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Predictors of becoming not in education, employment or training: A dynamic comparison of the direct and indirect determinants

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Abstract

This paper uses a dynamic latent factor model to investigate the determinants of not in education, employment or training (NEET) status among adolescents in the United Kingdom. We bring together within one framework various determinants of NEET status, such as educational achievements, non-cognitive skills, family socio-economic factors, aspirations, mental health and local labour market conditions. We model the educational progress over multiple periods through the life of the young person, up to the completion of compulsory schooling. By taking into account this progression, we can determine the direct and indirect impacts of different determinants of NEET status, and the stage in the life of the young person at which each determinant is important. Our findings suggest that cognitive ability (as measured by educational achievements) remains the key predictor of NEET status. Further, while a range of individual and family factors determines NEET status, the impact of most of these factors is largely indirect, through ability formation and not necessarily direct. To gauge the relative contributions of various determinants, we conduct simulations to predict the probability of the young person being NEET under different scenarios and assumptions. The exercise indicates that the effects of aspirations of the young person, their school engagement, and the local youth unemployment rate on the likelihood of the young person being NEET are as large as boosting their cognitive skills.

KEYWORDS
adolescence, aspirations, educational achievements, local youth unemployment rates, locus of control, LSYPE, school engagement

1 | INTRODUCTION

NEET refers to young people who are Not in Education, Employment or Training. At the end of compulsory education, young people (YP) can either stay on in education, or choose employment or training. There are, however, a significant number who do neither of these and are classified as NEETs: 4% of the 16–17 and 10.7% of 18- to 20-year olds in the United Kingdom were classified as NEET in the last quarter of 2019, which includes those who are unemployed and looking for jobs, and those who are inactive (ONS, 2021). There are long-term consequences of being NEET, both for the individual and society. Those who leave full-time education early are unlikely to return to it (Dickerson & Jones, 2004; Polidano et al., 2015); and the resulting lower educational attainment is associated with both lower pecuniary outcomes such as lifetime consumption and wealth (Oreopoulos & Petronijevic, 2013), and poorer non-pecuniary outcomes regarding adult physical and mental health, marriage and parenting style (Grossman, 2006; Heckman et al., 2018; Oreopoulos & Salvanes, 2011). Further, youths who face spells of unemployment and inactivity following the end of their compulsory education demonstrate lower participation in the labour market in the long term (Gregg, 2001; Schmillen & Umkehrer, 2017), and lower earnings later in life (Gregg & Tominey, 2005; Mroz & Savage, 2006). There are associated societal costs: NEETs are more likely to claim benefits and attach themselves to the informal economy; and loss of individual earnings results in loss of tax revenues and increased welfare costs to the state (Coles et al., 2010; OECD, 2018).

Our paper uses a dynamic latent factor model to understand the process that leads to the outcome of a young person (or young people; YP) becoming NEET. We make two key contributions to the existing literature on NEET. Our first contribution is in looking separately at the key stages of educational progress through the compulsory schooling years. The existing literature generally takes the life of the YP as one period, at the end of which we observe the outcome of interest where each of the factors that determine NEET status are used as exogenous explanatory variables, with no regard for the dynamic relationships among themselves. Using educational achievements through time as measures of cognitive ability of the YP, we model the cumulative formation of cognitive ability together with the impact this ability has on NEET status. We allow for the fact that cognitive ability develops differentially by a range of individual and family socio-economic factors, and that it is the accumulation and interaction of these different factors over time that determine the later outcome of NEET status. By taking into account the progression of the YP through the compulsory years of education, we can determine the direct and indirect impacts of different determinants at the different stages of the YPs life.

The second main contribution of the paper is in bringing various determinants within one framework. The factors often discussed in the literature are cognitive and non-cognitive abilities (used interchangeably with 'skills') of the YP; parental socio-economic status; aspirations of the parents and the YP; health (general and mental) of the YP; engagement in the risky behaviour by the young; and local labour market conditions. Incorporating a number of determinants within a single framework means that we can look at the relative importance of the different determinants of NEET status, and the stage in the life of the YP at which each is important.

The methodology used in our paper allows us to address the issue of measurement error in estimating cognitive and non-cognitive ability. In addition, we are able to use the structural model and the estimated coefficients to calculate the probability of being NEET under different scenarios: this means we can interpret the coefficients as causal pathways from a policy perspective in terms of the maximum relative effect of influencing one of the covariates on the probability of NEET status, both directly and indirectly. From our estimated model, we are able to address questions such as: how much the likelihood of being NEET would change if the past ability of the YP were different, versus if their aspirations were different. This allows us to understand the relative importance of the various determinants of NEET status within one framework.

We use the data from the Longitudinal Survey of Young People in England (LSYPE, now known as the *Next Steps* study) which followed a group of adolescents, born in 1990, from 2004 when they were 14 years old and who completed compulsory education in 2006 (age 16 in the United Kingdom for this cohort). LSYPE was specifically funded and started by Department of Education, UK, to understand the educational attainment and school-to-work transition for the cohort born in 1990. Given its focus, the survey includes information on: the educational progress and attainment of these YP throughout their secondary education (starting age 11); their health; their socio-economic background; and their own and their parents' aspirations regarding higher education. The outcome we are interested in is being NEET 2 years after the end of compulsory education, which for this cohort is 2008 when they were on an average 18 years old. LSYPE is the most recent birth cohort study for the United Kingdom that allows us to look at NEET status.

In the next section, we briefly review the relevant literature on the determinants of NEET status. Section 3 presents the empirical specification that we use to estimate the dynamic model of ability formation and estimate the probability of NEET status. Section 4 describes the data and the different variables we use in our analysis. Section 5 presents our main results, and Section 6 draws some conclusions.

