0.011)	(0.040)	(0.026)	(0.763)	(0.500)	(0.034)	(0.020)
Unexplained	-0.018	-0.025	0.070**	0.079***	0.227	0.935**	0.052	0.054**
	(0.025)	(0.020)	(0.034)	(0.027)	(0.614)	(0.429)	(0.036)	(0.023)
No. of obs.	818	1,853	616	1,414	616	1,414	616	1,414

Sample of university graduates. Weighted using Wave 8 weights. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); region at age 13; whether born in the UK; mothers' and fathers' age, mothers' and fathers' social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. Details of HE degree: having an MA degree; course (7 categories: Medicine; Sciences; Engineering, tech, architecture; Law and business; Social sciences, humanities, languages; Education; other); going to a Russell Group university, having student loan; working while at university. Details of employment and finding a job: industry, occupation, preference for a high-paying job at age 13, finding job through social network, whether qualification was needed to get current job, working more than 45 hours a week; occupation (1-digit SOC); industry (1 digit SIC), living in London, firm size, employment tenure. Family and living conditions: having children; living with parents; having a partner. Non-cognitive skills: locus of control; preference for risk; patience; trust. The missing values of control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Looking at the role of endowments, FiF women seem to differ from FiF men over similar domains as they differ from non-FiF women (Table B3 in Appendix B). Interestingly, making it to the fifth quintile of age-11 test scores matters in terms of explaining the gender wage gap, as well as choosing Social science, humanities and languages and Education as university subjects.

To understand more how gender and FiF interacts, we look at how the university and labor market choices of FiF and non-FiF graduate women differ in Table A3 in Appendix A. Indeed, FiF women are significantly less likely to study Science, more likely to study Education, less likely to go to Russell Group universities, and less likely work for large firms than non-FiF women or men. FiF men, on the other hand, are more likely to study Science and less likely to study Social sciences, humanities and languages than non-FiF graduate men. They are also more likely to have worked while at university and more likely to think that having a well-paying job is important than non-FiF men.

6. Disentangling the returns to graduation from parental education

The results found in the first part of this paper show a wage penalty for FiF women as compared to non-FiF graduate women but not for men. This penalty for FiF women could be driven either by lower returns to graduation for FiF women or a large penalty for having non-graduate parents (i.e. a socio-economic or family background penalty). To probe these two mechanisms, we now turn to our attention to estimating the returns to graduation on a sample of university graduates and young people who had the potential to go to university but did not.

For men, we find that gradually adding the previously mentioned control variables (whether the individual belongs to the sample boost; demographic and family background characteristics (age in months, mother's and father's social class, region at age 13/14, ethnicity); pre-university educational attainment (GCSE and A-level raw scores); indicator variables for A-level subjects (Math, Sciences, Social science, Humanities, Arts, Languages and Other); whether attended Level 3 studies; whether obtained vocational qualifications and whether attended independent secondary school at age 13/14) decreases the estimated raw returns to graduation from 8.1 log points (significant at the one percent significance level) in Model 1 to a non-significant -0.008 log points in Model 3 (Table 8). When we control for parental non-graduation in Model 4, it does not change the estimated average effect on graduation, and children of non-graduated parents tend to earn 8.1 log points more on average.

Looking at the differential effects of graduation across individuals of non-graduate and graduate parents in Model 5 reveals no significant difference across the two groups for men.

Table 8: Returns to graduation in log hourly wages

	Model 1	Model 2	Model 3	Model 4	Model 5
			Men		
Graduation	0.081***	0.054**	-0.008	-0.006	-0.009
	(0.027)	(0.027)	(0.030)	(0.030)	(0.047)
Parents have no degree				0.081***	0.079*
				(0.028)	(0.041)
FiF (graduation* Parents have no degree)					0.004
					(0.053)
Constant	2.383***	2.507***	2.063**	2.053**	2.053**
	(0.018)	(0.852)	(0.842)	(0.843)	(0.843)
No. of obs.	1,389	1,389	1,389	1,389	1,389
R-squared	0.009	0.077	0.130	0.134	0.134
			Women		
Graduation	0.102***	0.083***	0.018	0.014	-0.033
	(0.023)	(0.022)	(0.024)	(0.024)	(0.056)
Parents have no degree				-0.104***	-0.136***
				(0.033)	(0.047)
FiF (graduation* Parents have no degree)					0.061
					(0.059)
Constant	2.264***	-0.065	-0.604	-0.555	-0.555
	(0.017)	(0.713)	(0.717)	(0.707)	(0.705)
No. of obs.	1,948	1,948	1,948	1,946	1,946
R-squared	0.014	0.061	0.114	0.122	0.123
			Control variables		
Sample boost	Yes	Yes	Yes	Yes	Yes
Family background	No	Yes	Yes	Yes	Yes
Early and pre-university educational attainment	No	No	Yes	Yes	Yes

Sample of those having at least 5 A*-C GCSE examinations. Linear regression models estimated by OLS, weighted using Wave 8 weights. Robust standard errors clustered by sampling school are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Family background: age in months as a continuous variable, mother's and father's social class, region, ethnicity. Early and pre-university educational attainment: GCSE and A-level raw scores, indicator variables for A-level subjects as Math, Sciences, Social science, Humanities, Arts, Languages and Other, Level 3 studies, a binary variable for having vocational qualifications, a binary variable capturing whether the individual attended independent secondary school at age 13/14. Missing observations are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

For women, we find that adding background and educational variables decreases returns to graduation from 10.2 log points (significant at the one percent level) in Model 1 to an insignificant 0.018 log points in Model 3. Young people with non-graduate parents tend to earn on average 10.4 log points less (Model 4), and decomposing the effects of graduation across children of graduate vs. non-graduate parents reveals that returns to graduation are somewhat higher for the potential FiF (Model 5), although the difference is not significant.

The effects of having non-graduate parents among women is so highly negative though, that it is larger than the returns to graduation themselves. Thus, the negative effect of FiF that we have found earlier for graduate women is not the consequence of the returns to graduation being smaller among potential FiF women, but the consequence of the large negative effects of having non-graduate parents among women in general, irrespective from graduation.

7. Discussion and conclusion

This paper is the first to investigate the early career labor market outcomes of first in family university graduates in England. Our empirical approach allows us to examine whether FiF university graduates face a premium or a penalty on the labor market as compared to their peers who match their parents with a degree. Comparing the wages of a recent cohort of university graduates, we find that there is a substantial gender difference in the association between being first in family to graduate from university and wages at age 25/26. While for men, being FiF is not associated with lower wages, FiF women earn on average 7.4 percent less than graduate women whose parents are also graduates, net of the effect of earlier educational attainment and other measures of family background.

Once we conduct a Blinder-Oaxaca decomposition of this female FiF gap, it seems that taking a job which did not require their university degree, having lower prior attainment, and a degree from a less prestigious institution are important factors in explaining the female FiF penalty. This result is in line with Campbell et al. (2020) who find that high-attaining women at university tend to choose courses that offer lower expected earnings than men. The fact that FiF women may be "undermatching" in the labor market could indicate a larger role for university career services targeted at this disadvantaged group. Interestingly, the theoretical FiF wage gap that arises from the endowments of men and women are of similar magnitudes for both genders. However, men are able to compensate for two-thirds of their theoretical endowment gap while women are not. The first potential explanation for this puzzle is that the social pressure to contribute financially to their families, or to be a financial success, might be felt more acutely for FiF men than FiF women and hence men have a higher preference for well-paying jobs.

Second, being FiF is clearly not random. While we control for a rich set of individual characteristics, it is likely that some unobserved selection remains. Our analysis suggests that potential FiF women are more likely to graduate than potential FiF men, while among children of graduate parents there is no gender gap in the probability of graduation. Thus, male FiF graduates are more strongly selected than female FiF graduates. In terms of their observable characteristics, we see that the raw FiF wage gap changes more for men once we extend our wage models with individual characteristics than for women, which could be an indication of stronger selection. As FiF men seem to be more selected in their observable characteristics than FiF women, it seems reasonable to assume that they might be more selected in terms of their unobservable characteristics as well. Thus, it is possible that FiF men are able to compensate their disadvantages because they are more selected also in their unobserved abilities, skills, motivations and choices. Such unobserved variables could be, for example, personality characteristics like overconfidence or motivation, which could contribute to these results.

The third potential mechanism how FiF men compensate their social disadvantages could be firm choice. As in this paper we cannot control for firm fixed effects (only for industry, occupation and firm size), we have to leave the question open as to whether firm choice matters in explaining this gender puzzle. Lastly, there is recent evidence that women use their cognitive skills less at work than men (Pető and Reizer 2021), which might also be heterogeneous by FiF status.

A growing literature documents that while the gender wage gap is decreasing on average, it has remained stable among university graduates (Blau and Kahn 2017; Costa Dias, Elming, and Joyce 2016). Our findings on FiF women being more likely to graduate than FiF men and also facing a FiF wage penalty compared to non-FiF women suggests that gendered intergenerational educational mobility might play a role in the persistence of the graduate gender wage gap. Indeed, looking at the heterogeneity of the graduate gender wage gap by FiF status reveals that a substantial share of the gender wage gap is realized among FiF graduates. While non-FiF men and women are very similar to each other in terms of their educational attainment, university and employment choices and labor market outcomes, FiF women earn less due to having lower educational attainment prior to university, being more likely to study social sciences, humanities and languages and education, being more likely to work in occupations related to personal services, being less likely to think that having a well-paying job is important and having lower locus of control than FiF men. Even though the share of female graduates is increasing in the UK and worldwide as women are overtaking men in higher education participation and graduation, it seems that educational mobility provides lower returns to women. This might explain why the gender wage gap is not decreasing among university graduates.

With respect to the question of whether the penalty for FiF women is driven by lower returns to graduation for FiF women or a large penalty for having non-graduate parents (i.e. a socio-economic or family background penalty), we find evidence to support the latter. We use a sample of university graduates and young people who had the potential to go to university but did not. We find that the returns to graduation are not lower for women whose parents are not graduates compared to women whose parents are graduates. However, women face a large penalty on the labor market for coming from a less educated family – hence the female FiF penalty that we have found earlier. The results for men are again quite different from those for women: men with non-graduate parents earn on average more than men with graduate parents, irrespective of whether they themselves graduate or not. This surprising result might be due to the social pressure on men towards financial success; men with lower initial financial resources might be more motivated to earn more than men from wealthier families. The very different findings for women might be explained by gender differences in the effects of lower initial levels of financial resources and social capital, or differential levels of motivation or social pressure to improve their financial standing. Either way, this is a stark finding that indicates women face a larger penalty for their low SES background than men in early career labor market outcomes. Of course, these labor market returns are measured at age 25/26, which is arguably a very early career point. In fact, we even find that the average (conditional) returns to graduation in terms of log hourly wage is close to zero for both genders at this young age. It is possible that within this high-ability group, having three more years of work experience vs. going to university have similar returns on average; however, at older ages, this difference widens as seen in Belfield et al. (2018).

As discussed before, our results are based on the assumption that we observe all relevant information that affects parental education, university graduation and labor market outcomes and it is possible that this is not the case. Despite these challenges, we believe that controlling for a rich set of control variables, in particular, for early educational attainment, corrects for the ability bias which would most likely be the main source of unobserved heterogeneity driving labor market success (Britton et al. 2016). However, we cannot rule out the possibility of remaining sources of biases and thus do not claim that our results are causal estimates. Further research in this area should proceed towards developing credible identification strategies to examine the labor market consequences of educational mobility on men and women, especially as they progress in their careers.

