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DISCUSSION PAPER SERIES

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ABSTRACT

The Labor Market Returns to 'First in Family' University Graduates*

We exploit linked survey-administrative data from England to examine how first in family (FiF) graduates (those whose parents do not have university degrees) fare on the labor market. We find that among graduate women, FiF graduates earn 8.3% less on average than graduate women whose parents have a university degree. For men, we find no such difference. A decomposition of the difference between FiF and non-FiF graduate women reveals that prior academic attainment, whether they attended an 'elite' institution, and whether they needed their degree for their job fully explains this gap. We also estimate returns to graduation for potential FiF and non-FiF young people. We find that although the wage returns to graduation are higher among FiF women compared to women who match their parents with a degree, the negative effects of coming from a lower educated family are so large that they counteract the high returns of graduation.

JEL Classification: I24, I26, J24

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

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1. Introduction

Previous literature on the returns to a university degree has presented convincing evidence that university degrees lead to large 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 (or do not gain) admission (Bertrand, Hanna, and Mullainathan 2010). In England, affirmative action policy for higher education fall 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 2020a) or increase the enrolment of students from disadvantaged backgrounds for post-graduate courses (e.g. Wakeling and Kyriacou 2010), there is very little work which looks at the relationship between markers of disadvantage, graduation, and labor market returns. This paper aims to fill this gap and document how students in England who are targeted as part of widening participation policies fare in the labor market after completing their degrees.

We provide the first evidence on the early labor market outcomes of first in family graduates in England. 'First in family' (FiF) graduates are those whose (step) parents do not have a university degree, but they go on to achieve one and is currently used as a WP indicator by a range of universities (Henderson, Shure, and Adamecz-Völgyi 2020). England is the ideal setting for this research thanks to its national, compulsory standardized examinations during school and centralized university admissions. We use linked survey-administrative data on a sample of young people born in 1989/90 to look at socioeconomic disadvantage in early career labor market outcomes. Our quasi-experimental identification strategy relies on a rich set of observed characteristics from linked survey-administrative data, including detailed childhood measures of family background and prior educational attainment, and entropy balancing.

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 the labor market returns by FiF status in England, it builds on existing work which 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 have 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. 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 returns to university for individuals 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. They follow the methodology used by Blundell, Dearden, and Sianesi (2005) which uses the National Child Development Study (NCDS), a cohort born in 1958. Unlike most other papers, they find little evidence of systematic differences in earnings by parental social class. There is a large and complementary literature on the intergenerational transmission of education and socioeconomic status (e.g. Blanden and Macmillan 2016; Blanden and Machin 2004).

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. 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. This paper extends this by explicitly examining the difference between the probability of employment and earnings of FiF and non-FiF university graduates at age 25/26.

We contribute to the previous literature in two key ways. First, we present the first ever results on the labor market earnings of FiF graduates in England. We want to know whether university serves as an equalizer for two university graduates who studied the same subject, at a similar institution, with similar prior attainment, but one is FiF and one is not. This is important evidence for university widening participation teams. As Henderson, Shure, and Adamecz-Völgyi (2020) point out, this is a commonly used indicator in the WP agenda, currently used by a majority of Russell Group and many other universities. These universities are not only interested in getting WP candidates 'through the door', but also in understanding how they fare at and beyond university. Second, we use a recent cohort of individuals, born in

1989/90, to update our knowledge about the strength of the relationship between intergenerational education mobility to university and individual labor market outcomes. This builds on previous work using earlier cohort studies from the UK, including the 1958 NCDS and the 1970 BCS (Blundell, Dearden, and Sianesi 2005; Bratti, Naylor, and Smith 2005).

The main empirical section of this paper is divided into two parts. First, we compare the probability of employment and the wages of FiF and non-FiF graduates. This allows us to explore whether FiF graduates face a penalty in the labor market as compared to their graduate peers whose parents are graduates. We probe the penalties uncovered in this analysis using regression techniques and an Oaxaca-Blinder decomposition. Second, 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 findings from the comparison of university graduates and disentangle the effect of an individual's graduation from an individual's family background. This is especially important in the case of women. In our main models, we implement entropy balancing, a quasi-experimental program evaluation technique, in order to compare our group of interest, FiF graduates, to the most comparable control group.

Our results show that FiF graduate women face an 8.3% wage penalty in the labor market compared to their female peers who match their parents with a university degree. We find no evidence of this penalty for male FiF university graduates. We also find no evidence of any FiF disadvantage for men or women in terms of the probability of employment. These results are robust to controlling for early educational attainment (as a proxy for cognitive abilities) and controlling for a series of university and employment characteristics such as university quality, course choice, industry, occupation, fertility and non-cognitive traits. We conduct an Oaxaca-Blinder decomposition of the FiF versus non-FiF graduate wage gap to see how much of the gap comes from the different distributions of these characteristics (*endowments*) between the two groups, and how much of it remains *unexplained*. We find that the theoretical FiF wage gap that emerges due to the different endowments of FiF and non-FiF graduates is the same for men and women. However, FiF men compensate about two-thirds of this gap by showing different (unexplained) returns to these characteristics. For women, on the other hand, different endowments explain the FiF penalty almost completely. Its main drivers are early educational attainment, whether they attended an elite (Russell Group) university and whether their highest qualification was needed to get their current job.