2 | BACKGROUND LITERATURE

At the end of compulsory schooling, YPs have an option to either continue in education (including apprenticeships), go into employment (full time or part time), or become NEET. All those who do not continue in education (i.e. those who are in employment including apprenticeships, and those who are NEET) are referred to as early school leavers. There exist several studies investigating the decision by YP to leave formal education after the compulsory years; see, for example, Eckstein and Wolpin (1999) for the United States; Bradley and Lenton (2007) for the United Kingdom; Falch and Strøm (2013) for Norway; Foley et al. (2014) for Canada; and Goux et al. (2017) for France. While our paper sits within this literature, the focus of our analysis is narrower than those who do not continue in education after compulsory years, as some of these might go onto jobs or training. We are interested in a subset of early school leavers: those who become NEETs. Outcomes of early school leavers who go onto jobs or training are distinct from those who become NEET (Dickerson et al., 2020).

Cognitive ability (as measured by educational attainment) remains the key predictor of NEET status. In the United Kingdom, those who have the highest prior educational attainment at age 16 are most likely to continue in education and those with the lowest attainment at age 16 most likely to be NEET 2 years on at age 18 (Crawford et al., 2011). De Luca et al. (2020) show similar findings for Italy and Spain. Other than educational attainment, there is now growing evidence that non-cognitive skills also matter for education and labour market success (Gutman & Schoon, 2013). Avey et al. (2011) provide a meta-analysis of the link between ‘psychological capital’ and labour market performance. Almlund et al. (2011) provide a review of studies looking at the link between ‘personality traits’ and a broader set of economic outcomes. Heckman and Kautz (2012) present evidence on importance of ‘soft skills’, over and above achievement test scores (used as proxies for cognitive ability) in predicting life success. Goodman et al. (2015) review the evidence on association between ‘socio emotional skills’ in childhood and adult outcomes.

Heckman et al. (2006), using data from the United States, show the influence of cognitive abilities, as measured by test scores, and non-cognitive abilities, as measured by locus of control and self-esteem, on schooling decisions, probabilities of employment, and choice of occupations. The authors show that while both types of skills affect school dropout decision, improving cognitive skills, relative to non-cognitive skills, has a bigger impact on reducing the probability of school dropout. Similarly, Carneiro et al. (2007), using data from the United Kingdom for a cohort born in 1958, show the relevance of both cognitive (as measured by test scores) and non-cognitive (as measured by social *mal*adjustment scale) skills for a range of educational and labour market outcomes, and find that performance in cognitive tests is more important for educational outcomes, such as staying on in education beyond age 16 and obtain higher degree, than social skills. Further, they also find an interaction such that the marginal impact of cognitive ability on educational outcomes is higher for the group of children who exhibit higher social skill.

Cunha et al. (2006) review the empirical literature on skill formation and provide a theoretical framework for the interpretation of these and similar findings. Their theoretical framework considers multiple life stages and two dimensions of skills, cognitive and non-cognitive, with both skills being interrelated and evolving jointly over time. Brunello and Schlotter (2011) review the empirical literature from Europe on the relative importance of non-cognitive skills for school and labour market outcomes. Key take-away points that emerge from their review are: first, data on measures of non-cognitive skills are less widely available relative to the measures of cognitive skills; and second, given the interlinkages between cognitive and non-cognitive skills, part of the observed correlation between cognitive test scores and economic outcomes is driven by non-cognitive skills, and especially by non-cognitive skills such as motivation and conscientiousness, which are correlated with cognitive test scores.

Mendolia and Walker (2014, 2015) and Schoon and Lyons-Amos (2017), using data from LSYPE, find a significant relationship between personality traits (measured at ages 15–16 years) and the probability of being NEET (at ages 18–20 years), after controlling for measures of cognitive skills and a range of individual and family characteristics. The personality traits considered include the YP’s ability to persevere with long-term goals (which the authors call ‘grit’), the extent to which an individual believes that they can affect and control events (locus of control), self-esteem and individual agency. Schoon and Lyons-Amos (2017) define individual agency as a combination of aspirations, school engagement and self-efficacy.

There is an extensive literature looking at the relationship between health and educational outcomes, with the relationship being potentially bidirectional: health determines education and vice versa (Gan & Gong, 2007; Suhrcke & de Paz Nieves, 2011). While these studies do not address NEET status as an outcome, given that prior (academic) ability is a predictor of NEET status and health has an impact on the acquisition of this ability, health can have an indirect effect on NEET status. Ding et al. (2009) use data from the United States to identify the impact of Attention Deficit Hyperactivity Disorder, depression and obesity on test scores at high school. They find all three health conditions are correlated significantly with lower test scores for both girls and boys; the results are robust to the inclusion of information on parents. Similarly, again using data from the United States but focussing only on mental health, and controlling for past educational attainment and parental socio-economic variables, Fletcher (2008) finds a negative association between depression at age 18 years and educational outcomes at age 22 years, but only for females.

Cornaglia et al. (2015) look at the direct impact of mental health on NEET status: they use LSYPE and, controlling for past achievements, family socio-economic status, and aspirations of both the YP and their parents, find a positive association between the past incidence of depression and later probability of being NEET; the association is stronger for girls. Egan et al. (2015), in addition to reporting similar findings for LSYPE, look further at this link in an older cohort of the National Child Development Study (born in 1958), where they explore the impact of the 1980 recession. Their findings show that childhood mental health (measured at ages 7 and 11) lead to higher unemployment between the ages of 16 and 23, and the relationship is pronounced during times of economic recession. Another study that looks at the link between mental health and NEET status is Goldman-Mellor et al. (2016). Using data from the United Kingdom, the authors find that NEET youths had higher rates of concurrent mental health and substance abuse problems; and these associations were independent of pre-existing mental health vulnerability. Risky behaviours (truancy, smoking, alcohol drinking, drug-taking) have also been shown to have an impact on the education and NEET status of the young, both directly (Mendolia & Walker, 2014) and indirectly via its effects on their mental health (Cornaglia et al., 2015).