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Appendix A: Descriptive statistics

Table A1: Descriptive statistics, sample of university graduates (employment outcomes and pre-university controls)

	Men			Women		
	Obs.	Mean	SD	Obs.	Mean	SD
Employed	1,155	0.88	0.33	1,534	0.89	0.32
Annual wage	887	27799	23920	1,210	24015	22335
Log annual wage	887	10.08	0.55	1,210	9.93	0.56
Hours worked per week	994	40.21	9.98	1,316	39.03	10.19
Hourly wage	869	13.18	8.97	1,176	11.89	10.32
Log hourly wage	869	2.47	0.44	1,176	2.36	0.41
Parents have no degree	1,147	0.65	0.48	1,524	0.71	0.45
Age	1,155	311.18	4.65	1,534	310.73	4.40
White	1,155	0.78	0.41	1,534	0.78	0.41
Boost sample	1,155	0.01	0.12	1,534	0.01	0.12
Region of school at age 13/14						
North East	1,155	0.03	0.16	1,534	0.06	0.25
North West	1,155	0.14	0.35	1,534	0.12	0.32
Yorkshire and The Humber	1,155	0.09	0.28	1,534	0.09	0.28
East Midlands	1,155	0.07	0.25	1,534	0.08	0.27
West Midlands	1,155	0.10	0.30	1,534	0.09	0.29
East of England	1,155	0.11	0.31	1,534	0.09	0.29
London	1,155	0.16	0.37	1,534	0.15	0.36
South East	1,155	0.15	0.35	1,534	0.13	0.34
South West	1,155	0.07	0.25	1,534	0.08	0.27
Region missing	1,155	0.10	0.29	1,534	0.11	0.31
Mother's age: below 35	1,155	0.04	0.20	1,,534	0.05	0.23
Mother's age: 35-44	1,155	0.57	0.50	1,534	0.56	0.50
Mother's age: 45-54	1,155	0.36	0.48	1,534	0.35	0.48
Mother's age: above 55	1,155	0.01	0.12	1,534	0.01	0.11
Mother's age: missing	1,155	0.02	0.12	1,534	0.02	0.13
Father's age: below 35	1,155	0.02	0.15	1,534	0.02	0.15
Father's age: 35-44	1,155	0.33	0.47	1,534	0.34	0.47
Father's age: 45-54	1,155	0.40	0.49	1,534	0.40	0.49
Father's age: above 55	1,155	0.07	0.26	1,534	0.06	0.24
Father's age: missing	1,155	0.18	0.38	1,534	0.18	0.38
Father's social class						
Higher Managerial and professional occupations	1,155	0.22	0.41	1,534	0.19	0.39

Lower managerial and professional o.	1,155	0.29	0.45	1,534	0.29	0.45
Intermediate occupations	1,155	0.07	0.25	1,534	0.07	0.26
Small employers and own account workers	1,155	0.13	0.34	1,534	0.13	0.34
Lower supervisory and technical o.	1,155	0.07	0.26	1,534	0.10	0.30
Semi-routine occupations	1,155	0.09	0.28	1,534	0.07	0.26
Routine occupations	1,155	0.06	0.24	1,534	0.07	0.26
Missing, or unemployed, or no parent	1,155	0.07	0.26	1,534	0.07	0.26
Mother's social class						
Higher Managerial and professional occupations	1,155	0.08	0.27	1,534	0.07	0.25
Lower managerial and professional o.	1,155	0.33	0.47	1,534	0.33	0.47
Intermediate occupations	1,155	0.17	0.38	1,534	0.18	0.39
Small employers and own account workers	1,155	0.05	0.22	1,534	0.06	0.23
Lower supervisory and technical o.	1,155	0.05	0.22	1,534	0.05	0.21
Semi-routine occupations	1,155	0.14	0.35	1,534	0.14	0.35
Routine occupations	1,155	0.06	0.24	1,534	0.07	0.25
Missing, or unemployed, or no parent	1,155	0.10	0.31	1,534	0.11	0.31
No. of siblings: 0	1,155	0.09	0.28	1,534	0.09	0.29
No. of siblings: 1	1,155	0.45	0.50	1,534	0.42	0.49
No. of siblings: 2	1,155	0.25	0.43	1,534	0.28	0.45
No. of siblings: 3	1,155	0.12	0.32	1,534	0.13	0.33
No. of siblings: 4 or more	1,155	0.08	0.27	1,534	0.07	0.26
No. of siblings: missing	1,155	0.02	0.14	1,534	0.01	0.11
FSM: eligible	1,155	0.07	0.25	1,534	0.06	0.23
FSM: missing	1,155	0.25	0.43	1,534	0.23	0.42
Born in the UK	1,155	0.90	0.30	1,534	0.91	0.28
Born in the UK missing	1,155	0.03	0.17	1,534	0.02	0.14
Math test score at age 11, lowest quintile	1,155	0.07	0.26	1,534	0.09	0.28
Math test score at age 11, 2nd quintile	1,155	0.10	0.30	1,534	0.15	0.36
Math test score at age 11, 3rd quintile	1,155	0.13	0.34	1,534	0.15	0.36
Math test score at age 11, 4th quintile	1,155	0.21	0.41	1,534	0.24	0.42
Math test score at age 11, highest quintile	1,155	0.34	0.47	1,534	0.25	0.43
Math test score at age 11, missing	1,155	0.15	0.36	1,534	0.13	0.33
Reading test score at age 11, lowest quintile	1,155	0.08	0.27	1,534	0.06	0.23
Reading test score at age 11, 2nd quintile	1,155	0.13	0.34	1,534	0.11	0.32
Reading test score at age 11, 3rd quintile	1,155	0.19	0.40	1,534	0.15	0.35
Reading test score at age 11, 4th quintile	1,155	0.22	0.42	1,534	0.24	0.43
Reading test score at age 11, highest quintile	1,155	0.24	0.42	1,534	0.32	0.47
Reading test score at age 11, missing	1,155	0.14	0.34	1,534	0.13	0.33
GCSE test score at age 16, lowest quintile	1,155	0.04	0.20	1,534	0.04	0.18
GCSE test score at age 16, 2nd quintile	1,155	0.11	0.32	1,534	0.08	0.27
GCSE test score at age 16, 3rd quintile	1,155	0.14	0.34	1,534	0.18	0.38
GCSE test score at age 16, 4th quintile	1,155	0.21	0.41	1,534	0.20	0.40
GCSE test score at age 16, highest quintile	1,155	0.29	0.45	1,534	0.31	0.46
GCSE test score at age 16, missing	1,155	0.21	0.41	1,534	0.19	0.39

Obs refers to the number of non-missing observations. Weighted using Wave 8 weights.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Table A2: Descriptive statistics, sample of university graduates (potential channels)

	Men		Women	
	Mean	SD	Mean	SD
Have student loan	0.86	0.34	0.87	0.34
Lives in London at age 25	0.25	0.43	0.22	0.41
Employment tenure in month	24.42	20.91	21.33	17.99
University subject: medicine	0.03	0.18	0.1	0.3
Sciences	0.29	0.45	0.2	0.4
Engineering, tech, architecture	0.11	0.31	0.02	0.13
Law and business	0.15	0.36	0.14	0.35
Social sciences, humanities, languages	0.31	0.46	0.38	0.48
Education	0.01	0.07	0.07	0.25
Other	0.01	0.11	0.01	0.11
Course missing	0.09	0.29	0.08	0.28
Russell Group university	0.26	0.44	0.24	0.43
Postgraduate degree	0.46	0.5	0.42	0.49
Worked while at uni as a part of career	0.06	0.24	0.07	0.26
Worked while at uniform other reasons	0.25	0.43	0.31	0.46
Found current job through social network	0.31	0.46	0.27	0.44
Found current job through social network: missing	0	0.07	0	0.03
Highest qualification was needed to get current job	0.66	0.48	0.65	0.48
Highest qualification was needed to get current job: missing	0	0.04	0	0.06
Works more than 45 hours per week	0.2	0.4	0.19	0.39
Occupation category: Managerial	0.03	0.18	0.02	0.12
Science and medical prof	0.14	0.35	0.14	0.35
Science associate	0.12	0.33	0.1	0.31
Administrative	0.07	0.26	0.11	0.32
Skilled trades	0.03	0.16	0.01	0.09
Personal service	0.04	0.19	0.12	0.32
Sales and customer service	0.18	0.39	0.23	0.42
Operative	0	0.06	0.01	0.08
Elementary trades	0.14	0.35	0.1	0.29
Missing	0.24	0.43	0.17	0.38
Industry: Agriculture, mining, construction	0.03	0.16	0.03	0.16
Manufacturing; food, textile	0.05	0.22	0.02	0.13
Manufacturing: electronics	0.03	0.16	0.02	0.15
Transportation	0.14	0.35	0.09	0.29
Trade	0.06	0.24	0.04	0.19
Finance	0.22	0.42	0.15	0.35
Services: trade	0.12	0.33	0.08	0.27
Services: caring	0.27	0.44	0.51	0.5
Public administration	0.04	0.19	0.03	0.17
Missing	0.05	0.21	0.04	0.19
Having well-paying job is important	0.65	0.48	0.54	0.5
Having well-paying job is important: missing	0.03	0.17	0.03	0.16
Working for a small firm	0.24	0.43	0.24	0.43
Working for a medium-sized firm	0.46	0.5	0.46	0.5
Working for a large firm	0.29	0.46	0.29	0.45
Firm size: missing	0.01	0.08	0	0.06
Having children	0.05	0.22	0.07	0.26
Partner	0.36	0.48	0.42	0.49
Living with parents	0.3	0.46	0.31	0.46
Living with parents: missing	0	0.05	0	0.02
High locus of control	0.21	0.4	0.15	0.36

Locus of control: missing	0.02	0.12	0	0.07
High risk tolerance	0.32	0.47	0.18	0.38
Risk tolerance: missing	0.01	0.09	0	0.05
High patience	0.38	0.48	0.37	0.48
Patience: missing	0.01	0.09	0	0.05
High trust	0.38	0.49	0.34	0.47
Trust: missing	0.01	0.08	0.00	0.05
No. of obs.	863		1167	

Sample of university graduates who have data on hourly wage and parental education (sample of Table 3 and Table 4). Weighted using Wave 8 weights.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Table A3: Gender*FiF gap in potential channels

Outcome variables	FiF		Female		FiF*female		Constant		Obs.	R-squared
University course: Medicine	-0.021	(0.018)	0.065**	(0.027)	-0.011	(0.029)	1.131***	(0.437)	1,872	0.081
Sciences	0.063*	(0.038)	-0.016	(0.036)	-0.075*	(0.044)	1.575**	(0.741)	1,872	0.048
Engineering, tech, architecture	0.005	(0.028)	-0.093***	(0.024)	-0.012	(0.027)	0.142	(0.393)	1,872	0.085
Law and business	0.025	(0.030)	-0.025	(0.028)	0.029	(0.036)	-1.412**	(0.613)	1,872	0.051
Social sciences, humanities, languages	-0.070*	(0.037)	0.032	(0.041)	0.028	(0.046)	-0.940	(0.742)	1,872	0.079
Education	-0.014	(0.009)	0.024**	(0.010)	0.059***	(0.015)	0.632*	(0.350)	1,872	0.088
Other	0.012*	(0.007)	0.013	(0.008)	-0.019*	(0.010)	-0.128	(0.195)	1,872	0.033
Russell Group university	-0.058*	(0.033)	0.034	(0.037)	-0.069*	(0.040)	0.910*	(0.539)	2,030	0.267
Postgraduate degree	-0.005	(0.038)	-0.028	(0.040)	-0.028	(0.048)	0.045	(0.792)	2,030	0.056
Student loan	0.004	(0.028)	-0.015	(0.029)	0.001	(0.033)	1.887***	(0.528)	2,030	0.065
Worked while at uni as a part of career	0.025*	(0.015)	0.011	(0.015)	0.014	(0.021)	0.281	(0.366)	2,030	0.060
Worked while at uni for other reasons	0.078**	(0.034)	0.087**	(0.036)	-0.075*	(0.043)	1.032	(0.715)	2,030	0.101
Found current job through social network	-0.016	(0.037)	-0.038	(0.038)	-0.011	(0.046)	-0.209	(0.723)	2,022	0.035
Highest qualification was needed to get current job	-0.004	(0.037)	0.037	(0.036)	-0.047	(0.043)	1.836**	(0.740)	2,027	0.074
Works more than 45 hours per week	-0.014	(0.031)	-0.035	(0.034)	0.045	(0.040)	0.296	(0.611)	2,030	0.042
Occupation										
Managerial	-0.012	(0.019)	-0.010	(0.020)	-0.000	(0.022)	-0.144	(0.229)	1,620	0.025
Science and medical prof	-0.046	(0.040)	-0.028	(0.040)	0.033	(0.046)	1.202*	(0.697)	1,620	0.065
Science associate	0.034	(0.033)	-0.046	(0.033)	-0.019	(0.038)	0.775	(0.619)	1,620	0.042
Administrative	0.045*	(0.026)	0.084***	(0.028)	-0.072**	(0.035)	-1.072*	(0.617)	1,620	0.047
Skilled trades	-0.008	(0.018)	-0.037***	(0.014)	0.024	(0.017)	-0.408*	(0.214)	1,620	0.055
Personal service	-0.002	(0.020)	0.060**	(0.025)	0.032	(0.030)	1.486***	(0.561)	1,620	0.067
Sales and customer service	0.039	(0.038)	0.042	(0.038)	-0.018	(0.046)	0.314	(0.829)	1,620	0.080
Operative	0.005	(0.004)	0.005	(0.004)	-0.004	(0.006)	-0.175	(0.124)	1,620	0.039
Elementary trades	-0.053	(0.036)	-0.069**	(0.035)	0.024	(0.040)	-0.978	(0.633)	1,620	0.061
Industry										
Agriculture, mining, construction	0.007	(0.013)	-0.006	(0.012)	0.014	(0.014)	0.172	(0.299)	1,949	0.044
Manufacturing; food, textile	0.018	(0.016)	-0.003	(0.015)	-0.036**	(0.018)	0.089	(0.267)	1,949	0.047
Manufacturing: electronics	0.026**	(0.012)	0.016	(0.012)	-0.027*	(0.014)	-0.284	(0.257)	1,949	0.039