Disentangling these effects further, we find that the returns to graduation are larger among FiF female graduates than among those whose parents are graduates. However, the negative effect of having non-graduate parents for female graduates is larger in magnitude than the positive returns to their own graduation. Thus, the negative wage effect that we find for FiF women is a consequence of the large negative effect of having non-graduate parents among women in general, 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.

Regarding men, we find similarly small and insignificant returns to graduation in both groups; thus, for men, having non-graduate or graduate parents does not seem to matter on the labor market at age 25/26. Our findings indicate that intergenerational educational mobility to university may be more challenging for women than for their male peers and may supply an explanation to the stagnant gender wage gap for university graduates.

The rest of this paper proceeds as follows. We present the data used in this paper in Section 2 and our empirical approach in Section 3. We compare the probability of employment and wages of FiF and non-FiF graduates in Section 4. In Section 5, 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 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

[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.

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 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 estimated using 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 WP measures or background variables, we take the first available response mentioned for parental

[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).

class, parental education and household tenure over the first four waves. We take care of any remaining item non-response of explanatory variables using missing flags.

Table 1 shows that 81% of the sample is employed at age 25/26 and wage information is available for 5,247 of those individuals (82% of those working). Thus, as robustness checks, we control for the inverse Mills ratio of the probability of employment and reporting wage conditional on employment estimated in a Heckman-style selection equation in our wage models (Section 1 in Appendix A). 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 (Adamecz-Völgyi, Henderson, and Shure 2020b, Table A1 in Appendix A).[3]

Out of the 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), 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.

[3] Following Belfield et al. (2018) as closely as possible, we estimated returns to graduation using a sample of individuals having at least 5 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 (Adamecz-Völgyi, Henderson, and Shure 2020b, Table A1 in Appendix A).

[4] Information on parental education is missing for 43 observations in the sample. We provide a robustness check to this problem in Section 2 in Appendix B.

Table 1: Descriptive statistics

	Total sample			Men			Women		
	Obs	Mean	SE	Obs	Mean	SE	Obs	Mean	SE
Employed	7683	0.81	0.01	3417	0.84	0.01	4266	0.78	0.01
Log hourly wage	5247	2.29	0.01	2345	2.34	0.01	2902	2.24	0.01
Parents have no degree	7664	0.84	0.00	3403	0.83	0.00	4261	0.84	0.00
Graduated	7707	0.27	0.01	3426	0.25	0.01	4281	0.28	0.01
FiF	7664	0.18	0.00	3403	0.16	0.00	4261	0.20	0.00
FiF among the graduated	2689	0.68	0.01	1155	0.64	0.01	1534	0.71	0.01
Descriptive statistics by groups									
Employment									
Graduated young people									
Parents are graduates	818	0.87	0.01	388	0.87	0.01	430	0.87	0.01
Parents are not graduates: FiF	1853	0.89	0.01	759	0.88	0.01	1094	0.89	0.01
Non-graduated young people									
Parents are graduates	667	0.86	0.02	317	0.88	0.02	350	0.83	0.02
Parents are not graduates	4302	0.77	0.01	1930	0.81	0.01	2372	0.72	0.01
No. of observations with non-missing data on employment									7683
Log hourly wage									
Graduated young people									
Parents are graduated	619	2.46	0.02	291	2.49	0.02	328	2.44	0.02
Parents are not graduated: FiF	1419	2.39	0.02	575	2.45	0.02	844	2.34	0.02
Non-graduated young people									
Parents are graduated	463	2.35	0.03	219	2.32	0.03	244	2.38	0.03
Parents are not graduated	2720	2.21	0.01	1248	2.28	0.01	1472	2.14	0.01
No. of observations with non-missing data on wage									5247

Obs refers to the number of non-missing observations. Total number of observations: 7,707. Weighted using Wave 8 weights. Data on parental graduation are missing for 47 individuals.
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

Comparing the raw averages of employment, FiF graduates are approximately as likely to be employed as graduates whose parents are also graduates (89% and 87% respectively, Table 1), but they are more likely to be employed than non-graduate individuals whose parents are not graduates (89% vs. 77%, Table 1). In terms of log hourly wages, graduates whose parents are also graduates earn the most, both on average and for each gender separately (Table 1). Interestingly, raw wage differences across FiF and non-FiF graduates are higher for women than for men (roughly 10% vs. 4%, Table 1).

