Journal of Population Economics
https://doi.org/10.1007/s00148-022-00908-y

ORIGINAL PAPER

The labor market returns to "first-in-family" university graduates

Anna Adamecz-Völgyi[1,2] · Morag Henderson[1] · Nikki Shure[1,3]

Received: 16 November 2020 / Accepted: 27 April 2022

Abstract

We examine how first-in-family (FiF) graduates — those whose parents do not have university degrees — fare in the labor market in England. We find that among women, FiF graduates earn 7.4% less on average than graduates 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 two interesting findings. First, two-thirds of the female FiF penalty is explained by certain characteristics, including having lower educational attainment, not attending an elite university, selecting particular degree courses, working in smaller firms, working in jobs that do not require their degree, and motherhood. Second, FiF graduate men also differ in their endowments from non-FiF graduate men; however, 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 estimate the returns to graduation for *potential* FiF and non-FiF young people. We find that the wage returns to graduation are not lower among FiF graduates compared to those who match their parents with a degree.

Keywords Socioeconomic gaps · Intergenerational educational mobility · Higher education · Labor market returns · Gender economics · First-generation · First in family

Responsible editor: Shuaizhang Feng

✉ Nikki Shure
nikki.shure@ucl.ac.uk

Anna Adamecz-Völgyi
a.adamecz-volgyi@ucl.ac.uk

Morag Henderson
morag.henderson@ucl.ac.uk

1 UCL Social Research Institute, University College London, 27 Woburn Square, London WC1H 0AA, UK

2 Institute of Economics, Centre for Economic and Regional Studies (KRTK KTI), Toth Kalman u. 4, 1097 Budapest, Hungary

3 Institute of Labor Economics (IZA), Schaumburg-Lippe-Str. 5-9, 53113 Bonn, Germany

Published online: 24 May 2022

JEL Classification Codes I24 · I26 · J24

1 Introduction

Previous literature has presented convincing evidence that earning a university degree leads to significant labor market returns in terms of earnings and income (Blundell et al. 2005; Card 1999; 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; Britton et al. 2016; Chetty et al. 2017, 2014). 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).

In this paper, we explore the labor market returns of a specific disadvantaged group that is targeted as part of the affirmative action policy in England, the Widening Participation (WP) agenda (Gorard and Smith 2006): "first-in-family" (FiF) university graduates, those whose (step) parents do not have a university degree. The goal is to understand whether university serves as an equalizer for their outcomes or if they face a penalty for their socioeconomic background in early career.

The existing evidence on how FiF individuals fare in the labor market is limited to the USA and is 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 USA. 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 90s, Nunez and Cuccaro-Alamin (1998) find no difference in wages one year after graduation among those employed in the USA. 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 in the labor market. To the best of our knowledge, there is no evidence on the labor market outcomes of FiF graduates outside the USA.

This paper documents how FiF university graduates fare in the labor market in England. First, we compare the probability of employment, hours worked, and the annual and hourly wages of FiF and non-FiF graduates using regression and decomposition methods. This allows us to explore whether FiF graduates have different labor market outcomes than their non-FiF graduate peers (those whose parents are also graduates). 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 earlier findings and disentangle the effect of an individual's graduation from their family background. This helps us understand whether *potential FiF* young people earn differential returns to graduating university than young people whose parents are graduates.

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.

Our results show that controlling for a rich set of pre-university individual characteristics, most importantly for early educational attainment, FiF graduate women face a 7.4% wage penalty in term of log hourly wages compared to non-FiF female graduates who match their parents with a university degree. The magnitude of this association is stable across several robustness checks, including entropy balancing and propensity score matching, but it loses significance in some specifications. 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 a meaningful FiF disadvantage for men or women in terms of the probability of employment or hours worked.