There are, however, a range of ‘protective factors’ that result in some YPs ‘beating the odds’, that is, avoiding NEET status despite unfavourable backgrounds defined as low parental socio-economic status, lone parents, social housing and workless households (Duckworth & Schoon, 2012). Using data from the United Kingdom, the authors show that prior attainment, educational aspirations (captured by the question asked at age 14, to both the YP and their parents, on whether or not they would like the YP to continue in post-compulsory education), and engagement with school can reduce the cumulative risk faced by a YP with multiple risk factors. Müller et al. (2016), using the German Socioeconomic Panel, find a causal link between parental unemployment and increased risk of children’s worklessness and lower participation in tertiary education. Schoon (2014), using LSYPE, find that while there is a positive association between parental worklessness and their children’s probability of being NEET, much of this association is explained by other risk factors such as past ability of the YP and family socio-economic status; furthermore, aspirations of the YP act as a mediating factor, especially for boys. The role of aspirations as the mediating factor between socio-economic disadvantage and NEET status is corroborated in the findings by Yates et al. (2011), using the 1970s British Cohort Study.

Social housing and poor neighbourhoods have also been long associated with social immobility, worklessness and welfare dependency (Coelli et al., 2007; Stroud, 2010). Feinstein et al. (2008) look at the link between social housing and disadvantage in the United Kingdom, using the 1970 British Cohort Study. They find that individuals who live in social housing are four (11) times more likely to be NEETs at age 18 (30) years than the rest of the cohort, after controlling for parental socioeconomic status and the individual's prior achievements.

Evidence for the link between local labour markets and NEET status is mixed. Petrongolo and San Segundo (2002) use micro-level data from Spain, covering period of 1987–1996, and show that higher local youth unemployment rates do not determine the demand for education beyond age 16; the key determinant of staying in post-secondary education is parental socio-economic status. On the other hand, Meschi et al. (2019) use LSYPE and consider the impact of local labour market conditions (unemployment rates and wage rates) on the choices that 16-/17-year-olds make at the end of their compulsory education, which for this cohort is 2006. In addition to confirming the importance of the YP's own past achievements, parental socio-economic status, and aspirations (of both the YP and their parents) as the key determinants of continued participation in schooling for 16-year-olds, they find that while young males choose to continue education in response to higher local unemployment rates, there is no significant response for young females. Caroleo et al. (2020) analyse the determinants of NEET status among 19- to 30-year olds across a range of European countries, including United Kingdom, using cross-sectional data from 2007 and 2016. They compare the micro determinants (individual factors such as gender and educational attainment), with the macro determinants of labour market factors (such as local unemployment rates), and institutional factors (such as active labour market policies and vocational educational programmes). Their findings suggest that for 19- to 24-year olds NEET status is explained mainly by the micro determinants, while for the older cohorts the macro determinants are more important.

Before we present the empirical specification and discuss our data, we briefly explain the English education system. Compulsory formal education in England is divided into four key stages (KS), and at the end of each stage children sit standardised national exams. It is a statutory requirement for children to be in formal education after they turn 5 years old, although in practice most children start formal education in the first September after they turn 4 years old, and stay in education until the last Friday in June of the school year in which they turn 16. Primary education, ages 5 to 11 years, is divided into two stages, at the end of each children sit standardized exams: the KS1 exams at age 7 and the KS2 exams at age 11 (the end of primary education). Secondary education, ages 12–16, is divided into two further stages, at the end of each children sit standardised exams: the KS3 exams at age 14 and the KS4 exams at age 16 (also referred to as the GCSEs, or the General Certificate of Secondary Education).

In our paper, we bring within one framework the different determinants of NEET status: academic attainment, measures of non-cognitive skills, family socio-economic status, aspirations, health of the YP, their engagement in risky behaviour, and local labour market conditions. We model the educational progress over multiple periods through the life of the YP, up to the completion of compulsory schooling, allowing for the fact that cognitive ability develops differentially by a range of individual and family socio-economic factors, and that it is the accumulation and interaction of these different factors over time that determine the later outcome of NEET status.

3 | EMPIRICAL SPECIFICATION

To model the educational progress of the YP through the years of compulsory education we look separately at the key stages of schooling in England. Period from birth to the end of primary school (ages 0–11 years) sets the initial conditions with $t = 0$. The YP's life from age 12–18 years is then divided into three time periods: $t = 1, \dots, T$, with $T = 3$. Of these, the first two periods represent years of compulsory secondary education (12–16 years), and are divided into two periods based on the two key stages of educations. $t = 1$ captures the KS3 phase at the end of which the YP is on an average14 years old, and $t = 2$ captures the KS4 phase at the end of which the YP is on an average 16 years old. Time period $t = 3$ covers the period following post-compulsory education (16–18 years): for this period, the outcome of interest is NEET status.

Educational progress of the YP is captured by the scores on the tests taken at the end of each key stage; we take these test scores as measures of latent cognitive ability of the YP. Cumulative formation of cognitive ability is modelled using the *value-added model of ability formation*, whereby an adolescent's current ability is a function of their prior ability and a host of variables which impact on the acquisition of ability (Todd & Wolpin, 2003, 2007). At the end of compulsory education, the stock of cognitive ability is then used to explain the YP's post-compulsory-education outcomes, in our case NEET status.

Value-added models of ability formation are a subset of models of ability formation used to examine the relationship between the ability of the child/YP and a range of input variables. In an ideal situation, the input variables would capture all the past and present characteristics of the YP, their family, school and teachers; further, we should be able to distinguish these inputs from the inheritable endowments. However, given data limitations, where all the desired information is rarely available to the researcher, certain assumptions are made to estimate these models. In the value-added specification, it is assumed that the past measures of ability capture all the historical home and school inputs, as well as inherited endowments for which researchers often do not have data. This framework allows for self-productivity of skills, where self-productivity exists when higher ability at time $t - 1$ is associated with higher ability at time t.