3. Empirical approach

Throughout this analysis, we look at the relationship between intergenerational educational mobility and two outcome variables at age 25/26: the probability of employment and wages. Employment is a binary variable indicating whether the individual is employed or not; wage is a continuous variable capturing the natural logarithm of self-assessed gross hourly wages. This allows us to normalize the wage distribution and take into account hours worked. Naturally, we only observe wages only for those who were working at the time of the data collection and report wage data. As mentioned before, on average, 81% of the sample work and 82% of those employed report wage data (Table 1). In Section 1 in Appendix A, we provide a robustness check to investigate any potential estimation bias due to selection to employment and reporting 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. Thus, we are restricted to the use of descriptive and quasi-experimental methods. 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, and entropy balancing techniques, to get closer to the causal impacts of intergenerational educational mobility on labor market outcomes.

This paper looks at FiF graduates from two angles. First, we look at differences in the labor market outcomes of FiF and non-FiF university graduates. Second, 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 probability of employment and wages of FiF and non-FiF graduates

We start by examining whether being first in family influence the probability of employment and wages among graduates. 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 our outcome variable (either employment or log hourly wage);
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 individual characteristics; and
u_{1i}	is an error term, robust and clustered by sampling schools.

All models that we estimate are weighted using the final Wave 8 weights. In the first model, we do not include any control variables besides FiF (Model 1). 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, 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 2.[5] Lastly, we extend the model with Key Stage 2 exam scores[6], measured at age 11, in math and reading as a proxy for cognitive abilities, and with capped linear GCSE score quintiles measured at age 16 to control for educational progression in compulsory schooling in Model 3.

We go one step further and attempt to decrease any potential observed selection bias using entropy balancing (Hainmueller 2011). Entropy balancing (EB) is a quasi-experimental method that relies 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-graduate parents is as good and random (Angrist and Pischke 2008). The unconfoundedness assumption also implies that there should be no unobserved characteristics that affect both parental education and the labor market outcomes of individuals. Compared to similar methods that rely on unconfoundedness, such as regression or statistical matching, entropy balancing has been shown to have superior empirical characteristics (Hainmueller 2011; Zhao and Percival 2017).

EB is a reweighting procedure to achieve covariate balance with binary treatment variables based on the first, second or higher-order moments of the covariates (Harvey et al. 2017). The procedure has two steps. In the first step, using the ebalance procedure in Stata (Hainmueller and Xu 2013), we construct the balancing weights that satisfy a set of balance conditions requiring that the entropy distance between the first and second moments of the explanatory variables used in Model 3 (whether individual *i* belongs to the sample boost;

[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).

individuals' age measured in months; ethnicity; fixed effects (FE) for the regions of individual's school; mother's and father's age; mother's and father's social class; number of siblings; FSM eligibility; Key Stage 2 exam scores in math and reading; and capped linear GCSE score quintiles) is below a certain threshold between FiF and non-FiF graduates, separately by gender. In the second step, we re-estimate the model applying the entropy balanced weights constructed in the first step (Model 4). Thus, both Model 3 and Model 4 include the same control variables, but Model 4 is extended with entropy balanced weights (see the balance of the sample before and after applying the EB weights in Adamecz-Völgyi, Henderson, and Shure 2020b, Figure C1 in Appendix C). We consider Model 4, the entropy balanced model, as our main model in this paper and extend it with further control variables in subsection 4.2 to investigate whether they attenuate the FiF penalty among graduates. As entropy balancing does not differentiate between observations within or outside of a common support, we re-estimated our main results using propensity score matching as well which led to the same conclusions (Section 3 in Appendix A).

The previous methods estimate the magnitude of the FiF gap holding all other explanatory variables constant; however, FiF and non-FiF graduates might differ in terms of their individual characteristics substantially. Thus, in subsection 4.3, we decompose the raw FIF wage gap using Oaxaca-Blinder 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. 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.

3.2. Estimating returns to graduation

In the second part of the paper 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 in Next Steps 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:

$$wage_i = a_2 + b_2*graduate_i + c_2*X_i + u_{2i} \tag{2}$$

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:
$parents\_nodegree_i$	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 and entropy-balanced weights as before.[7] 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 apply entropy-balanced weights, estimated based on these variables. In Model 5, we add potential FiF (i.e. parents without a university degree, non-graduates) and in Model 6 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. Comparing the probability of employment and wages of FiF and non-FiF graduates

4.1. **Main results**

Table 2 shows the association between being first in family and the probability of employment, estimated using linear probability models. All coefficients are interpreted as one-hundredths of a percentage point, i.e. 100 times the coefficients are interpreted as percentage points. According to Model 1, in which no additional control variables are included, the relationship

[7] See the balance of the sample before and after applying the entropy balanced weights in Adamecz-Völgyi, Henderson, and Shure 2020b, Appendix D.

between first in family and the probability of employment is positive, 0.7 percentage points among men and 1.9 percentage points among women, and both coefficients are insignificant. Adding various demographic and family background characteristics in Model 2 and controls for early educational attainment in Model 3 do not change these small and insignificant effects, neither does applying entropy balanced weights (Model 4). Thus, we do not find evidence of any systematic statistical relationship between the probability of employment and being FiF for university graduates.