We investigate the potential channels of these differences using a Kitagawa-Blinder-Oaxaca decomposition, which decomposes 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. We find that for women, some characteristics of FiF graduates explain two-thirds of the female FiF penalty. These include lower pre-university educational attainment, a lower probability of going to an elite university, a higher likelihood of working in a job that does not require their highest educational attainment, a higher likelihood of choosing "Education" as a university course (major), a lower likelihood of working at large firms, and a higher likelihood of having a child than non-FiF graduate women. Interestingly, some of these characteristics are true for FiF men, too: FiF men are also more likely to work in a job that does not require their highest degree and less likely to work at large firms than non-FiF graduate men. While theoretically, FiF graduate men also should earn less than non-FiF graduate men based on their endowments, they close this endowment gap by about two-thirds via different returns to these characteristics. We propose that as men are less likely to graduate on average than women, men are more positively selected not just in their observed but most likely also in their unobserved characteristics, which could explain why men overcome some of their social disadvantage, but women do not.

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 is significantly positive among men and significantly negative among women. Thus, the gendered FiF-wage relationship that we observe in the sample of graduates is not exclusive to graduates. It is clear, however, 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 for 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 an overview of related literature in Section 2, the data in Section 3, and our empirical approach in Section 4. We compare the labor market outcomes of FiF and non-FiF graduates 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. In Section 7, we offer some discussion before concluding.

2 Related Literature

Whilst this paper uniquely focuses on labor market outcomes by FiF status in England, it builds on existing work that examines differences in labor market outcomes within groups of individuals who obtain university degrees (Britton et al. 2016, 2015; Chetty et al. 2017; Chevalier and Conlon 2003). Recently, research on returns to university in the UK has benefitted from the linkage of administrative schooling, higher education, and tax authority data (Belfield et al. 2018). 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% more than their peers from low-income households, but that this earning premium shrinks to 10% once institution and subject are included in their model.

More recently, Britton et al. (2021) look at the heterogeneity of returns to graduation by ethnicity and socio-economic status (SES) also using the LEO data. As this data has no information on parental income or education, they construct a measure of SES based on Free School Meal (FSM) 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 study data, including parental education. Recent work by Lee and Vignoles (2021) shows that university can serve as an earnings equalizer for men from disadvantaged backgrounds in South Korea, but not for women. This is similar to the results found in this work and underscores that the gender differences in achieving intergenerational educational mobility may exist in different contexts.

Previous work on the labor market outcomes of graduates from disadvantaged backgrounds in the UK has been limited and relied on older cohorts than the one used in this paper. 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 7% more than their peers who attended state school almost 4 years after completing university. Other studies from the UK have affirmed this difference in earnings for private school pupils later in life (Dolton and Vignoles 2000; Green et al. 2012).

Laurison and Friedman (2016) document similar class earning gaps within professional and higher managerial occupations, something they refer to as the "class ceiling." Since these differences hold for university graduates from advantaged and disadvantaged backgrounds in the same occupation, this indicates that this gap is not driven by university course or occupational choice. In a related measure of labor market returns, Macmillan et al. (2015) and Sullivan et al. (2018) find that graduates from disadvantaged backgrounds are less likely to end up in "top jobs" (jobs with higher earnings, more job security, and better career trajectories) than their advantaged peers, even after controlling for university and school performance, degree subject and institution, and current family situation. Thus, there is convincing evidence that socioeconomic penalties persist even for individuals who beat the odds and make it to university or certain occupations.

None of these previous studies explicitly examine first in family university graduates as the specific type of socioeconomic disadvantage. Henderson et al. (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% significance level and they have not looked at any gender differences. This paper extends that work by explicitly examining the difference between the labor market outcomes of FiF and non-FiF male and female graduates at age 25/26.

3 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

[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.

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 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 7707 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

[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).

check, we reproduce our main results with mean imputation of the missing values in Table A3 in the Appendix A.

We are looking at four outcome variables: employment, log annual wage, hours worked, and log hourly wage. Out of the 7683 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 A2 in the Appendix A to show that this step does not change our results. After this step, we are left with a total sample of 5213 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 A6 in the 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 (Table A1 in the Appendix A).[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

[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 A1 Appendix A).

[4] Information on parental education is missing for 43 observations in the sample. We provide a robustness check to this problem in subsection A5 in Appendix A.

