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Unequal learning and labour market losses in the crisis: consequences for social mobility

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Abstract
The unequal learning and labour market losses arising in the UK due to the Covid-19 pandemic are used to assess the consequences for social mobility. Labour market and learning losses have been more pronounced for people from poorer families and this is incorporated into a generalisation of the standard, canonical social mobility model. A calibration shows a significantly higher intergenerational elasticity – reflecting lower social mobility – because of the uneven nature of losses by family income, and from dynamic scarring. Results from a randomised information experiment incorporated in a bespoke Social Mobility Survey corroborate this, as participants become more sceptical about the social mobility prospects of the Covid generation when given information about the losses that have occurred in the crisis.

Key words: learning loss, labour market loss, crisis, social mobility, Covid-19
JEL codes: I24; J63; J21; J62

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1. Introduction

The inequalities induced by the Covid-19 crisis have potentially important consequences for social mobility. Society wide inequalities have emerged as the crisis has had an uneven impact on school children, college students, and workers. Socioeconomic gaps in learning time have increased due to school closures.[1] Low-income university students have delayed graduation at a higher rate than their high-income peers.[2] And sizable labour market losses have magnified pre-crisis inequalities.[3]

This paper presents new evidence on unequal learning and labour market loss, during lockdown and subsequently, and assesses the consequences for social mobility. The impetus for looking at education and labour market loss together is that a high-quality education and a strong start in one's labour market career are generally seen as the two most efficacious routes to economic success. These learning and labour market losses are studied in a unified framework that enables evaluation of social mobility prospects of the Covid-19 generation.

The social mobility consequences of inequality and economic scarring turn out to be important. These scars – the permanent impact of negative education and labour market experiences – are, as shown by past research, real phenomena. Scars from entering a weak labour market and from unemployment spells when young are not transitory (Machin and Manning, 1999; Von Wachter, 2020). Studies of school closures show evidence of resultant learning losses that damage educational attainment – for example, in 'random' closures caused by bad weather (Goodman, 2014), strikes (Johnson, 2011; Baker, 2013), or school year reductions (Pischke, 2007).[4]

[1] Studies of school closure in different settings are: UK - Andrew et al (2020) or Green (2020); US - Agostinelli et al (2020); Germany - Grewenig et al (2020); for 45 countries - Donnelly and Patrinos (2020).
[2] See the US study by Aucejo et al (2020).
[3] See evidence for Germany, UK and US in Adams-Prassl et al (2020) and for 13 countries in IZA (2021).
[4] Pischke (2007) studies significant changes in schooling hours.

The first part of the paper presents evidence on unequal learning and labour market losses in the UK during the pandemic. There is a need to define these carefully, as the nature of losses has emerged in different ways from “typical” recessions. Traditional measures fail to adequately pinpoint the losses in this crisis. For learning loss, schools, colleges, and universities shut down during national lockdowns. For labour market loss, the government’s flagship Job Retention Scheme (the furlough) kept people in jobs even though many were working hardly any (frequently zero) hours.

Care is taken to measure “realistic” rates of employment and education. The former accounts for falls in working hours, and is a better metric of labour market loss in the crisis than job loss alone. A capacity based measure for learning loss – the proportionate reduction in learning hours relative to full capacity – is also adopted. During school closure, learning was administered by schools using online and offline activity and was instigated by both parents and students at home. Estimates allow for substitution between in class and home instruction, which is important as students from different socioeconomic backgrounds were differentially affected.

There is strong evidence of unequal learning and labour market loss which acted to exacerbate pre-crisis inequalities. Realistic employment rates have fallen more rapidly for young people. Work loss is greater for individuals from poorer family backgrounds, for women, and for the self-employed. Learning losses incurred during the first lockdown in 2020 are large, particularly so for poorer pupils. Sizable learning losses are also seen for university and college students.

The second part of the paper evaluates the social mobility consequences of these uneven learning and labour market losses. It does so in two ways. First, via a generalisation of the canonical model of social mobility that has been used in an extensive social science literature (Becker and Tomes, 1986; Corak, 2013; Elliot Major and Machin, 2018, 2020;

Solon, 1999). In this model, the relationship between parental resources and educational attainment, and the relationship between education and income, create an intergenerational dependency between parental and child income. It is extended to introduce potential education and labour market scarring effects from the crisis and, through a calibration exercise, to evaluate implications for the intergenerational elasticity (IGE), which measures the persistence of economic status across generations. A significant decline in social mobility emerges as the IGE rises by 11.4 percent (going from 0.377 to 0.420).

Second, results from a randomised information experiment incorporated in a bespoke Social Mobility Survey corroborate this finding of falling social mobility. The experiment displays some design similarities with related research which looks at how beliefs and redistributive preferences are swayed by giving information on the extent of inequality and mobility in society (Alesina et al, 2018; Kuziemko et al, 2015; Lergetporer et al, 2020). Survey participants become more sceptical about the social mobility prospects of the Covid generation when given information about the losses that have occurred in the crisis, thereby reinforcing the key finding of declining social mobility in the crisis.

2. Data Description and Approach

Data Sources

Learning and labour market losses are computed from three UK data sources – Understanding Society (USoc), the Longitudinal Labour Force Survey (LLFS), and the LSE-CEP Social Mobility Survey (SMS). More information on each is given in the Data Appendix. Their common key feature is the availability of economic and education outcomes at baseline (pre-crisis) and subsequent to the March 2020 lockdown. Exhibit 1 shows key timelines and available months of data, featuring a baseline of February 2020 running to September 2020.