The approach we take to modelling cognitive ability is same as proposed by Cunha and Heckman (2007, 2008). However, unlike the Cunha and Heckman approach we do not consider multiplicity of ability and hence do not dynamically model the formation of non-cognitive ability, along with cognitive ability. Our choice is driven by two main considerations, first, we wish to model progress through compulsory years of education, which is captured by educational attainment, which we use as measures of cognitive ability. Second, is the data limitation, while schooling affects both cognitive and non-cognitive ability (Heckman & Kautz, 2012), data on non-cognitive ability is limited. Although we are not able to model formation of non-cognitive ability over time, we do incorporate non-cognitive ability in our analysis as a covariate. We explain this more in the next section, where we discuss data. To model NEET status we use the set-up proposed by Cameron and Heckman (1998, 2001), who model schooling attainment as a stochastic process, where, instead of modelling highest grade completed (or college entry), one divides schooling into stages and looks at a sequence of grade transition probabilities to generate the likelihood of schooling attainment (in our case NEET status).

The estimated dynamic latent factor model has two components: a structural model for the dynamic pathway of interest from the cognitive ability to NEET status; and a measurement model to estimate the latent factors (Cunha et al., 2010; Cunha & Heckman, 2007, 2008). Since previous studies have indicated that the predictors of remaining in education can vary between genders (Goldin et al., 2006), the models are estimated separately for females and males.

3.1 | Structural model

Let θ_{it} be the stock of latent ability (skill) of young person i $(= 1, \ldots, n)$ at time t. θ_{it}, depends on: past ability, θ_{it-1}; and a set of covariates X_{it-1}, which in the value-added model are assumed to include all inputs or proxies of inputs which impact on skill formation, in our specification we also include latent non-cognitive ability in this set. Formation of cognitive ability over time is given as:

$$\theta_{it} = \gamma_{1t}\theta_{it-1} + \gamma_{2t} X_{it-1} + \eta_{it}^{\theta} \quad \text{for} \;\; t = 1, 2, \tag{1}$$

where γ_{jt} for $j = 1, 2$ are vectors of time-varying parameters to be estimated; and η_{it}^{θ} is the random shock (or innovation) to ability formation assumed to be independent across individuals and over time for the same individuals.

For the outcome of interest, NEET status at time t, the dynamics are given as:

$$Y_{it}^{*} = \beta_{1t}\theta_{it-1} + \beta_{2t} X_{it-1} + \eta_{it}^{Y} \quad \text{for} \;\; t = 3, \tag{2}$$

where Y_{it}^{*} is the underlying unobserved variable that determines NEET status; β_{jt} for $j = 1, 2$ are vectors of time-varying parameters to be estimated; and η_{it}^{Y} is the random zero mean error term, assumed to be independent across individuals and over time for the same individuals.

3.2 | Measurement model

Cognitive ability is assumed to be latent in our framework, so while we cannot observe ability, the data we use has a series of observable indicators or measures which are correlated with the latent ability, and measure it with an error. We take into account this error in our measurement model:

$$Z_{it,j} = \mu_{t,j} + \alpha_{t,j}\theta_{it} + \delta_{t,j}Q_{it} + \varepsilon_{it,j} \quad \text{for} \;\; t = 0, 1, 2, \tag{3}$$

where $Z_{it,j}$ for $j = 1, \ldots, m_t$ are the measures (which may vary across time) available for the latent variables at time t; for identification, $m_t \geq 3$ is necessary. $\alpha_{t,j}$ are the factor loadings, which can be interpreted as the amount of information that the measures ($Z_{it,j}$) contain about the latent variable (θ_{it}). $\mu_{t,j}$ are the intercepts; and $\varepsilon_{it,j}$ are the measurement errors, which capture the difference between the observed measures and the unobserved latent variables. The specification assumes that that correlation between the observable measures at time t is entirely due to the underlying effect of the latent variables and the covariate Q_{it}. Not all measures we have are continuous, but where the measures are continuous a linear in parameters regression is used to estimate Equation (3). For measures that are binary or categorical, the link function in Equation (3) is adapted accordingly.

For NEET status, we observe the discrete outcome, which we code as a binary variable, Y_{it}, taking value 1 if the young person is observed as NEET and 0 otherwise. Probability of observing the young person as NEET in time period $t = 3$, is modelled as:

$$\begin{aligned} P\left(Y_{it} = 1 | \theta_{it-1}, X_{it-1}\right) &= P\ \left(Y_{it}^{*} > 0 |\ \beta_{1t}\theta_{it-1} + \beta_{2t} X_{it-1}\right) \\ &= P\ \left(\eta_{it}^{Y} > -\beta_{1t}\theta_{it-1} - \beta_{2t} X_{it-1}\right) \\ &= 1 - F\left(-\beta_{1t}\theta_{it-1} - \beta_{2t} X_{it-1}\right) = F \\ &\quad \left(\beta_{1t}\theta_{it-1} + \beta_{2t} X_{it-1}\right), \end{aligned} \tag{4}$$

where $F(.)$ is the cumulative distribution function for the error η_{it}^{Y}. We assume η_{it}^{Y} has a normal distribution, and therefore estimate a probit model.

The full set of assumptions needed to identify and estimate the econometric specification are given in Appendix A in Data S1. Given our specification, we can look at both the direct and the indirect effects of one variable upon another. For example, we know mental health and risky behaviour of the YP have a direct impact on their NEET status, but both mental health and risky behaviour also impact NEET status indirectly via their impact on education. The indirect effects, as described here, ignore any correlations between the error terms and are based on only the latent and observed variables included in the model. For the estimation of the indirect effect and its statistical significance, see Muthén (2011).