Table 1 Descriptive statistics

	Total sample			Men			Women			Gender gap (women – men)
	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	−6 pp
Annual wage	5374	22,413	377	2381	24,901	617	2993	19,834	417	−20%
Hours worked per week	6196	37.99	0.18	2870	40.28	0.25	3326	35.41	0.25	−4.9
Hourly wage	5213	11.20	0.15	2328	11.70	0.22	2885	10.69	0.22	−9%
Parents have no degree	7664	0.84	0.00	3403	0.83	0.01	4261	0.84	0.01	1 pp
Graduated	7707	0.27	0.01	3426	0.25	0.01	4281	0.28	0.01	3 pp
FiF	7664	0.18	0.00	3403	0.16	0.01	4261	0.20	0.01	4 pp
FiF among the graduated	2689	0.68	0.01	1155	0.64	0.02	1534	0.71	0.01	7 pp

Obs refers to the number of non-missing observations. Total number of unweighted observations: 7707. 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. https://doi.org/10.5255/UKDA-SN-7104-4 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.

Women are six percentage points less likely to work, and if they do, they work about 5 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 one percentage points less likely to graduate than men; among the potential FiF (i.e. whose parents are not graduates), women are four 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%).

4 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 A6 in the Appendix A, 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

Table 2 Descriptive statistics by groups

Group	Total			Men			Women			Gender gap (women – men)
	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)	1490	0.52	0.01	706	0.53	0.02	784	0.51	0.02	− 1 pp
Potential FiF (neither parent is graduate)	6174	0.22	0.01	2697	0.20	0.01	3477	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	4302	0.77	0.01	1930	0.81	0.01	2372	0.72	0.01	− 9 pp
FiF	1853	0.89	0.01	759	0.88	0.01	1094	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	2010	222	27,920	3552	254	23,550	1824	− 16%
Matching parental non-graduation	2789	20,095	458	1265	23,176	761	1524	16,646	441	− 28%
FiF	1447	24,464	555	583	26,742	923	864	22,604	658	− 15%
Matching parental graduation	635	28,558	1407	298	29,646	1933	337	27,376	2056	− 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	3321	37.04	0.25	1598	40.21	0.34	1723	33.08	0.34	− 7.1
FiF	1606	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%

Table 2 (continued)

Group	Total			Men			Women			Gender gap (women – men)
	Obs	Mean	SE of mean	Obs	Mean	SE of mean	Obs	Mean	SE of mean	
Matching parental non-graduation	2699	10.41	0.20	1237	11.02	0.30	1462	9.71	0.27	– 12%
FiF	1414	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: 7707. 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. https://doi.org/10.5255/UKDA-SN-7104-4 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 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.

4.1 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 2008). 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 Section 5.1, while variables observed after going to university are considered as channels and added to the model in Section 5.2.

We estimate the following linear regression models:

$$y_i = a_1 + b_1 \times \mathrm{FiF}_i + c_1 \times X_i + u_{1i} \tag{1}$$

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 et al. (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 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 A3 in the Appendix A 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 A5 in the Appendix A. We provide a robustness check where we employ mean imputation for the missing values of the key control variables in Table A3 in the Appendix A. The descriptive statistics of all variables in the models are shown in Table A1 in the Appendix A of Adamecz-Völgyi et al. (2022).

We provide three further robustness checks to these main results in the Appendix. First, we apply two quasi-experimental evaluation methods in Section A4: 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 A4).

[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, and 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.

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 A6 in the Appendix A. 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 Section 5.2. Second, we decompose the raw FiF gaps using a Kitagawa-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 Section 5.3. 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.

4.2 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:

$$\text{wage}_i = a_2 + b_2 \times \text{graduate}_i + c_2 \times X_i + u_{2i} \tag{2}$$

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 Eq. (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.