Measuring Labour Market Loss

The working age population, P, can be partitioned as:

$$P = E + U + I \tag{1}$$

where E denotes the employed, U the unemployed, and I the economically inactive. The conventionally defined employment rate is E/P - a capacity based measure measuring the state of the labour market across the business cycle.

Problems arise with this metric (or the unemployment rate, U/P) in the context of the pandemic. To cushion negative market consequences and to aid employers, the UK government implemented a large, costly Job Retention Scheme. Under this furlough, many individuals remain employed but report not working any hours. The same lack of work arose for some self-employed individuals. As a result, the employment capacity of the economy is not well captured by the conventionally defined employment rate.

Aggregate employment capacity can be better measured by "realistic" employment rates – employment rates that take into account the large number of individuals working zero hours due to Covid-19 shutdowns. To do so, employed workers are split into two groups: those working zero hours – $H = 0$ – or positive hours – $H > 0$. The working age population definition now comprises four groups, including those who have a job and are working (E_1) or are not working (E_2):

$$P = E_1 + E_2 + U + I \tag{2}$$

where $E_1 = (E|H > 0)$ and $E_2 = (E|H = 0)$, so a 'realistic' employment rate is $E_1/P = (E|H > 0)/P$.

The analysis utilises longitudinal data tracking people working in the baseline month of February 2020. For an individual i in crisis period c compared to baseline period b, a job loss is a transition from being employed to unemployed, defined as $Pr(U_{ic} = 1 \mid E_{ib} = 1)$. But this fails to incorporate the probability of being employed but not working. For individuals, a “realistic” measure of the probability of losing work conditional on being employed in the baseline then becomes $Pr(U_{ic} = 1 \mid E_{ib} = 1) + Pr(E_{2ic} = 1 \mid E_{ib} = 1)$.

The upper panel A of Exhibit 2 uses longitudinal data from LLFS, USoc, and SMS to show these transitions from pre-lockdown baseline respectively to May, June, and September. The definitional issues matter. The LLFS transitions to May, just after the month long lockdown that started on March 23 had ended, show that 3.4 percent of those in work in February had lost their job. This, however, masks a higher pattern of worklessness since a further 26.9 percent reported still being in work, but working zero hours. Overall, the rate of not working was therefore just over 30 percent.

As the economy partially reopened as lockdown restrictions were relaxed, the overall rate of not working comes down to 20 percent in July (USoc data) before reaching 13 percent in September (SMS data). Much of this bounce back is due to fewer people in work but working zero hours. Job loss, however, rises and reaches 5.4 percent by September.

Measuring Learning Loss

The closure of schools, colleges, and universities also leads to needing a different conceptualisation of learning losses in the Covid-19 crisis.[5] In “usual” times, the student population S (in numbers or in hours of the day) can be partitioned as being in education T or absent A, so that S = T + A. The rate of education is T/S which in conventional times is close to 1. In the early lockdown period, T/S fell to very low levels. Only vulnerable children and children of key workers attended school.

In parallel to the arguments about the employment rate, the education rate T/S does not paint a realistic picture during lockdown as, for the most part, lack of face-to-face

[5] Ager et al. (2020) estimate larger effects from Covid-19 US school closures than those observed in the influenza pandemic of 1918-19.

instruction did not result in zero teaching hours. Many students still had online and offline lessons. Therefore, a realistic education rate can be defined by allowing for students to receive teaching while absent from their education institution. Defining L_1 and L_2 respectively as learning time received at school and at home then leads to:

$$S = T.L_1 + A.L_2 \tag{3}$$

Under lockdown and full closure (when T = 0 and A=1) the "realistic" education rate becomes L_2/S.

Estimates of learning loss for school pupils during lockdown in April are calculated from USoc data. Measures come from parental responses regarding the number of lessons provided by schools and daily hours spent on schoolwork.[6] Children spending more than 5 hours a day, on average, on schooling, or having at least 4 lessons provided, are treated as receiving a full school day, i.e. $L_2 = 1$. Children receiving either zero lessons, or spending less than an hour a day, are treated as having no schooling, i.e. $L_2 = 0$. For intermediate cases, hours spent on schoolwork are converted to the proportion of normal schooling being received.[7]

Education rates can also be computed from our own SMS survey undertaken from mid-September to early October (when children returned to school and universities/colleges partially reopened). To measure L_1, parents were asked what percentage of a full school day their children were receiving. Although schools were open, they were operating below normal levels (presumed to be at or near $L_1 = 1$) occurring before the lockdown.[8] The same

[6] Private tuition is not included in these estimates as the aim is to measure schoolwork done at home rather than additional inputs to schooling. (see Elliot Major, Eyles and Machin, 2021, for evidence on the very sizable inequalities in private tutoring).

[7] Those receiving less than an hour are treated as having 0 percent, between 1 and 2 hours 20 percent, 2 and 3 hours 40 percent, 3 and 4 hours 60 percent, 4 and 5 hours 80 percent, and more than 5 hours 100 percent. The summation is then over the set {0, 0.2, 0.4, 0.6, 0.8, 1}.

[8] Data from the Department for Education's Education Settings Survey show that when schools reopened on September 9 2020 attendance was 87 percent. This rose in mid/late October, then fell before recovering to 85 percent on the final Thursday of term on December 10. See Department for Education (2021).

question was asked to survey participants in full time education. Their answers, reported in 20 percent intervals, are converted into learning losses by subtracting them from 100 percent.

The lower panel B of Exhibit 2 shows the estimated losses for school pupils and for those in full-time education. Column (1) shows learning losses, during school closures, for school children and column (2) shows results, for adults in full-time education, under lockdown in April. Column (3) shows the same estimate of learning loss for pupils when schools reopened in September. For each of these comparisons, three metrics for learning losses are shown - no learning loss relative to normal, full learning loss relative to normal, and a measure of the proportion of lost learning time.