Table 2: The effects of being FiF among graduates on the probability of employment

	Model 1	Model 2	Model 3	Model 4
		Men		
First in family	0.007	0.028	0.024	0.010
	(0.024)	(0.029)	(0.030)	(0.034)
Constant	0.872***	1.260	1.084	1.127
	(0.017)	(0.844)	(0.849)	(1.142)
Observations	1,147	1,147	1,147	1,147
		Women		
First in family	0.019	0.011	0.001	-0.007
	(0.020)	(0.023)	(0.023)	(0.025)
Constant	0.875***	1.434**	1.004	1.373
	(0.017)	(0.681)	(0.659)	(0.870)
No. of observations	1,524	1,524	1,524	1,524
	Control variables and entropy balanced weights			
Sample boost in Wave 4	+	Yes	Yes	Yes
Demographics and family background		Yes	Yes	Yes
Early educational attainment and educational progression			Yes	Yes
Entropy balanced weights				Yes

Linear probability models estimated by OLS. Robust standard errors clustered by sampling school are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models are 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); fixed effects for the region of school at age 13/14; mother's and father's age, mother's and father's social class, number of siblings in 2004; FSM eligibility at age 15/16. 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. Due to missing information on parental education, eight male and 10 female observations were dropped from the sample. The missing values of all other explanatory variables are controlled for using missing flags. [+]Note that adding the sample boost dummy to Model 1 would lead to almost identical results. Sources: Model 1-2: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2018). Next Steps: Sweeps 1-8, 2004-2016. DOI: 10.5255/UKDA-SN-5545-6. Model 3-5: 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

In terms of log hourly wages, on the other hand, we find clear gender differences (Table 3). In all wage models, coefficients are reported in log points, and may be transformed to percentages through the following transformation: $100*(e^{beta} – 1)$, where beta is the estimated coefficient.

Among men, adding controls to the empty model turns the initially small, negative insignificant relationship (-0.036 log points in Model 1) to positive and significant (0.089 log points in Model 3) but applying the entropy balanced weights brings down the estimated coefficient close to zero (-0.009). Among women, the initially large negative relationship (-0.102 log points) gets smaller in magnitude by sequentially controlling for demographic and family background variables and early educational attainment, but it is still large and significant in Model 3 (-0.075 log points). It remains negative and statistically significant even after entropy balancing in Model 4 (-0.087 log points). In terms of percentages, in our preferred Model 4, we find that FiF female graduates earn on average 8.3% less than graduate women who have graduate parents.

Table 3: The effects of being FiF among graduates on log hourly wages at age 25/26

	Model 1	Model 2	Model 3	Model 4
		Men		
First in family	-0.036	0.062	0.089*	-0.009
	(0.039)	(0.046)	(0.046)	(0.033)
Constant	2.486***	3.038*	2.439	-0.277
	(0.035)	(1.593)	(1.612)	(1.241)
Observations	866	866	866	866
		Women		
First in family	-0.102***	-0.087**	-0.075*	-0.087*
	(0.038)	(0.038)	(0.038)	(0.047)
Constant	2.442***	1.643	1.977	1.953
	(0.032)	(1.134)	(1.322)	(1.583)
No. of observations	1,172	1,172	1,172	1,172
	Control variables and entropy balanced weights			
Sample boost in Wave 4	+	Yes	Yes	Yes
Demographics and family background		Yes	Yes	Yes
Early educational attainment and educational progression			Yes	Yes
Entropy balanced weights				Yes

Linear models estimated by OLS. 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. All models are 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); fixed effects for the region of school at age 13/14; mother's and father's age, mother's and father's social class, number of siblings in 2004; FSM eligibility at age 15/16. 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. Due to missing information on parental education, six male and nine female individuals were dropped from the sample. The missing values of all other explanatory variables are controlled for using missing flags. [+]Note that adding the sample boost dummy to Model 1 would lead to almost identical results. Sources: Model 1-2: University College London, UCL Institute of Education, Centre for Longitudinal Studies.

(2018). Next Steps: Sweeps 1-8, 2004-2016. DOI: 10.5255/UKDA-SN-5545-6. Model 3-5: 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

4.2. Exploring alternative explanations

In Table 4, we extend our main wage model, the *entropy balanced model* (Model 4 in Table 3) to look at whether adding further control variables to the model changes the magnitude of the estimated FiF wage penalty on the sample of graduates. The goal here is to identify variables that may be driving the FiF penalty, particularly for female graduates. We include measures on the details of HE 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 any 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 Table 4 is our 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 HE degree of individuals, on top of the variables used in the main model:

- Having an MA/MSc degree (as opposed to a BA/BSc);
- University course in four categories (STEM, LEM, OSSAH and other);
- Attending a Russell Group university (a measure of elite university attendance);

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;
- 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).

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 explains part of the FiF penalty. Similarly, they might also make different living and mating choices. Thus, in Model 4, we add variables on their current family and living circumstances 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).

