CENTRE FOR EDUCATION POLICY & EQUALISING OPPORTUNITIES

Working Paper No. 23-08

Intergenerational educational mobility and the COVID-19 pandemic

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We examine the differential impact of the COVID-19 pandemic on the labour market outcomes of graduate workers by their family background. Specifically, we compare first in family (FiF) graduates, young people who obtained a university degree even though their parents did not, with their graduate peers whose parents have university degrees. We compare their labour market outcomes using multiple waves of data collected during the pandemic, which are linked to an existing longitudinal study and administrative data. We find that FiF graduates, both men and women, were just as likely to keep working during the pandemic as the graduate children of graduate parents. Our results, however, reveal substantial differences in the outcomes of graduates who stopped working, and these differences are heterogenous by gender. Female FiF graduates were more likely to stop working altogether or to be put on an unpaid leave and less likely to be put on furlough or paid leave than non-FiF female graduates. However, we find no such differences between FiF and non-FiF male graduates. Our results highlight how the COVID-19 recession has exacerbated the disadvantage arising from the intersectionality of socioeconomic background and gender and the prolonged impact of parental human capital for women.

VERSION: August 2023

Suggested citation: Adamecz, A., Jiang, Y., Shure, N. & Wyness, G. (2023). *Intergenerational educational mobility and the COVID-19 pandemic* (CEPEO Working Paper No. 23-08). Centre for Education Policy and Equalising Opportunities, UCL.

Highlights

- The COVID-19 pandemic has dramatically affected many aspects of people's lives in England, especially for disadvantaged groups, and has exacerbated some pre-existing inequalities.
- This paper examines the impact of the COVID-19 pandemic on the labour market experiences of "first in family" (FiF) graduates with their non-FiF peers across three time points from May 2020 to March 2021 in England.
- We find that FiF female graduates were more likely to stop working altogether or to be put on unpaid leave, but less likely to be put on furlough or paid leave than non-FiF female graduates. There was no difference between FiF men and non-FiF men.
- Our findings indicate an exacerbated disadvantage in the labour market arising from the intersectionality of socio-economic background and gender.

Why does this matter?

The detrimental impact of a recession experienced in early career could potentially have long-term scarring effects on 'first in family' females and on social mobility more broadly.

Intergenerational educational mobility and the COVID-19 pandemic

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Keywords: Socioeconomic gaps, Intergenerational educational mobility, Higher education, First-generation, First in family, COVID-19

We thank Morag Henderson for her comments and guidance. This work was supported by Yuyan Jiang's UBEL DTP PhD scholarship from the Economic and Social Research Council (ESRC).

1. Introduction

Since the first national lockdown in March 2020, the COVID-19 pandemic has dramatically affected the economy and labour market in the UK. Overall, gross domestic product (GDP) dropped 9.8% in 2020 (Harari et al., 2021), and although economic activity started to recover from spring 2021, GDP in September 2021 was still 0.6% below its pre-pandemic level (February 2020) (Office for National Statistics, 2021a). To minimise the effect of the pandemic on the labour market and support employers, the Coronavirus Job Retention Scheme (CJRS), also known as the "furlough scheme", was announced in March 2020, providing grants to employers to ensure that they could retain and keep to pay their staff. Even with the CJRS, the UK unemployment rate rose gradually from 4.0% before the pandemic to 5.2% between October to December 2020 (Office for National Statistics, 2021b). Moreover, UK total actual weekly hours worked also declined greatly after the first national lockdown, from 1.05 billion hours before the pandemic to 0.845 billion hours in April to June 2020 (Office for National Statistics, 2021b).

Although the COVID-19 recession affects everyone in the country, there is concern that it may have a greater impact on the disadvantaged. Several recent studies from the US and Europe provide evidence that the pandemic may have had a greater impact on those from lower socio-economic status (SES) groups. For example, examining the impact of school closures on learning loss and time spent learning, several studies (Andrew et al., 2020; Dietrich et al., 2021; Grätz and Lipps, 2021; Green, 2020; Wößmann et al., 2020) show a disproportionate effect on young people from disadvantaged backgrounds. In the labour market context, several studies have shown that workers from disadvantaged groups have suffered both larger increases in employment losses and larger reductions in earnings during the COVID-19 pandemic (Cortes and Forsythe, 2020; Dang and Nguyen, 2020; Hupkau et al., 2021). In particular, studies to date have highlighted the disadvantage of being younger and from a poor background. Elliot Major et al.(2020) show that unemployment during the first wave of the pandemic was disproportionately higher for young people, while Eyles (2021) finds that young people who grew up in the poorest households are over twice as likely to have lost work since the pandemic began. Montenovo et al. (2020) examine job losses during the early months of the COVID-19 recession in the US and find that large drops in employment younger workers, and non-college graduates. Focusing on the UK, (Adams-Prassl et al., 2020) suggest that younger workers and those on low incomes are much more likely to have lost their job due to

COVID-19, and are more likely to have experienced a reduction in earnings, than older and higher-income workers.

Unlike recent recessions in developed economies which disproportionately hit men's employment, the COVID-19 recession was a "shecession", which had a more significant impact on women, and especially mothers, than on men (Alon et al., 2021). Albanesi & Kim (2021) examine the real-time labour market data in the US and find that women's employment, specially the employment of married women with children, falls more than men's at every stage of the pandemic. Using a sample of 30 advanced economies and 8 emerging market economies, Bluedorn et al. (2021) show that compared with the average employment rate in 2019, the employment rate in the second quarter of 2020 falls by around 2.5 and 2 percent for women and men, respectively. The gendered impact of COVID-19 recession the is due to women being more likely to work in contact-intensive industries (e.g. service industries) that were shut down during the pandemic, or due to the so called "motherhood penalty" where mothers assumed increased caring responsibilities as a result of school and nursery closures, resulting in them being unable to maintain unemployment (Alon et al., 2020; Andrew et al., 2020; Blundell et al., 2020; Couch et al., 2020).

While the literature on the impacts of the pandemic is rapidly growing, to date, none of this work has explored the potentially differential impact of the pandemic on first in family or first-generation university graduates even though there is evidence that this group has worse labour market outcomes already in early career (Adamecz-Völgyi et al., 2022). In this paper, we examine the impact of the COVID-19 pandemic on the labour market experiences of 'first in family' (FiF) students. FiF is defined as individuals who attend university and obtain a university degree but whose (step) mother and (step) father did not (Henderson et al., 2020). We use data from three waves of the Next Steps COVID-19 survey to investigate the heterogeneous labour market impacts of the COVID-19 pandemic on the FiF graduates as compared to their non-FiF peers. These young people were born in 1989/90 and were approximately age 30 by the time the pandemic began. This means they would have already completed higher education and be settled into early career when the pandemic hit. There is evidence that the long-term scarring effects of experiencing labour market shocks early in career can be detrimental (Arulampalam, 2001; Bell and Blanchflower, 2011; Gregg, 2001; Gregg and Tominey, 2005; Schmillen and Umkehrer, 2017), making this an issue of policy relevance.

We examine the relationship between FiF status and labour market outcomes during the pandemic using a range of outcomes across three time points from May 2020 to March 2021. We only focus on those who were "employed, self-employed, unpaid/voluntary workers or apprentices" before the outbreak. There are three possible scenarios arising from the pandemic on the circumstances of workers. First, they could have simply carried on working "employed and working (employed)". Second they could have been placed on the government's CJRS scheme, whereby they were put on paid leave, but paid up to 80% of their usual wage "employed but on furlough or paid leave[1] (on furlough)", or third, they could have been put on unpaid leave, become unemployed, or left the workforce altogether "Unemployed, inactive or other non-employed (Non-employed)". While some of these scenarios have advantages and disadvantages (e.g. many would prefer to be on paid leave than to keep working) this is also a plausible order of attractiveness to the individual as per the order set out above. In particular, among those who did not keep working, those who were put on furlough continued to be paid at up to 80% of their usual wage and thus were far better off in financial terms than those who became unemployed or who were put on unpaid leave.

We compare FiF graduates with their non-FiF graduate peers using linear probability regressions and controlling for a rich set of covariates, including personal and household characteristics, pre-COVID labour market characteristics, COVID-related factors, time spent on children and caring for others, and personal network at age 25. We focus only on university graduates to attempt to disentangle the effects of prior attainment and socioeconomic status during adolescence. Based on a range of literature highlighting differential effects of the pandemic on women, we explore these outcomes separately by gender. Since we have three waves of data collected during the pandemic, we are also able to estimate how these outcomes change over time.

We do not find a statistically significant difference in the probability that FiF and non-FiF graduates keep working, either among men or women. In terms of what happened to those who did not keep working, however, our results highlight the disadvantage arising from the intersectionality of socioeconomic background and gender. We find that FiF female graduates are more likely to be non-employed but less likely to be on furlough or paid leave than non-FiF female graduates (those whose parents have a university degree).

[1] Paid leave here refers to any forms of statutory leave and time off, including but not limited to maternity and paternity leave, holiday entitlement and sick pay.

However, we find no statistically significant difference between FiF and non-FiF male graduates.

This paper contributes to the previous literature in several important ways. First, we provide the first analysis of the labour market outcomes for FiF graduates during the COVID-19 pandemic in England. Unlike other indicators of disadvantaged groups, using FiF status focuses on the prolonged impact of parental human capital rather than their family income or another type of disadvantage. Also, FiF status is of policy interest as it is used as a measure by universities to increase the diversity of their student intake in Widening Participation and contextualised admissions (Henderson et al., 2020). Second, we use the 'millennial' generation, a relatively young cohort facing a number of challenges during their early adulthood (Henderson, 2019). The Great Recession started when they were about to enter the university at age 18 and they also faced higher university fees than any previous cohorts as higher education tuition fees increased gradually from £3,000 in 2006 to £9,000 in 2012. Previous studies have shown that younger workers are more likely to lose their job and have experienced a decrease in earnings during the pandemic than older workers (Adams-Prassl et al., 2020; Belot et al., 2020; Chatterji and Li, 2021). Thus, using this cohort enables us to reduce the influence of age heterogeneous effects and focus on the more at-risk age group. The potential long-term scarring of these effects and the scope for policymakers to intervene makes this analysis particularly important. Third, our data include three waves collected from May 2020 to March 2021. Instead of focusing on a single point in time, we analyse how our results change as the economic environment and government policies change over time. Importantly, these pandemic survey waves are linked to eight existing waves of data providing us with rich information on family background.