Learning losses are large and unequal. Under lockdown, the USoc data show significantly dispersed learning losses. Whilst 38.1 percent carried on learning as usual, 24.6 percent experienced full learning loss. Overall, learning capacity fell sharply, with an average learning loss of 57.6 percent. The same is true of adults in full-time education. The SMS data show an average learning loss of 48.3 percent, with wide dispersion. Finally, once schools reopened in September, the big losses abated, but did not fall back to zero. In the SMS data for school age children, the average learning loss is 14.7 percent, but still with only 58.5 percent at full capacity.[9]

3. Unequal Learning and Labour Market Losses in the Crisis

The descriptive analysis so far uncovered sizable learning and labour market losses. This section studies variation across different groups of individuals and shows uneven patterns which acted to magnify pre-crisis inequalities.

[9] Learning loss of 14.7 percent lines up well with Department for Education (2020) numbers on school attendance when schools reopened for the autumn term: 87 percent of children were in school in September according to their Daily Education Settings Survey.

Labour Market Losses

The empirical analysis considered how job loss, working hours, not working, and earnings falls differ by individual and family background characteristics. The SMS survey also has information on whether people grew up in richer or poorer families. Exhibit 3 presents estimates from SMS data assessing how labour market losses differ by age, gender, baseline employment status, and family background. The estimates refer to individuals who were working before lockdown. Appendix Table A1 shows analogous results from the LLFS, USoc, and SMS without family income measures. The results are consistent with what those presented here, the fuller SMS specification, and across the three data sources.

Looking at results on age in Exhibit 3 shows that those aged 18-25 have been particularly hard hit. The results of the first column show that, once September is reached, job loss is 7 percentage points higher for this group compared to the oldest age group – the 55-64 year olds. A similar result holds for earnings losses, which are 13 percent higher for the youngest age group.

In line with previous evidence, Exhibit 3 shows that some of the labour market outcomes (all except job loss) were worse for women and the self-employed. Not working, driven by zero hours, is strongly prevalent amongst women. Earnings loss for the self-employed is especially stark. The likelihood of earnings losses is a striking 31 percentage points higher for self-employed individuals. The likelihood of job loss, being employed but working no hours, and therefore the rate of not working, also differs by family background. People who grew up in a family in the lowest quintile of the income distribution exhibit higher rates for all measures.

Thus, for the most part, labour market losses tended to exacerbate already existing inequalities (though the earning loss probability does not always show this pattern of unevenness). The social mobility implications are pertinent, especially in the light of the large losses experienced by young people and those who grew up in poorer families.

Learning Losses

Exhibit 4 assesses how learning losses of school children and adults in full-time education vary with individual characteristics (age, gender) and family income. For school children, the income distribution measures are for their parents measured at the time of the relevant survey (USoc or SMS). For adults in full-time education, it is the same measure used in the labour market loss regressions.

The upper panel A of Exhibit 4 shows results, using USoc data, for the 2020 lockdown. The proportion of learning time lost is higher for the younger primary school students and lower for female pupils. It also differs significantly by self-reported family income. Children from the poorest fifth of families experienced significantly higher learning loss, whilst those from the richest fifth experienced much lower learning loss. The gap is sizable at 12.3 percentage points [= {0.037 – (-0.086)}x100], revealing an uneven pattern of learning loss by family income.

The middle panel B of Exhibit 4 shows the evidence on learning losses of adults in full-time education under lockdown in April. Most of these are young people. The regression results again uncover sizable inequality connected to family background – those born into the highest income families are far less likely to report having suffered learning losses than those at the bottom or in the middle of the income spectrum.

Lastly, the lower panel C of Exhibit 4 looks at what happened when schools reopened in September. The inequalities seen under school closures are no longer observed. The estimated pattern of coefficients, in terms of qualitative sign, are similar to those in Panel A, but all are small in magnitude and fall short of statistical significance. The key driver of growing inequality in learning loss amongst children was not attending school and experiencing unequal resources available at home, as emphasised in other research detailing the interaction between effective learning and parental inputs and resources (Agostinelli et al, 2020, Hupkau et al, 2020).

4. Social Mobility

This section evaluates the consequences of uneven earning and learning loss for social mobility. This is important because the fallout from the crisis has scope to affect economic outcomes of children and young adults not just now, but through dynamic effects that persist. Social mobility consequences are drawn out in two complementary, ways. First by generalising the orthodox widely used economic intergenerational mobility model, and second from a randomized information experiment.

Social Mobility Consequences

In the canonical model of social mobility, the twin drivers of low social mobility are education and income inequalities. Defining the income and completed education of generation t respectively as Y_t and E_t the following equations can be considered:

i) Income equation in generation t: income gaps by education for generation t (measuring between education group income inequality) are defined as the education return γ in the income equation $Y_t = \gamma E_t + u_t$, where u_t is an error term.

ii) Education equation in generation t: completed education gaps for individuals in generation t are determined by the income of their parents in generation t-1 and measured by δ from the education equation $E_t = \delta Y_{t-1} + v_t$, with v_t being an error term.