5 The FiF gap in labor market outcomes

5.1 Main results and robustness checks

We begin with a discussion of the main results obtained from estimating the model described in Eq. (1). Table 3 shows the association between being first in family and the probability of employment, log annual wages, hours worked, and log hourly wages estimated in linear models on the sample of university graduates in our main models (model 4).[8] There is no meaningful difference in the probability of employment and hours worked between FiF and non-FiF graduates, neither for men nor for women. In terms of log annual wages, FiF graduate men earn an insignificant 0.044 log points more than non-FiF graduate men, while in terms of log hourly wages, they earn 0.075 log points (7.8%) more. This difference is statistically significant at the 5% significance level. Among women, this relationship is reversed: FiF graduate women earn 0.059 log points less per annum and − 0.077 log points (7.4%) less per hour than non-FiF graduate women. This relationship is significant at the 10% significance level.

[8] The results of all models together (models 1–4) are shown in Table B1 in Appendix B, and the detailed results of the main models (model 4), including the estimated coefficients of all control variables, are shown in Table O1 in the Online Appendix of Adamecz-Völgyi et al. (2022).

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

	Employed Men (1)	Employed Women (2)	Log annual wage Men (3)	Log annual wage Women (4)	Hours worked Men (5)	Hours worked Women (6)	Log hourly wage Men (7)	Log hourly wage Women (8)
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	1147	1524	863	1167	863	1167	863	1167
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. *$p<0.1$, **$p<0.05$, ***$p<0.01$. 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: $100 \times (e^{\text{beta}} - 1)$, 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. https://doi.org/10.5255/UKDA-SN-7104-4

We provide several robustness checks to these results in the Appendix. We get very similar results when we do not exclude the outlier values of wages and hours worked (Table A2), when we use mean imputation to handle the missing values of the control variables instead of missing flags (Table A3), and when we assign all missing values of FiF to be either 0 or 1 (Table A5). Applying entropy-balanced weights and propensity score matching (Table A4) 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 A6).

5.2 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 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 the following: (1) having an MA/MSc degree (as opposed to a BA/BSc); (2) university course in seven categories: medicine; sciences; engineering, tech, architecture; law and business; social sciences, humanities, languages; education; other; (3) attending a Russell Group university[9] (a group of 24 research intensive universities, often used as a measure of elite university); (4) having a student loan; (5) 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: (1) preference for a high-paying job at age 13/14; (2) finding job through social network; (3) whether qualification was needed to get current job; (4) working more than 45 h a week; (5) working part-time; (6) occupation (1-digit Standard Occupational Classification (SOC) code); (7) industry (1-digit Standard Industrial

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

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

	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)	Model 5 (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	1167	1167	1167	1167	1167
R-squared	0.140	0.202	0.348	0.353	0.363
Potential channels					
Details of HE degree	No	Yes	Yes	Yes	Yes
Details of employment and finding a job	No	No	Yes	Yes	Yes
Family and living conditions	No	No	No	Yes	Yes
Non-cognitive skills	No	No	No	Yes	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 parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$. 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 h 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. https://doi.org/10.5255/UKDA-SN-7104-4

Classification (SIC) code); (8) living in London; (9) employment tenure in month; (10) 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 family and living circumstances at age 25/26 on top of the variables used in the previous model: (1) having a partner: defined as a partner living in the same household; (2) living with parents; (3) 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: (1) 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 in Lefcourt (1991); (2) trust: how trusting individuals would say themselves in other people on a scale from 0 to 10; (3) risk-taking: how willing individuals are to take risks on a scale from 0 to 10; and (4) patience: how patient individuals believe themselves on a scale from 0 to 10.

5.3 Kitagawa-Blinder-Oaxaca decomposition of the FiF gap

The Kitagawa-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; 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 KBO 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 the Appendix B of Adamecz-Völgyi et al. (2022) 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, to go to a Russell Group university and to work at large firms, and being more likely to choose Education as a university course, to work in jobs that would not require their highest educational

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

	Employed Women	Employed Men	Log annual wage Women	Log annual wage Men	Hours worked Women	Hours worked Men	Log hourly wage Women	Log hourly wage Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	1524	1147	1167	863	1167	863	1167	863

Sample of university graduates. Weighted using wave 8 weights. Robust standard errors clustered by sampling school are in parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$. 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 h 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. https://doi.org/10.5255/UKDA-SN-7104-4 attainment, and to have a child than non-FiF graduate women explains about two-thirds of the FiF wage 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. As the interpretation of individual variables in their contribution to the unexplained portion of the gap is not as straightforward as in their contributions to the endowment gap (Jann 2008), we do not provide further interpretation here.