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;
- Life satisfaction: how dissatisfied or satisfied individuals are about their life (five choices);
- 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 estimated coefficients on FiF in these five models.[8] Among men, we find small and non-significant estimates in all models, ranging from -0.009 to 0.036. Among women, adding information on the type of the HE degree slightly decreases the originally estimated coefficient from -0.087 to -0.079. Adding the details of employment has a small effect on the magnitude of the coefficient (-0.071), while adding information on family circumstances causes a further small decrease (-0.057). Lastly, adding variables on non-cognitive traits produces a coefficient of -0.055. These results show that among graduate women, FiF graduates earn on average 0.055 log points (5.4%) less than non-FiF graduates, even after controlling for a rich

[8] If we added these variables to the main model one by one, as opposed to in groups, none of them would change the estimated effect significantly (Adamecz-Völgyi, Henderson, and Shure 2020b, Table C2 in Appendix C). Thus, there is no one specific variable that seems to be more important than the others based on this exercise. We have also estimated regression models including these variables one by one along with their interaction terms with FiF to see whether the FiF gap is heterogeneous across these categories. The estimated coefficients from these models are very imprecise. We have found it hard to draw conclusions from these results, so we do not report them; however, they are available from the authors upon request.

set of potential mediators. While this effect is not significant, its magnitude is not different in a statistical sense from the one estimated in Model 1 (H0: -0.087 (0.047)=-0.055 (0.040), t-test p=0.6042).

Table 4: The FiF wage gap among men and women (linear models with entropy balanced weights; outcome variable: log hourly wage)

	Model 1	Model 2	Model 3	Model 4	Model 5
			Men		
FiF	-0.009	-0.006	0.014	0.027	0.036
	(0.033)	(0.034)	(0.029)	(0.030)	(0.031)
Constant	-0.277	-0.135	-0.015	0.066	0.143
	(1.241)	(1.208)	(1.106)	(1.076)	(1.034)
No. of observations	866	866	866	866	866
			Women		
FiF	-0.087*	-0.079*	-0.071*	-0.057	-0.055
	(0.047)	(0.044)	(0.041)	(0.040)	(0.040)
Constant	1.953	2.457	2.745**	2.316*	2.559**
	(1.583)	(1.542)	(1.249)	(1.226)	(1.279)
No. of observations	1,172	1,172	1,172	1,172	1,172
			Control variables		
Sample boost	Yes	Yes	Yes	Yes	Yes
Demographics and family background	Yes	Yes	Yes	Yes	Yes
Early educational attainment and 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
Fertility and living conditions				Yes	Yes
Non-cognitive skills					Yes

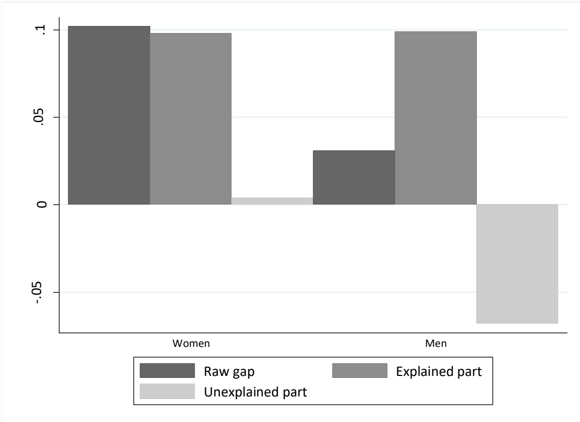
Sample of university graduates. Linear regression models estimated by OLS, weighted using entropy-balanced weights. Robust standard errors clustered by sampling school are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Control variables: Sample boost: whether the individual belongs to the sample boost 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; 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 (STEM, LEM, OSSAH, other); going to a Russell Group 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 code); industry (1-digit SIC code). Family and living conditions: having children; living with parents; having a partner. Non-cognitive skills: locus of control; preference for risk; patience; trust. Due to missing information on parental education (i.e., first in family), 6 male and 9 female individuals were dropped from the sample. The missing values of all other explanatory 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

4.3. Oaxaca-Blinder decomposition of the wage gap

The Oaxaca-Blinder 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.

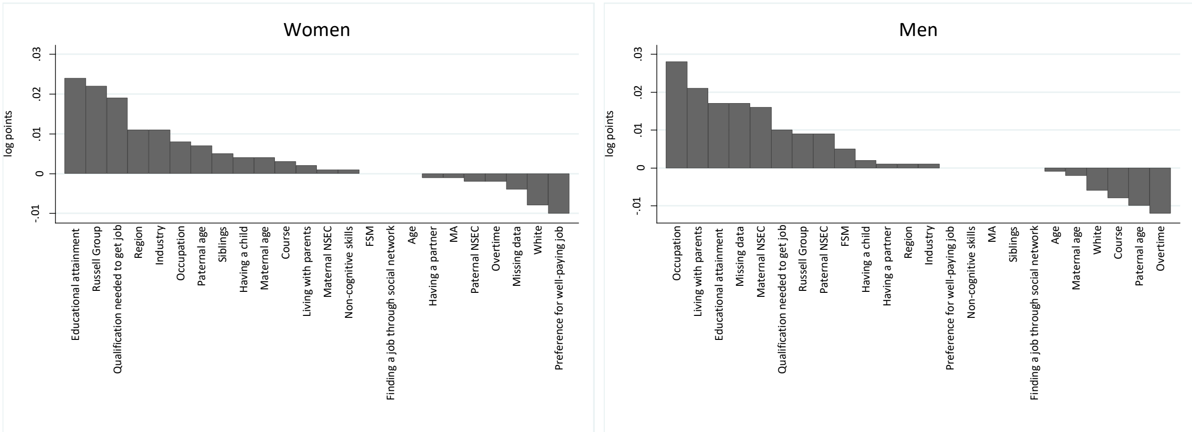
Figure 1: The Oaxaca-Blinder decomposition of the FiF wage gap