Substituting for E_t in the income equation produces the intergenerational mobility equation $Y_t = \gamma\delta Y_{t-1} + \varepsilon_t = \beta Y_{t-1} + \varepsilon_t$. If Y measures log(income) then β is the intergenerational elasticity (IGE), the product of income inequality and education inequality parameters δ and γ.[10]

Many estimates of the IGE have been produced for the UK, from a range of data sources and time periods (Elliot Major and Machin, 2018, 2020). We produced our own estimate from the 1970 British Cohort Survey (BCS) by calculating the IGE in the same way as earlier work (for example, Blanden et al, 2004; Blanden, Gregg and Macmillan, 2007). For individuals aged 42 in the 2012 wave of the BCS, the IGE is estimated as 0.377 (β), with a corresponding 0.634 log earnings premium to having a degree (γ).[11]

Labour market and learning losses can be built into a generalisation of this canonical model. Firstly, relative to non-crisis generations, completed education is potentially reduced from two routes – learning losses experienced by individual pupils and work loss experienced by their parents. Evidence from a number of settings, shows Covid-19 induced learning losses have reduced attainment (for Belgium see Maldonado and De-Witte, 2020, and for the Netherlands see Engzell et al, 2020). In these, disadvantaged pupils suffered bigger falls in attainment. In England, where pupils aged 6-7 sat exams in Autumn 2020, test scores in reading and maths have been shown to be 0.14 and 0.17 of a standard deviation lower than the scores of a previous cohort (Rose et al, 2021). Again, disadvantaged pupils experienced the largest falls. Alongside learning loss, unemployment spells experienced by parents have been shown to lower attainment (Ruiz-Valenzuela, 2020). Falls in income caused by unemployment spells affect the ability to purchase resources and inputs that

[10] The product of the least squares coefficients from regressions of Y_t on E_t and E_t on Y_{t-1} generally do not equal the least squares coefficient from a regression on Y_t on Y_{t-1}. If factors, such as ability or 'drive', that shift earnings, net of education, are uncorrelated between parents and children, the least squares regression of Y_t on Y_{t-1} will yield the product of the two structural coefficients (γ and δ). In other words, the decomposition holds exactly if the only channel by which parental earnings influence one's own earnings is through education (formally in this case, Y_{t-1} acts as a valid instrument for E_t).

[11] Rather than use estimates from existing work, we estimate these ourselves from age 42 data from the BCS. Haider and Solon (2006) argue that age 42 seems the best point to use measures representative of permanent income.

support learning. Rege et al. (2011) argue the mental stress caused by job loss can also lead to worse outcomes for children.

The income equation can also be affected. Existing evidence shows that entering the labour market in economic downturns generates adverse outcomes that can persist for a long time (Von Wachter, 2020). Similarly, evidence on scars from unemployment spells shows they can depress earnings for many years after workers find a new job. In the UK, Arulampalam (2001) finds that an unemployment spell brings a wage penalty of up to 14 percent after three years. Tumino (2015) finds that workers who experience unemployment are 9 percentage points more likely to experience a further job loss than similar workers. Other studies show the impact is particularly pronounced for young men (Gregg, 2001). These results are consistent with research from the US, where Yagan (2019) finds, in the aftermath of the Great Recession, that a 1 percentage point larger 2007–9 local unemployment shock resulted in employment rates in those localities still being 0.3 percentage points lower eight years later.

Generalised income and education equations enable study of these additional factors and permit an evaluation of the consequences for social mobility. The generalised equations are:

i) Crisis income equation: includes effects of unemployment spells (U) directly into the income equation with the expectation that U reduces income by θ_1 so that $Y_t = \gamma E_t + \theta_1 U_t + u_t$.

ii) Crisis education equation: becomes $E_t = \delta Y_{t-1} + \lambda_1 LL_t + \lambda_2 U_{t-1} + v_t$ where an individual's educational attainment now depends upon whether their parents have suffered an unemployment spell, parental income, and any learning losses due to Covid.

iii) Income gradient equations: the generalised crisis model is completed by relating each of the generation t losses to parental income: $LL_t = \pi_1 Y_{t-1} + \upsilon_{1t}$ and $U_t = \pi_2 Y_{t-1} + \upsilon_{2t}$. The parental (generation t-1) labour market loss is $U_{t-1} = \pi_3 Y_{t-1} + \upsilon_{3t-1}$ (the υ terms are errors).

This general setup permits learning and labour market losses of the crisis generation and the labour market losses of parents to impact directly and indirectly on the crisis generation's completed education and incomes. One can substitute for LL and U in the Y and E equations and for E in the Y equation to generate a more general intergenerational mobility equation, $Y_t = [\beta + \gamma(\lambda_1\pi_1 + \lambda_2\pi_3) + \theta_1\pi_2)]Y_{t-1} + \varepsilon_t, = \beta^c Y_{t-1} + \varepsilon_t$. If Y is measured as log(income), the crisis generation IGE is $\beta^c = [\beta + \gamma(\lambda_1\pi_1 + \lambda_2\pi_3) + \theta_1\pi_2)]$.[12]

At first glance, this expression may look unwieldy, but it allows us to generate predictions about what underpins the social mobility prospects of the Covid-19 generation. The extra terms now appearing in the IGE formula predict that $\beta^c > \beta$ if there is a negative income gradient of learning and labour market losses (i.e. $\pi_1 < 0$, $\pi_2 < 0$ and $\pi_3 < 0$, as shown in the empirical evidence of section 3) or if there are negative scars to income ($\theta_1 < 0$) or education ($\lambda_1 < 0$, $\lambda_2 < 0$). In other words, social mobility prospects are worsened for the crisis generation.

Numerical implications for the IGE can be calibrated. To do so, requires estimation of the magnitudes of the additional crisis parameters in the β^c expression. Firstly, note that the empirical counterparts to the measures discussed above are: log earnings (Y); whether one has a degree (E); whether one has worked zero hours or been made unemployed since lockdown (U); and hours of learning lost during the initial lockdown (LL).[13] With these, π_1, π_2, and π_3 can be estimated from USoc data.