Transportation	0.029	(0.028)	-0.048*	(0.026)	-0.008	(0.033)	0.706	(0.544)	1,949	0.048
Trade	-0.006	(0.017)	0.006	(0.018)	-0.021	(0.021)	0.213	(0.355)	1,949	0.043
Finance	0.012	(0.038)	-0.094**	(0.037)	-0.004	(0.044)	-0.604	(0.631)	1,949	0.061
Services: trade	-0.032	(0.031)	-0.065**	(0.028)	0.035	(0.035)	0.072	(0.472)	1,949	0.049
Services: caring	-0.057	(0.038)	0.185***	(0.042)	0.061	(0.052)	0.871	(0.780)	1,949	0.095
Public administration	0.002	(0.015)	0.009	(0.017)	-0.014	(0.020)	-0.234	(0.309)	1,949	0.033
Having well-paying job is important	0.070*	(0.038)	-0.088**	(0.042)	-0.046	(0.049)	-1.086	(0.758)	1,965	0.085
Living in London at age 25	-0.031	(0.028)	-0.019	(0.031)	0.002	(0.034)	-0.112	(0.481)	2,030	0.527
Employment tenure	0.668	(1.442)	-1.790	(1.379)	-0.970	(1.780)	-88.729***	(30.498)	2,030	0.056
Working for a small firm	0.024	(0.033)	0.041	(0.035)	-0.035	(0.041)	0.253	(0.725)	2,019	0.037
Working for a medium-sized firm	-0.015	(0.039)	-0.068	(0.042)	0.111**	(0.049)	-0.072	(0.822)	2,019	0.033
Working for a large firm	-0.008	(0.035)	0.027	(0.039)	-0.077*	(0.046)	0.819	(0.689)	2,019	0.054
Having children	-0.004	(0.015)	0.009	(0.015)	0.018	(0.019)	-0.870**	(0.382)	2,030	0.061
Partner	-0.019	(0.036)	0.013	(0.039)	0.073	(0.047)	-1.900**	(0.740)	2,030	0.141
Living with parents	0.104***	(0.033)	0.060*	(0.032)	-0.056	(0.040)	1.205*	(0.728)	2,028	0.145
High locus of control	-0.031	(0.031)	-0.075**	(0.032)	0.037	(0.038)	-0.215	(0.656)	2,007	0.038
High risk tolerance	0.051	(0.035)	-0.100***	(0.032)	-0.015	(0.040)	-0.934	(0.702)	2,023	0.069
High patience	-0.032	(0.038)	-0.096**	(0.041)	0.078	(0.049)	1.337*	(0.769)	2,023	0.028
High trust	0.026	(0.040)	-0.013	(0.042)	-0.001	(0.050)	0.189	(0.762)	2,024	0.031

Sample of university graduates who have data on hourly wage and parental education (sample of Table 3 and Table 4). Weighted using Wave 8 weights. Linear regression models, each row comes from different models.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Appendix B: Detailed output tables

Table B1: The FiF gap in labor market outcomes: detailed tables (Model 1-4)

	Men Model 1	Men Model 2	Men Model 3	Men Model 4	Women Model 1	Women Model 2	Women Model 3	Women Model 4
				Employment				
FiF	0.007	0.007	0.030	0.026	0.019	0.019	0.012	0.003
	(0.024)	(0.024)	(0.031)	(0.031)	(0.020)	(0.020)	(0.024)	(0.024)
Constant	0.872***	0.872***	1.160	0.996	0.875***	0.875***	1.369**	0.894
	(0.017)	(0.017)	(0.812)	(0.827)	(0.017)	(0.017)	(0.696)	(0.674)
No. of obs.	1,147	1,147	1,147	1,147	1,524	1,524	1,524	1,524
R-squared	0.000	0.000	0.063	0.086	0.001	0.001	0.037	0.076
				Log annual wage				
FiF	-0.090**	-0.090**	0.017	0.044	-0.181***	-0.181***	-0.093**	-0.059
	(0.039)	(0.039)	(0.046)	(0.042)	(0.037)	(0.037)	(0.044)	(0.044)
Constant	10.154***	10.154***	9.347***	8.466***	10.088***	10.088***	8.369***	8.154***
	(0.035)	(0.035)	(1.318)	(1.309)	(0.033)	(0.033)	(1.118)	(1.147)
No. of obs.	863	863	863	863	1,167	1,167	1,167	1,167
R-squared	0.007	0.007	0.120	0.218	0.025	0.025	0.112	0.186
				Hours worked				
FiF	-1.593**	-1.593**	-1.234	-1.129	-1.752**	-1.752**	0.153	0.523
	(0.758)	(0.758)	(0.827)	(0.781)	(0.724)	(0.724)	(0.690)	(0.688)
Constant	41.931***	41.931***	25.828	14.832	40.907***	40.907***	50.878**	51.895**
	(0.636)	(0.636)	(28.941)	(28.594)	(0.611)	(0.611)	(23.394)	(23.415)
No. of obs.	863	863	863	863	1,167	1,167	1,167	1,167
R-squared	0.007	0.007	0.097	0.144	0.007	0.007	0.093	0.139
				Log hourly wage				
FiF	-0.043	-0.043	0.049	0.075**	-0.133***	-0.133***	-0.101**	-0.077*
	(0.032)	(0.032)	(0.038)	(0.037)	(0.030)	(0.030)	(0.040)	(0.040)
Constant	2.494***	2.494***	2.432**	1.981	2.457***	2.457***	0.798	0.637
	(0.027)	(0.027)	(1.198)	(1.206)	(0.028)	(0.028)	(0.858)	(0.899)
No. of obs.	863	863	863	863	1,167	1,167	1,167	1,167
R-squared	0.002	0.002	0.125	0.186	0.022	0.022	0.094	0.140
				Control variables				
Sample boost		yes	yes	yes		yes	yes	yes
Demographics and family background			yes	yes			yes	yes
Early educational attainment				yes				yes
Educational progression				yes				yes

Sample of university graduates. Weighted using Wave 8 weights. Robust standard errors clustered by school in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers' and fathers' age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Table B2: Detailed Oaxaca decomposition results for log hourly wages of graduate men and women, by FiF

	Men		Women	
Explanatory variables	Explained gap	Unexplained gap	Explained gap	Unexplained gap
Age	-0.001	1.409	0.001	1.027
	(0.002)	(2.154)	(0.001)	(1.620)
White	-0.000	0.142*	-0.000	0.109*
	(0.002)	(0.082)	(0.001)	(0.064)
Region at age 13/14	0.001	0.034	0.005	0.050
	(0.006)	(0.184)	(0.007)	(0.083)
Mother’s age	0.004	-0.159	0.005	-0.368***
	(0.005)	(0.159)	(0.007)	(0.136)
Father’s age	-0.008	-0.009	-0.005	0.187**
	(0.010)	(0.217)	(0.009)	(0.089)
Father’s NS-SEC	0.023	-0.037	-0.017	0.037
	(0.017)	(0.052)	(0.012)	(0.040)
Mother’s NS-SEC	0.017	0.106	0.001	-0.110*
	(0.012)	(0.119)	(0.008)	(0.059)
No. of siblings	-0.001	0.004	-0.002	-0.011
	(0.004)	(0.104)	(0.003)	(0.059)
FSM	0.012**	-0.003	-0.001	-0.006
	(0.006)	(0.005)	(0.003)	(0.005)
Born in the UK	-0.004	-0.425***	0.000	-0.116
	(0.004)	(0.163)	(0.001)	(0.096)
Math test score quintiles at age 11. Baseline category: first quintile.				
Second quintile	-0.001	0.014	-0.006	-0.015
	(0.003)	(0.013)	(0.004)	(0.012)
Third quintile	-0.003	-0.000	-0.006	-0.030*
	(0.004)	(0.017)	(0.004)	(0.016)
Fourth quintile	-0.007	-0.006	-0.002	-0.031
	(0.007)	(0.032)	(0.006)	(0.030)
Fifth quintile	0.007	-0.074	0.018**	-0.011
	(0.008)	(0.071)	(0.008)	(0.048)
Reading test score quintiles at age 11. Baseline category: first quintile.				
Second quintile	0.002	-0.002	-0.000	0.007
	(0.006)	(0.015)	(0.002)	(0.011)
Third quintile	0.003	0.042	0.006	0.040**
	(0.004)	(0.026)	(0.004)	(0.017)
Fourth quintile	0.001	0.049	0.002	0.059*
	(0.003)	(0.037)	(0.003)	(0.032)
Fifth quintile	-0.002	0.081*	-0.002	0.125*
	(0.004)	(0.041)	(0.007)	(0.064)
GCSE capped linear test score quintiles at age 16. Baseline category: first quintile.				
Second quintile	0.007	0.006	-0.003	-0.004
	(0.008)	(0.013)	(0.003)	(0.015)
Third quintile	-0.002	0.001	-0.012*	-0.018
	(0.008)	(0.020)	(0.007)	(0.035)
Fourth quintile	-0.001	-0.014	-0.007	-0.007
	(0.003)	(0.039)	(0.005)	(0.059)
Fifth quintile	0.012	0.048	0.017	-0.110
	(0.012)	(0.064)	(0.012)	(0.159)
University subject, baseline category: medicine				
Sciences	0.013	-0.027	-0.002	0.039**
	(0.008)	(0.038)	(0.003)	(0.018)
Engineering, tech, architecture	-0.002	-0.046**	-0.002	0.004
	(0.003)	(0.023)	(0.002)	(0.004)
Law and business	0.010	-0.029	0.004	0.020
	(0.006)	(0.022)	(0.003)	(0.014)

Social sciences, humanities, languages	-0.024**	-0.054	-0.009	0.071**
	(0.011)	(0.051)	(0.007)	(0.033)
Education	0.001	0.001	0.007*	0.004
	(0.001)	(0.001)	(0.004)	(0.005)
Other	0.001	-0.002	0.000	0.006
	(0.002)	(0.002)	(0.001)	(0.004)
Russell Group university	0.004	0.024	0.014*	-0.008
	(0.007)	(0.023)	(0.008)	(0.021)
Postgraduate degree	0.000	0.116***	0.002	0.014
	(0.001)	(0.029)	(0.002)	(0.022)
Worked while at uni as a part of career	-0.001	0.002	0.003	0.001
	(0.002)	(0.005)	(0.002)	(0.006)
Worked while at uniform other reasons	-0.001	-0.023	-0.004	-0.001
	(0.004)	(0.015)	(0.003)	(0.015)
Have student loan	0.000	-0.131*	-0.002	0.048
	(0.000)	(0.071)	(0.003)	(0.067)
Found current job through social network	0.001	-0.011	-0.000	0.032**
	(0.001)	(0.020)	(0.000)	(0.015)
Highest qualification was needed to get job	0.013*	-0.000	0.017***	0.006
	(0.007)	(0.049)	(0.006)	(0.043)
Works more than 45 hours per week	-0.006	0.014	-0.005	-0.001
	(0.005)	(0.015)	(0.006)	(0.012)
Occupation category. Baseline: Managerial				
Science and medical prof	-0.000	0.029	-0.005	-0.028
	(0.004)	(0.023)	(0.008)	(0.031)
Science associate	0.001	0.045**	-0.003	-0.013
	(0.002)	(0.019)	(0.005)	(0.022)
Administrative	0.004	0.037***	0.002	-0.020
	(0.004)	(0.012)	(0.005)	(0.023)
Skilled trades	0.000	0.003	0.001	-0.001
	(0.001)	(0.008)	(0.001)	(0.001)
Personal service	0.003	0.010	0.011	-0.007
	(0.003)	(0.006)	(0.008)	(0.022)
Sales and customer service	0.007	0.046*	0.011	-0.045
	(0.008)	(0.024)	(0.009)	(0.046)
Operative	0.001	0.001	0.003	0.001
	(0.001)	(0.001)	(0.003)	(0.002)
Elementary trades	0.000	0.042**	-0.008	-0.022
	(0.003)	(0.022)	(0.007)	(0.022)
Industry codes. Baseline: Agriculture, mining, construction				
Manufacturing; food, textile	-0.001	0.000	-0.002	-0.003
	(0.002)	(0.009)	(0.002)	(0.008)
Manufacturing: electronics	-0.002	0.007	0.001	-0.005
	(0.002)	(0.005)	(0.001)	(0.010)
Transportation	-0.002	0.021	0.003	-0.004
	(0.003)	(0.023)	(0.003)	(0.016)
Trade	-0.000	0.001	-0.000	-0.003
	(0.001)	(0.012)	(0.001)	(0.012)
Finance	0.003	0.002	0.001	0.020
	(0.005)	(0.036)	(0.002)	(0.044)
Services: trade	0.003	0.008	-0.000	0.002
	(0.004)	(0.023)	(0.001)	(0.022)
Services: caring	0.000	0.039	0.002	0.052
	(0.001)	(0.042)	(0.003)	(0.111)
Public administration	0.000	0.003	-0.003	0.004
	(0.001)	(0.007)	(0.003)	(0.011)
Having well-paying job is important	-0.003	0.060	-0.009**	0.006
	(0.004)	(0.039)	(0.004)	(0.025)
Lives in London	0.008	-0.005	0.010**	0.003
	(0.006)	(0.025)	(0.005)	(0.017)