Sample of university graduates. No. of observations: Men: 866, Women: 1,172. 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; mothers' and fathers' age, mothers' and fathers' social class (NSEC), 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 (STEM, LEM, OSSAH, other); going to a Russell Group 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 code); industry (1-digit SIC code). Family and living conditions: having children; living with parents; having a partner. Non-cognitive skills: locus of control; preference for risk; patience; trust. Due to missing information on parental education (i.e., first in family), 6 male and 9 female individuals were dropped from the sample. The missing values of all other explanatory 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

Among women (left panel of Figure 1), the raw wage gap is 0.102 log points: FiF female graduates earn 0.102 log points less than non-FiF female graduates. Most of this gap (96%) is explained by their endowments, i.e. by the difference of the distributions of characteristics across the two groups. Among men (right panel of Figure 1), the raw wage gap is 0.031 log points: FiF graduates earn on average 0.031 log point less than non-FiF graduates. The difference in the endowments between FiF and non-FiF graduates would suggest an even larger wage penalty for FiF graduates, 0.099 log points; however, almost 2/3 of this difference is counterbalanced by the differential returns to those characteristics (unexplained gap) for FiF male graduates. Interestingly, the hypothetical FiF wage gap that is due to endowments is very similar among men and women (0.099 and 0.098 log points, respectively); however, some unexplained differences can counterbalance this penalty among men but not among women.

Figure 2: Log points of the raw wage gap explained by endowments (Oaxaca-Blinder decomposition)



Sample of university graduates. No. of observations: Men: 866, Women: 1,172. 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; mothers' and fathers' age, mothers' and fathers' social class (NSEC), 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 (STEM, LEM, OSSAH, other); going to a Russell Group 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 code); industry (1-digit SIC code). Family and living conditions: having children; living with parents; having a partner. Non-cognitive skills: locus of control; preference for risk; patience; trust. Due to missing information on parental education (i.e., first in family), 6 male and 9 female individuals were dropped from the sample. The missing values of all other explanatory 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

Among women, early educational attainment, whether they went to an elite university, and whether they work in positions that require them to have a HE degree contributes the most to the FiF wage penalty (Figure 2). Among men, their occupation seems to the most important, followed by whether they live with their parents. As seen on Figure 1, most of these negative effects for men, however, are counterbalanced by unexplained wage differences across FiF and non-FiF male graduates. The wages of FiF women, on the other hand, are more determined by their endowments.

5. 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 and no difference for FiF men as compared to non-FiF graduate 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.

We find a 0.072 log point return to graduation for men and 0.105 log point return to graduation for women if we do not include any control variables (Table 5). 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) and applying entropy-balanced weights decreases the estimated returns to graduation to 0.028 log points among men and to 0.030 log points among women in Model 4 (Table 5).

We first look at the role of parental education by including a binary variable for non-graduate parents (i.e. being a potential FiF) to the model in Model 5 and then look at the heterogeneity of the returns to graduation with respect to parental non-graduation by adding the interaction term of an individual's own graduation and parental non-graduation to the model in Model 6. Among men, when we control for parental non-graduation in Model 5, it does not change the average returns to graduation estimated earlier. Interestingly, we find that men with non-graduate parents earn 0.083 log points (8.7%) more on average (Model 5 in Table 5). Looking at the differential effects of graduation across men with non-graduate versus graduate parents in Model 6 reveals no significant difference across the two groups and underlines our earlier results that among men, being FiF does not matter in the labor market at this age.

Table 5: Returns to graduation among those having at least 5 A-C GCSE grades (linear models predicting log hourly wages at age 25/26)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
			Men			
Graduation	0.072**	0.046	-0.013	0.028	0.032	0.065
	(0.034)	(0.036)	(0.036)	(0.035)	(0.035)	(0.066)
Parents have no degree					0.083**	0.109*
					(0.037)	(0.060)
FiF						-0.049