[12] The impact of learning losses is limited to working through reductions in completed education in our model. An additional term for LL_t would appear in the income equation if losses also have a direct impact on income as well. The discrepancy between normal and crisis IGE would become $\beta^c - \beta = \gamma(\lambda_1\pi_1 + \lambda_2\pi_3) + \theta_1\pi_2 + \theta_2\pi_1)$.
[13] Learning losses subsequent to school closures in 2020 are left out (i.e. any from September onwards when children returned to school) as these do not display a socioeconomic gradient (as was shown in Table 4). It is

To do so the fraction of normal teaching time into hours lost over lockdown is related to parental income (π_1); zero hours spells for parents during April are related to baseline income (π_3); and observed zero hours spells are regressed on parental income for young workers (π_2).[14] These produced the following empirical estimates: π_1 - a one percent decrease in parental income is associated with an increase of 0.24 learning hours; π_3 - a decrease in the likelihood of job loss by 0.12 percentage points for each percentage rise of baseline income; π_2 - a partial elasticity of zero hours spells with respect to parental income of -0.07.

The remaining parameters refer to future outcomes (λ_1 and λ_2 for completed education and θ_1 for income) and need to be calibrated from existing literature. First, for λ_1 estimates of how hours of learning map onto degree attainment are required. There are numerous studies using OECD PISA data on international tests looking at how learning hours change attainment (Lavy, 2015; Rivkin and Schiman, 2015). As a baseline, results were used from a randomized trial of the effect of instruction time on learning, which assumes an hour of lost learning each week over the course of a school year is associated with an attainment reduction of 0.15 of a standard deviation (Andersen et al, 2016). This is converted into an estimate of how each hour lost decreases the likelihood of university enrolment by multiplying by 0.4 (the assumed effect of a standard deviation increase in test scores on the probability of university enrolment[15]), dividing by 39 (the length of the school year in weeks), and then assuming effects of an hour lost are the negative of an hour gained.

also worth noting that further school closures have re-occurred in early 2021, and so estimates of the change in the IGE should be viewed as a lower bound if, as seems likely, socio-economic divides in learning loss again occur.

[14] Strictly speaking, those in compulsory education and those in the labour force are separate cohorts. By using this estimate, we assume the socioeconomic gradient on job loss/zero hours amongst young workers during April, is a good proxy for the gradient that will face those in education once in the labour market.

[15] We were unable to find an estimate of the effect a standard deviation change on the probability of getting a degree. We use the free school meal/Non free school meal university enrolment gap and the standard deviation difference in test scores between the two groups. This gap, in the UK, is driven largely by attainment (Chowdry et al, 2013). The effect of a standard deviation change in test scores on enrolment can be derived

Numerous studies meanwhile have assessed labour market scarring and how unemployment spells of parents affect pupil achievement. Ruiz-Valenzuela (2020) estimates the latter using job losses during the Great Recession in Spain, finding a 0.15 standard deviation fall in test scores. Using our estimate of how exam attainment impacts university enrolment, this would reduce enrolment amongst the group affected by 6 percentage points. This sits in the middle of the range of other estimates. Hilger (2016) estimates parental job loss results in a 1 percentage point decrease in university enrolment, while Kalil and Wightman (2011) estimate a 10 percentage point decrease. For λ_2 it is therefore assumed there is a fall of 6 percentage points.

Finally, estimates of how job loss affects future earnings are needed for the scarring parameter θ_1. Looking at UK workers, Arulampalam (2001) finds an unemployment spell brings a wage penalty of up to 14 percent after three years. Gregg and Tominey (2005) provide estimates ranging from 9-21 percent for age 42 males who experience an unemployment spell. Again, the midpoint is used, assuming a 14 percent wage scar for those who experience youth unemployment.

After plugging the six additional parameters into the crisis period IGE formula, a bleak picture for social mobility prospects emerges. The calibration produces an increase in the IGE of 0.043, from 0.377 in normal times to 0.420 (i.e. going up by 11.4 percent) as a result of the shocks suffered in 2020 due to Covid. It is the uneven spread of shocks that generates the increase. This is highlighted by breaking down the 0.043 increase into contributions from learning losses of 0.030, parental employment loss of 0.004, and employment scarring of 0.009.[16] This represents a sharp decline in social mobility due to

under the assumptions that, a) the enrolment gap is driven entirely by test score differences, and b) the conditional probability of enrolment is a linear function of (standardised) test scores.

[16] Exact estimates are: learning losses ($\gamma\lambda_1\pi_1$ = 0.634x-0.002x-23.539 = 0.030); parental employment loss ($\gamma\lambda_2\pi_3$ = 0.634x-0.060x-0.115 = 0.004); and employment scarring ($\theta_1\pi_2$ = -0.140x-0.066 = 0.009).

the crisis, a finding which, as will be seen next, also arises in the randomized information experiment implemented in the SMS.

Information Experiment

Despite the prospect of decreasing social mobility uncovered in the calibration exercise, one issue is whether society correctly perceives the consequences the pandemic could have on social mobility. Surveys have shown that participants from numerous countries are overconfident when it comes to evaluating an individual's likelihood of becoming socially mobile (Alesina et al, 2018). To examine this, an information experiment was included in the SMS. Participants were asked about social mobility and their views on prospects amongst members of their own generation. The following information was then randomly assigned to three sets of respondents, giving the first two information on the nature of labour market and learning losses, while not providing any information to the third:

1 Recent research suggests that the coronavirus pandemic has led to many individuals experiencing job loss, hours cuts, and earnings losses. The worst hit have been the young, the low-paid, and the self-employed. Those who can work from home (on average, richer individuals) are significantly less likely to be furloughed, have reduced work hours, and suffer earnings losses.