Employment tenure	-0.003	0.081*	-0.000	0.016
	(0.004)	(0.044)	(0.004)	(0.029)
Works for a medium-sized firm	-0.010	-0.023	-0.008*	0.011
	(0.006)	(0.030)	(0.004)	(0.026)
Works for a large firm	0.017**	0.005	0.025***	0.012
	(0.008)	(0.028)	(0.007)	(0.023)
Has a child	-0.000	0.007	0.006**	-0.009
	(0.002)	(0.005)	(0.003)	(0.006)
Partner	-0.000	-0.042	-0.000	0.005
	(0.001)	(0.026)	(0.001)	(0.022)
Living with parents	0.017**	0.035*	0.005	-0.031*
	(0.007)	(0.019)	(0.004)	(0.016)
High locus of control	-0.000	0.016	-0.000	-0.014
	(0.001)	(0.019)	(0.003)	(0.010)
High risk preference	-0.002	0.035	0.001	-0.020**
	(0.003)	(0.023)	(0.001)	(0.010)
High patience	-0.001	-0.015	0.003	-0.002
	(0.002)	(0.024)	(0.002)	(0.016)
High trust	-0.001	-0.008	-0.000	-0.019
	(0.002)	(0.025)	(0.001)	(0.017)
Constant		-1.571		-0.902
		(2.115)		(1.694)
Overall gap				
Non-FiF group	2.494***		2.457***	
	(0.027)		(0.027)	
FiF group	2.451***		2.324***	
	(0.021)		(0.015)	
Raw difference	0.043		0.133***	
	(0.034)		(0.031)	
Explained difference	0.143***		0.086***	
	(0.031)		(0.026)	
Unexplained difference	-0.100***		0.047	
	(0.034)		(0.031)	
No. of obs.	863	863	1,167	1,167

Sample of university graduates. Weighted using Wave 8 weights. The missing values of control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Table B3: Detailed Oaxaca decomposition results for log hourly wages of non-FiF and FiF graduates, by gender

	Non-FiF graduates		FiF graduates	
Explanatory variables	Explained gap	Unexplained gap	Explained gap	Unexplained gap
Age	-0.000	-0.825	0.002	-1.208
	(0.001)	(2.284)	(0.002)	(1.431)
White	0.002	0.068	-0.001	0.037
	(0.002)	(0.088)	(0.001)	(0.055)
Region at age 13/14	0.005	-0.129	0.004	-0.108
	(0.007)	(0.183)	(0.004)	(0.083)
Mother’s age	0.000	0.207	-0.001	-0.001
	(0.003)	(0.190)	(0.002)	(0.081)
Father’s age	-0.002	-0.174	0.001	0.021
	(0.008)	(0.213)	(0.002)	(0.091)
Father’s NS-SEC	0.002	-0.030	0.003	0.003
	(0.006)	(0.037)	(0.003)	(0.057)

Mother's NS-SEC	0.002	0.188**	-0.000	-0.042
	(0.003)	(0.078)	(0.002)	(0.110)
No. of siblings	-0.002	-0.010	0.001	-0.029
	(0.007)	(0.103)	(0.002)	(0.060)
FSM	-0.000	-0.003	-0.001	-0.018**
	(0.003)	(0.004)	(0.001)	(0.007)
Born in the UK	-0.003	-0.300*	0.001	0.010
	(0.005)	(0.161)	(0.002)	(0.099)
Math test score quintiles at age 11. Baseline category: first quintile.				
Second quintile	0.000	0.011	-0.000	-0.023
	(0.001)	(0.013)	(0.003)	(0.015)
Third quintile	0.001	0.006	-0.004	-0.022
	(0.002)	(0.018)	(0.003)	(0.018)
Fourth quintile	-0.001	-0.023	0.001	-0.044
	(0.005)	(0.034)	(0.003)	(0.030)
Fifth quintile	-0.000	-0.101	0.011*	-0.037
	(0.006)	(0.076)	(0.006)	(0.035)
Reading test score quintiles at age 11. Baseline category: first quintile.				
Second quintile	-0.001	-0.004	0.001	0.002
	(0.002)	(0.015)	(0.002)	(0.015)
Third quintile	0.002	0.004	-0.002	0.009
	(0.007)	(0.025)	(0.003)	(0.020)
Fourth quintile	-0.000	-0.005	0.001	0.005
	(0.001)	(0.042)	(0.002)	(0.025)
Fifth quintile	-0.007	-0.024	0.002	0.011
	(0.015)	(0.072)	(0.004)	(0.026)
GCSE capped linear test score quintiles at age 16. Baseline category: first quintile.				
Second quintile	0.000	0.008	-0.000	-0.011
	(0.001)	(0.016)	(0.003)	(0.016)
Third quintile	-0.000	0.019	-0.003	-0.008
	(0.002)	(0.036)	(0.003)	(0.025)
Fourth quintile	0.003	0.003	0.001	0.006
	(0.005)	(0.064)	(0.003)	(0.032)
Fifth quintile	-0.006	0.156	-0.003	-0.000
	(0.011)	(0.166)	(0.004)	(0.036)
University subject, baseline category: medicine				
Sciences	-0.003	-0.066**	-0.020***	0.003
	(0.004)	(0.030)	(0.006)	(0.029)
Engineering, tech, architecture	-0.011	-0.037**	-0.004	0.006
	(0.009)	(0.017)	(0.005)	(0.009)
Law and business	-0.000	-0.032*	-0.002	0.014
	(0.003)	(0.018)	(0.003)	(0.021)
Social sciences, humanities, languages	0.002	-0.090*	0.020***	0.032
	(0.006)	(0.052)	(0.007)	(0.031)
Education	-0.000	-0.000	0.009*	-0.001
	(0.003)	(0.002)	(0.005)	(0.003)
Other	-0.002	-0.004	-0.001	0.003
	(0.002)	(0.003)	(0.001)	(0.003)
Russell Group university	-0.004	0.014	0.001	-0.012
	(0.004)	(0.030)	(0.001)	(0.011)
Postgraduate degree	0.001	0.053*	-0.001	-0.044**
	(0.005)	(0.030)	(0.001)	(0.020)
Worked while at uni as a part of career	-0.000	0.005	0.000	0.007
	(0.001)	(0.006)	(0.001)	(0.006)
Worked while at uniform other reasons	-0.003	-0.029*	-0.001	-0.011
	(0.003)	(0.016)	(0.002)	(0.015)
Have student loan	-0.000	-0.238***	-0.001	-0.060
	(0.001)	(0.081)	(0.002)	(0.054)
Found current job through social network	-0.000	-0.041**	-0.001	0.003
	(0.001)	(0.019)	(0.001)	(0.016)

Highest qualification was needed to get job	-0.003	-0.010	0.002	-0.004
	(0.007)	(0.055)	(0.005)	(0.033)
Works more than 45 hours per week	-0.002	0.016	-0.001	0.001
	(0.005)	(0.016)	(0.005)	(0.010)
Occupation category. Baseline: Managerial				
Science and medical prof	0.001	0.046	0.000	-0.016
	(0.003)	(0.039)	(0.001)	(0.016)
Science associate	0.000	0.046*	-0.004	-0.012
	(0.002)	(0.026)	(0.003)	(0.014)
Administrative	0.005	0.042**	0.006	-0.018
	(0.008)	(0.020)	(0.004)	(0.014)
Skilled trades	-0.004	-0.000	-0.001	-0.006*
	(0.006)	(0.005)	(0.002)	(0.003)
Personal service	0.008	0.009	0.015**	-0.006
	(0.006)	(0.013)	(0.007)	(0.013)
Sales and customer service	0.009	0.058	0.004	-0.024
	(0.009)	(0.037)	(0.004)	(0.029)
Operative	0.000	-0.000	0.002	-0.001
	(0.001)	(0.001)	(0.003)	(0.002)
Elementary trades	-0.004	0.044	-0.009	-0.023
	(0.006)	(0.030)	(0.005)	(0.014)
Industry codes. Baseline: Agriculture, mining, construction				
Manufacturing; food, textile	-0.000	0.009	-0.001	0.006
	(0.001)	(0.011)	(0.004)	(0.006)
Manufacturing: electronics	-0.002	0.013	0.000	0.003
	(0.003)	(0.011)	(0.001)	(0.004)
Transportation	0.001	0.030	-0.001	0.011
	(0.008)	(0.022)	(0.003)	(0.019)
Trade	-0.001	0.004	-0.001	0.000
	(0.002)	(0.015)	(0.003)	(0.008)
Finance	0.008	0.009	0.003	0.030
	(0.007)	(0.051)	(0.005)	(0.024)
Services: trade	-0.000	0.024	0.000	0.014
	(0.005)	(0.028)	(0.002)	(0.013)
Services: caring	-0.007	0.012	0.018	0.002
	(0.015)	(0.109)	(0.015)	(0.046)
Public administration	0.001	0.004	-0.002	0.006
	(0.002)	(0.011)	(0.002)	(0.006)
Having well-paying job is important	0.005	0.007	0.007**	-0.054*
	(0.004)	(0.034)	(0.003)	(0.031)
Lives in London	-0.001	0.013	0.004	0.019
	(0.004)	(0.026)	(0.003)	(0.016)
Employment tenure	0.008	0.059	0.006*	-0.001
	(0.007)	(0.045)	(0.003)	(0.027)
Works for a medium-sized firm	0.003	0.011	-0.002	0.051**
	(0.003)	(0.031)	(0.003)	(0.025)
Works for a large firm	-0.008	0.004	0.003	0.009
	(0.008)	(0.034)	(0.005)	(0.014)
Has a child	0.000	0.014**	0.002	0.001
	(0.001)	(0.006)	(0.002)	(0.006)
Partner	0.000	-0.041	-0.001	0.006
	(0.000)	(0.027)	(0.002)	(0.021)
Living with parents	0.002	0.033*	-0.000	-0.043**
	(0.003)	(0.018)	(0.002)	(0.020)
High locus of control	0.003	0.013	0.005*	-0.020*
	(0.003)	(0.017)	(0.003)	(0.012)
High risk preference	-0.001	0.057***	0.003	0.002
	(0.006)	(0.018)	(0.004)	(0.013)
High patience	-0.004	-0.005	0.001	0.007
	(0.004)	(0.023)	(0.001)	(0.016)

High trust	-0.000	-0.001	0.000	-0.013
	(0.002)	(0.025)	(0.001)	(0.017)
Constant		0.950		1.619
		(2.274)		(1.475)
Overall gap				
Men	2.494***		2.451***	
	(0.027)		(0.021)	
Women	2.457***		2.324***	
	(0.027)		(0.015)	
Raw gender gap	0.037		0.127***	
	(0.038)		(0.026)	
Explained gender gap	-0.015		0.073***	
	(0.034)		(0.020)	
Unexplained gender gap	0.052		0.054**	
	(0.036)		(0.023)	
No. of obs.	616	616	1,414	1,414

Sample of university graduates. Weighted using Wave 8 weights. The missing values of control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Appendix C: Robustness checks

C1: Comparing returns to graduation in Next Steps to those in Belfield et al. (2018)

Next Steps contains self-reported information on wages. This subsection compares estimates of returns to graduation in Next Steps to a recent study, Belfield et al. (2018), that used administrative data on wage, the Longitudinal Education Outcomes (LEO). We follow the empirical strategy of Belfield et al. (2018) as closely as possible. We aim at producing similar results as published in the second column of Table 8 (page 38 in Belfield et al. 2018), in the fashion of Table 7 (page 36 in Belfield et al. 2018): we restrict the sample to those having at least five A*-C GCSE examinations, use log annual wage as the outcome variable, university graduation as the treatment variable, and sequentially add the same controls variables to the wage model as reported in Table 7 in Belfield et al. 2018.

Note that there are some inherent differences between Next Steps and LEO that do not enable us to proceed the exact same way. The key difference is that while LEO captures wages up until age 29, Next Steps measures wages at age 25/26. A further difference is that Belfield et al. (2018) looks at those in sustained employment only, i.e. those who have worked five out of the last six months of the tax year, while we look at everybody in employment. While we expect to have similar results to those of Belfield et al. (2018) in terms of estimating higher returns to graduation for women than for men, the magnitude of both estimates is expected to be lower at age 25/26 than at age 29. While Belfield et al. (2018) does not publish returns to graduation at age 25/26, on Figure 2 (page 16) they plot the raw wages of graduates relative to those with at least five A*-C GCSE's, by age and gender. According to this graph, the raw wage difference seems to be 22-28% among women and 2-9% among men at ages 25-26 between graduates and the five A*-C GCSE group. Taken all those differences into account, we find similar patterns in returns to graduation in Next Steps as Belfield et al. (2018) (Table C1).