A further contribution is that we study inequalities in access to an important labour market insurance policy – the furlough scheme (CJRS). This scheme was created during the pandemic to protect workers whose jobs were not viable during government lockdowns. Our results suggest FiF workers were less likely to benefit from the scheme, highlighting an important dimension of inequality that requires further investigation.

The rest of this paper is organised as follows. We review evidence on the pre-existing inequalities in section 2 and government policy responses to the COVID-19 pandemic in England in section 3. Section 4 introduces the data and methodology used in this paper, followed by section 5, where we present the descriptive statistics. Our results are discussed in section 6, and section 7 provides conclusions with a discussion of policy implications.

2. Inequalities before the COVID-19 pandemic

There is a well-established body of literature focusing on socioeconomic gaps in educational and labour market outcomes in the UK. Individuals from disadvantaged backgrounds tend to have lower pre-university educational attainment (Blanden and Gregg, 2004; Blanden and Macmillan, 2016; Machin et al., 2013), have less chance to attend and complete university (Boliver, 2013; Chowdry et al., 2013; Crawford, 2014) and to attend a selective university (Campbell et al., 2021), and are less likely to enter high-status occupations and earn less than their peers from more affluent families once they enter labour market (Blanden et al., 2007; Gregg et al., 2017; Macmillan et al., 2015). Most of the existing studies use social class or family (parental) income indicators to identify who belongs to the disadvantaged group.

According to Henderson et al. (2020), a large proportion of recent university graduates in England (approximately 68%) are FiF. FiF students are less privileged than their non-FiF peers since non-graduate parents tend to have fewer economic resources to invest in their children's education and early development (Blundell et al., 2000; O'Leary and Sloane, 2005; Walker and Zhu, 2011). Moreover, potential FiF students have limited access to information about university admission and experiences from their parents (Radford, 2013; Thayer, 2000) and are more likely to enrol in vocational programmes, which impede their progress toward a university degree (Striplin, 1999), which is a stepping stone for high-status jobs. Without the social networks and family wealth of graduate parents, FiF might still be disadvantaged in the labour market even they have achieved a university degree.

Evidence from the US has shown that FiF students are less likely to be prepared for college admission (Choy, 2001; Horn and Nunez, 2000; Lohfink and Paulsen, 2005), have a lower chance to go to college (Engle, 2007; Wilbur and Roscigno, 2016), enrol in less academically selective institutions (Berkner and Chavez, 1997; Pascarella et al., 2004), and are less likely to stay enrolled or attain a bachelor's degree than non-FiF students (Warburton et al., 2001; Wilbur and Roscigno, 2016). As for labour market outcomes, some studies find a wage gap between FiF and non-FiF students (Thomas and Zhang, 2005; Zhang, 2012), while others suggest that a university degree fills that gap (Choy, 2001; Nunez and Cuccaro-Alamin, 1998). Manzoni and Streib (2019) summarise the mixed evidence from previous studies and find that a substantial wage gap between first- and continuing-generation students remains ten years after completing college though the gap for women disappears when individual characteristics are added into the model and the gap for men fades once labour market characteristics are controlled.

In the UK, there are limited studies focusing specifically on FiF students. Stuart (2006) uses life story methods to examine the university experience of first-generation students and suggests that friendship, as a form of social capital, play an important role in their HE decision and success at university. The first quantitative study looking at FiF students in the England is Henderson et al. (2020), where they employ a combination of logit models and multinomial logit models to investigate who FiF students are and how parental education influences children's university access, subject studied, institution attended and risk of dropout. They find that FiF graduates tend to come from ethnic minority backgrounds and have higher prior attainment than those who match their parents without a degree. Moreover, the results suggest that FiF graduates are more likely to study 'high earning' subjects, such as Law, Economics and Management, but are less likely to attend elite universities and are at greater risk of dropout. These findings are supported by Adamecz-Völgyi et al. (2022a), where they explore potential FiF[2] and examine whether or not potential FiF picks up additional information beyond other indicators of disadvantaged and vulnerable groups. They suggest that even after other measures of disadvantage are controlled, being FiF is still shown to be an important barrier to university participation and graduation, and this association is likely to operate through the channel of early educational attainment. The only study exploring the early career labour market outcomes of FiF in England examines the wage gap between FiF and non-FiF and estimate their returns to a degree (Adamecz-Völgyi et al., 2022). They find no wage difference for male graduates, while for females, FiF graduates earn 7.4 percent less than non-FiF, and this gap can be explained by the difference in prior academic attainment, whether they attended a prestigious institution and whether their degree is required for their job. Even though returns to a degree are higher for female FiF graduates

[2] 'Potential FiF' refers to young people who could be the first in their family to achieve a university degree because neither of their parents has one (Adamecz-Völgyi et al., 2022).

than for female non-FiF graduates, the negative impacts of having non-graduated parents offset the high returns to their own degree.

3. England's policy responses to the COVID-19 pandemic

On 11 March 2020, the World Health Organisation (WHO) declared COVID-19 a pandemic, which became one of the biggest threats faced by the UK for decades.[3] In response to the pandemic, the Prime Minister urged people to work from home where they possibly can on 16 March 2020. Then, almost two months after the first two cases of coronavirus in the UK were confirmed, the Prime Minister announced the first national lockdown on 23 March 2020 with lockdown measures legally came into force on 26 March 2020. Meanwhile, the Coronavirus Job Retention Scheme (CJRS) was announced on 20 March 2020, providing grants to employers to ensure that they could retain and keep to pay their staff (Powell et al., 2022). The CJRS initially covered 80% of an employee's wages (up to £2,500 per month)[4] as well as Employer's National Insurance contributions (NIC) and pension contributions from 1 March to 30 June 2020. This grant was available to all businesses of all sizes and there was no limit on funding per employer making it easier for businesses to keep their workers during the pandemic so that they can resume speedily and efficiently after the crisis. In the meantime, these policies also protect workers from losing their incomes and welfares to avoid the negative impacts of unemployment on individuals and society.

Figure 1 provides an overview of the timeline of all policy developments in this area and how they relate to the waves of the survey used in this paper. The first survey (wave one) was carried out in May 2020 when the Prime Minister was about to announce a conditional plan for lifting the first national lockdown. From 11 May 2020, those who could not work from home, such as construction workers and those in manufacturing, were encouraged to return to their work. On 12 May, the government announced the CJRS would be extended from 1 July to 31 October, only for employees already furloughed. The CJRS still covered 80% of an employee's wages during this period, but as the lockdown

[3] Due to the devolved nature of much of the policymaking around the COVID-19 pandemic and the fact that Next Steps includes only young people in England, we focus on England as opposed to the UK in this paper.

[4] The wages of furloughed workers can be further topped up to 100% by the employer.

restriction eased, the NICs and pension contributions were not covered from 1 August 2020.

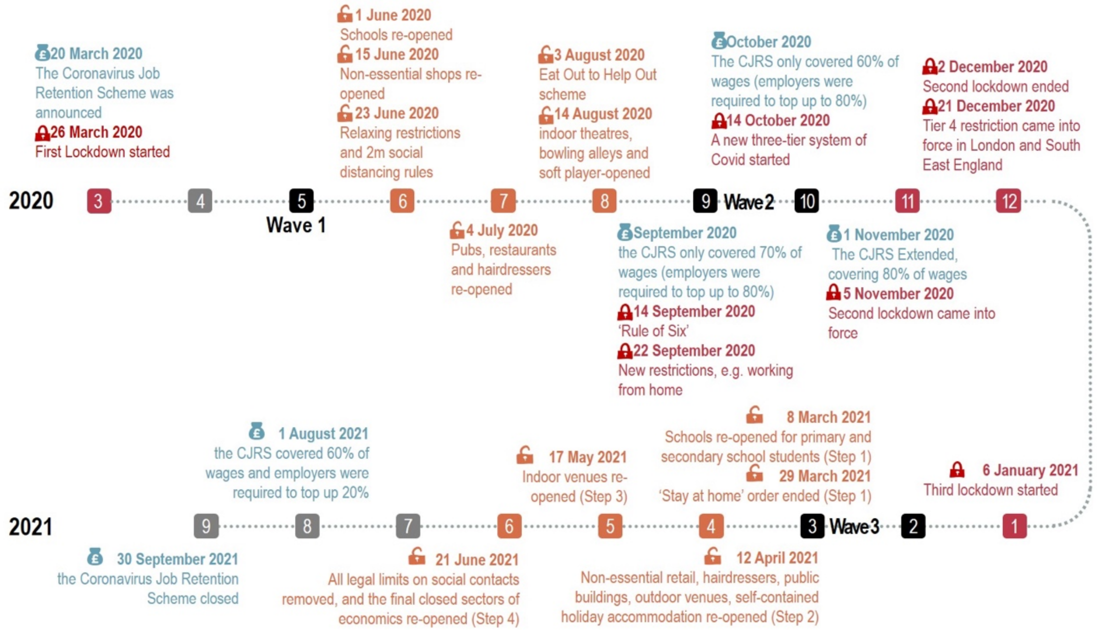

Figure 1. Timeline of England's policy responses to the pandemic and the COVID-19 survey

Source: Authors' own graphic. Data on lockdowns from Institute for Government (2021).

The second survey (wave two) was carried out from September to October 2020 when the CJRS only covered 70% and 60% of wages in September and October, respectively, and the employers were required to top up to at least 80%. As the cases of COVID-19 increased rapidly, a second national lockdown came into force on 5 November 2020, followed by a third lockdown which started on 6 January 2021. Due to these restrictions, the Prime Minister further extended the CJRS and employers were not required to have previously used the CJRS to be eligible. Employers should pay employees' wages for hours worked, as well as Employer's National Insurance contributions and pension contributions, while the government contributed 80% of employees' wages for furloughed hours (up to £2,500 per month).

The most recent survey (wave three) took place from February to March 2021 when the Prime Minister published a road map for lifting the third lockdown. During that period, the initial scheme was subsequently extended from 1 November 2020 to 30 September 2021 and the level of grant available to employers under the scheme stayed the same (80%

of wages) until 30 June 2021[5]. By 21 November 2021, 11.7 million jobs have been furloughed through the scheme, costing the government £70 billion (Powell et al., 2022).