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 1% significance level) in model 1 to a non-significant −0.008 log points in model 3 (Table 6). 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.

For women, we find that adding background and educational variables decreases returns to graduation from 10.2 log points (significant at the 1% 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). 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

Table 6 Returns to graduation in log hourly wages

	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)	Model 5 (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	1389	1389	1389	1389	1389
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	1948	1948	1948	1946	1946
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 parentheses. *$p<0.1$, **$p<0.05$, ***$p<0.01$. 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. https://doi.org/10.5255/UKDA-SN-7104-4

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 outside the USA. Our empirical approach allows us to examine whether FiF university graduates face a premium or a penalty in 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 in England, 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% less than graduate women whose parents are also graduates, net of the effect of pre-university educational attainment and other measures of family background. This is similar to recent findings from South Korea (Lee and Vignoles 2021). Although Lee and Vignoles (2021) do not look at FiF graduates explicitly, they show that female university graduates from disadvantaged backgrounds have lower earnings than their female peers from advantaged backgrounds, but that university serves as an equalizer for men.

Once we conduct a Kitagawa-Blinder-Oaxaca decomposition, we find that six factors explain two-thirds of the female FiF gap: taking a job which did not require their university degree, having lower prior attainment, earning a degree from a less prestigious institution, being less likely to work at large firms, being more likely to have a child, and choosing Education as their university course. This 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, i.e. Education. Furthermore, we find that it is also true for FiF men that working in jobs that do not require their highest degree and being less likely to work at large firms reduces their average pays compared to non-FiF male graduates. Thus, both FiF men and women "undermatch" in the labor market (that is to say they work at smaller firms and in jobs that do not require their highest educational attainment). This indicates 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. We propose that as men are less likely to go to university than women, male FiF graduates might be 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 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.

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 socioeconomic 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 in 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.

Furthermore, we have found that FiF women are less likely to make it to the top quintile of math test scores at age 11 and are more likely to have a child at age 25 than non-FiF women, and these factors contribute to the female FiF penalty. This paper explicitly focuses on FiF graduates, and formally looking at the factors in the relationship between parental graduation and wages for non-graduates is beyond our scope. However, it seems to be intuitive to expect that lower educational attainment and family-related choices might drive the relationship between parental graduation and wages for non-graduate women, too. 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.

Appendix A: Robustness checks

A1: 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 6 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, in 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 A1).

A2: 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 A2 shows that the results are very similar to those in Table 3.

Table A1 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 Fig. 2 on page 16	Returns to graduation (2nd column of Table A2 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)	1426	1426	1426		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)	2015	2015	2015		700,533
Control variables					
Sample boost	No	Yes	Yes	No	No
Family background	No	Yes	Yes	No	Yes
Early and pre-university educational attainment	No	No	Yes	No	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: $100\times(e^{beta}-1)$, where beta is the estimated coefficient. Robust standard errors clustered by sampling school are in parentheses. * $p<0.1$, **$p<0.05$, ***$p<0.01$. 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. https://doi.org/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

Table A2 The FiF gap in labor market outcomes: main results without excluding the outlier values of annul wage, hours worked, and hourly wage

	Employed	Employed	Log annual wage	Log annual wage	Hours worked	Hours worked	Log hourly wage	Log hourly wage
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	1147	1524	866	1172	866	1172	866	1172
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. *$p<0.1$, **$p<0.05$, ***$p<0.01$. 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 h per week (9 observations) or more than 80 h 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. https://doi.org/10.5255/UKDA-SN-7104-4

A3: 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 A3 shows, the results are very similar to those in Table 3.