Table C1: Comparing returns to graduation in log annual wages among those having at least five A*-C GCSE grades in Next Steps to those in Belfield et al. (2018)

	Next Steps data (own estimation)			LEO data (Belfield et al., 2018)	
Type of wage data	Self-reported survey data			Administrative data	
Sample	Those who are employed and reported wage			Those in sustained employment, i.e. those who have worked five out of the last six months of the tax year	
	Model 1 (raw wage difference)	Model 2	Model 3	Raw wage difference computed based on Figure 2 on page 16	Returns to graduation (2nd column of Table 8 on page 38)
Age of observation	25/26	25/26	25/26	25/26	29
Men					
Graduation	0.078**	0.059*	-0.012	2-9%	0.08**
	(0.035)	(0.035)	(0.037)		(0.00)
Constant	NR	10.645***	10.131***		
		(1.141)	(1.196)		
No. of obs. (individuals)	1,426	1,426	1,426		593,974
Women					
Graduation	0.233***	0.207***	0.073**	22-28%	0.25**

	(0.033)	(0.033)	(0.032)	(0.000)
Constant	NR	7.831***	6.657***	
		(1.197)	(1.220)	
No. of obs. (individuals)	2,015	2,015	2,015	700,533
	Control variables			
Sample boost		Yes	Yes	
Family background		Yes	Yes	Yes
Early and pre-university educational attainment			Yes	Yes

Next Steps estimates are linear models estimated by OLS, weighted using Wave 8 weights. Sample of those having at least five A*-C GCSE examinations. All coefficients are in log points and may be transformed to percentages through the following transformation: 100*(e^{beta} – 1), where beta is the estimated coefficient. Robust standard errors clustered by sampling school are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Family background: age in months as a continuous variable, mother's and father's social class, region, ethnicity. Early and pre-university educational attainment: GCSE and A-level raw scores, indicator variables for A-level subjects as Math, Sciences, Social science, Humanities, Arts, Languages and Other, Level 3 studies, a binary variable for having vocational qualifications, a binary variable capturing whether the individual attended independent secondary school at age 13/14. Missing observations are controlled for using missing flags.

Sources: Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4 and Belfield et al. (2018) [+]Note that adding the sample boost dummy to Model 1 would lead to almost identical results.

C2: The FiF gap in labor market outcomes: main results without excluding the outlier values of annul wage, hours worked and hourly wage

This subsection re-estimates the FiF gap in labor market outcomes, i.e., the main results of Model 4 in Table 3, without excluding the outlier values of annul wage, hours worked and hourly wage. Table C2 shows that the estimated coefficients are very similar to those in Table 3.

Table C2: The FiF gap in labor market outcomes: main results without excluding the outlier values of annul wage, hours worked and hourly wage

	(1) Employed Men	(2) Employed Women	(3) Log annual wage Men	(4) Log annual wage Women	(5) Hours worked Men	(6) Hours worked Women	(7) Log hourly wage Men	(8) Log hourly wage Women
FiF	0.026	0.003	0.060	-0.055	-0.943	0.537	0.088*	-0.074*
	(0.031)	(0.024)	(0.051)	(0.045)	(0.791)	(0.690)	(0.048)	(0.042)
Constant	0.996	0.894	9.180***	8.638***	22.631	42.139*	2.566*	2.204
	(0.827)	(0.674)	(1.564)	(1.197)	(29.386)	(24.332)	(1.486)	(1.390)
No. of obs.	1,147	1,524	866	1,172	866	1,172	866	1,172
R-squared	0.086	0.076	0.175	0.169	0.141	0.168	0.140	0.104

Sample of university graduates. Weighted using Wave 8 weights. Robust standard errors clustered by school in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Excluded observations from the sample: those whose annual wage is less than 50 GBP (14 observations) or more than 1,000,000 GBP (6 observations), those who reported working less than 1 hour per week (9 observations) or more than 80 hours per week (10 observations), and those earning less than 1 GBP per hour (9 observations) or more than 200 GBP per hour (7 observations). Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers' and fathers' age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

C3: The FiF gap in labor market outcomes: handling the missing values of the control variables with mean imputation

This subsection re-estimates the FiF gap in labor market outcomes, i.e., the main results of Model 4 as in Table 3, handling the missing values of the control variables with mean imputation as well as a binary variable indicating which observations were imputed. Furthermore, we use the continuous age 11 and age 16 test score variables instead of their quintiles that we use in our main models. As Table C3 shows, the results are very similar to those in Table 3.

Table C3: The FiF gap in labor market outcomes: handling the missing values of the control variables with mean imputation

	(1) Employed Men	(2) Employed Women	(3) Log annual wage Men	(4) Log annual wage Women	(5) Hours worked Men	(6) Hours worked Women	(7) Log hourly wage Men	(8) Log hourly wage Women
FiF	0.028	0.012	0.065	-0.041	-0.574	0.813	0.076**	-0.070*
	(0.031)	(0.024)	(0.042)	(0.043)	(0.813)	(0.683)	(0.036)	(0.039)
Constant	0.864	1.267*	7.710***	7.735***	10.382	38.924*	1.333	0.573
	(0.834)	(0.665)	(1.248)	(1.132)	(28.239)	(22.885)	(1.152)	(0.859)
No. of obs.	1,147	1,524	863	1,167	863	1,167	863	1,167
R-squared	0.060	0.052	0.220	0.183	0.130	0.126	0.177	0.124

Sample of university graduates. Weighted using Wave 8 weights. Robust standard errors clustered by school in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers' and fathers' age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are handled via mean imputation.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

C4: The FiF gap in labor market outcomes: Entropy balancing and propensity score matching

This subsection applies two quasi-experimental evaluation methods as robustness checks: entropy balancing and propensity score matching. Both methods rely on the unconfoundedness assumption, i.e. that we observe all variables that affect both parental graduation and labor market outcomes, and, conditional on these characteristics, assignment to having non-graduated parents is as good and random (Angrist and Pischke, 2009). The unconfoundedness assumption also implies that there should be no such unobserved characteristics that affect both parental education and the labor market outcomes of individuals. Entropy balancing (Hainmuller, 2012) is a reweighting procedure to achieve covariate balance with binary treatments based on the first, second or higher-order moments of the covariates (Harvey et al, 2016). As entropy balancing does not differentiate between observation within or outside of a common support, we also apply propensity score matching as a robustness check. We estimate the propensity scores in probit models that predict the probability of being FiF for men and women separately, using the same control variables as in Model 4. Then, we apply Gaussian kernel-weighted matching on the estimated propensity scores using psmatch in Stata and construct 95% confidence intervals around the estimated effect via bootstrapping (n=200). These results (Table C4) confirm that the negative FiF hourly wage gap is robust among women; however, the positive FiF wage gap among men is not.

Table C4: The FiF gap in labor market outcomes: Entropy balancing and propensity score matching

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employed		Log annual wage		Hours worked		Log hourly wage	
	Men	Women	Men	Women	Men	Women	Men	Women
	Entropy balancing							
FiF	0.089**	0.023	0.151***	-0.137**	3.173***	0.337	0.054*	-0.134**
	(0.039)	(0.030)	(0.042)	(0.068)	(0.806)	(0.773)	(0.032)	(0.056)
Constant	1.254	1.414	4.434***	7.580***	-28.306	51.415**	-0.491	0.045
	(1.172)	(1.074)	(1.479)	(1.435)	(28.096)	(23.749)	(1.250)	(1.251)
No. of obs.	1,147	1,524	863	1,167	863	1,167	863	1,167
R-squared	0.285	0.172	0.487	0.378	0.415	0.173	0.298	0.433
	Propensity score matching							
FiF	0.046	0.032	0.078	-0.061	1.432	1.444	0.032	-0.093*
SD	0.040	0.031	0.060	0.063	1.213	.782	0.042	0.051
95% confidence intervals	-0.034; 0.125	0.028; 0.093	-0.039; 0.196	-0.185; 0.063	-0.961; 3.824	-0.099; 2.988	-0.051; 0.115	-0.193; 0.008
No. of obs. (on the common support)	1,020	1,413	774	1,028	774	1,028	774	1,028

Sample of university graduates. Entropy balancing: Robust standard errors clustered by school in parentheses, Propensity score matching: bootstrapped standard errors via 200 replications, "Normal" confidence intervals from psmatch in Stata. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers' and fathers' age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

C5: The FiF gap in labor market outcomes: assigning all 0/1 values to missing FiF

In our main models, we drop observations with no information about parental education. The number of missing values of FiF among graduates is eight among men and 10 among women in the total sample of graduates and six and nine, respectively, among those reporting hourly wage. This subsection provides a robustness check showing that not dropping these observations lead our results. In particular, we re-estimate our main results allocating either 0 or 1 to all individuals with missing FiF and show in Table C5 that our results stay similar in both cases.

Table C5: The FiF gap in labor market outcomes: assigning all 0/1 values to missing FiF

	(1) Employed Men	(2) Employed Women	(3) Log annual wage Men	(4) Log annual wage Women	(5) Hours worked Men	(6) Hours worked Women	(7) Log hourly wage Men	(8) Log hourly wage Women
				All missing FiF=0				
FiF	0.022	0.008	0.050	-0.057	-1.284*	0.524	0.084**	-0.075*
	(0.032)	(0.024)	(0.042)	(0.044)	(0.776)	(0.699)	(0.038)	(0.039)
Constant	0.782	0.820	7.941***	8.001***	21.899	44.826*	1.303	0.686
	(0.833)	(0.669)	(1.335)	(1.143)	(28.626)	(23.542)	(1.267)	(0.881)
No. of obs.	1,155	1,534	869	1,176	869	1,176	869	1,176
R-squared	0.085	0.080	0.217	0.188	0.141	0.136	0.185	0.141
				All missing FiF=1				
FiF	0.025	0.004	0.051	-0.052	-1.133	0.543	0.082**	-0.071*
	(0.031)	(0.024)	(0.043)	(0.043)	(0.781)	(0.681)	(0.038)	(0.040)
Constant	0.785	0.823	7.955***	7.964***	21.576	45.131*	1.326	0.638
	(0.833)	(0.668)	(1.334)	(1.146)	(28.665)	(23.512)	(1.264)	(0.880)
No. of obs.	1,155	1,534	869	1,176	869	1,176	869	1,176
R-squared	0.085	0.080	0.217	0.188	0.140	0.136	0.184	0.141

Sample of university graduates. Weighted using Wave 8 weights. Robust standard errors clustered by school in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers' and fathers' age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are handled via missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

C6: The FiF gap in labor market outcomes: controlling for selection into employment and reporting wage

As mentioned before, 88% of graduates are employed and out of them about 76% reported wages. Thus, individuals might be selected in terms of their probability of employment and reporting wage data. This subsection aims at controlling for these two additional sources of selection by estimating a selection model (Heckman, 1979) to predict the probability of employment and reporting wage, and using the predicted individual-level inverse Mills-ratio as a further control variable (Table C6). While we cannot exploit an instrumental variable in this selection model and we have to rely on the same control variables that we used before, we believe that the fact that these models are estimated on the full sample (as opposed to the subsample of those who were employed and reported wage, that we used before), we still exploit additional information. These results again confirm that the negative FiF wage gap in hourly wages is robust among women; however, the positive FiF wage gap among men is not.

Table C6: The FiF gap in labor market outcomes: controlling for selection into employment and reporting wage

	(1) Employed Men	(2) Employed Women	(3) Log annual wage Men	(4) Log annual wage Women	(5) Hours worked Men	(6) Hours worked Women	(7) Log hourly wage Men	(8) Log hourly wage Women
FiF	0.012	0.015	0.034	-0.108**	-1.355	-0.033	0.058	-0.103**
	(0.024)	(0.017)	(0.098)	(0.050)	(1.557)	(0.767)	(0.089)	(0.044)
Mills ratio	0.293***	0.278***	-0.141	-2.248**	-3.107	-25.453*	-0.230	-1.183*
	(0.019)	(0.017)	(1.164)	(0.951)	(20.395)	(14.713)	(1.043)	(0.648)
Constant	1.208**	0.885	8.580***	9.951***	17.354	72.250***	2.168	1.582
	(0.581)	(0.540)	(1.662)	(1.397)	(33.928)	(27.561)	(1.443)	(1.014)
No. of obs.	1,147	1,524	863	1,167	863	1,167	863	1,167
R-squared	0.470	0.458	0.218	0.194	0.144	0.142	0.186	0.143

Sample of university graduates. Weighted using Wave 8 weights. Robust standard errors clustered by school in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers' and fathers' age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are handled via missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Online Appendix