2 As a result of the coronavirus pandemic, most of the nation's children have not been attending school. Recent research suggests that those from disadvantaged backgrounds have had less homework set, less access to online learning material, and, as a result, have spent fewer hours a day on schoolwork than their peers.

3 show nothing

After this, participants were asked how much they agreed or disagreed[17] with statements about 16-25 year olds born into the poorest families in society. The main statement is as follows:

Think of individuals (aged 16-25), who are either in education or starting their career during the pandemic. For those from a low socioeconomic background – those whose parents have the lowest income, least education, and the lowest status jobs – we are going to make a number of statements.
Statement: These individuals have the same opportunity to move up in society as those from the average family.

The treatment differs slightly in structure from what has been considered in previous studies. Firstly, rather than provide a generic statement about inequality, there are two separate treatments, focused on labour market inequality (treatment 1) and educational inequality (treatment 2). It is also specified that the inequalities were due to the pandemic – a large idiosyncratic and unforeseen event.

Exhibit 5 shows how receiving the treatment affects agreement with the aforementioned statement. Multinomial probit models were estimated, computing marginal effects, to see how the probability of responses alters according to receipt of the randomised information.[18] In line with previous information experiment research, showing participants information about inequality changes their opinions. Rather than expressing neutrality about life chances of the poorest 16-25 year olds, treated groups are between 4 and 6

[17] Answers are taken on values from the set strongly disagree, disagree, nether agree or disagree, agree, and strongly agree.
[18] Other variables are not included as these potential covariates – baseline opinions and demographic variables – are balanced across treated groups and control group. Appendix Table A2 shows formal tests of covariate balance. Due to covariates being fully balanced across the randomized groups, results are unchanged when they are added.

percentage points less likely to agree that the poorest individuals have the same life chances as individuals of average income. They are also between 6 and 7 percentage points more likely to disagree with the statement. Effects are similar whether participants are informed about labour market or education inequality. Take the labour market treatment. Percent shifts relative to the control group mean are as follows: towards strongly disagree 22 percent (= [.012/.048]x100); towards agree 34 percent (= [.061/.183]x100); away from agree 12 percent (= [.039/.372]); from strongly agree 20 percent (= [.016/.077]).

Thus the information experiment supports the notion that learning and labour market losses induced by the Covid-19 crisis have worrying consequences for social mobility, which looks set to worsen for the Covid-19 generation in the face of the negative education and economic outcomes experienced by the disadvantaged during the crisis.

5. Conclusions

Bringing together evidence from national longitudinal studies and a bespoke survey, this paper reports evidence that both education and labour market inequalities have been exacerbated during the Covid-19 crisis, and that these have disproportionately affected the social mobility prospects of the younger generation. The reverberations of these dramatic shocks, and the heterogeneity of their impacts, mean that those born into the most disadvantaged families are likely to find it increasingly hard to rise out of the class or income group into which they were born.

Evidence of reduced social mobility due to these unequal education and labour market losses for the Covid-19 generation comes from two sources. First, a generalisation of the standard intergenerational model incorporates scarring effects in education and the labour market and the disproportionate losses suffered in the crisis by those from poorer backgrounds. This extended model is used to predict a significant decline in social mobility, with the IGE rising by just over 11 percent (going from 0.377 to 0.420). Second, this conclusion is reinforced by randomised information experiment results which show that making people aware of the emerging inequalities makes them significantly less optimistic about social mobility prospects of the Covid generation.

Finally, and to conclude, the findings here are from the UK. There is ample evidence of education and labour market losses due to Covid-19 from around the world and, as with the findings reported here, these are disproportionately harming economic and social outcomes for people from less advantaged backgrounds. This does not bode well for the social mobility prospects of the Covid-19 generation more generally.

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Exhibit 1: Timeline and Longitudinal Survey Structures in 2020

	February	March	April	May	June	July	August	September
A. Timeline	Baseline	Lockdown		Post-Lockdown				
School closures		✓	✓	✓	✓	✓		
B. Survey Structures								
Understanding Society	✓		✓	✓	✓	✓		
Longitudinal Labour Force Survey	✓			✓			✓	
LSE-CEP Social Mobility Survey	✓							✓

Notes: Lockdown occurred on March 23 2020. Schools were closed from 23 March 2020 to 17 July 2020, there was then the regular summer break and schools reopened on 9 September 2020.

Exhibit 2: Labour Market and Learning Loss

	Labour Market Losses		
Data source:	Longitudinal Labour Force Survey	Understanding Society	LSE-CEP Social Mobility Survey
Sample:	Working in February, Age 18-64	Working in February, Age 18-64	Working in February, Age 18-64
Month:	May	July	September
Job loss	0.034	0.053	0.054
Employed, Zero hours	0.269	0.148	0.072
Not working	0.303	0.201	0.126
Earning loss	-	0.390	0.345
Sample size	7147	5657	5923

	Learning Losses		
Data source:	Understanding Society	LSE-CEP Social Mobility Survey	LSE-CEP Social Mobility Survey
Sample:	School children, Age 5-18	In full time education, Age 18 and above	School children, Age 5-18
Month:	April	April	September
No learning	0.246	0.089	0.01
Full learning	0.381	0.120	0.585
Learning loss	0.576	0.483	0.147
Sample size	4114	1521	2417

Notes: The sample sizes for earnings loss in panel A are smaller because of non-response on earnings at 5357 for Understanding Society and 4380 for the LSE-CEP Social Mobility Survey.