4 | DATA AND MEASUREMENT

4.1 | Overview of the dataset

The analysis is undertaken using data from the first five waves of LSYPE. The study follows a cohort of 15,770 YP in English secondary schools, born between September 1989 and August 1990. In the first wave, in 2004, participants were aged on average 14 years. The survey was conducted annually, and by wave 5 the individuals were aged on an average 18 years. LSYPE is the first national survey for many years to follow a group of English adolescents through much of their secondary education and into early adulthood (LSYPE users guide, 2011). The main aim of the study was to provide evidence on the factors central to individuals' educational progress and attainment (Department for Education, 2013).

For the first five waves, the data set contains responses from individual face-to-face interviews with both the YP and their parents or guardians. The information for the initial conditions ($t = 0$) and $t = 1$ comes from waves 1 and 2 of LSYPE; information for $t = 2$ comes from waves 3 and 4; and $t = 3$ corresponds to wave 5. LSYPE is linked to the National Pupil Database (NPD), an administrative database that contains information on national examination results: KS2, KS3, KS4-GCSE. We use these national examination results as measures for latent cognitive ability.

While the longitudinal nature of the data allows for dynamic analysis, this also imposes an important limitation. Over the five waves of interviews, several individuals drop out of the study; 10,158 YP were interviewed in all five waves. It was only possible to include individuals if they responded to a number of questions across all five waves of data collection and if their examination results were available from the LSYPE-NPD link. This leaves us with a final sample for analysis comprising of 6385 YP (3217 girls and 3168 boys). LSYPE used a stratified sampling approach; in our analysis, we use robust SEs and sampling weights from wave 5 (the final wave in our study). These weights take into account both the sample design and non-response bias. See the report by Anders (2012) for further details on weights in LSYPE.

4.2 | Variables incorporated in the dynamic model

A list of all the variables along with detailed descriptions is provided in Appendix B, Table B1. The outcome variables, cognitive ability and NEET status, and the covariates, including measures of non-cognitive ability, in each time period are discussed below.

4.2.1 | Cognitive ability

Cognitive ability has multiple facets, with psychologist distinguishing between fluid intelligence (processing speed) and crystallised intelligence (acquired knowledge); see Ackerman and Heggestad (1997), Heckman and Kautz (2012). The measures we have for cognitive ability are the academic achievements of the YP, which capture crystallised intelligence. These measures, while not comprehensive, are standard for those used in the literature specifically for the life-stage of the cohort we study—YP progressing through compulsory schooling. Further, measures of crystallised intelligence, such as test scores and academic achievements, are strongly correlated with the measures of fluid intelligence.

The measurement model for baseline cognitive ability, θ_0, incorporates indicators from the national KS2 exams, which were taken when the individuals were aged 11, 3 years before being interviewed for LSYPE. The measurement model for θ_1 is estimated using test scores from the KS3 exams, taken when the YP were aged 14 (wave 1). The measurement model for θ_2 is estimated by indicators based on the test scores in KS4 (GCSEs), undertaken at the end of compulsory education when the YP were aged 16 (wave 3). Table B2 in Appendix B shows the summary statistics for the measures of cognitive ability for the analysed sample. At ages 11 and 14 years there is no significant difference in the performance of girls and boys across the different tests. However, the girls' mean points in their GCSE exams (age 16) are higher than the boys' in the sample; similarly, a larger proportion of girls achieve C or higher in their GCSE English exam.

4.2.2 | NEET status

When individuals are aged 16+, they are no longer in compulsory education, at which point LSYPE contains data on the education or labour market status of the YP: whether they are in full-time education, in a job with training or without training, in training, or NEET. A binary variable (Y_t) from wave 5 ($t = 3$) is created from this information: the variable takes value 1 if the YP is NEET and 0 otherwise. Two years after the end of compulsory education, at age 18, 6.6% of the girls and 10.1% of the boys in our sample are NEETs.

We choose the outcome NEET from wave 5, and not from wave 4 immediately after completion of compulsory education, as the year immediately after the end of compulsory education is often a year of transition, especially for YP choosing not to stay in full-time education and transitioning to jobs or training. Furthermore, choosing NEET status from wave 5 allows us to include all the relevant covariates (discussed below), some of which come from wave 4, with a lag (Cornaglia et al., 2015).

4.2.3 | Covariates

We use a range of covariates in our analysis, which capture the economic, social and cultural status of the YPs background (Lagravinese et al., 2020), their non-cognitive ability, the neighbourhoods they live in, and the local labour markets that they face.

Initial conditions

For initial conditions, the variables incorporated in the analysis include YP's birth weight, the month of the year they were born and their ethnicity, mother's age (at wave 1, i.e. in 2014), dummies for mother's education, and the local index of multiple deprivations (IMD). Birth weight is included as a proxy for genetic endowments (Del Bono et al., 2012). Previous findings in the literature suggests that children born later in the academic year have lower educational attainments (Crawford et al., 2014); to account for any age effects we control for the month the YP is born in. Mother's age is included to capture any early disadvantage that the child might face given that young mothers often come from disadvantaged backgrounds (Hawkes & Joshi, 2012). Maternal education captures the advantageous environment that more educated mothers provide their children, not only in terms of time in active child care they provide but also in terms of altering the composition of that time to suit child's development needs as they age from infancy to adolescence (Kalil et al., 2012); maternal education is also associated with other (unobservable) environmental factors which can influence risk preferences and attitudes of YP (Björklund & Salvanes, 2011).

IMD is used to capture the negative impact of impoverished neighbourhoods on child development (Chetty et al., 2016). We use the local IMD as an initial condition as the residential mobility, once in secondary school, is very low in England (Machin et al., 2006). Ethnicity is included as an initial condition to capture differential home learning environments across different ethnic minorities (Bradley et al., 2001; Brooks-Gunn et al., 1996). We include ethnicity again in the analysis when exploring the predictors of NEET status after compulsory education. This is because ethnicity may have an independent effect on the YPs choices over the education-labour market if racial discrimination is perceived to be present by the YP.