						(0.074)
Constant	NR	3.416**	3.062**	0.289	0.287	0.303
		(1.340)	(1.414)	(1.288)	(1.296)	(1.290)
No. of observations	1,401	1,401	1,401	1,401	1,401	1,401
			Women			
Graduation	0.105***	0.089***	0.022	0.030	0.023	-0.095**
	(0.026)	(0.026)	(0.027)	(0.026)	(0.026)	(0.045)
Parents have no degree					-0.128***	-0.216***
					(0.033)	(0.049)
FiF						0.159***
						(0.051)
Constant	NR	-0.319	-0.980	-0.139	-0.110	-0.089
		(0.818)	(0.850)	(0.919)	(0.902)	(0.893)
No. of observations	1,958	1,958	1,958	1,958	1,958	1,958
			Control variables and entropy balancing			
Sample boost	+	Yes	Yes	Yes	Yes	Yes
Family background		Yes	Yes	Yes	Yes	Yes
Early and pre-university educational attainment			Yes	Yes	Yes	Yes
Entropy balance weights				Yes	Yes	Yes

Linear models estimated by OLS, weighted using Wave 8 weights. Sample of those having at least 5 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 in the case of all explanatory variables, including first in family. [+]Note that adding the sample boost dummy to Model 1 would lead to almost identical results. 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

Among women, we find that those with non-graduate parents tend to earn on average 0.128 log points (13.7%) less (Model 5, Table 5). Using the coefficient of the interaction term of an individual's own graduation and parental non-graduation to decompose the effects of graduation across women with graduate versus non graduate parents reveals that the positive returns to graduation are realized solely on the potential FiF group, i.e. on women with non-graduate parents (Model 6, Table 5). The wage returns to graduation among women with graduate parents are in fact negative (-0.095 log points), while the returns to graduation among women with non-graduate parents are positive (0.159-0.095=0.064 log points). The negative effect of having non-graduate parents for women is so large (-0.216 log points), however, that it is larger than the return to graduation for the FiF group. Thus, the negative effect of FiF that we found earlier for graduate women is the consequence of the large negative effect of having non-graduate parents for women in general.

6. 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 individuals face a premium or a penalty on the graduate 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 the first in family to graduate from university is not associated with lower wages, FiF women earn on average 8.3 percent less than graduate women whose parents are also graduates, net of the effect of earlier educational attainment (ability differences) and other measures of family background. Controlling for a long list of variables, including university, subject, industry, occupation, fertility and non-cognitive traits, does not eliminate the FiF penalty that we find for graduate women.

Once we conduct the Oaxaca-Blinder decomposition of this female FiF vs. non-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 this gap. 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 the same for both genders. However, men are able to compensate for two-thirds of this gap while women are not. One 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. It might also be that some unobserved personality characteristics, for example, overconfidence, drive these results.

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 higher for women whose parents are not graduates compared to women whose parents are graduates. However, women face such a large penalty on the labor market for coming from a less educated family that it completely counterbalances their high returns to graduation – 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. 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.

A growing literature documents that while the gender wage gap is decreasing on average, it has remained stable among university graduates (Costa Dias, Joyce, and Parodi 2018). Our findings supply a potential explanation to this puzzle. We find that even though the negative relationship between wages and having non-graduate parents is smaller for women who achieve a degree and the returns to graduation are higher for FiF than for non-FiF women, the sum of the coefficients on having non-graduate parents and women's own graduation is still negative. Thus, 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.

Our results are based on quasi-experimental methods that assume 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

Robustness checks to the main results

1. Selection to employment and reporting wage

As previously mentioned, 81% of the sample is employed at the time of the data collection and of these individuals, 82% report wages. Thus, individuals might be selected not just in terms of parental education (which has been addressed by EB balancing, conditional on the unconfoundedness assumption), but they may also be selected in terms of their probability of working and reporting wage data. To see whether taking this further potential selection mechanism into account eliminates our earlier results on the FiF penalty estimated on the graduate sample, we use two-stage Heckman-type selection models (Heckman 1979) to control for the individual heterogeneity in terms of the probability of employment and reporting wages across the sample.

In the first stage, we estimate a probit model to predict the probability of employment and reporting wage data. 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. In the second stage, we predict the individual-level inverse Mills ratios of the individuals and add them to our main specification as a further control variable. The inverse Mills ratio is the ratio of the probability density function (pdf) to the cumulative distribution function (cdf) of a given distribution. In our case, it captures the relative probability of each individual to be employed and report wage, compared to the cumulative probability of the individual's decision. See the estimated selection model in Adamecz-Völgyi, Henderson, and Shure 2020b, Table C1 in Appendix C.

In Table A 1, we add the inverse Mills ratios from the selection equation on top of the same control variables that we have used before: whether the individual belongs to the sample boost added to the survey in Wave 4; age measured in months as a continuous variable; ethnicity (White); fixed effects for the region of school at age 13/14; mother's and father's age, mother's and father's social class, number of siblings in 2004; FSM eligibility at age 15/16; 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.