4. Data and descriptive statistics

In this paper, we use a series of COVID-19 surveys which link to the national longitudinal cohort study, Next Steps, formerly known as the First Longitudinal Study of Young People in England (LSYPE) (University College London, UCL Institute of Education, Centre for Longitudinal Studies, 2021). Next Steps is nationally representative[6] and collects information on young people's family life, relationships and friends, education and employment, social participations and activities, health and happiness, and behaviour and attitudes. The cohort members, along with their parents, were first interviewed in the spring of 2004 (aged between 13 and 14) and were interviewed annually until the age of 20 in 2010. There are currently eight waves of data, and the last wave was carried out in 2015/16 when the approximately 8,000 cohort members were aged 25. The data has been linked to National Pupil Database (NPD) records, which provides data on compulsory, national high-stakes examinations.

The COVID-19 surveys for this cohort were created to ask about the experiences of the participants during the pandemic (and so are linked to the existing Next Steps study). Currently, there are three waves of the survey, from May 2020 to March 2021. All three waves cover topics including physical and mental health, time, financial situation, family

[5] From 1 July 2021, the Government contribution supported 70% of wages for hours not worked, reducing to 60% from 1 August. The scheme ended on 30 September 2021.

[6] In order to be representative of young people in England, Next Steps adopted a two-stage probability proportional to size (PPS) sampling procedure. First, schools, considered as the primary sampling units (PSUs), were sampled separately for the maintained schools, the independent schools, and pupil referral units (PRUs) to obtain the sample stratum. Maintained schools were stratified based on their deprivation levels, with deprived schools oversampled by 50%. Independent schools were stratified by the proportion of pupils obtaining five or more A*-C GCSE grades in 2003 within boarding status and gender of pupils. As for the pupil referral units (PRUs), they formed a stratum of their own. Then, within selected schools, pupils from major minority ethnic groups were oversampled to achieve 1,000 sampling units in each group. Furthermore, Next Steps excluded those solely educated at home, boarders and those who resided in England for education purposes only.

and household, employment, and education. In addition to these topics, Wave 3 also asks questions about pay and household income.

4.1 Sample selection and measures of variables

Non-response and sample attrition are common in longitudinal surveys. Overall, the missing values not only reduce the reliability and efficiency of our estimates because of the smaller sample size but also affect the external validity of the study as respondents are often systematically different from non-respondents. Furthermore, it would threaten the internal validity of our results if attrition and non-response were related to being FiF. In COVID-19 surveys, the response rates of the cohort members within the target population are 11.9%, 22.9%, and 26.4% for waves one, two and three respectively. Only a quarter of Next Step cohort members who participated in at least one wave of the COVID survey responded to all three waves. Thus, we can treat our sample as repeated cross-sectional data.

We handle missing data using weights that combine the original sample design weight of Next Steps with the survey non-response weight in the corresponding wave. The design weight is the reciprocal of the cohort member's selection probability scaled so that the weighted and unweighted achieved sample sizes are equal. As for the non-response weight, it is the inverse of the probability of response in the target population, which is modelled on a set of covariates using logistic regression. We investigate how being FiF is related to attrition and non-response in the second panel of Table 1 in Section 4.2. Overall, non-FiF graduates tend to have higher response rate than the non-FiF graduates.

As we focus on economic activity among FiF and non-FiF graduates, non-graduates as well as those who were not employed before the pandemic are excluded from the sample. Of the 884, 1,573 and 1,814 graduates who responded to the surveys in wave one, two and three, 779, 1,396 and 1,338 were working before the pandemic. This subset of Next Steps is our main sample for the analysis in this paper. To avoid dropping cases with missing values, we use missing flags for all variables except for the outcome variables and our main variable of interest.

Our main variable of interest is FiF status, which depends on the university graduation of the cohort members and their parents. The cohort members are regarded as university graduates if they have gained a university higher degree, a first-degree level qualification, a diploma in higher education, a teaching qualification or a nursing or other medical qualification by the age of 25. Information on parental graduation is available in the first four waves, up until the cohort members were aged 17. It is possible that the parents could have gained a university degree when the cohort member was older than 17; however, we focus on the influence of growing up with parents without university degrees and therefore restrict parental degree attainment to this point.

In this paper, we are interested in whether the pandemic affects labour market outcomes differently according to an individual's FiF status. We mainly look at three binary outcome variables: whether the participant was employed and working, whether the participant was employed but on furlough or paid leave, or whether the participant was unemployed, inactive or other non-employed. All variables are derived from the last wave of the main surveys and the respective wave of the COVID-19 surveys. As there are very few people in voluntary jobs and apprenticeships both before and after the pandemic, we combine them with the employed and working group. *Employed and working* is defined as "employed, self-employed, unpaid/voluntary workers or apprentices" both before and during the pandemic. *Furlough or paid leave* refers to "employed, self-employed, unpaid/voluntary workers or apprentices" before the pandemic and "employed but on paid leave (including furlough)" during the pandemic. *Unemployed, inactive or other non-employed* is defined as "employed, self-employed, unpaid/voluntary workers or apprentices" before the pandemic but "employed and on unpaid leave, self-employed but not currently working, unemployed, permanently sick or disabled, looking after home or family, or doing something else" post-outbreak.

To limit the influence of confounding factors and enhance the internal validity of our study, we include four groups of control variables in this paper:

- *Personal and household characteristics:* gender, ethnicity, whether attended a Russell Group university, marital status, having (school-aged) children, and the interaction term of gender and having (school-aged) children;

- *Pre-COVID labour market characteristics:* occupation (SOC code 2010), whether self-employed, whether on zero hours contract, and pre-COVID working hours;

- *COVID-related variable:* whether has had Coronavirus;

- *Time use variables (wave one and two only)*: time on home schooling, time on other activity with children, and time on caring for others;

- *Personal network at age 25*: whether found job through personal contacts, and whether found job by professional networking.

4.2 Descriptive statistics

We start our analysis by exploring the prevalence of our main variable of interest and main outcome variables. The first panel of Table 1 shows sample composition by FiF status. As we are focusing on those who were employed, the proportions of graduates in all three waves of the COVID-19 surveys are around 40%, higher than in the target population[7]. FiF graduates accounts for approximately 70% of the graduates in our sample for all waves. In order to examine the impact of growing up with non-graduate parents, we compare FiF graduates with non-FiF graduates (those who match their parents with a degree). Thus, group 2 (non-FiF graduates) is used as the baseline group in the empirical analysis.

Table 1. Sample used in this paper

		Group 1: FiF graduates (parents no degree)	Group 2: non-FiF graduates (parents with degree)
Sample size		Male: N=908 (69.3%) Female: N=1,625 (73.7%)	Male: N=401 (30.7%) Female: N=579 (26.3%)
Response and non-attrition rate within the target population	Wave 1	26.5%	34.5%
	Wave 2	49.8%	55.3%
	Wave 3	56.5%	61.2%

Notes: The number of observations refers to those who were working pre-COVID. Sample size is weighted using the combined weight for each wave.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

Table 2 compares the proportions of graduates who were employed and working, were employed but on furlough or paid leave, and unemployed, inactive or other non-employed by FiF status and gender and wave. In general, both male and female graduates were less likely to have kept working in the first wave compared to their status before the pandemic (when they were all in work). With the lifting of the first national lockdown, the probability that graduates kept working increases in wave two for both males and females, but it drops for females in wave three during the third national lockdown. Among all three

[7] Target population includes original sample only (i.e. not ethnic minority boost sample). N=15,770

waves, the rate of unemployed, inactive or other non-employed is highest in wave two, while the probability of being on furlough or paid leave is highest in wave one and much more than the probability in wave two when the CJRS was reduced to cover 60 to 70% of wages. When comparing FiF and non-FiF graduates, we find that both male and female FiF graduates were less likely to keep working than their non-FiF peers in all three waves. The gap is most significant in wave one for males (15.7 percentage points) and wave three for females (7.1 percentage points). Among those who did not keep working, FiF males were more likely to be put on furlough or paid leave than non-FiF males in all three waves, whereas FiF females were more likely to be unemployed, inactive or other non-employed than their non-FiF peers in all waves. Specifically, FiF males were 13.5 percentage points more likely to be on furlough or paid leave than non-FiF males in wave one and this gap narrows in the following two waves as the probability of being on furlough or paid leave decreases greatly from 17.2% in wave one to just 3% and 5% in wave two and three respectively for FiF male workers. Although FiF female workers were slightly less likely to be on furlough or paid leave than their non-FiF peers, they were much more likely to become unemployed, inactive or other non-employed especially in wave two.

Table 2. Labour market status by FiF status and gender and wave

		Male			Female		
Outcome		Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Employed	FiF	0.783	0.867	0.897	0.677	0.829	0.772
		(0.414)	(0.340)	(0.305)	(0.468)	(0.377)	(0.420)
	non-FiF	0.940	0.881	0.910	0.716	0.835	0.843
		(0.239)	(0.324)	(0.287)	(0.452)	(0.372)	(0.364)
	Total	0.826	0.872	0.900	0.688	0.830	0.791
		(0.380)	(0.335)	(0.300)	(0.464)	(0.375)	(0.407)
Furlough or paid leave	FiF	0.172	0.030	0.050	0.170	0.035	0.068
		(0.378)	(0.172)	(0.218)	(0.377)	(0.183)	(0.253)
	non-FiF	0.037	0.006	0.039	0.232	0.111	0.084
		(0.189)	(0.079)	(0.194)	(0.424)	(0.315)	(0.278)
	Total	0.134	0.022	0.047	0.188	0.053	0.073
		(0.341)	(0.148)	(0.211)	(0.391)	(0.225)	(0.260)
Non-employed	FiF	0.046	0.099	0.050	0.152	0.136	0.155
		(0.210)	(0.299)	(0.218)	(0.360)	(0.344)	(0.362)
	non-FiF	0.024	0.113	0.046	0.052	0.046	0.085
		(0.152)	(0.317)	(0.211)	(0.223)	(0.210)	(0.280)
	Total	0.040	0.104	0.049	0.124	0.115	0.130
		(0.196)	(0.305)	(0.216)	(0.330)	(0.319)	(0.336)

Notes: Standard errors in parentheses. Weighted using the combined weight for each wave.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

Table 3 and Figure 2 show how the amount of time spent on children and caring for others varies by FiF status, gender and wave. For example, about 78% of male FiF graduates were employed and working in wave one. As time use variables are not available in wave three, we impute missing values in time use variables in wave three using the average of the first two waves. If the variable is missing in one of the two waves, we just use the value in the other wave instead of the average. In general, female workers spent more time on children and caring for someone other than a child than male workers in all three waves. Focusing on the FiF status, we find that both male and female FiF graduates spent more time on children and caring for others than their non-FiF peers.