Summary statistics for the variables used as initial condition are reported in Table 1. Girls on an average have lower birth weight relative to boys, the average age of mothers is 42 years, 14%–16% of mothers have no qualifications while 28% of the mothers have A-levels or more, and 88%–89% of the sample is White.

Non-cognitive ability

Non-cognitive skills encompass a range of skills, with the terminology used to define them evolving over time and varying both across and within different disciplines (economics, sociology and psychology). The terms often used to describe them include, but are not limited to, personality traits, character skills, soft skills, psychological capital and socio-emotional skills. Regardless of how they are labelled they are conceptualised in terms of work habits (such as effort, discipline and determination), and behavioural traits (such as self-confidence, and emotional stability); see reviews by Weel (2008), and Luthans and Youssef-Morgan (2017). Not all terms and concepts, however, necessarily capture the same thing; Heckman and Kautz (2012, 2014) present a wider discussion on different concepts used in the literature, and review literature on measuring and boosting the non-cognitive skills; and Duckworth and Yeager (2015) specifically discuss the advantages and limitations of various non-cognitive measures used in the context of educational practice and policy.

LSYPE is limited in the measures it has to capture non-cognitive skills; specifically, it does not have measures of the Big 5 personality traits that are commonly used in the literature to capture non-cognitive skills. However, it does have measures that capture the young person's attitude and behaviour towards learning, we use these in our analysis to capture non-cognitive skills. The first construct we use is *school engagement* (also referred to as *self-directedness*), which is closely related to 'conscientiousness', a dimension of Big 5. Conscientiousness is defined as, 'the tendency to be organized, responsible, and hardworking'; skills related to it are: grit, perseverance, impulse control, achievement striving, ambition and work ethic (Heckman & Kautz, 2014: Table 1; OECD, 2015, chapter 2). School engagement captures YP's motivation and attitudes towards

TABLE 1 Summary statistics: initial conditions

	Girls		Boys	
Variable	**Mean**	**SD**	**Mean**	**SD**
Birthweight	3.262	0.578	3.406	0.602
School year month	6.386	3.465	6.377	3.529
Mothers age	41.91	5.253	41.83	5.202
Mothers education:				
No qualifications	0.162		0.144	
GCSE's or below	0.558		0.573	
A-levels or above	0.280		0.282	
IMD score	20.69	15.65	20.11	15.28
Ethnicity:				
White	0.886		0.897	
Mixed	0.026		0.023	
Indian	0.021		0.027	
Pakistani/Bangladeshi	0.026		0.020	
Caribbean/African	0.020		0.019	
Other	0.022		0.014	
N	3217		3168	

Notes: SDs are only reported for continuous, integer and ordered categorical variables. Sample weights have been used in all analysis.

learning, which also captures their work ethic. Conscientiousness as a trait has been shown to predict education and labour market success (Almlund et al., 2011; Heckman & Kautz, 2014); school-engagement, specifically, has been identified as important in shaping school-to-work transition of YP (Fredricks et al., 2004; Gutman & Schoon, 2013; Schoon & Heckhausen, 2019; Schoon & Lyons-Amos, 2017). The second construct we use is *locus of control*, which is related with the 'emotional stability' component of Big 5, it measures the extent to which individuals believe that they have control over their lives, and has been shown to be correlated with the probability of being NEET (Mendolia & Walker, 2014, 2015).

In LSYPE, at ages 14 and 16, YP are asked about their *school engagement*, reflecting their attitude and motivation towards learning. They are asked to indicate whether they agree or disagree with, on a 4-point Likert scale going from strongly disagree to strongly agree, the following five statements: 'I am happy when I am at school'; 'schoolwork is worth doing'; 'I work as hard as I can in school'; 'I am bored in lessons' and 'on the whole I like being at school'. A high score indicates positive school motivation and a low score suggests school disengagement. We use responses to these statements as one measure of non-cognitive ability.

At age 15, YP were also asked about their locus of control. They are asked to indicate whether they agree or disagree with seven statements: 'if someone is not a success in life, it is usually their fault'; 'working hard at school now will help me get on later in life'; 'I can pretty much decide what will happen in my life'; 'if you work hard at something you will usually succeed'; 'even if I do well in school, I will have a hard time'; 'people like me, do not have much of a chance'; and 'how well you get on in this world is mostly a matter of luck'. Response to each statement was on a four point Likert scale going from 1 = *strongly agree*, to 4 = *strongly disagree*. The first four questions are referred to as indicting 'internal locus of control' and these have been reverse coded as 1 = *strongly disagree*, to 4 = *strongly agree*. The last three questions are referred to as 'external locus of control', for these original coding is kept. With the recoding of the first four statements, all questions are such that a higher score indicates a more internal locus of control, the belief that events are contingent upon their own behaviour. Conversely, lower scores are associated with external locus of control, the belief that events are contingent upon either luck or the control of powerful others (Rotter, 1966).

Given that non-cognitive ability is hard to define, measurement error is likely to be large for this measure; consequently we model both school engagement and locus of control as latent, unobserved, constructs captured by a range of indicators measured with error. Table B2 in Appendix B shows the sample summary statistics for the measures of school-engagement and locus of control. For age 11 ($t = 0$), we do not have any measures of non-cognitive ability in our data set.

Other time-varying covariates

Along with non-cognitive ability, we include a range of covariates in our analysis that vary over time, to capture the changing situation in the YP's lives, summary statistics of these variables are reported in Table 2. Inclusion of most of these variables is guided by the literature review discussed above. Ideally, we would have liked to use household income. However, in LSYPE, the household income variable has an unusually high number of missing observations, and if this variable were included in the analysis the number of observations available for inclusion would be reduced substantially. To avoid this, alternative variables which are highly correlated with household income and reflect the family's socio-economic status are incorporated into the analysis as controls, namely family socio-economic occupational class, homeownership, lone parent status and the number of siblings of the YP in the household. The last two are included to capture the limits on resources (financial and time) that might be available within the household (Black et al., 2005).