Exhibit 3: Inequality in Labour Market Loss

	Job Loss	Zero Hours	Not Working	Earnings Loss
LSE-CEP Social Mobility Survey, September				
Age 18-25	0.072 (0.013)	-0.032 (0.013)	0.040 (0.018)	0.131 (0.029)
Age 26-34	0.013 (0.009)	-0.028 (0.012)	-0.015 (0.014)	0.030 (0.022)
Age 35-44	0.007 (0.008)	-0.037 (0.011)	-0.030 (0.014)	0.018 (0.022)
Age 45-54	0.003 (0.008)	-0.024 (0.011)	-0.021 (0.014)	-0.004 (0.021)
Female	0.003 (0.006)	0.044 (0.007)	0.046 (0.009)	0.035 (0.015)
Self employed	-0.030 (0.007)	0.059 (0.014)	0.028 (0.015)	0.312 (0.026)
Bottom income quintile when growing up	0.016 (0.007)	0.014 (0.008)	0.030 (0.010)	0.017 (0.016)
Top income quintile when growing up	0.008 (0.014)	-0.009 (0.013)	-0.001 (0.018)	0.070 (0.033)
Sample size	5923	5923	5923	4380

Notes: Standard errors in parentheses. Sample is those aged 18-64 in work in February.

Exhibit 4: Inequality in Learning Loss

	Learning loss
A. Understanding Society, April, School children	
Primary pupil	0.045 (0.010)
Female	-0.054 (0.010)
Bottom income quintile	0.037 (0.014)
Top income quintile	-0.086 (0.014)
Sample size	4114
B. LSE-CEP Social Mobility Survey, April, Full time education	
University student	-0.008 (0016)
Female	0.039 (0015)
Bottom income quintile when growing up	0.029 (0.019)
Top income quintile when growing up	-0.061(0.019)
Sample size	1521
C. LSE-CEP Social Mobility Survey, September, School children	
Primary pupil	-0.006 (0.009)
Female	-0.009 (0.009)
Bottom income quintile	0.007 (0.010)
Top income quintile	-0.013 (0.014)
Sample size	2417

Notes: Standard errors in parentheses.

Exhibit 5: Social Mobility Information Experiment

	Statement: 16-25 year olds born into the poorest families have the same chance of moving up in society as those born into the average family			
	Strongly Disagree	Disagree	Agree	Strongly Agree
Labour market treatment	0.012	0.061	-0.039	-0.016
	(0.006)	(0.011)	(0.012)	(0.006)
Education treatment	0.009	0.069	-0.059	-0.012
	(0.006)	(0.011)	(0.012)	(0.006)
Sample Size	9682	9682	9682	9682
Control Group Mean	0.048	0.183	0.372	0.077

Notes: Standard errors in parentheses. Estimates are marginal effects from a multinomial probit with expressing indifference – neither agreeing nor disagreeing – as the reference category. See the main text for the precise wording of the information treatments. Sample if the LSE-CEP Social Mobility Survey of those aged 18-64.

Online Appendix

Data Appendix

1. Labour Market Losses

The focus is on labour market losses since the March/April Lockdown. To measure labour market outcomes in publicly available longitudinal data, we use extracts from the longitudinal Labour Force Survey (LFS) and the Covid-19 modules of Understanding Society (USoc). Losses are measured for those who were in employment at baseline, so we restrict our sample to those who report being self-employed or employed in January/February in USoc and in the LFS to those who report being self-employed or employed in February. In both cases, we are interested in earnings falls alongside job loss. This is undertaken for USoc data, but sample sizes on earnings preclude and analysis of the LFS. In each case, we focus on labour market outcomes of those aged 18-64.

Data collected in our own LSE-CEP Social Mobility Survey (SMS) is also used. We collected data from a nationally representative sample of 16-65 year olds. In line with the estimates produced using USoc and the LFS, we focus on those aged 18-64 in our labour market analysis. Our sample consists of those who reported being employed or in self-employment in January/February. We asked participants how many hours they were working as a result of Covid, whether their employment status has changed, and whether their earnings (net of taxes) had changed. These three variables form our outcome variables.

2. Learning Losses

Our main results on learning loss for children of compulsory schooling age are taken from the April Covid-19 module of Understanding Society. This module provides information, provided by parents, on the provision of lessons (online and offline), time spent with children on homework, and time spent by children on schoolwork. In order to construct our sample, we match parental records with earnings information in Wave 9 of USoc. While baseline information is collected in the April wave, more comprehensive earnings measures are available in the previous wave where positions in the national distributions of earnings can also be computed. Our measure of earnings is total net earnings per month which we normalise using OECD equivalence scales. We are interested in relating gender, age (schooling key stage), and parental earning percentiles with learning losses as well as estimating the proportion of our sample who have, on average, full schooling and no schooling during the April lockdown.

Our measures are constructed as follows. For those who are set no work during lockdown, they are coded as having no work, not having a full day of schooling, and having 0 percent of their normal teaching hours. For the remainder of the sample, for whom we have answers on the number of lessons administered and the number of hours spent on schoolwork, we treat a full day as being 5 or more hours spent on schoolwork or 4 or more lessons administered (either online or offline). Conversely, those with 0 lessons or less than an hour spent on schooling a day are treated as having no schooling. In order to get a more granular measure of learning, we convert the answer to how many hours a day the child spends on schooling into a percent measure of a full day of normal schooling as follows: those reporting less than an hour get 0 percent, those reporting 1-2 hours get 20 percent, those reporting 2-3 hours, 40 percent, 3-4 hours 60 percent, 4-5 hours 80 percent, and 5+ hours 100 percent. In each case, we exclude those observations for which parents do not know how much schooling their children are getting. We then convert these estimates to estimates of learning losses by subtracting them from 1 i.e. a child with 20 percent of a full school day suffers a learning loss of 80 percent

We produce a similar measure using our survey. For those who have dependent children, we ask the percentage of normal teaching hours they are currently receiving. The question is asked irrespective of whether their children are attending school in September and so captures variation in home learning alongside absences during the first weeks of the autumn term and limited school hours. In line with USoc, this measure is then converted into learning losses.