Table 3. Time use variables by FiF status and gender and wave

		Male			Female		
Outcome		Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Time on home schooling	FiF	0.127	0.106	0.259	0.334	0.240	0.337
		(0.669)	(0.588)	(0.548)	(1.197)	(1.645)	(1.392)
	non-FiF	0.053	0.061	0.117	0.063	0.097	0.101
		(0.450)	(0.226)	(0.300)	(0.353)	(0.661)	(0.256)
	Total	0.106	0.091	0.219	0.219	0.205	0.273
		(0.617)	(0.498)	(0.495)	(0.495)	(1.468)	(1.200)
Time on other activity with children	FiF	0.586	1.019	1.235	1.772	2.314	1.952
		(1.549)	(2.519)	(1.943)	(4.146)	(4.464)	(3.885)
	non-FiF	0.328	0.387	0.556	0.730	1.387	1.148
		(1.121)	(1.028)	(1.024)	(2.610)	(2.993)	(2.397)
	Total	0.515	0.807	1.044	1.044	2.088	1.733
		(1.446)	(2.158)	(1.761)	(1.761)	(4.172)	(3.559)
Time on caring for others	FiF	0.109	0.372	0.376	0.387	0.315	0.453
		(0.418)	(2.057)	(1.548)	(2.307)	(1.968)	(2.040)
	non-FiF	0.006	0.141	0.137	0.164	0.192	0.261
		(0.059)	(0.442)	(0.350)	(0.621)	(0.949)	(0.911)
	Total	0.081	0.295	0.309	0.309	0.285	0.401
		(0.360)	(1.700)	(1.330)	(1.330)	(1.775)	(1.805)

Notes: Standard errors in parentheses. Weighted using the combined weight for each wave.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

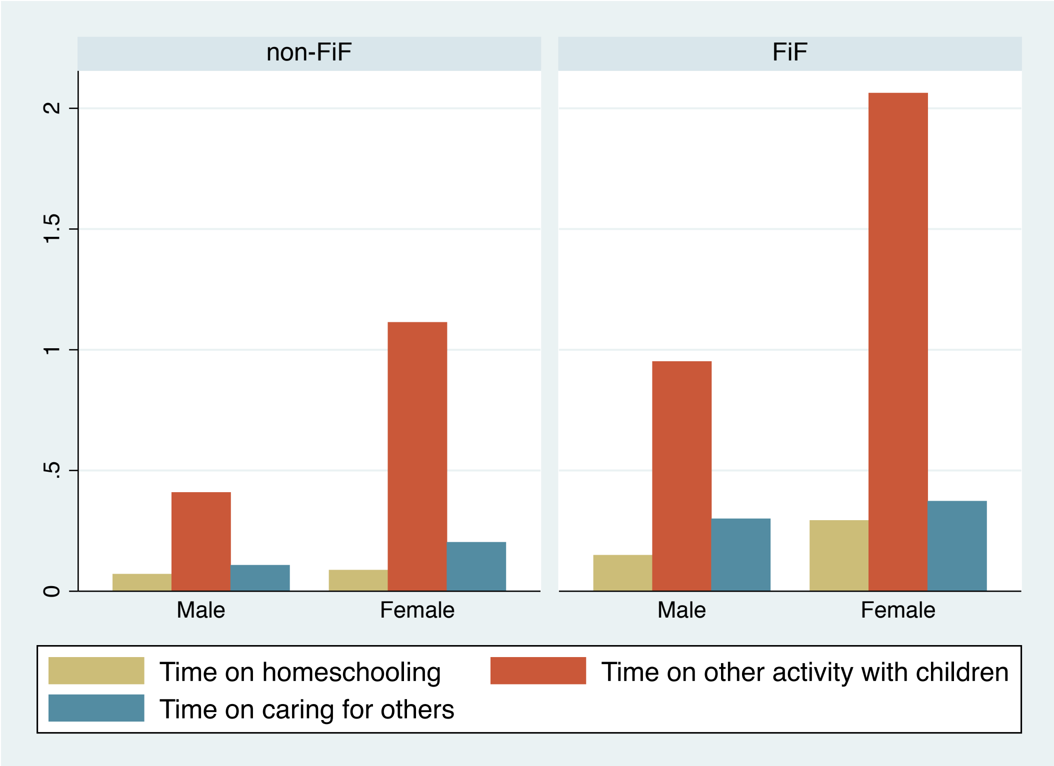

Figure 2. Time use variables by FiF status and gender

Notes: Standard errors in parentheses. Weighted using the combined weight for each wave.

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

Figure 3 shows how graduates found their jobs at the age of 25. We find that FiF female graduates were less likely to find their jobs through personal contacts or professional networking than their non-FiF peers. For men, however, FiF men were more likely to find their jobs by personal contacts but less likely to get employed through professional networking. Thus, FiF female graduates were in a more disadvantaged place when comparing their non-FiF peers in terms of the personal network, but the difference in the personal network is not obvious between FiF and non-FiF men.

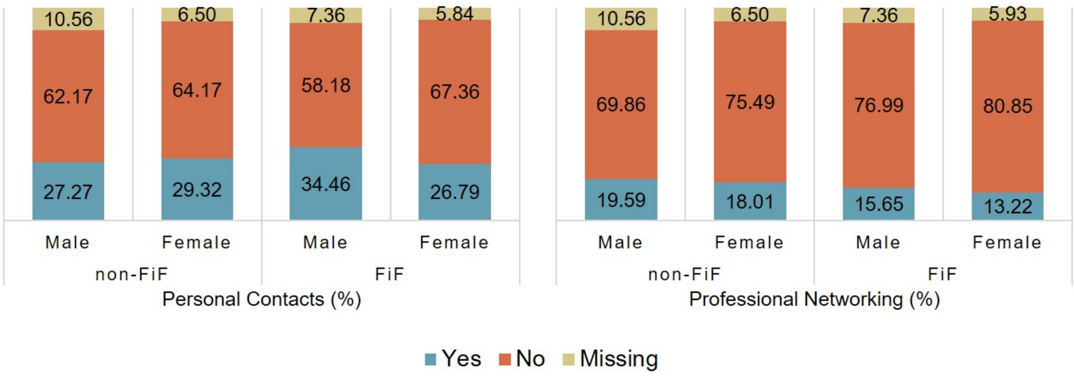

Figure 3. Personal network variables by FiF status and gender

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

5. Empirical strategy

In this paper, we want to examine the relationship between FiF status and our three outcome variables: whether the participant was employed and working, whether the participant was employed but on furlough or paid leave and whether the participant was unemployed, inactive or other non-employed. While our setup does not allow us to estimate the causal effects of being FiF on labour market outcomes during the pandemic, we control for a rich set of individual characteristics to reduce the selection bias and estimate a less biased association between the outcome variable and the variable of interest. We estimate linear probability models as:

$$Y_i = \alpha + \beta FiF_i + \gamma X_i + \varepsilon_i \qquad (1)$$

where Y_i represents one of our outcome variables. FiF_i measures 'first in family' status. X_i is a vector of controls, including personal and household characteristics, pre-COVID-19 labour market characteristics, COVID-19-related variables, time use variables and personal network at age 25. i identifies the cohort member, ε_i is the error term, and α, β, and γ are the parameters we estimate. All models are weighted using the COVID-19 combined weights in the respective waves in the respective waves as detailed above. As men and women follow very different roles in the labour market and in the home and the pandemic might have interacted with both, we estimate all models separately for men and women.

We start with a univariate baseline model (Model 1) to estimate the FiF gaps in labour market outcomes by gender. To minimise the influence of the heterogeneity between cohort members, we then estimate the second model (Model 2), controlling for their personal characteristics (ethnicity), educational attainment (whether graduated from a Russell Group university), and family situation (marital status, whether have child, and whether have school-aged children). In Model 3, we further control for their pre-COVID-19 labour market characteristics, including occupation (SOC code 2010), whether self-employed, whether on zero hours contract, and pre- COVID-19 working hours. As we focus on labour market outcomes during the pandemic, in the fourth model (Model 4), we add the COVID-19-related indicator, whether they had COVID. Previous work has found that time spent home schooling and other interactive activities with children is associated with gender and employment status (Villadsen et al., 2020). Thus, the fifth model (Model 5) includes time spent on home schooling and interacting with children and caring for others. Time use variables are not available in the third wave of the COVID-19 Survey, thus we only estimate the first four models for wave three. In our final specification (Model 6), we also control for how they found out their job at age 25 as personal network could have protected them from losing their during the pandemic.

In addition, we also explore whether the associations we find are heterogenous by wave with the results available in the Appendix. As shown in Figure 1, the policy environment changed over time. Thus, different time and COVID-19-related policies could have an impact on the influence of the pandemic on labour market outcomes.

6. Results

As mentioned before, the estimated impact of being a FiF graduate in this paper refers to the association between FiF status and labour market outcomes rather than the causal effect of being FiF. Even though we have included a rich set of covariates in our model[8], there is still a possibility that some unobserved factors are correlated with both the FiF status and labour market outcomes. Therefore, the terms, such as ‘impact’ and ‘influence’, used in this paper demonstrate only the statistical association.

[8] The results of the full models with all the covariates can be found in Appendix B.

6.1 How does the probability of being employed and working differ by FiF status?

To compare FiF and non-FiF graduates, we use non-FiF graduates as our baseline group for all models. Table 4 shows the relationship between FiF status and the probability of being employed and working, separately for men and women. As shown in the first panel in Table 4, among males, the association between being FiF and the probability of keeping working is negative but not statistically significant in any specification. Specifically, FiF males are 5.0 percentage points less likely to keep working than non-FiF males in the baseline model. The gap drops greatly to 1.1 percentage points once we control for pre-COVID labour market characteristics in model 3. Further adding COVID-19-related variables, time use variables and personal network at age 25 in Models 4, 5 and 6 has a very limited impact on both the estimated coefficients and the explanatory power of the model. Although these last three sets of controls variables could potentially be *bad controls* (i.e., might already be affected by the pandemic), controlling for them does not change our previous results.