Table O1: The FiF gap in labor market outcomes (Model 4) – detailed results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employed		Log annual wage		Hours worked		Log hourly wage	
	Men	Women	Men	Women	Men	Women	Men	Women
FiF	0.026	0.003	0.044	-0.059	-1.129	0.523	0.075**	-0.077*
	(0.031)	(0.024)	(0.042)	(0.044)	(0.781)	(0.688)	(0.037)	(0.040)
Age	-0.001	-0.001	0.004	0.004	0.061	-0.068	0.001	0.004
	(0.003)	(0.002)	(0.004)	(0.004)	(0.091)	(0.072)	(0.004)	(0.003)
White	0.050	0.054**	0.002	-0.109**	0.670	-0.349	-0.023	-0.101**
	(0.044)	(0.027)	(0.057)	(0.054)	(0.942)	(0.835)	(0.048)	(0.050)
Region of school at age 13/14. Baseline category: North East								
North West	0.058	0.033	0.015	0.114	0.506	1.553	0.014	0.076
	(0.062)	(0.047)	(0.105)	(0.073)	(2.675)	(1.322)	(0.093)	(0.057)
Yorkshire and The Humber	0.120*	0.102**	0.033	-0.016	-1.236	-0.598	0.046	0.018
	(0.062)	(0.047)	(0.102)	(0.079)	(2.392)	(1.438)	(0.092)	(0.054)
East Midlands	0.024	0.033	0.015	0.243***	-1.460	2.310	0.045	0.195**
	(0.069)	(0.046)	(0.113)	(0.090)	(2.474)	(1.485)	(0.099)	(0.078)
West Midlands	0.023	0.036	0.037	0.103	0.219	1.915	0.020	0.066
	(0.068)	(0.043)	(0.107)	(0.093)	(2.608)	(1.478)	(0.093)	(0.078)
East of England	0.049	0.065	0.068	0.084	0.268	0.625	0.087	0.094*
	(0.063)	(0.046)	(0.101)	(0.075)	(2.664)	(1.672)	(0.091)	(0.056)
London	0.031	0.058	0.102	0.143*	-0.103	0.245	0.102	0.141**
	(0.070)	(0.048)	(0.102)	(0.079)	(2.554)	(1.305)	(0.093)	(0.063)
South East	0.022	0.028	0.121	0.157**	0.019	-1.022	0.119	0.193***
	(0.066)	(0.045)	(0.097)	(0.076)	(2.423)	(1.350)	(0.088)	(0.062)
South West	0.028	0.018	0.060	-0.008	-1.019	0.113	0.089	-0.012
	(0.067)	(0.051)	(0.126)	(0.082)	(2.817)	(1.603)	(0.109)	(0.063)
Mother's age. Baseline category: below 35.								
35-44	-0.109***	0.003	0.175*	0.078	3.460**	1.387	0.094	0.041
	(0.038)	(0.047)	(0.095)	(0.070)	(1.491)	(1.545)	(0.072)	(0.052)
45-54	-0.084**	-0.039	0.153	0.081	3.687**	0.783	0.082	0.068
	(0.042)	(0.053)	(0.102)	(0.079)	(1.813)	(1.696)	(0.078)	(0.063)
55+	0.010	0.084	0.099	-0.203	2.116	-6.389	0.035	-0.013
	(0.084)	(0.064)	(0.165)	(0.164)	(2.112)	(4.197)	(0.135)	(0.156)
Father's age. Baseline category: below 35.								
35-44	-0.060	-0.040	-0.134	-0.093	-1.097	-0.547	-0.092	-0.078
	(0.048)	(0.056)	(0.103)	(0.086)	(1.626)	(2.626)	(0.109)	(0.085)
45-54	-0.058	-0.030	-0.179*	-0.084	-3.331**	0.416	-0.089	-0.101
	(0.049)	(0.057)	(0.101)	(0.093)	(1.655)	(2.681)	(0.108)	(0.099)
55+	-0.069	-0.052	-0.125	0.040	-1.986	0.357	-0.061	0.026
	(0.068)	(0.070)	(0.124)	(0.122)	(1.899)	(2.577)	(0.125)	(0.118)
Father’s social class. Baseline category: Higher Managerial and professional occupations.								
Lower managerial and professional o.	0.026	-0.020	-0.003	0.008	0.060	-2.188**	0.006	0.056
	(0.033)	(0.028)	(0.047)	(0.042)	(0.848)	(0.877)	(0.042)	(0.037)
Intermediate occupations	-0.017	0.021	-0.121	-0.104	-0.579	-3.471**	-0.086	-0.020

	(0.061)	(0.036)	(0.085)	(0.075)	(1.446)	(1.446)	(0.066)	(0.058)
Small employers and own account workers	-0.000	-0.009	-0.092	-0.006	1.612	-2.718**	-0.110**	0.081
	(0.040)	(0.032)	(0.065)	(0.070)	(1.187)	(1.237)	(0.054)	(0.064)
Lower supervisory and technical o.	0.062*	-0.012	-0.067	-0.005	0.013	-1.563	-0.037	0.027
	(0.038)	(0.041)	(0.072)	(0.064)	(1.599)	(1.238)	(0.068)	(0.054)
Semi-routine occupations	-0.059	-0.016	0.111	-0.095	-0.086	-3.465**	0.134	0.008
	(0.053)	(0.047)	(0.085)	(0.071)	(1.604)	(1.596)	(0.085)	(0.054)
Routine occupations	0.028	-0.014	-0.166*	-0.072	-2.150	-3.237**	-0.107	-0.002
	(0.056)	(0.042)	(0.097)	(0.063)	(1.589)	(1.282)	(0.077)	(0.054)
Unemployed or no parent	-0.083	-0.007	-0.118	-0.195*	0.823	-6.031***	-0.142	-0.007
	(0.065)	(0.048)	(0.116)	(0.107)	(1.902)	(1.561)	(0.091)	(0.091)
Mother's social class. Baseline category: Higher Managerial and professional occupations.								
Lower managerial and professional o.	-0.016	-0.008	0.006	-0.086*	-2.130	-0.189	0.070	-0.058
	(0.046)	(0.044)	(0.075)	(0.051)	(1.315)	(1.204)	(0.075)	(0.045)
Intermediate occupations	-0.012	0.036	-0.070	-0.006	-1.751	-0.520	-0.040	0.023
	(0.053)	(0.048)	(0.080)	(0.060)	(1.431)	(1.368)	(0.080)	(0.048)
Small employers and own account workers	0.009	0.056	0.044	-0.167**	-1.567	-1.312	0.053	-0.124*
	(0.064)	(0.052)	(0.098)	(0.079)	(1.803)	(1.725)	(0.090)	(0.064)
Lower supervisory and technical o.	-0.004	0.066	-0.092	-0.091	-1.442	-1.393	-0.033	-0.048
	(0.064)	(0.054)	(0.102)	(0.083)	(1.967)	(1.628)	(0.093)	(0.068)
Semi-routine occupations	-0.014	0.001	-0.023	-0.070	-2.055	0.127	0.040	-0.052
	(0.052)	(0.053)	(0.080)	(0.070)	(1.485)	(1.439)	(0.080)	(0.056)
Routine occupations	-0.048	0.008	-0.099	-0.170**	0.242	-2.478	-0.124	-0.097
	(0.068)	(0.069)	(0.099)	(0.083)	(1.997)	(1.508)	(0.089)	(0.077)
Unemployed or no parent	-0.090	-0.035	-0.007	-0.224**	-3.562	-2.544	0.086	-0.131
	(0.085)	(0.056)	(0.146)	(0.111)	(2.170)	(1.648)	(0.120)	(0.102)
No. of siblings. Baseline: no siblings.								
1	0.092**	-0.008	0.019	0.081*	-0.330	-0.773	0.044	0.113***
	(0.047)	(0.035)	(0.080)	(0.049)	(1.142)	(1.077)	(0.068)	(0.042)
2	0.052	0.014	-0.059	0.070	-0.644	-0.256	-0.029	0.084**
	(0.047)	(0.035)	(0.077)	(0.047)	(1.265)	(1.130)	(0.071)	(0.042)
3	0.108**	0.009	-0.106	0.074	-3.559**	0.542	-0.003	0.064
	(0.053)	(0.042)	(0.090)	(0.062)	(1.485)	(1.231)	(0.072)	(0.051)
4+	0.068	-0.020	0.080	0.063	0.474	-0.749	0.064	0.097

	(0.060)	(0.054)	(0.089)	(0.112)	(1.337)	(1.510)	(0.083)	(0.096)
Boost sample	0.268	-0.135	0.271	-0.462***	11.936***	-3.735	-0.020	-0.360***
	(0.207)	(0.120)	(0.229)	(0.151)	(4.465)	(3.793)	(0.169)	(0.103)
FMS eligible	0.006	-0.001	-0.136	-0.050	1.298	-2.838**	-0.148*	0.035
	(0.065)	(0.049)	(0.121)	(0.097)	(2.466)	(1.392)	(0.077)	(0.075)
Born in the UK	-0.026	0.067	-0.017	0.010	4.051**	0.142	-0.191***	0.020
	(0.050)	(0.044)	(0.075)	(0.062)	(1.938)	(1.129)	(0.072)	(0.057)
Math test score quintiles at age 11. Baseline category: first quintile.								
Second quintile	0.124	0.044	0.028	0.105	-0.492	2.400	0.042	0.020
	(0.081)	(0.052)	(0.137)	(0.079)	(2.244)	(1.558)	(0.100)	(0.045)
Third quintile	0.139*	0.082	0.197	0.170**	2.040	1.768	0.133	0.105**
	(0.077)	(0.054)	(0.125)	(0.082)	(2.317)	(1.656)	(0.100)	(0.043)
Fourth quintile	0.134*	0.063	0.264**	0.211**	3.907*	1.809	0.149	0.141***
	(0.075)	(0.056)	(0.123)	(0.086)	(2.246)	(1.582)	(0.101)	(0.053)
Fifth quintile	0.139*	0.100*	0.273**	0.270***	3.978*	3.918**	0.166	0.144***
	(0.079)	(0.058)	(0.126)	(0.083)	(2.272)	(1.592)	(0.103)	(0.051)
Reading test score quintiles at age 11. Baseline category: first quintile.								
Second quintile	-0.022	0.046	0.000	-0.014	-1.736	-1.825	0.052	0.059
	(0.059)	(0.053)	(0.116)	(0.090)	(2.029)	(1.914)	(0.094)	(0.052)
Third quintile	0.033	0.010	-0.036	-0.058	-0.693	-1.283	-0.008	-0.008
	(0.054)	(0.052)	(0.113)	(0.094)	(2.002)	(1.998)	(0.084)	(0.054)
Fourth quintile	0.012	-0.059	-0.089	-0.081	-1.945	-1.608	-0.037	-0.014
	(0.059)	(0.054)	(0.114)	(0.092)	(1.939)	(2.008)	(0.092)	(0.054)
Fifth quintile	0.043	-0.050	-0.044	-0.066	-1.939	-2.017	0.016	0.016
	(0.061)	(0.052)	(0.117)	(0.094)	(2.032)	(2.069)	(0.091)	(0.057)
Capped linear GCSE score quintiles at age 16. Baseline category: first quintile.								
Second quintile	0.057	0.183*	0.024	0.402**	2.080	7.260**	-0.104	0.121*
	(0.091)	(0.097)	(0.171)	(0.173)	(3.077)	(3.118)	(0.120)	(0.070)
Third quintile	0.004	0.198**	0.251	0.523***	4.893	9.344***	0.018	0.180***
	(0.091)	(0.098)	(0.162)	(0.166)	(3.033)	(3.038)	(0.119)	(0.069)
Fourth quintile	0.008	0.219**	0.240	0.599***	4.176	9.119***	0.040	0.256***
	(0.092)	(0.097)	(0.163)	(0.165)	(2.992)	(3.040)	(0.125)	(0.070)
Fifth quintile	-0.046	0.150	0.384**	0.627***	4.586	10.151***	0.166	0.254***
	(0.092)	(0.100)	(0.166)	(0.169)	(3.083)	(3.072)	(0.125)	(0.073)
Constant	0.996	0.894	8.466***	8.154***	14.832	51.895**	1.981	0.637
	(0.827)	(0.674)	(1.309)	(1.147)	(28.594)	(23.415)	(1.206)	(0.899)
No. of obs.	1,147	1,524	863	1,167	863	1,167	863	1,167
R-squared	0.086	0.076	0.218	0.186	0.144	0.139	0.186	0.140

Sample of university graduates. Weighted using Wave 8 weights. Robust standard errors clustered by school in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); whether born in the UK; region at age 13; mothers' and fathers' age and social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. The missing values of the control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Table O2: The FiF gap in log hourly wage: potential channels – detailed results, men