A4: 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 2008). 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. 2017). 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 A4) confirm that the negative FiF hourly wage gap is robust among women; however, the positive FiF wage gap among men is not.

A5: 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 A5 that our results stay similar in both cases.

A6: 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 A6).

Table A3 The FiF gap in labor market outcomes: handling the missing values of the control variables with mean imputation

	Employed	Employed	Log annual wage	Log annual wage	Hours worked	Hours worked	Log hourly wage	Log hourly wage
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	1147	1524	863	1167	863	1167	863	1167
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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. 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. https://doi.org/10.5255/UKDA-SN-7104-4

Table A4 The FiF gap in labor market outcomes: Entropy balancing and propensity score matching

	Employed		Log annual wage		Hours worked		Log hourly wage	
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	1147	1524	863	1167	863	1167	863	1167
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)	1020	1413	774	1028	774	1028	774	1028

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. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. 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. https://doi.org/10.5255/UKDA-SN-7104-4

Table A5 The FiF gap in labor market outcomes: assigning all 0/1 values to missing FiF

	Employed	Employed	Log annual wage	Log annual wage	Hours worked	Hours worked	Log hourly wage	Log hourly wage
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	1155	1534	869	1176	869	1176	869	1176
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	1155	1534	869	1176	869	1176	869	1176
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. $*p<0.1$, $**p<0.05$, $***p<0.01$. 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. https://doi.org/10.5255/UKDA-SN-7104-4

Table A6 The FiF gap in labor market outcomes: controlling for selection into employment and reporting wage

	Employed	Employed	Log annual wage	Log annual wage	Hours worked	Hours worked	Log hourly wage	Log hourly wage
	Men	Women	Men	Women	Men	Women	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	1147	1524	863	1167	863	1167	863	1167
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. *$p<0.1$, **$p<0.05$, ***$p<0.01$. 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. https://doi.org/10.5255/UKDA-SN-7104-4

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.

Acknowledgements The Nuffield Foundation is an endowed charitable trust that aims to improve social wellbeing in the widest sense. It funds research and innovation in education and social policy and also works to build capacity in education, science, and social science research. More information is available at www.nuffieldfoundation.org. We thank Alex Bryson, John Jerrim, Zoltán Hermann, and seminar and conference participants at the Centre for Longitudinal Studies (CLS), German Centre for Higher Education Research and Science Studies, Leibniz Institute for Economic Research, Leibniz Centre for European Economic Research, Ifo Institute, Institute of Economics, Centre for Economic and Regional Studies, the Hungarian Society of Economics, EALE-SOLE-AASLE, and Royal Economic Society. We are grateful to Shuaizhang Feng and three anonymous referees as their comments and suggestions improved the paper substantially.

Funding This research was supported by the Nuffield Foundation (grant number EDO/43570).

Data availability The authors use the Secure Access version of the Next Steps cohort study that contains linked administrative data (NPD) that is not available in the public use (safeguarded) version of the data. These data are available from the UK Data Service; see https://www.ukdataservice.ac.uk/get-data for further information.

Declarations

Conflict of interest The authors declare no competing interests.

Disclaimer The Nuffield Foundation has funded this project (grant number EDO/43570), but the views expressed are those of the authors and not necessarily those of the foundation.

References

Abadie A, Athey S, Imbens GW, Wooldridge J (2017) When should you adjust standard errors for clustering? (Working Paper No. 24003), Working Paper Series. Natl Bur Econ Res https://doi.org/10.3386/w24003

Adamecz-Völgyi A, Henderson M, Shure N (2022) The labor market returns to "first in family" university graduates. GLO Discussion Papers. Global Labor Organization (GLO)

Anders J, Henderson M (2019) Socioeconomic inequality and student outcomes in English schools, in: Socioeconomic inequality and student outcomes — national trends, policies, and practices. Springer

Angrist JD, Pischke J-S (2008) Mostly harmless econometrics: an empiricist's companion. Princeton University Press