Among females (the second panel in Table 4), the association between being FiF and the probability of being employed and working is also small and insignificant in all specifications. Specifically, FiF female graduates are 3.4 percentage points less likely to keep working than non-FiF graduates before we add any controls in the model. The coefficient decreases once we control for personal and household characteristics in Model 2 (-1.6 percentage points) and becomes positive once pre-COVID-19 labour market characteristics are added in Model 3 (0.2 percentage points). In the final model, FiF female graduates have 0.8 percentage points higher probability of keeping working than non-FiF female graduates and this result is statistically insignificant. Thus, we can conclude that there is no statistically significant relationship between being FiF and the probability of being employed and working during the pandemic for both male and female graduates.

Table 4. The probability of being employed and working by FiF status

		(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Male							
Group (base=non-FiF)	FiF	-0.0499	-0.0433	-0.0106	-0.0151	-0.0112	-0.00994
		(0.0423)	(0.0445)	(0.0262)	(0.0260)	(0.0260)	(0.0258)
	Observations	1,309	1,309	1,309	1,309	1,309	1,309
	R-squared	0.011	0.036	0.342	0.347	0.355	0.357
Female							
Group (base=non-FiF)	FiF	-0.0342	-0.0156	0.00185	0.00165	0.00546	0.00790
		(0.0413)	(0.0412)	(0.0275)	(0.0272)	(0.0267)	(0.0264)
	Observations	2,204	2,204	2,204	2,204	2,204	2,204
	R-squared	0.022	0.046	0.292	0.293	0.302	0.304
Control variables							
Personal and household characteristics			✓	✓	✓	✓	✓
Pre-COVID labour market characteristics				✓	✓	✓	✓
COVID-related variables					✓	✓	✓
Time on homeschooling and caring						✓	✓
Personal network at age 25							✓

*Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.*

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

6.2 How does the probability of being employed but on furlough or paid leave differ by FiF status?

In Table 5, we find gender differences in terms of the relationship between being a FiF and the probability of being employed but on furlough or paid leave. Among males, the relationship between first in family and the probability of being employed but on furlough or paid leave is positive and significant without any controls. Once we add in personal and household characteristics, the coefficient decreases slightly from 4.9 percentage points to 4.3 percentage points, but is still statistically significant. However, adding pre-COVID labour market characteristics to the model brings down the coefficient considerably to 1.6 percentage points and turns the relationship to insignificant, suggesting that FiF male graduates are more likely to be found in certain occupations where furlough was more common. The relationship remains small and statistically insignificant even after we further control for COVID-19-related variables, time use variables and personal network at age 25 in Models 4, 5 and 6.

Unlike the relationship among males, the relationship among female workers is negative and statistically significant in all models. The raw relationship (-5.5 percentage points) gets larger in magnitude when we account for personal and household characteristics in Model 2 (-6.3 percentage points) and then become smaller but still statistically significant after controlling for pre-COVID labour market characteristics in model 3 (-4.7 percentage points), indicating that occupations play a less important role in explaining the difference for women than for men. In our final and preferred model, we find that FiF females are 5.0 percentage points less likely than non-FiF females to be on furlough or paid leave.

Table 5. The probability of being employed but on furlough or paid leave by FiF status

		(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Male							
Group	FiF	0.0490***	0.0431**	0.0158	0.0173	0.0139	0.0139
(base=non-FiF)		(0.0171)	(0.0171)	(0.0166)	(0.0167)	(0.0166)	(0.0166)
	Observations	1,309	1,309	1,309	1,309	1,309	1,309
	R-squared	0.050	0.067	0.284	0.286	0.296	0.300
Female							
Group	FiF	-0.0550*	-0.0625**	-0.0473**	-0.0474**	-0.0503**	-0.0502**
(base=non-FiF)		(0.0292)	(0.0282)	(0.0206)	(0.0205)	(0.0203)	(0.0200)
	Observations	2,204	2,204	2,204	2,204	2,204	2,204
	R-squared	0.045	0.070	0.216	0.217	0.229	0.231
Control variables							
Personal and household characteristics			✓	✓	✓	✓	✓
Pre-COVID labour market characteristics				✓	✓	✓	✓
COVID-related variables					✓	✓	✓
Time on homeschooling and caring						✓	✓
Personal network at age 25							✓

*Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.*

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6.3 How does the probability of being unemployed, inactive, or other non-employed differ by FiF status?

Table 6 presents the estimated relationship between FiF status and the probability of being unemployed, inactive or other non-employed for males and females, respectively. Focusing on males only, we find that FiF men were less likely to being unemployed, inactive or other non-employed, but this result is small (0.6 percentage points in the final specification) and not statistically significant.

Unlike the insignificant result for their male peers, female FiF graduates are 9.4 percentage points more likely to being unemployed, inactive or other non-employed than non-FiF female graduates before we control for other factors. After controlling for personal and household characteristics in Model 2, we find that the estimated difference between FiF and non-FiF decreases slightly to 8.3 percentage points. The difference becomes much smaller (5.1 percentage points) but still significant in Model 3, once we add in pre-COVID-19 labour market characteristics, indicating that being a FiF graduate is associated with the probability of being unemployed, inactive or other non-employed partly through their pre-COVID-19 labour market characteristics. For example, compared to their FiF graduate peers, non-FiF female graduates are more likely to take managerial, directorial, professional and technical occupations, which are less likely to be affected by the pandemic. Finally, the estimated relationships in Models 4, 5 and 6, where COVID-19-related variables, time use variables and personal network at age 25 are included, are similar to estimates in Model 3.

Table 6. The probability of being unemployed, inactive or other non-employed by FiF status

		(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Male							
Group (base=non-FiF)	FiF	-0.000566 (0.0394)	-0.00148 (0.0419)	-0.00590 (0.0218)	-0.00295 (0.0217)	-0.00422 (0.0219)	-0.00550 (0.0219)
	Observations	1,309	1,309	1,309	1,309	1,309	1,309
	R-squared	0.013	0.035	0.384	0.387	0.396	0.405
Female							
Group (base=non-FiF)	FiF	0.0939*** (0.0310)	0.0831*** (0.0317)	0.0507*** (0.0177)	0.0510*** (0.0175)	0.0500*** (0.0174)	0.0470*** (0.0172)
	Observations	2,204	2,204	2,204	2,204	2,204	2,204
	R-squared	0.016	0.052	0.399	0.401	0.402	0.406
Control variables							
Personal and household characteristics			✓	✓	✓	✓	✓
Pre-COVID labour market characteristics				✓	✓	✓	✓
COVID-related variables					✓	✓	✓
Time on homeschooling and caring						✓	✓
Personal network at age 25							✓

*Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.*

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7. Discussion

This paper focuses on the labour market outcomes of FiF and non-FiF university graduates during the COVID-19 pandemic. Looking at the probability that graduates keep working, we don't find a difference between FiF and non-FiF graduates, either among men or among women. Our results however demonstrate a differential impact of the pandemic for FiF graduates by gender when we look at what happened to those who did not keep working. The government created a brand new means of protecting workers in industries that were forced to close during the pandemic, known as the Coronavirus Job Retention Scheme or furlough. However, we find that among women, FiF graduates became more likely to be unemployed, inactive or other non-employed and less likely to go on a furlough or paid leave than non-FiF graduates.

Thus, our results show that FiF graduate women were more likely to have worse labour market outcomes than female graduates whose parents attended university. Among men, however, we do not find a significant differential effect for FiF versus non-FiF graduates once we control for pre-Covid labour market characteristics.

This is consistent with the results from (Adamecz-Völgyi et al., 2022) that found FiF females tend to face a penalty on the graduate labour market, while FiF males do not. They suggest that one possible explanation for this result is the gender differences in social pressure and motivation. FiF males may face more social pressure than FiF females, and thus, have a higher motivation to find higher paid jobs. By the same reckoning, males may also have a greater motivation to negotiate with their employer to be put on furlough. Friedman (2022) also finds a "double disadvantage" for females from working-class backgrounds in the labour market than their male counterparts. He suggests that females from working-class backgrounds are less likely to talk openly about their background and this feeling of shame and inferiority tends to adversely affect their career progression.

This may be a reason that they are less likely to be placed on furlough, and therefore retained by their employers.

When comparing within gender, there are also several explanations for why FiF female graduates experienced worse outcomes than non-FiF female graduates. First, we have controlled for their occupations but not their specific jobs or tasks. In this paper, we use the 3-digit Standard Occupational Classification (SOC) 2010 code and there are 90 groups in total. It is still possible that FiF females were doing different jobs or working in different firms than their non-FiF female peers within the same SOC code. Laurison and Friedman (2016) find that individuals from non-privileged backgrounds are more likely to be employed in smaller firms and outside London.

It has also been argued that FiF females face a penalty in social networks and resources. In our sample, FiF female graduates were less likely to find their job through personal contacts and professional networking at age 25 than their non-FiF peers. A large number of previous studies have found that parental social class and networks play an important role in children's labour market performance, especially during early adulthood (Erola et al., 2016; Härkönen and Bihagen, 2011; Skeggs, 1997; Smith, 2017). Individuals from lower socioeconomic backgrounds are less likely to accumulate the same economic, cultural and social capital as the privileged ones through family relationships. Compared with graduates with graduated parents, FiF graduates have limited occupational knowledge, information, and resources to make suitable career choices and find stable jobs. As furloughed workers are not allowed to undertake any work for their employers in the first few months when the CJRS started, it could be more attractive for employers to lay off some of the workers than keep them when no work could be done (Adams-Prassl et al., 2020). Moreover, in our sample, FiF graduates are more likely to be on a zero-hours contract that places them in a vulnerable situation where they are more likely to be laid off or put on an unpaid leave when there is a shock in the economy.

8. Conclusion

One of the major impacts of the COVID-19 pandemic was on jobs. Entire sectors were shut down during the UK's lockdowns and the impact of the pandemic has been felt unequally across socioeconomic groups. In this paper, we examine the impacts of the COVID-19 pandemic on labour market outcomes of first in family graduates. This group has received little attention in terms of how they have fared during the pandemic, despite FiF status having been shown to provide additional information over and above other measures of disadvantage. Previous research has also shown that FiF females go on to earn significantly less than those women with university-educated parents (Adamecz-Völgyi et al., 2020), and that females have been hit harder by the COVID-19 recession than in other recessions (Andrew et al., 2020; Couch et al., 2021). Hence, we explore the impact of the pandemic at the intersection of gender and FiF status.

We find that female FiF graduates experienced a higher likelihood of being unemployed, inactive or other non-employed than female graduates whose parents attended university, but no such effect for males. This result is driven by the disadvantage of both being a female and being a first in family. On the one hand, FiF females may be, on average, less motivated and less willing to express their "authentic self" than their male peers. On the other hand, they have fewer family resources to rely on and thus are less likely to find a job that is as good as their non-FiF female peers.