Variables relating to household socio-economic status are based on the National Statistics socio-economic classification (NS-SEC) of the household reference person. The household reference person is the person who owns or rents the property the YP lives in. If the property is jointly owned or rented then it is the parent with the higher income. Homeownership is a binary variable, taking value 1 if the house is owned outright, being bought on a mortgage, or has shared ownership; and is 0 if the house is rented from the council, rented from a housing association, rented privately, rent-free or some other arrangement. About 44% of the YP come from a household with the highest occupational category—managerial/professional. Between the first and subsequent waves, there is an increase in the number of households in the category unemployed, which is due to the change in the wording of the question: while the first wave asked about long-term unemployment, subsequent waves asked about current unemployment. The homeownership rates remain stable over time at just under 80%. About a fifth of the cohort members, at any wave, come from lone-parent households.

Aspirations and expectations, of the parents and YP, are included in the model not only as the 'protective factors' but also to capture aspects of the YP's family and social capital environment. Aspirations and expectations capture a broader set of beliefs, attitudes and cultural values, which are often passed on from parents to children (Goodman et al., 2011; Lazarus & Khattab, 2018). Two variables relating to parental aspirations for the child are included. In the first question, the parent (the primary carer) is asked what they *think* their child will do 'when he/she reaches

TABLE 2 Summary statistics: time-varying covariates

Variable	Girls $t = 1$ Age 14/15 years	Girls $t = 2$ Age 16 years	Boys $t = 1$ Age 14/15 years	Boys $t = 2$ Age 16 years
Household SES:				
Unemployed	0.0391	0.129	0.0252	0.122
Routine/Manual	0.339	0.297	0.354	0.310
Intermediate	0.170	0.130	0.174	0.124
Managerial/professional	0.452	0.444	0.446	0.444
Home ownership	0.777	0.777	0.798	0.795
Lone parent household	0.195	0.203	0.170	0.184
Siblings	1.415	1.351	1.418	1.369
	(1.045)	(1.046)	(1.036)	(1.055)
Self-assessed health low	0.037	0.037	0.021	0.015
Mental health (GHQ score)	2.101	2.480	1.082	1.495
	(2.757)	(2.944)	(1.905)	(2.192)
Parent thinks YP will continue into education	0.865	0.887	0.715	0.756
Parent would like YP to continue into education	0.900	0.902	0.762	0.770
YP has University plans	0.711	0.704	0.632	0.599
Risky behaviour	1.181	1.277	1.250	1.530
	(1.647)	(1.587)	(1.704)	(1.781)

Notes: SDs are only reported for continuous, integer and ordered categorical variables. Sample weights have been used in all analysis.
Abbreviations: GHQ, General Health Questionnaire; YP, young people.

16 and can leave school'; in the second, they are asked what they would *like* their child to do when they reach this same stage. The parent's responses to these questions when their child is aged 15 and 16 are included in the analysis as predictions and preferences. The variables are coded as taking the value 1 if the parent indicates they think their child will stay in education (preferences) and 0 otherwise; similarly for preferences the variable takes value 1 if the parent would like their child to stay in education, and 0 otherwise. Within the literature on aspirations, there exists evidence that there is a difference between predictions and preferences, where the former is a more realistic assessment of the future outcomes and the latter represents hopes and dreams (Jerrim, 2011; Khattab, 2015). The aspiration of the YP is incorporated in the analysis by including their response to the question 'How likely do you think it is that you will ever apply to go to university to do a degree?' Their responses to this question when they are aged 15 and 16 are included in the analysis. The aspiration variable of the YP is coded as taking the value 1 if the YP thinks it fairly or very likely that they will apply to university and 0 otherwise.

There is a difference in the aspirations of the parents across YP's gender. At age 15, 90% of the parents of girls would like their daughters to stay in education after age 16, and 86.5% think that their daughters will remain in education; the corresponding numbers for boys are 76.2%

and 71.5%. By age 16, there is an upward revision in aspirations of the parents where 88.7% (75.6%) of parents for girls (boys) think that the young person will stay on in education. There is an aspiration gap between girls and boys themselves, with 70% of the girls at age 16 thinking they are fairly likely or very likely to apply to university, while the corresponding number for boys is 60%.

We also control for the risky behaviours that YP engage in; risky behaviour during adolescence is often associated with peer influence, growing up in poverty or poor neighbourhoods, it captures aspects of parent–child relationship, and decision-making among YP, specially their risk-preference (Hao et al., 2008). In our analysis, we use an index going from 0 to 8 which counts the number of risky behaviours the YP reports having engaged in, in the last 12 months. This includes truancy, cigarette, alcohol and cannabis usage, experience of graffiti, vandalism, shoplifting or fighting. On an average, a YP engages in between 1 and 2 risky behaviour, with boys at age 16 having a higher average at 1.5 relative to girls at 1.3.

We use variables to capture both the mental health and general health of YP. Mental health is measured by the 12-item 'General Health Questionnaire' (GHQ-12; Goldberg & Williams, 1988) which captures anxiety, depression, social dysfunction and loss of confidence. GHQ-12 was included in the survey when the individuals were aged 15 and when they were aged 16. In our analysis, we use the GHQ score, which combines answers to the items of the GHQ12 into a 12-point scale, with a higher score indicating higher mental distress. At both ages, girls report a higher GHQ score relative to boys. A self-assessed health variable captures general health. At ages 15 and 16, the YP were asked 'In the last 12 months would you say your health has been very good, fairly good, not very good or not good at all?'. In the analysis, these responses are coded zero (for the responses 'very good' or 'fairly good') or 1 (for the responses 'not very good' or 'not good at all'). Girls report worse self-assessed health relative to boys.