Arcidiacono P, Lovenheim M (2016) Affirmative action and the quality-fit trade-off. J Econ Lit 54:3–51. https://doi.org/10.1257/jel.54.1.3

Belfield C, Britton J, Buscha F, Dearden L, Dickson M, Erve L van der, Sibieta L, Vignoles A, Walker I, Zhu Y (2018a) The impact of undergraduate degrees on early-career earnings [WWW Document]. URL https://www.ifs.org.uk/publications/13731 (accessed 2.15.19)

Blanden J, Machin S (2004) Educational inequality and the expansion of UK higher education. Scott J Political Econ 51:230–249

Blinder AS (1973) Wage discrimination: reduced form and structural estimates. J Hum Resour 8:436–455. https://doi.org/10.2307/144855

Blundell R, Dearden L, Sianesi B (2005) Evaluating the effect of education on earnings: models, methods and results from the National Child Development Survey. J R Stat Soc A Stat Soc 168:473–512. https://doi.org/10.1111/j.1467-985X.2004.00360.x

Britton J, Shephard N, Vignoles A (2015) Comparing sample survey measures of English earnings of graduates with administrative data during the Great Recession (Working Paper No. W15/28). IFS Work Pap. https://doi.org/10.1920/wp.ifs.2015.1528

Britton J, Dearden L, Waltmann B (2021) The returns to undergraduate degrees by socio-economic group and ethnicity (IFS Research Report). Inst Fiscal Stud. https://doi.org/10.1920/re.ifs.2021.0186

Britton J, Dearden L, Shephard N, Vignoles A (2016) How English domiciled graduate earnings vary with gender, institution attended, subject and socio-economic background [WWW Document]. URL https://www.ifs.org.uk/publications/8233 (accessed 11.21.18)

Bukodi E, Goldthorpe JH (2011) Class origins, education and occupational attainment in Britain. Eur Soc 13:347–375. https://doi.org/10.1080/14616696.2011.568259

Campbell S, Macmillan L, Murphy R, Wyness G (2020) Matching in the dark? Inequalities in student to degree match (CEPEO Working Paper Series No. 20–01). Centre for Education Policy and Equalising Opportunities, UCL Institute of Education

Card D (1999) Chapter 30 - The causal effect of education on earnings, in: Ashenfelter, O.C., Card, D. (Eds.), Handbook of labor economics. Elsevier, pp. 1801–1863. https://doi.org/10.1016/S1573-4463(99)03011-4

Centre for Longitudinal Studies (2018) Next steps age 25 survey: User Guide. Centre for Longitudinal Studies

Chetty R, Hendren N, Kline P, Saez E, Turner N (2014) Is the United States still a land of opportunity? Recent trends in intergenerational mobility. Am Econ Rev 104:141–147. https://doi.org/10.1257/aer.104.5.141

Chetty R, Friedman JN, Saez E, Turner N, Yagan D (2017) Mobility report cards: the role of colleges in intergenerational mobility (Working Paper No. 23618). Natl Bur Econ Res. https://doi.org/10.3386/w23618

Chevalier A, Conlon G (2003) Does it pay to attend a prestigious university? (SSRN Scholarly Paper No. ID 435300). Social Science Research Network, Rochester, NY

Crawford C, Vignoles A (2014) Heterogeneity in graduate earnings by socio-economic background (Working Paper No. W14/30). IFS Work Pap. https://doi.org/10.1920/wp.ifs.2014.1430

Department for Education (2011) LSYPE user guide to the datasets: Wave 1 to Wave 7

Dickson M (2013) The causal effect of education on wages revisited*. Oxford Bull Econ Stat 75:477–498. https://doi.org/10.1111/j.1468-0084.2012.00708.x

Dolton P, Vignoles A (2000) The incidence and effects of overeducation in the U.K. graduate labour market. Econ Educ Rev 19:179–198. https://doi.org/10.1016/S0272-7757(97)00036-8

Gorard S, Smith E (2006) Beyond the 'learning society': what have we learnt from widening participation research? Int J Lifelong Educ 25