Despite the fact that recent recessions have usually disproportionally affected male workers, previous evidence has suggested that the COVID-19 recession is a possible 'she-cession' as women's labour market outcomes have deteriorated disproportionally during the pandemic. Our results confirm this point and further suggest that women from non-privileged backgrounds, those with non-graduate parents are the group that has been hit the hardest by the pandemic. As the cohort members we focus on are still in their early adulthood, experiencing labour market shocks can have a long-term scarring effect on their career development.

In order to narrow gender and socioeconomic gaps, the government should consider how the education system and policies can help equalise experiences across young people from different backgrounds by targeting resources to those most in need. Firstly, policymakers should ensure that affordable and reliable childcare options are available to support women's entry into and continuance of employment. It is also important to make sure family leave is available for equitable use by males and females. Moreover, supporting policies and schemes should focus more on the poorer population through social protection measures that better preserve employment and insure workers against shocks. In addition, there should be more flexibility in working hours across sectors and occupations. Relevant policies should aim at promoting and facilitating for everyone, especially the low-income groups.

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Appendices

A. Standard Occupational Classification

Table 7. Standard Occupational Classification: SOC 2010

Major groups	Minor groups
1 Managers, directors and senior officials	111 Chief executives and senior officials 112 Production managers and directors 113 Functional managers and directors 115 Financial institution managers and directors 116 Managers and directors in transport and logistics 117 Senior officers in protective services 118 Health and social services managers and directors 119 Managers and directors in retail and wholesale 121 Managers and proprietors in agriculture related services 122 Managers and proprietors in hospitality and leisure services 124 Managers and proprietors in health and care services 125 Managers and proprietors in other services
2 Professional occupations	211 Natural and social science professionals 212 Engineering professionals 213 Information technology and telecommunications professionals 214 Conservation and environment professionals 215 Research and development managers 221 Health professionals 222 Therapy professionals 223 Nursing and midwifery professionals 231 Teaching and educational professionals 241 Legal professionals 242 Business, research and administrative professionals 243 Architects, town planners and surveyors 244 Welfare professionals 245 Librarians and related professionals 246 Quality and regulatory professionals 247 Media professionals
3 Associate professional and technical occupations	311 Science, engineering and production technicians 312 Draughtspersons and related architectural technicians 313 Information technology technicians 321 Health associate professionals 323 Welfare and housing associate professionals 331 Protective service occupations 341 Artistic, literary and media occupations 342 Design occupations 344 Sports and fitness occupations

	351 Transport associate professionals 352 Legal associate professionals 353 Business, finance and related associate professionals 354 Sales, marketing and related associate professionals 355 Conservation and environmental associate professionals 356 Public services and other associate professionals
4 Administrative and secretarial occupations	411 Administrative occupations: government and related organisations 412 Administrative occupations: finance 413 Administrative occupations: records 415 Other administrative occupations 416 Administrative occupations: office managers and supervisors 421 Secretarial and related occupations
5 Skilled trades occupations	511 Agricultural and related trades 521 Metal forming, welding and related trades 522 Metal machining, fitting and instrument making trades 523 Vehicle trades 524 Electrical and electronic trades 525 Skilled metal, electrical and electronic trades supervisors 531 Construction and building trades 532 Building finishing trades 533 Construction and building trades supervisors 541 Textiles and garments trades 542 Printing trades 543 Food preparation and hospitality trades 544 Other skilled trades
6 Caring, leisure and other service occupations	612 Childcare and related personal services 613 Animal care and control services 614 Caring personal services 621 Leisure and travel services 622 Hairdressers and related services 623 Housekeeping and related services 624 Cleaning and housekeeping managers and supervisors
7 Sales and customer service occupations	711 Sales assistants and retail cashiers 712 Sales related occupations 713 Sales supervisors 721 Customer service occupations 722 Customer service managers and supervisors
8 Process, plant and machine operatives	811 Process operatives 812 Plant and machine operatives 813 Assemblers and routine operatives 814 Construction operatives 821 Road transport drivers 822 Mobile machine drivers and operatives 823 Other drivers and transport operatives

9 Elementary occupations	911 Elementary agricultural occupations 912 Elementary construction occupations 913 Elementary process plant occupations 921 Elementary administration occupations 923 Elementary cleaning occupations 924 Elementary security occupations 925 Elementary sales occupations 926 Elementary storage occupations 927 Other elementary services occupations

Source: HESA (2022) https://www.hesa.ac.uk/support/documentation/occupational/soc2010.

B. Full model results

Table 8. Regression results of the full model: Male

		(1) Kept working	(2) On furlough or paid leave	(3) Left work or on unpaid leave
Group	FiF	-0.00994	0.0139	-0.00550
(base=non-FiF)		(0.0258)	(0.0166)	(0.0219)
Wave	Wave two	0.105***	-0.128***	0.0226
(base=Wave one)		(0.0304)	(0.0254)	(0.0218)
	Wave three	0.146	-0.132*	0.0590
		(0.102)	(0.0709)	(0.0405)
Ethnicity	Mixed	0.0989	-0.0202	-0.0940*
(base=White)		(0.0686)	(0.0250)	(0.0482)
	Indian	0.00226	0.0155	-0.0113
		(0.0520)	(0.0261)	(0.0469)
	Pakistani and Bangladeshi	0.172***	-0.0418	-0.115***
		(0.0465)	(0.0272)	(0.0419)
	Black	-0.0742	0.127**	-0.0496
		(0.0688)	(0.0610)	(0.0411)
	Other	0.0549	-0.0625**	0.0121
		(0.0622)	(0.0262)	(0.0529)
RGU	Yes	0.0489*	-0.00755	-0.0411**
(base=No)		(0.0282)	(0.0188)	(0.0198)

	Missing	-0.150	-0.0551	0.204**
		(0.101)	(0.0416)	(0.101)
Marital status	Married	-0.0877	0.0804*	0.00795
(base=Single)		(0.0568)	(0.0471)	(0.0315)
	Divorced	-0.0342	-0.00702	0.0419
		(0.0841)	(0.0280)	(0.0742)
	Civil Partnership	0.0342	0.0319	-0.0605
		(0.0459)	(0.0267)	(0.0374)
Child		0.0777	-0.0147	-0.0638*
		(0.0562)	(0.0502)	(0.0372)
School-aged child		-0.00445	-0.0390	0.0471
		(0.0762)	(0.0580)	(0.0553)
SOC2010	110	0.198**	-0.0747	-0.0923*
(base=Missing)		(0.0798)	(0.0670)	(0.0520)
	112	0.132	-0.0648	-0.0364
		(0.0811)	(0.0616)	(0.0546)
	113	0.179**	-0.144**	-0.00271
		(0.0761)	(0.0661)	(0.0457)
	115	0.116	-0.125	0.0996
		(0.114)	(0.0784)	(0.0608)
	116	-0.472***	0.339	0.162
		(0.179)	(0.228)	(0.175)
	119	-0.183	0.241*	-0.0292
		(0.143)	(0.128)	(0.0437)
	122	-0.0391	0.106	-0.0272
		(0.165)	(0.166)	(0.0462)
	124	0.280***	-0.223***	-0.0330
		(0.0877)	(0.0734)	(0.0488)
	125	-0.136	-0.0290	0.192
		(0.170)	(0.0672)	(0.152)
	211	0.148*	-0.115*	-0.00590
		(0.0856)	(0.0658)	(0.0676)
	212	0.183**	-0.131*	-0.0289
		(0.0720)	(0.0677)	(0.0373)

213	0.205**	-0.131**	-0.0463
	(0.0791)	(0.0661)	(0.0442)
214	0.172**	-0.131**	-0.0141
	(0.0856)	(0.0597)	(0.0588)
215	0.218***	-0.166***	-0.0269
	(0.0730)	(0.0607)	(0.0417)
221	0.140*	-0.145**	0.0315
	(0.0812)	(0.0643)	(0.0561)
222	-0.0346	0.101	-0.0359
	(0.195)	(0.193)	(0.0503)
223	0.252***	-0.156*	-0.0713
	(0.0895)	(0.0798)	(0.0535)
231	0.163**	-0.147**	0.0116
	(0.0748)	(0.0628)	(0.0393)
241	0.0247	0.0414	-0.0389
	(0.181)	(0.165)	(0.0450)
242	0.147**	-0.111*	-0.00902
	(0.0719)	(0.0610)	(0.0445)
243	0.212***	-0.156**	-0.0303
	(0.0799)	(0.0675)	(0.0437)
244	0.178**	-0.206***	0.0542
	(0.0844)	(0.0715)	(0.0493)
245	0.116	-0.105	0.0128
	(0.0918)	(0.0779)	(0.0544)
246	0.0287	-0.127**	0.131
	(0.177)	(0.0631)	(0.139)
247	0.116	-0.118*	0.0328
	(0.116)	(0.0655)	(0.106)
311	0.250***	-0.123*	-0.0987*
	(0.0855)	(0.0739)	(0.0580)
312	0.00535	0.0751	-0.0533
	(0.217)	(0.205)	(0.0510)
313	0.197***	-0.143**	-0.0212
	(0.0720)	(0.0645)	(0.0381)

323	0.212**	-0.113	-0.0761
	(0.0933)	(0.0762)	(0.0531)
331	0.181**	-0.145**	-0.00942
	(0.0755)	(0.0613)	(0.0471)
341	-0.150	0.0411	0.140
	(0.148)	(0.0836)	(0.110)
342	0.149	-0.106	-0.0135
	(0.103)	(0.0796)	(0.0596)
344	0.108	0.00702	-0.0872
	(0.161)	(0.140)	(0.0603)
351	0.149	-0.200**	0.0837
	(0.163)	(0.0890)	(0.108)
352	0.123	-0.0974	-0.00428
	(0.0831)	(0.0741)	(0.0402)
353	0.156*	-0.148**	0.0162
	(0.0833)	(0.0632)	(0.0580)
354	-0.00203	0.00399	0.0251
	(0.0966)	(0.0860)	(0.0473)
356	0.00210	-0.0439	0.0649
	(0.122)	(0.106)	(0.0686)
411	0.212***	-0.130*	-0.0539
	(0.0781)	(0.0678)	(0.0436)
412	0.117	-0.0928	-0.0147
	(0.0896)	(0.0736)	(0.0446)
413	0.187**	-0.174***	0.0112
	(0.0743)	(0.0643)	(0.0508)
415	0.159*	-0.111*	-0.0228
	(0.0828)	(0.0667)	(0.0552)
416	0.171**	-0.106*	-0.0382
	(0.0733)	(0.0604)	(0.0424)
511	0.224	0.0160	-0.218**
	(0.207)	(0.175)	(0.0952)
521	0.212***	-0.216***	0.0334
	(0.0805)	(0.0721)	(0.0756)