	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
FiF	0.075**	0.075**	0.099***	0.106***	0.100***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Age	0.001	0.000	0.001	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
White	-0.023	0.004	0.014	-0.005	-0.000
	(0.048)	(0.049)	(0.045)	(0.046)	(0.047)
Region of school at age 13/14. Baseline category: North East					
North West	0.014	0.033	-0.034	-0.023	-0.035
	(0.093)	(0.091)	(0.096)	(0.101)	(0.101)
Yorkshire and The Humber	0.046	0.064	0.006	-0.000	-0.022
	(0.092)	(0.088)	(0.092)	(0.097)	(0.098)
East Midlands	0.045	0.068	-0.007	-0.003	-0.002
	(0.099)	(0.096)	(0.099)	(0.104)	(0.105)
West Midlands	0.020	0.039	-0.058	-0.045	-0.052
	(0.093)	(0.089)	(0.090)	(0.094)	(0.095)
East of England	0.087	0.101	0.024	0.035	0.019
	(0.091)	(0.088)	(0.094)	(0.099)	(0.100)
London	0.102	0.135	-0.053	-0.025	-0.040
	(0.093)	(0.092)	(0.097)	(0.103)	(0.103)
South East	0.119	0.146*	0.043	0.050	0.037
	(0.088)	(0.085)	(0.087)	(0.093)	(0.094)
South West	0.089	0.112	0.068	0.077	0.075
	(0.109)	(0.108)	(0.114)	(0.118)	(0.116)
Mother's age. Baseline category: below 35.					
35-44	0.094	0.094	0.091	0.081	0.092
	(0.072)	(0.070)	(0.066)	(0.064)	(0.066)
45-54	0.082	0.064	0.083	0.070	0.086
	(0.078)	(0.076)	(0.071)	(0.070)	(0.071)
55+	0.035	0.039	0.022	0.003	0.034
	(0.135)	(0.138)	(0.112)	(0.107)	(0.110)
Father's age. Baseline category: below 35.					
35-44	-0.092	-0.067	-0.075	-0.078	-0.079
	(0.109)	(0.097)	(0.090)	(0.086)	(0.089)
45-54	-0.089	-0.049	-0.073	-0.068	-0.074
	(0.108)	(0.097)	(0.090)	(0.087)	(0.090)
55+	-0.061	-0.027	-0.021	-0.016	-0.020
	(0.125)	(0.114)	(0.104)	(0.102)	(0.105)
Father’s social class. Baseline category: Higher Managerial and professional occupations.					
Lower managerial and professional o.	0.006	0.015	0.017	0.015	0.011

	(0.042)	(0.043)	(0.038)	(0.039)	(0.038)
Intermediate occupations	-0.086	-0.100	-0.089	-0.086	-0.086
	(0.066)	(0.065)	(0.059)	(0.060)	(0.060)
Small employers and own account workers	-0.110**	-0.112**	-0.064	-0.060	-0.069
	(0.054)	(0.054)	(0.051)	(0.052)	(0.051)
Lower supervisory and technical o.	-0.037	-0.050	-0.099	-0.084	-0.091
	(0.068)	(0.069)	(0.063)	(0.062)	(0.062)
Semi-routine occupations	0.134	0.128	0.063	0.063	0.053
	(0.085)	(0.086)	(0.079)	(0.078)	(0.079)
Routine occupations	-0.107	-0.103	-0.111*	-0.126*	-0.116*
	(0.077)	(0.077)	(0.067)	(0.068)	(0.068)
Unemployed or no parent	-0.142	-0.150	-0.087	-0.103	-0.097
	(0.091)	(0.097)	(0.092)	(0.094)	(0.093)
Mother's social class. Baseline category: Higher Managerial and professional occupations.					
Lower managerial and professional o.	0.070	0.068	0.028	0.028	0.039
	(0.075)	(0.077)	(0.075)	(0.075)	(0.076)
Intermediate occupations	-0.040	-0.030	-0.050	-0.052	-0.040
	(0.080)	(0.082)	(0.076)	(0.074)	(0.075)
Small employers and own account workers	0.053	0.056	-0.055	-0.048	-0.026
	(0.090)	(0.090)	(0.084)	(0.083)	(0.085)
Lower supervisory and technical o.	-0.033	-0.010	-0.034	-0.025	-0.009
	(0.093)	(0.093)	(0.085)	(0.084)	(0.086)
Semi-routine occupations	0.040	0.045	0.020	0.026	0.040
	(0.080)	(0.082)	(0.076)	(0.075)	(0.077)
Routine occupations	-0.124	-0.106	-0.102	-0.103	-0.078
	(0.089)	(0.092)	(0.087)	(0.087)	(0.092)
Unemployed or no parent	0.086	0.094	-0.022	-0.016	0.003
	(0.120)	(0.118)	(0.114)	(0.112)	(0.113)
No. of siblings. Baseline: no siblings.					
1	0.044	0.038	0.054	0.059	0.063
	(0.068)	(0.069)	(0.055)	(0.054)	(0.054)
2	-0.029	-0.035	0.023	0.021	0.030
	(0.071)	(0.073)	(0.059)	(0.059)	(0.059)
3	-0.003	-0.006	0.019	0.011	0.022
	(0.072)	(0.074)	(0.057)	(0.057)	(0.057)
4+	0.064	0.047	0.088	0.091	0.092
	(0.083)	(0.084)	(0.072)	(0.070)	(0.070)
Boost sample	-0.020	0.053	0.027	0.007	-0.000
	(0.169)	(0.166)	(0.217)	(0.217)	(0.216)
FMS eligible	-0.148*	-0.153*	-0.187**	-0.198**	-0.197**
	(0.077)	(0.078)	(0.076)	(0.077)	(0.078)
Born in the UK	-0.191***	-0.197***	-0.144*	-0.139*	-0.128

	(0.072)	(0.074)	(0.080)	(0.081)	(0.080)
Math test score quintiles at age 11. Baseline category: first quintile.					
Second quintile	0.042	0.051	0.024	0.021	0.018
	(0.100)	(0.100)	(0.088)	(0.089)	(0.090)
Third quintile	0.133	0.121	0.091	0.089	0.084
	(0.100)	(0.100)	(0.089)	(0.088)	(0.089)
Fourth quintile	0.149	0.129	0.102	0.095	0.087
	(0.101)	(0.103)	(0.094)	(0.094)	(0.095)
Fifth quintile	0.166	0.144	0.093	0.088	0.082
	(0.103)	(0.107)	(0.098)	(0.099)	(0.100)
Reading test score quintiles at age 11. Baseline category: first quintile.					
Second quintile	0.052	0.056	-0.035	-0.037	-0.021
	(0.094)	(0.091)	(0.080)	(0.081)	(0.080)
Third quintile	-0.008	-0.006	-0.062	-0.071	-0.055
	(0.084)	(0.083)	(0.072)	(0.072)	(0.072)
Fourth quintile	-0.037	-0.013	-0.084	-0.094	-0.075
	(0.092)	(0.094)	(0.083)	(0.083)	(0.084)
Fifth quintile	0.016	0.029	-0.032	-0.041	-0.031
	(0.091)	(0.090)	(0.079)	(0.080)	(0.081)
Capped linear GCSE score quintiles at age 16. Baseline category: first quintile.					
Second quintile	-0.104	-0.089	-0.080	-0.079	-0.083
	(0.120)	(0.117)	(0.099)	(0.102)	(0.104)
Third quintile	0.018	0.023	0.020	0.018	0.027
	(0.119)	(0.115)	(0.097)	(0.099)	(0.101)
Fourth quintile	0.040	0.044	0.050	0.049	0.055
	(0.125)	(0.122)	(0.101)	(0.102)	(0.105)
Fifth quintile	0.166	0.133	0.098	0.088	0.100
	(0.125)	(0.125)	(0.105)	(0.106)	(0.108)
University subject, baseline category: medicine					
Sciences		-0.144**	-0.179***	-0.180***	-0.202***
		(0.064)	(0.066)	(0.068)	(0.070)
Engineering, tech, architecture		0.044	-0.095	-0.100	-0.126
		(0.081)	(0.084)	(0.087)	(0.089)
Law and business		-0.056	-0.105	-0.116	-0.146*
		(0.079)	(0.079)	(0.081)	(0.083)
Social sciences, humanities, languages		-0.160**	-0.162**	-0.166**	-0.193***
		(0.066)	(0.065)	(0.068)	(0.070)
Education		-0.271**	-0.205	-0.215	-0.231
		(0.113)	(0.133)	(0.137)	(0.144)
Other		-0.021	-0.100	-0.067	-0.091
		(0.144)	(0.112)	(0.111)	(0.115)
Russell Group university		0.077*	0.018	0.020	0.024
		(0.043)	(0.039)	(0.039)	(0.038)
Postgraduate degree		0.016	0.013	0.009	0.005

		(0.038)	(0.034)	(0.033)	(0.033)
Worked while at uni as a part of career		0.026	0.039	0.042	0.034
		(0.055)	(0.053)	(0.051)	(0.052)
Worked while at uniform other reasons		0.008	0.005	0.007	0.005
		(0.039)	(0.036)	(0.036)	(0.035)
Have student loan		0.021	0.005	0.002	0.004
		(0.047)	(0.041)	(0.042)	(0.041)
Found current job through social network			-0.031	-0.024	-0.022
			(0.031)	(0.031)	(0.032)
Highest qualification was needed to get current job			0.154***	0.155***	0.152***
			(0.036)	(0.036)	(0.036)
Works more than 45 hours per week			-0.145***	-0.143***	-0.145***
			(0.037)	(0.037)	(0.037)
Occupation category. Baseline: Managerial					
Science and medical prof			0.008	0.006	-0.000
			(0.098)	(0.097)	(0.096)
Science associate			-0.045	-0.054	-0.065
			(0.095)	(0.093)	(0.092)
Administrative			-0.104	-0.102	-0.099
			(0.096)	(0.093)	(0.093)
Skilled trades			-0.089	-0.088	-0.086
			(0.121)	(0.118)	(0.118)
Personal service			-0.153	-0.154	-0.146
			(0.101)	(0.098)	(0.100)
Sales and customer service			-0.097	-0.082	-0.082
			(0.092)	(0.090)	(0.089)
Operative			-0.342	-0.328	-0.269
			(0.214)	(0.205)	(0.221)
Elementary trades			-0.131	-0.109	-0.114
			(0.089)	(0.086)	(0.086)
Industry codes. Baseline: Agriculture, mining, construction					
Manufacturing; food, textile			0.120	0.110	0.115
			(0.093)	(0.091)	(0.093)
Manufacturing: electronics			0.180*	0.159*	0.185*
			(0.097)	(0.095)	(0.095)
Transportation			0.112	0.087	0.098
			(0.091)	(0.088)	(0.088)
Trade			0.008	-0.005	0.014
			(0.114)	(0.111)	(0.112)
Finance			0.149*	0.127	0.142*
			(0.084)	(0.083)	(0.082)
Services: trade			0.095	0.071	0.092
			(0.084)	(0.080)	(0.080)
Services: caring			0.020	-0.009	0.005
			(0.079)	(0.077)	(0.077)

Public administration			-0.016	-0.027	-0.011
			(0.103)	(0.100)	(0.099)
Having well-paying job is important			0.027	0.034	0.025
			(0.032)	(0.032)	(0.032)
Living in London at age 25			0.141***	0.131***	0.135***
			(0.047)	(0.047)	(0.046)
Employment tenure in month			0.002***	0.002**	0.002***
			(0.001)	(0.001)	(0.001)
Working for a medium-sized firm			0.157***	0.150***	0.150***
			(0.036)	(0.036)	(0.037)
Working for a large firm			0.211***	0.198***	0.198***
			(0.037)	(0.037)	(0.038)
Having children				-0.010	0.001
				(0.061)	(0.061)
Partner				-0.012	-0.005
				(0.038)	(0.038)
Living with parents				-0.104***	-0.099**
				(0.038)	(0.039)
High locus of control					0.026
					(0.040)
High risk tolerance					0.057
					(0.035)
High patience					-0.048
					(0.032)
High trust					-0.034
					(0.031)
Constant	1.981	2.222*	1.812	1.753	1.596
	(1.206)	(1.213)	(1.123)	(1.114)	(1.127)
No. of obs.	863	863	863	863	863
R-squared	0.186	0.213	0.377	0.386	0.394

Sample of university graduates. Linear regression models estimated by OLS, weighted using Wave 8 weights. Robust standard errors clustered by sampling school are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); region at age 13; whether born in the UK; mothers' and fathers' age, mothers' and fathers' social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. Details of HE degree: having an MA degree; course (7 categories: Medicine; Sciences; Engineering, tech, architecture; Law and business; Social sciences, humanities, languages; Education; other); going to a Russell Group university, having student loan; working while at university. Details of employment and finding a job: industry, occupation, preference for a high-paying job at age 13, finding job through social network, whether qualification was needed to get current job, working more than 45 hours a week; occupation (1-digit SOC); industry (1 digit SIC), living in London, firm size, employment tenure. Family and living conditions: having children; living with parents; having a partner. Non-cognitive skills: locus of control; preference for risk; patience; trust. The missing values of control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4

Table O3: The FiF gap in log hourly wage: potential channels – detailed results, women