Green F, Machin S, Murphy R, Zhu Y (2012) The changing economic advantage from private schools. Economica 79:658–679. https://doi.org/10.1111/j.1468-0335.2011.00908.x

Hainmueller J (2012) Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. Polit Anal 20(1):25–46. https://doi.org/10.1093/pan/mpr025

Harvey RA, Hayden JD, Kamble PS, Bouchard JR, Huang JC (2017) A comparison of entropy balance and probability weighting methods to generalize observational cohorts to a population: A simulation and empirical example. Pharmacoepidemiol Drug Saf 26(4):368–377. https://doi.org/10.1002/pds.4121

Heckman JJ (1979) Sample selection bias as a specification error. Econometrica 47(1):153–161. https://doi.org/10.2307/1912352

Henderson M, Shure N, Adamecz-Völgyi A (2020) Moving on up: 'first in family' university graduates in England. Oxf Rev Educ. https://doi.org/10.1080/03054985.2020.1784714

Jann B (2008) The Blinder-Oaxaca decomposition for linear regression models. Stand Genomic Sci 8:453–479. https://doi.org/10.1177/1536867X0800800401

Laurison D, Friedman S (2016) The class pay gap in higher professional and managerial occupations. Am Sociol Rev 81:668–695

Lee S, Vignoles A (2021) Does college level the playing field? Socioeconomic Gaps in the Earnings of Similar Graduates: Evidence from South Korea. High Educ. https://doi.org/10.1007/s10734-021-00745-0

Lefcourt HM (1991) Locus of control, in: Measures of personality and social psychological attitudes. Elsevier, pp. 413–499. https://doi.org/10.1016/B978-0-12-590241-0.50013-7

Macmillan L, Tyler C, Vignoles A (2015) Who gets the top jobs? The role of family background and networks in recent graduates' access to high-status professions. J Soc Policy 44:487–515. https://doi.org/10.1017/S0047279414000634

Manzoni A, Streib J (2019) The equalizing power of a college degree for first-generation college students: disparities across institutions, majors, and achievement levels. Research in Higher Education 577–605

Neumark D (1988) Employers' discriminatory behavior and the estimation of wage discrimination. J Hum Resour 23:279–295. https://doi.org/10.2307/145830

Nunez A-M, Cuccaro-Alamin S (1998) First-generation students: undergraduates whose parents never enrolled in postsecondary education (Statistical Analysis Report). National Center for Education Statistics

Oaxaca R (1973) Male-female wage differentials in urban labor markets. Int Econ Rev 14:693–709. https://doi.org/10.2307/2525981

Office For National Statistics, SSD (2019) Annual population survey, July 2015 - June 2016. 10.5255/UKDA-SN-8054-5

Oreopoulos P, Petronijevic U (2013) Making college worth it: a review of research on the returns to higher education (Working Paper No. 19053). Natl Bur Econ Res. https://doi.org/10.3386/w19053

Pető R, Reizer B (2021) Gender differences in the skill content of jobs. J Popul Econ. https://doi.org/10.1007/s00148-021-00825-6

Roberts N (2018) The school curriculum in England (House of Commond Library Briefing Paper No. 06798)

Sullivan A, Parsons S, Green F, Wiggins RD, Ploubidis G (2018) The path from social origins to top jobs: social reproduction via education. Br J Sociol 69:776–798. https://doi.org/10.1111/1468-4446.12314

Thomas SL, Zhang L (2005) Post-baccalaureate wage growth within four years of graduation: the effects of college quality and college major. Res High Educ 46:437–459. https://doi.org/10.1007/s11162-005-2969-y

Walker I, Zhu Y (2011) Differences by degree: Evidence of the net financial rates of return to undergraduate study for England and Wales. Econ Educ Rev 30:1177–1186. https://doi.org/10.1016/j.econedurev.2011.01.002

Wyness G (2010) Policy changes in UK higher education funding, 1963–2009 (No. 10–15), DoQSS Working Papers. Department of Quantitative Social Science - UCL Institute of Education, University College London