522	0.142*	-0.138*	0.0224
	(0.0805)	(0.0733)	(0.0399)
523	-0.318**	-0.279***	0.625***
	(0.126)	(0.107)	(0.0640)
524	-0.233	-0.0685	0.330*
	(0.207)	(0.0700)	(0.192)
525	0.151*	-0.0893	-0.0292
	(0.0908)	(0.0821)	(0.0537)
531	-0.0500	0.0747	0.0149
	(0.115)	(0.0936)	(0.0590)
543	0.108	-0.0136	-0.0585
	(0.0908)	(0.0836)	(0.0486)
612	0.277***	-0.204***	-0.0460
	(0.0779)	(0.0649)	(0.0410)
614	0.326**	-0.161*	-0.135**
	(0.130)	(0.0872)	(0.0662)
621	-0.371***	0.506***	-0.108*
	(0.0836)	(0.0593)	(0.0552)
711	-0.327	0.0982	0.253
	(0.256)	(0.193)	(0.264)
712	0.146*	-0.159**	0.0374
	(0.0851)	(0.0694)	(0.0570)
713	-0.201	-0.124*	0.0188
	(0.244)	(0.0665)	(0.0510)
722	0.0388	-0.0188	0.00377
	(0.158)	(0.150)	(0.0775)
811	0.0944	-0.0838	0.0204
	(0.150)	(0.150)	(0.0522)
812	-0.631***	0.673**	-0.0143
	(0.215)	(0.265)	(0.0800)
813	-0.725***	0.834***	-0.0818
	(0.0830)	(0.0588)	(0.0572)
814	0.336***	-0.0502	-0.260***
	(0.105)	(0.0638)	(0.0846)

	821	0.388***	-0.225**	-0.140
		(0.130)	(0.0991)	(0.0900)
	823	0.130	-0.205***	0.105
		(0.0930)	(0.0697)	(0.0665)
	911	-0.807***	-0.143**	0.975***
		(0.0745)	(0.0633)	(0.0364)
	912	0.105	-0.114*	0.0395
		(0.0813)	(0.0664)	(0.0512)
	921	-0.141	-0.0945	0.261
		(0.296)	(0.0666)	(0.256)
	923	0.306***	-0.268***	-0.00964
		(0.107)	(0.101)	(0.0560)
	924	0.362***	-0.166*	-0.176**
		(0.127)	(0.0904)	(0.0855)
	925	0.311***	-0.133*	-0.150**
		(0.0915)	(0.0793)	(0.0668)
	Not applicable	0.0716	-0.0563	0.0133
		(0.0732)	(0.0615)	(0.0404)
	Unable to code	0.108	-0.105*	0.0313
		(0.107)	(0.0611)	(0.0810)
Self-employed		-0.147*	-0.137***	0.284***
		(0.0777)	(0.0381)	(0.0673)
Zero-hours contracts		-0.270*	-0.0169	0.292**
		(0.143)	(0.0408)	(0.136)
Working hours		0.00586***	-0.000706	-0.00510***
		(0.00221)	(0.000977)	(0.00192)
Working hours missing		-0.293	0.239	0.0556
		(0.217)	(0.189)	(0.151)
COVID	Yes	0.00640	-0.00993	-0.00334
(base=No)		(0.0294)	(0.0184)	(0.0257)
	Unsure	-0.0409	0.0219	0.0138
		(0.0331)	(0.0236)	(0.0255)
	Missing	0.135*	-0.0337	-0.105*
		(0.0753)	(0.0479)	(0.0559)

Time on home schooling		0.0266	-0.00518	-0.0208
		(0.0223)	(0.0175)	(0.0154)
Time on other activity with children		-0.0159	0.0161*	0.000345
		(0.0130)	(0.00910)	(0.00887)
Time on caring for others		-0.0131	-0.00583	0.0187
		(0.0209)	(0.00435)	(0.0193)
Time use missing		-0.0506	0.0307	-0.0523
		(0.0992)	(0.0662)	(0.0383)
Personal contacts	Yes	-0.0335	-0.0284	0.0614**
(base=No)		(0.0342)	(0.0223)	(0.0260)
	Missing	0.00373	-0.0288	0.0271
		(0.0542)	(0.0246)	(0.0480)
Networking	Yes	0.00800	0.0326	-0.0390
(base=No)		(0.0436)	(0.0328)	(0.0335)
	Missing	-	-	-
	Constant	0.511***	0.233***	0.228***
		(0.122)	(0.0860)	(0.0783)
	Observations	1,309	1,309	1,309
	R-squared	0.357	0.300	0.405

*Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.*

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

Table 9. Regression results of the full model: Female

		(1) Kept working	(2) On furlough or paid leave	(3) Left work or on unpaid leave
Group	FiF	0.00790	-0.0502**	0.0470***

(base=non-FiF)		(0.0264)	(0.0200)	(0.0172)
Wave	Wave two	0.142***	-0.129***	-0.0148
(base=Wave one)		(0.0353)	(0.0287)	(0.0231)
	Wave three	0.0820	-0.0929***	-0.000373
		(0.0577)	(0.0330)	(0.0423)
Ethnicity	Mixed	-0.165***	0.137**	0.0233
(base=White)		(0.0582)	(0.0546)	(0.0377)
	Indian	-0.155*	-0.0234	0.180**
		(0.0935)	(0.0221)	(0.0898)
	Pakistani and Bangladeshi	-0.0807*	0.0652	0.0171
		(0.0476)	(0.0444)	(0.0298)
	Black	-0.0266	-0.0220	0.0498
		(0.0666)	(0.0286)	(0.0556)
	Other	-0.0360	-0.0135	0.0499
		(0.0660)	(0.0351)	(0.0556)
RGU	Yes	0.0483	-0.0339	-0.0101
(base=No)		(0.0313)	(0.0268)	(0.0171)
	Missing	0.109	-0.153**	0.0425
		(0.0818)	(0.0652)	(0.105)
Marital status	Married	0.0586	0.0275	-0.0840***
(base=Single)		(0.0367)	(0.0290)	(0.0241)
	Seperated	-0.111	-0.0452	0.151
		(0.107)	(0.0371)	(0.0923)
	Divorced	0.0926	0.0583	-0.154
		(0.124)	(0.0613)	(0.117)
	Civil Partnership	0.251***	-0.239***	-0.00912
		(0.0847)	(0.0801)	(0.0393)
	Missing	0.426***	-0.218**	-0.209
		(0.149)	(0.102)	(0.129)
Child		0.0193	-0.0628**	0.0478
		(0.0530)	(0.0313)	(0.0437)
School-aged child		0.00639	0.0224	-0.0274
		(0.0778)	(0.0480)	(0.0646)
SOC2010	112	0.228**	-0.260***	0.0283

(base=Missing)		(0.0882)	(0.0853)	(0.0637)
	113	0.207**	-0.192**	-0.0213
		(0.0834)	(0.0811)	(0.0595)
	116	0.256***	-0.229***	-0.0298
		(0.0888)	(0.0826)	(0.0655)
	118	0.284***	-0.265***	-0.0128
		(0.0964)	(0.0896)	(0.0687)
	119	-0.278	0.296	-0.0227
		(0.220)	(0.240)	(0.0580)
	121	0.325***	-0.270***	-0.0617
		(0.0845)	(0.0802)	(0.0584)
	122	0.0190	0.0448	-0.0697
		(0.128)	(0.118)	(0.0656)
	124	0.100	-0.0468	-0.0556
		(0.154)	(0.161)	(0.0616)
	125	0.202*	-0.131	-0.0792
		(0.105)	(0.0948)	(0.0759)
	211	0.266***	-0.235***	-0.0316
		(0.0836)	(0.0778)	(0.0632)
	212	-0.0190	-0.0154	0.0269
		(0.140)	(0.115)	(0.0984)
	213	0.248**	-0.174**	-0.0774
		(0.0972)	(0.0828)	(0.0768)
	214	0.0240	-0.243**	0.219
		(0.150)	(0.0978)	(0.182)
	215	0.0945	-0.168	0.0691
		(0.215)	(0.121)	(0.141)
	221	0.0972	-0.101	-0.00153
		(0.107)	(0.107)	(0.0686)
	222	0.250***	-0.230***	-0.0253
		(0.0872)	(0.0872)	(0.0590)
	223	0.258***	-0.211***	-0.0539
		(0.0815)	(0.0778)	(0.0607)
	231	0.125	-0.194**	0.0585

	(0.0905)	(0.0791)	(0.0695)
241	0.277***	-0.198**	-0.0831
	(0.0863)	(0.0814)	(0.0669)
242	0.0354	-0.104	0.0643
	(0.135)	(0.0930)	(0.106)
243	0.221***	-0.222***	-0.000409
	(0.0819)	(0.0836)	(0.0613)
244	0.266***	-0.204**	-0.0684
	(0.0874)	(0.0829)	(0.0645)
245	0.322***	-0.253***	-0.0726
	(0.0819)	(0.0790)	(0.0572)
246	0.263***	-0.241***	-0.0249
	(0.0986)	(0.0841)	(0.0655)
247	0.0590	-0.197**	0.135
	(0.129)	(0.0854)	(0.117)
311	-0.194	-0.276***	0.466**
	(0.184)	(0.0914)	(0.225)
313	0.352***	-0.272***	-0.0864
	(0.0859)	(0.0768)	(0.0609)
321	-0.165	-0.0942	0.250**
	(0.133)	(0.105)	(0.116)
323	0.304***	-0.223***	-0.0860
	(0.0819)	(0.0850)	(0.0616)
331	0.246***	-0.210**	-0.0408
	(0.0818)	(0.0817)	(0.0599)
341	0.0375	-0.178**	0.134
	(0.121)	(0.0881)	(0.104)
342	-0.347**	0.348**	-0.00376
	(0.160)	(0.162)	(0.0630)
344	-0.204	-0.176**	0.375
	(0.329)	(0.0800)	(0.329)
350	0.222**	-0.219**	0.00512
	(0.0863)	(0.0858)	(0.0661)
352	0.191**	-0.197**	0.00166