	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
FiF	-0.077*	-0.059	-0.054	-0.051	-0.047
	(0.040)	(0.038)	(0.036)	(0.036)	(0.035)
Age	0.004	0.006**	0.003	0.004	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
White	-0.101**	-0.057	-0.006	-0.012	-0.012
	(0.050)	(0.049)	(0.045)	(0.046)	(0.045)
Region of school at age 13/14. Baseline category: North East					
North West	0.076	0.092*	0.058	0.043	0.035
	(0.057)	(0.053)	(0.042)	(0.041)	(0.043)
Yorkshire and The Humber	0.018	0.014	0.021	0.008	0.006
	(0.054)	(0.052)	(0.042)	(0.041)	(0.043)
East Midlands	0.195**	0.231***	0.225***	0.206***	0.196***
	(0.078)	(0.074)	(0.068)	(0.067)	(0.065)
West Midlands	0.066	0.086	0.084	0.077	0.067
	(0.078)	(0.071)	(0.057)	(0.056)	(0.056)
East of England	0.094*	0.115**	0.104**	0.093**	0.091**
	(0.056)	(0.053)	(0.044)	(0.043)	(0.045)
London	0.141**	0.165***	0.110**	0.113**	0.095*
	(0.063)	(0.059)	(0.054)	(0.053)	(0.053)
South East	0.193***	0.231***	0.225***	0.216***	0.206***
	(0.062)	(0.061)	(0.050)	(0.049)	(0.051)
South West	-0.012	-0.003	-0.005	-0.020	-0.026
	(0.063)	(0.060)	(0.052)	(0.053)	(0.054)
Mother's age. Baseline category: below 35.					
35-44	0.041	0.020	0.048	0.040	0.062
	(0.052)	(0.050)	(0.047)	(0.049)	(0.050)
45-54	0.068	0.053	0.057	0.048	0.063
	(0.063)	(0.060)	(0.054)	(0.056)	(0.057)
55+	-0.013	-0.003	0.021	0.001	-0.003
	(0.156)	(0.162)	(0.164)	(0.165)	(0.163)
Father's age. Baseline category: below 35.					
35-44	-0.078	-0.040	-0.106	-0.099	-0.083
	(0.085)	(0.080)	(0.072)	(0.076)	(0.078)
45-54	-0.101	-0.056	-0.117	-0.108	-0.090
	(0.099)	(0.091)	(0.082)	(0.086)	(0.088)
55+	0.026	0.074	0.031	0.036	0.053
	(0.118)	(0.110)	(0.098)	(0.101)	(0.103)
Father’s social class. Baseline category: Higher Managerial and professional occupations.					
Lower managerial and professional o.	0.056	0.057	0.047	0.052	0.052*
	(0.037)	(0.036)	(0.032)	(0.032)	(0.031)
Intermediate occupations	-0.020	-0.021	-0.026	-0.026	-0.037
	(0.058)	(0.058)	(0.050)	(0.051)	(0.050)
Small employers and own account workers	0.081	0.091	0.091	0.098*	0.095

	(0.064)	(0.062)	(0.058)	(0.059)	(0.059)
Lower supervisory and technical o.	0.027	0.029	0.049	0.056	0.054
	(0.054)	(0.051)	(0.047)	(0.048)	(0.048)
Semi-routine occupations	0.008	0.030	0.082	0.091*	0.087*
	(0.054)	(0.052)	(0.052)	(0.052)	(0.052)
Routine occupations	-0.002	-0.001	0.020	0.030	0.036
	(0.054)	(0.051)	(0.050)	(0.051)	(0.050)
Unemployed or no parent	-0.007	-0.006	0.009	0.013	0.014
	(0.091)	(0.088)	(0.085)	(0.085)	(0.083)
Mother's social class. Baseline category: Higher Managerial and professional occupations.					
Lower managerial and professional o.	-0.058	-0.065	-0.030	-0.031	-0.033
	(0.045)	(0.045)	(0.038)	(0.037)	(0.037)
Intermediate occupations	0.023	-0.004	0.028	0.029	0.022
	(0.048)	(0.048)	(0.043)	(0.043)	(0.043)
Small employers and own account workers	-0.124*	-0.113*	-0.069	-0.068	-0.068
	(0.064)	(0.064)	(0.058)	(0.057)	(0.058)
Lower supervisory and technical o.	-0.048	-0.064	-0.026	-0.022	-0.031
	(0.068)	(0.068)	(0.058)	(0.058)	(0.057)
Semi-routine occupations	-0.052	-0.080	-0.048	-0.045	-0.049
	(0.056)	(0.055)	(0.049)	(0.049)	(0.049)
Routine occupations	-0.097	-0.126*	-0.090	-0.085	-0.092
	(0.077)	(0.070)	(0.070)	(0.070)	(0.071)
Unemployed or no parent	-0.131	-0.156	-0.102	-0.095	-0.091
	(0.102)	(0.095)	(0.088)	(0.087)	(0.085)
No. of siblings. Baseline: no siblings.					
1	0.113***	0.080**	0.055	0.054	0.053
	(0.042)	(0.041)	(0.035)	(0.035)	(0.034)
2	0.084**	0.053	0.032	0.032	0.030
	(0.042)	(0.040)	(0.036)	(0.036)	(0.035)
3	0.064	0.042	0.049	0.049	0.054
	(0.051)	(0.049)	(0.045)	(0.045)	(0.044)
4+	0.097	0.100	0.099	0.104	0.111
	(0.096)	(0.088)	(0.078)	(0.080)	(0.080)
Boost sample	-0.360***	-0.343***	-0.351***	-0.353***	-0.360***
	(0.103)	(0.123)	(0.133)	(0.131)	(0.134)
FMS eligible	0.035	0.043	0.033	0.026	0.028
	(0.075)	(0.072)	(0.070)	(0.072)	(0.072)
Born in the UK	0.020	0.015	-0.027	-0.023	-0.027
	(0.057)	(0.054)	(0.056)	(0.056)	(0.057)
Math test score quintiles at age 11. Baseline category: first quintile.					
Second quintile	0.020	0.033	0.067	0.069	0.062
	(0.045)	(0.046)	(0.043)	(0.044)	(0.045)
Third quintile	0.105**	0.088**	0.109**	0.123***	0.135***
	(0.043)	(0.044)	(0.042)	(0.043)	(0.044)
Fourth quintile	0.141***	0.135***	0.171***	0.177***	0.184***
	(0.053)	(0.052)	(0.049)	(0.050)	(0.050)
Fifth quintile	0.144***	0.118**	0.146***	0.150***	0.154***
	(0.051)	(0.054)	(0.048)	(0.048)	(0.048)

Reading test score quintiles at age 11. Baseline category: first quintile.					
Second quintile	0.059	0.024	0.010	0.005	0.006
	(0.052)	(0.053)	(0.049)	(0.049)	(0.049)
Third quintile	-0.008	-0.053	-0.059	-0.057	-0.071
	(0.054)	(0.056)	(0.053)	(0.053)	(0.054)
Fourth quintile	-0.014	-0.039	-0.041	-0.046	-0.053
	(0.054)	(0.054)	(0.050)	(0.050)	(0.050)
Fifth quintile	0.016	-0.007	-0.002	-0.003	-0.012
	(0.057)	(0.057)	(0.053)	(0.054)	(0.053)
Capped linear GCSE score quintiles at age 16. Baseline category: first quintile.					
Second quintile	0.121*	0.102	0.064	0.066	0.061
	(0.070)	(0.068)	(0.068)	(0.069)	(0.067)
Third quintile	0.180***	0.154**	0.122*	0.113*	0.114*
	(0.069)	(0.066)	(0.064)	(0.064)	(0.066)
Fourth quintile	0.256***	0.221***	0.127**	0.119*	0.118**
	(0.070)	(0.067)	(0.062)	(0.061)	(0.059)
Fifth quintile	0.254***	0.187***	0.098	0.090	0.089
	(0.073)	(0.072)	(0.069)	(0.069)	(0.068)
University subject, baseline category: medicine					
Sciences		-0.180***	-0.096**	-0.093**	-0.104***
		(0.039)	(0.039)	(0.039)	(0.040)
Engineering, tech, architecture		-0.069	-0.069	-0.068	-0.067
		(0.080)	(0.065)	(0.066)	(0.065)
Law and business		-0.116**	-0.065	-0.057	-0.077
		(0.052)	(0.049)	(0.049)	(0.050)
Social sciences, humanities, languages		-0.280***	-0.185***	-0.178***	-0.185***
		(0.037)	(0.036)	(0.038)	(0.038)
Education		-0.229***	-0.112*	-0.108*	-0.108*
		(0.063)	(0.063)	(0.064)	(0.063)
Other		-0.097	0.030	0.037	0.020
		(0.083)	(0.065)	(0.062)	(0.060)
Russell Group university		0.068**	0.059**	0.057**	0.054*
		(0.031)	(0.028)	(0.028)	(0.028)
Postgraduate degree		0.032	0.032	0.032	0.037
		(0.027)	(0.025)	(0.025)	(0.025)
Worked while at uni as a part of career		-0.126***	-0.065	-0.060	-0.064
		(0.047)	(0.041)	(0.042)	(0.042)
Worked while at uniform other reasons		0.089***	0.080***	0.080***	0.076***
		(0.031)	(0.029)	(0.029)	(0.029)
Have student loan		0.037	0.087***	0.084**	0.093***
		(0.039)	(0.033)	(0.034)	(0.035)
Found current job through social network			-0.011	-0.004	-0.001
			(0.028)	(0.029)	(0.029)
Highest qualification was needed to get current job			0.160***	0.156***	0.150***

			(0.027)	(0.026)	(0.027)
Works more than 45 hours per week			-0.170***	-0.178***	-0.175***
			(0.028)	(0.029)	(0.028)
Occupation category. Baseline: Managerial					
Science and medical prof			-0.091	-0.078	-0.086
			(0.127)	(0.126)	(0.128)
Science associate			-0.187	-0.181	-0.186
			(0.124)	(0.123)	(0.125)
Administrative			-0.231*	-0.220*	-0.220*
			(0.124)	(0.124)	(0.126)
Skilled trades			-0.101	-0.113	-0.098
			(0.138)	(0.137)	(0.135)
Personal service			-0.219*	-0.211*	-0.214*
			(0.124)	(0.123)	(0.125)
Sales and customer service			-0.215*	-0.207	-0.205
			(0.127)	(0.126)	(0.127)
Operative			-0.440***	-0.426***	-0.424***
			(0.146)	(0.150)	(0.152)
Elementary trades			-0.228*	-0.215*	-0.221*
			(0.131)	(0.130)	(0.131)
Industry codes. Baseline: Agriculture, mining, construction					
Manufacturing; food, textile			-0.087	-0.088	-0.086
			(0.076)	(0.075)	(0.082)
Manufacturing: electronics			0.006	0.019	0.038
			(0.063)	(0.063)	(0.064)
Transportation			-0.064	-0.059	-0.049
			(0.058)	(0.058)	(0.060)
Trade			-0.057	-0.053	-0.032
			(0.068)	(0.068)	(0.070)
Finance			0.016	0.021	0.033
			(0.056)	(0.055)	(0.057)
Services: trade			-0.039	-0.039	-0.020
			(0.060)	(0.059)	(0.059)
Services: caring			-0.054	-0.047	-0.027
			(0.046)	(0.045)	(0.048)
Public administration			-0.218**	-0.208**	-0.195**
			(0.097)	(0.093)	(0.096)
Having well-paying job is important			0.093***	0.098***	0.095***
			(0.025)	(0.026)	(0.026)
Living in London at age 25			0.101**	0.094**	0.101**
			(0.042)	(0.042)	(0.041)
Employment tenure in month			0.003***	0.003***	0.002***
			(0.001)	(0.001)	(0.001)
Working for a medium-sized firm			0.062**	0.063**	0.064**
			(0.028)	(0.028)	(0.028)
Working for a large firm			0.173***	0.174***	0.172***
			(0.029)	(0.029)	(0.029)
Having children				-0.116**	-0.120**
				(0.048)	(0.049)
Partner				0.008	0.009

				(0.029)	(0.030)
Living with parents				-0.040	-0.037
				(0.032)	(0.031)
High locus of control					0.093***
					(0.033)
High risk tolerance					-0.018
					(0.032)
High patience					-0.052**
					(0.023)
High trust					0.023
					(0.026)
Constant	0.637	0.418	1.008	0.917	1.057
	(0.899)	(0.905)	(0.820)	(0.821)	(0.822)
No. of obs.	1,167	1,167	1,167	1,167	1,167
R-squared	0.140	0.202	0.348	0.353	0.363

Sample of university graduates. Linear regression models estimated by OLS, weighted using Wave 8 weights. Robust standard errors clustered by sampling school are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost added to the survey in Wave 4. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); region at age 13; whether born in the UK; mothers' and fathers' age, mothers' and fathers' social class, number of siblings, FSM eligibility. Early educational attainment: math and reading Key stage 2 test scores in quintiles measured at age 11. Educational progression: capped linear GCSE score quintiles at age 16. Details of HE degree: having an MA degree; course (7 categories: Medicine; Sciences; Engineering, tech, architecture; Law and business; Social sciences, humanities, languages; Education; other); going to a Russell Group university, having student loan; working while at university. Details of employment and finding a job: industry, occupation, preference for a high-paying job at age 13, finding job through social network, whether qualification was needed to get current job, working more than 45 hours a week; occupation (1-digit SOC); industry (1 digit SIC), living in London, firm size, employment tenure. Family and living conditions: having children; living with parents; having a partner. Non-cognitive skills: locus of control; preference for risk; patience; trust. The missing values of control variables are controlled for using missing flags.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016: Secure Access. DOI: 10.5255/UKDA-SN-7104-4