Table A 1: The effect of FiF on log hourly wages (entropy-balanced selection model)

	Men	Women
FiF	0.029	-0.124**
	(0.063)	(0.056)
Constant	-0.845	3.174*
	(1.398)	(1.684)
No. of observations	866	1,172
Control variables and entropy weighting		
Sample boost in Wave 4	Yes	Yes
Demographics and family background	Yes	Yes
Early educational attainment and educational progression	Yes	Yes
Entropy balancing weights	Yes	Yes
Selection to employment and reporting wage	Yes	Yes

Sample of university graduates. 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. The entropy and the selection models are weighted using Wave 8 weights, the outcome models are weighted using entropy-balanced weights. 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. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); region at age 13; mother's and father's age, mother's and father's 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. Due to missing information on parental education, six male and nine female individuals were dropped from the sample. The missing values of all other explanatory variables are controlled for using missing flags. The inverse Mills ratios of selection to employment and reporting wage have been estimated by separate probit 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

Among men, controlling for selection to employment and reporting wage produces a small and insignificant coefficient on FiF, just as earlier (Table A 1). Among women, controlling for selection to employment and reporting wage slightly increases the magnitude of the estimated relationship from the earlier -0.087 (Model 4, Table 3) to -0.124 log points (Table A 1); however, in a statistical sense the two estimates are not different from each other (H0: -0.087 (0.047)=-0.124(0.056), t-test p=0.6128). These results suggest that unobserved selection to employment and reporting wages do not drive our main results.

2. Handling missing values of first in family

Information on parental education, the key variable to identify FiF individuals, is missing for 43 observations in the total sample (Table 1 in Section 2); however, the number of missing observations is lower if we look at only graduates in our main analytical sample (18 observations) or graduates who reported wages (15 observations). While we apply missing flags in our models in the case of all other explanatory variables, these observations were excluded from the estimation of the FiF penalty on the sample of graduates (Table 2 in subsection 4.1). In this section we provide a robustness check to show that non-random missingness does not drive our main results.

We re-estimate our main results on the FiF penalty in two hypothetical scenarios. In the first scenario, we assign FiF=0, while in the second, we assign FiF=1 to all observations with missing parental graduation information. Among men, we find that if all men with missing information were children of non-graduates (FiF=0), the effect of FiF on wages would become significant and positive, while if all missing observations would belong to the FiF group (FiF=1), the results would be close to zero as before (Table A 2). Among women, our earlier results do not change in either of the hypothetical scenarios.

Table A 2: Robustness check addressing missing values of FiF

	Probability of employment, entropy balanced models		Log hourly wage, entropy balanced models	
Men				
	FiF=0	FiF=1	FiF=0	FiF=1
First in family	0.034	0.005	0.060*	-0.026
	(0.036)	(0.034)	(0.035)	(0.034)
Constant	0.930	0.690	0.183	-0.419
	(1.088)	(1.119)	(1.356)	(1.235)
No. of observations	1,155	1,155	872	872
No. of observations with missing FiF	8	8	6	6
Women				
First in family	-0.007	-0.001	-0.112**	-0.107**
	(0.023)	(0.023)	(0.047)	(0.047)
Constant	0.537	0.480	0.496	0.525
	(0.951)	(0.953)	(1.264)	(1.254)
No. of observations	1,534	1,534	1,181	1,181
No. of observations with missing FiF	10	10	9	9
Control variables				
Sample boost in Wave 4	Yes	Yes	Yes	Yes
Demographics and family background	Yes	Yes	Yes	Yes
Early educational attainment and educational progression	Yes	Yes	Yes	Yes
Entropy balancing weights	Yes	Yes	Yes	Yes

Sample of university graduates. All coefficients in the wage models are in log points and may be transformed to percentages through the following transformation: $100*(e^{beta} - 1)$, where beta is the estimated coefficient. The entropy and the selection models are weighted using Wave 8 weights, the outcome models are weighted using entropy-balanced weights. 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. Demographics and family background: age measured in months in 2015 as a continuous variable; ethnicity (White); region at age 13; mother's and father's age, mother's and father's 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 explanatory 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

3. Using propensity score matching instead of entropy balancing

As entropy balancing does not differentiate between observations within or outside of a common support, we 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 before. To re-estimate the effects of being FiF on log hourly wages we apply a 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).

The propensity score estimates of the FiF wage gaps are similar to our earlier results (Table A 3). For men, we find a 0.041 log points FiF wage gap, while for women, we find a -0.064 log points FiF gap. While this latter effect is not significant either, its magnitude is very similar to those estimated using entropy balancing before. Note that it is not straightforward the construct standard errors to pscore matching estimates.

Table A 3: The effect of FiF on log hourly wages (propensity score kernel matching on the common support)

	Men	Women
FiF	.041	-.064
95% confidence intervals (bootstrapped, bias corrected)	[-0.33; 0.131]	[-.154; .016]
No. of observations on the common support#	758	1,063
Variables used to estimate the propensity score		
Sample boost in Wave 4	Yes	Yes
Demographics and family background	Yes	Yes
Early educational attainment and educational progression	Yes	Yes

Sample of university graduates. Estimated using psmatch in Stata (Gaussian kernel-weighted matching on a pre-estimated propensity score). The bias corrected confidence intervals are reported from 200 bootstrapped replication. The confidence intervals do not take into account that the propensity scores have been estimated. 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; 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. Due to missing information on parental education, 6 male and 9 female individuals were dropped from the sample. The missing values of all other explanatory variables are controlled for using missing flags. #At the first bootstrap replication. 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