	(0.0927)	(0.0837)	(0.0711)
353	0.203**	-0.211**	0.00450
	(0.0864)	(0.0818)	(0.0626)
354	0.0486	-0.0442	-0.00778
	(0.0969)	(0.0916)	(0.0639)
356	0.303***	-0.238***	-0.0697
	(0.0930)	(0.0863)	(0.0625)
411	0.308***	-0.218**	-0.0932
	(0.0982)	(0.0909)	(0.0687)
412	-0.217	-0.140	0.355*
	(0.199)	(0.0940)	(0.204)
413	-0.0292	-0.0918	0.116
	(0.165)	(0.106)	(0.158)
415	0.00780	-0.00502	-0.0139
	(0.142)	(0.139)	(0.0715)
416	-0.00360	-0.246***	0.247
	(0.229)	(0.0879)	(0.236)
421	0.165	-0.217**	-0.00108
	(0.124)	(0.0899)	(0.0818)
541	-0.700***	0.725***	-0.0289
	(0.0944)	(0.0859)	(0.0686)
542	0.549***	-0.188	-0.361***
	(0.130)	(0.121)	(0.0895)
543	-0.187	0.201	-0.0179
	(0.335)	(0.322)	(0.0612)
612	-0.0232	0.0246	-0.00424
	(0.123)	(0.114)	(0.0672)
613	-0.299	0.409**	-0.114
	(0.240)	(0.192)	(0.0886)
614	0.0761	-0.116	0.0118
	(0.108)	(0.0933)	(0.0733)
621	-0.367	0.421	-0.0605
	(0.240)	(0.262)	(0.0696)
622	-0.0372	-0.132	0.162

		(0.204)	(0.0915)	(0.184)
	623	-0.515***	0.580***	-0.0645
		(0.106)	(0.0949)	(0.0819)
	711	0.147	-0.0724	-0.0778
		(0.111)	(0.105)	(0.0634)
	712	-0.514***	-0.233**	0.745***
		(0.124)	(0.0920)	(0.0812)
	713	0.252***	-0.269***	0.00589
		(0.0890)	(0.0791)	(0.0617)
	721	-0.0969	-0.0335	0.128
		(0.158)	(0.119)	(0.136)
	722	0.266***	-0.187**	-0.0838
		(0.0801)	(0.0750)	(0.0601)
	813	-0.0840	0.164	-0.0829
		(0.253)	(0.195)	(0.132)
	823	0.331***	-0.202***	-0.136
		(0.108)	(0.0749)	(0.0965)
	921	0.325***	-0.233***	-0.0999
		(0.0840)	(0.0817)	(0.0632)
	923	-0.698***	0.0579	0.645**
		(0.104)	(0.264)	(0.292)
	924	-0.241	0.278	-0.0368
		(0.196)	(0.189)	(0.0812)
	926	0.243	-0.154	-0.0920
		(0.150)	(0.127)	(0.117)
	927	-0.235	0.133	0.103
		(0.162)	(0.120)	(0.141)
	Not applicable	0.108	-0.118	0.00172
		(0.0809)	(0.0808)	(0.0591)
	Unable to code	-0.250*	-0.111	0.353**
		(0.143)	(0.0865)	(0.139)
Self-employed		-0.242***	-0.125***	0.371***
		(0.0798)	(0.0342)	(0.0683)
Zero-hours contracts		0.00884	-0.0958	0.0913

		(0.164)	(0.0667)	(0.138)
Working hours		0.00358*	-0.00155	-0.00176
		(0.00186)	(0.00142)	(0.00112)
Working hours missing		-0.352***	-0.140***	0.492***
		(0.127)	(0.0387)	(0.137)
COVID	Yes	0.0284	-0.0198	-0.00327
(base=No)		(0.0274)	(0.0205)	(0.0207)
	Unsure	-0.0123	-0.00769	0.0231
		(0.0437)	(0.0269)	(0.0365)
	Missing	0.0945*	-0.00416	-0.0853**
		(0.0558)	(0.0421)	(0.0419)
Time on home schooling		-0.00455	0.00885	-0.00427
		(0.00827)	(0.00731)	(0.00628)
Time on other activity with children		-0.0108***	0.00854***	0.00257
		(0.00412)	(0.00328)	(0.00227)
Time on caring for others		0.00594	-0.00432	-0.00117
		(0.00469)	(0.00325)	(0.00350)
Time use missing		0.0205	-0.0236	0.00607
		(0.0433)	(0.0190)	(0.0338)
Personal contacts	Yes	0.0234	-0.0131	-0.0172
(base=No)		(0.0330)	(0.0219)	(0.0249)
	Missing	-0.190*	0.0828	0.0934
		(0.0971)	(0.0670)	(0.0623)
Networking	Yes	0.0343	0.0227	-0.0556***
(base=No)		(0.0320)	(0.0264)	(0.0203)
	Missing	0.246***	-0.119**	-0.120**
		(0.0847)	(0.0539)	(0.0591)
	Constant	0.490***	0.416***	0.0871
		(0.122)	(0.0976)	(0.0858)
	Observations	2,204	2,204	2,204
	R-squared	0.304	0.231	0.406

Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in *parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.*

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

C. Robustness checks

C.1. Interaction effect between FiF status and time

As discussed in section 3, the changes in lockdown and furlough policies in the country could affect the impact of the pandemic on the labour market. Thus, in this section, we explore the interaction effect between FiF status and time by including an interaction term.

Table 10 shows the time-varying results. For both male and female FiF graduates, they are less likely to be on put on furlough or paid leave in wave two. Thus, we explore the policy context during the period when the three waves were carried out (see Figure 1). Unlike in waves one and three, employers were required to cover part of the furloughed employees' wages (10-20%) in wave two. Moreover, the unemployment rate in the UK was higher in wave two (5.1%) than in wave one (4.1%) and wave three (4.8%). The change of the CJRS and the higher unemployment rate could be two of the reasons that there is a gap in the probability of being put on furlough or paid leave between FiF and non-FiF graduates in the second wave.

Table 10. Labour market status by FiF status and wave

		(1) Kept working	(2) On furlough or paid leave	(3) Left work or on unpaid leave
Male				
Group	FiF	-0.140***	0.0950***	0.0440
(base=non-FiF)		(0.0430)	(0.0344)	(0.0269)
Wave	Wave two	-0.0153	-0.0552**	0.0724*
(base=Wave one)		(0.0453)	(0.0218)	(0.0407)
	Wave three	0.00831	-0.0392	0.101**
		(0.104)	(0.0683)	(0.0460)
Interactions	FiF*Wave two	0.176***	-0.106***	-0.0737
		(0.0586)	(0.0375)	(0.0448)

	FiF*Wave three	0.185***	-0.125***	-0.0570*
		(0.0516)	(0.0401)	(0.0308)
	Observations	1,309	1,309	1,309
	R-squared	0.366	0.308	0.407
Female				
Group	FiF	0.00230	-0.0454	0.0413
(base=non-FiF)		(0.0574)	(0.0480)	(0.0314)
Wave	Wave two	0.111*	-0.105*	-0.0155
(base=Wave one)		(0.0568)	(0.0540)	(0.0272)
	Wave three	0.115*	-0.117**	-0.0137
		(0.0666)	(0.0505)	(0.0452)
Interactions	FiF*Wave two	0.0415	-0.0319	0.00115
		(0.0670)	(0.0594)	(0.0362)
	FiF*Wave three	-0.0425	0.0311	0.0183
		(0.0651)	(0.0574)	(0.0424)
	Observations	2,204	2,204	2,204
	R-squared	0.306	0.232	0.406
Control variables				
Personal and household characteristics		√	√	√
Pre-COVID labour market characteristics		√	√	√
COVID-related variables		√	√	√
Time on homeschooling and caring		√	√	√
Interaction term between FiF and wave		√	√	√
Personal network at age 25		√	√	√

*Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.*

Source: University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2021). Next Steps: Sweeps 1-8, 2004-2016. [data collection]. 16th Edition. UK Data Service. SN: 5545, http://doi.org/10.5255/UKDA-SN-5545-8

C.2. Key worker status

Key workers have played an important role during the pandemic. Compared to non-key workers, key workers were more likely to continue working and less likely to become financially worse off after the outbreak (Wielgoszewska et al., 2020). Thus, in addition to the labour market characteristics controlled in our previous models, we further look at how the FiF difference is mediated by key worker status of the participants.

In consistent with previous studies, both male and female keyworkers were more likely to keep working but less likely to be on furlough or be non-employed. Non-keyworker FiF females were 10.2 percentage points more likely to become unemployed or be put on an unpaid leave. However, key worker status protects FiF females from stopping working and being unpaid. Key worker status also offers a protection for FiF males as being a FiF key worker is associated with higher probability of keeping working post-outbreak.

Table 11. Labour market status by FiF status and key worker status

		(1)	(2)	(3)
		Kept working	On furlough or paid leave	Left work or on unpaid leave
Male				
Group	FiF	-0.0587*	0.0542**	0.000883
(base=non-FiF)		(0.0350)	(0.0225)	(0.0306)
Keyworker	Yes	0.112***	-0.0313	-0.0794***
(base=No)		(0.0323)	(0.0201)	(0.0295)
Interactions	FiF*Keyworker	0.125***	-0.115***	-0.00489
		(0.0410)	(0.0304)	(0.0345)
	Observations	1,309	1,309	1,309
	R-squared	0.409	0.341	0.418
Female				

Group	FiF	-0.0451	-0.0483	0.102***
(base=non-FiF)		(0.0385)	(0.0321)	(0.0256)
Keyworker	Yes	0.346***	-0.231***	-0.0985***
(base=No)		(0.0415)	(0.0373)	(0.0236)
Interactions	FiF*Keyworker	0.0845*	0.0199	-0.116***
		(0.0438)	(0.0388)	(0.0286)
	Observations	2,204	2,204	2,204
	R-squared	0.452	0.312	0.458
Control variables				
Personal and household characteristics		√	√	√
Pre-COVID labour market characteristics		√	√	√
COVID-related variables		√	√	√
Time on homeschooling and caring		√	√	√
Interaction term between FiF and wave		√	√	√
Personal network at age 25		√	√	√

*Notes: All coefficients are estimated using ordinary least squares (OLS) regression. Missing values of the variables are controlled by using missing flags. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using the combined weight for each wave.*

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