We ask the same question of those who report being in full time education. As participants are aged over 16, this amounts to asking about learning losses for those in their final year of schooling, those in university, and those in further education. These participants are asked about their stage of education alongside questions asked of other survey participants.

Because interest lies in how learning losses differ by income, we ask participants (who are the parents of the children for whom losses are measured), about their level of prosperity. Specifically, we ask "now think about your family situation growing up. How would best describe your family's position in society?" and "Think about your financial position relative to others of your age group. Which best describes your position in the earnings distribution for those of your age?". Answers to this question are of the form "the poorest 10 percent, the next poorest 10 percent, the middle, the second richest 10 percent, and the richest 10 percent". We use the former question when focusing on FTE students and the latter when looking at learning losses reported by parents on schoolchildren.

3. Information Experiment

SMS participants were randomly assigned information as part of an information experiment. Participants were allocated to a labour market treatment (giving information about labour market inequality), an education treatment (giving information about educational inequality), or a control group (given no information). Randomisation was done so as to keep the number of participants allocated to each group equal. For example, if participants 1 was allocated to the control, participant 2 would be randomised between the two treatments, and participant 3 would be allocated the treatment that participant 2 was not allocated to.

After seeing the information (or not for the controls), participants were asked about the extent to which they agreed with the following statement:

Q78: Think of individuals (aged 16-25), who are either in education or starting their career during the pandemic. For those from a low socioeconomic background – those whose parents have the lowest income, least education, and the lowest status jobs – we are going to make a number of statements.

These individuals have the same opportunity to move up in society as those from the average family.

Answers to this form our outcome studied in Exhibit 5.

Additional Figures and Tables

Table A1: Inequality in Labour Market Loss

	Job Loss	Zero Hours	Not Working	Earnings Loss
A. Longitudinal Labour Force Survey, May				
Age 18-25	0.023 (0.014)	0.098 (0.027)	0.121 (0.028)	-
Age 26-34	-0.028 (0.007)	-0.004 (0.018)	-0.032 (0.019)	-
Age 35-44	-0.020 (0.007)	-0.050 (0.016)	-0.070 (0.017)	-
Age 45-54	-0.016 (0.007)	-0.057 (0.016)	-0.073 (0.016)	-
Female	0.002 (0.005)	0.032 (0.012)	0.035 (0.013)	-
Self employed	0.013 (0.008)	0.124 (0.018)	0.137 (0.019)	-
Sample size	7147	7147	7147	-
B. Understanding Society, July				
Age 18-25	0.054 (0.031)	0.013 (0.029)	0.067 (0.039)	0.048 (0.045)
Age 26-34	-0.020 (0.019)	-0.010 (0.024)	-0.030 (0.029)	0.017 (0.035)
Age 35-44	-0.044 (0.015)	-0.002 (0.021)	-0.046 (0.025)	0.010 (0.027)
Age 45-54	-0.034 (0.014)	-0.025 (0.018)	-0.060 (0.022)	-0.004 (0.025)
Female	-0.007 (0.010)	0.051 (0.014)	0.044 (0.017)	-0.014 (0.020)
Self employed	-0.015 (0.014)	0.036 (0.022)	0.021 (0.025)	0.205 (0.034)
Sample size	5657	5657	5657	5357
C. LSE-CEP Social Mobility Survey, September				
Age 18-25	0.070 (0.013)	-0.034 (0.013)	0.037 (0.018)	0.134 (0.029)
Age 26-34	0.011 (0.009)	-0.029 (0.012)	-0.018 (0.014)	0.031 (0.022)
Age 35-44	0.006 (0.008)	-0.038 (0.011)	-0.032 (0.014)	0.018 (0.020)
Age 45-54	0.002 (0.008)	-0.025 (0.011)	-0.022 (0.014)	-0.004 (0.021)
Female	0.002 (0.006)	0.044 (0.007)	0.046 (0.009)	0.033 (0.015)
Self employed	-0.030 (0.007)	0.059 (0.014)	0.029 (0.015)	0.313 (0.026)
Sample size	5923	5923	5923	4380

Notes: Standard errors in parentheses. Data in panels A, B, and C measure outcomes in May, July, and September respectively.

Table A2: Covariate Balance, Information Experiment

	Sample Mean	Control Group Mean	Labour Treatment	Education Treatment
Age	40.046	40.097	40.059 (0.909)	39.981 (0.730)
Monthly Income	1.375	1.386	1.359 (0.246)	1.379 (0.767)
Number of Children	1.788	1.805	1.765 (0.347)	1.794 (0.810)
Male	0.502	0.490	0.515 (0.048)	0.500 (0.456)
UK Born	0.898	0.902	0.897 (0.549)	0.896 (0.482)
Employed	0.535	0.534	0.537 (0.778)	0.535 (0.953)
Self Employed	0.076	0.072	0.075 (0.681)	0.082 (0.126)
Not Employed	0.225	0.232	0.221 (0.325)	0.222 (0.377)
Student	0.158	0.157	0.163 (0.560)	0.155 (0.825)
GCSE or Less	0.237	0.243	0.233 (0.335)	0.235 (0.460)
Further Qualifications	0.385	0.391	0.383 (0.532)	0.380 (0.374)
Degree or Higher	0.378	0.366	0.384 (0.14)	0.385 (0.122)
Sample Size	9682	3229	3234	3219

Notes: P-values of randomization tests in parentheses.

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