To capture local labour market conditions, we control for the local unemployment rate. We can identify the government office regions (GOR) that the young person lives in. For each GOR, nine in total for England, we use the local youth (age 16–24) unemployment rate from the Office of National Statistics. The unemployment rate is defined separately for men and women; the unemployment rate is higher for men than for women. In our analysis, while all other covariates are included with a lag, the local unemployment rate included is contemporaneous. The average local unemployment rate for females in 2008 ($t = 3$ for the cohort members) was 13.27%, for males the average rate was 17.24%.

We include a dummy variable for English not being the main language, which takes the value 1 if English is not the main language spoken at home and 0 otherwise, as a covariate in the measurement Equation (3) for cognitive ability at $t = 0, 1$. For $t = 2$ we include a dummy that takes the value 1 if the YP had special educational needs at the time of taking their GCSE (KS4) exams. These covariates are used to capture systematic differences in the observed measures for the same level of latent cognitive ability. For our sample, about 3% of YP report that English is not their main language, and 8% of them report having special education needs; the latter is reported more frequently for boys than for girls, with 10% of the boys and 6% of the girls reporting special educational needs.

Table B3 in the Appendix B compares the summary statistics of all variables in the analysed sample versus the LSYE sample. The LSYPE sample is of those YP for whom there was a productive interview in wave 5 (the last wave used in the analysis) of data collection. There are differences in the analysed and the LSYPE sample, and while these differences are small in magnitude they are statistically significant. YP in the analysed sample are less likely to be NEET and, on average, come from a higher socio-economic background, and have higher test scores. As socio-economic factors and test scores are likely to be correlated with NEET status, it is likely that our estimates are biassed. However, use of non-response weights and robust estimators reduce much of this bias and increases the validity of any inferences made with respect to the general adolescent population (Anders, 2012). It is possible, nevertheless, that there are differences on unobservable characteristics between our analytic sample and the wider population that could lead to remaining bias in the estimates.

5 | RESULTS

5.1 | Estimates from the structural model

In Tables 3 and 4 we present the estimates from the structural equation. Estimates from the measurement models for the latent variables are presented in Tables B4 and B5, and discussed in Appendix B. While the estimates are reported in different tables, all equations for the structural and measurement model are estimated jointly.

In Table 3 we present results for $t = 1$, where we control for past cognitive ability and the initial conditions. Past cognitive ability, that is, the stock of ability with which the YP leave the primary education, θ_0, has a positive and a significant impact on ability at the end of KS3, θ_1; one SD increase in θ_0 leads to a 0.857 (0.861) SD increase in θ_1 for girls (boys). We therefore have evidence supporting the ‘self-productivity’ of skills. Most of the variables capturing the initial conditions have a significant effect on the cognitive ability for both girls and boys, with being born earlier in the school year, higher mothers age, and higher mothers education all having a positive impact on the cognitive ability of children, while living in a deprived neighbourhood has a negative effect on cognitive ability. Birth weight is significant only for boys, with higher birthweight being positively associated with cognitive ability.

In Table 4 we present the estimates of the structural equations for $t = 2$ and $t = 3$. Looking at cognitive ability at the end of compulsory education $t = 2$, θ_2, past cognitive ability remains significant: one SD increase in cognitive ability θ_1 for girls (boys) leads to an increase of 0.786 (0.808) SD in θ_2. We also find evidence of positive and significant relationship between measures of non-cognitive ability and cognitive ability. One SD increase in locus of control increases the cognitive ability of girls (boys) by 0.106 (0.086); similarly a one SD increase in school engagement increases the cognitive ability of girls (boys) by 0.045 (0.080). While the relative size of the coefficients on locus of control and school engagement is similar for boys, for girls coefficient on locus of control is twice that on school engagement.

Among other time-varying covariates, for both boys and girls, higher socio-economic status has a significant positive effect on cognitive ability; low self-assessed health has a significant negative impact on cognitive ability, while poor mental health has no significant impact on cognitive ability; higher risky behaviour is associated with lower cognitive ability. Higher prior aspirations of the YP for university, and prior predictions of their parent that the YP will stay on in education after compulsory education have a significant positive effect on cognitive ability; prior parental preference that the YP stay on in education after compulsory education, however, is significant only for girls.

For NEET status, $t = 3$, for both boys and girls, higher prior cognitive ability lowers the probability of being NEET, while higher local unemployment rates increase the likelihood of being NEET. For girls, no other factor is significantly associated with NEET status. For boys, school engagement is associated with lower probability of being NEET; coming from a higher

TABLE 3 Parameter estimates of the structural model for $t = 1$

	Girls	Boys
Age (years)	**14/15**	**14/15**
Dependent variable:	**Cognitive ability**	**Cognitive ability**
Explanatory variables, all from $t = 0$		
Cognitive ability	0.857***	0.861***
	(0.011)	(0.010)
Initial conditions		
Birthweight	0.012	0.062***
	(0.020)	(0.021)
School year month	0.102***	0.105***
	(0.019)	(0.020)
Mothers age	0.094***	0.087***
	(0.022)	(0.022)
Mothers education:		
GCSE's or below	0.292***	0.225***
	(0.058)	(0.067)
A-levels or above	0.608***	0.463***
	(0.069)	(0.075)
IMD score	−0.198***	−0.094***
	(0.024)	(0.024)
Ethnicity controls	Yes	Yes
Model fit statistics		
Comparative fit index	0.841	0.848
Root mean square error approximation	0.027	0.027
Chi-square	20,993.491***	20,736.608***
Observations	3217	3168

Notes: For continuous latent outcome, ability, $t = 1$, standardised coefficients are reported; for continuous covariates, the coefficient represents the change in the dependent variable associated with a 1 SD change in the covariate, and for the binary covariates the coefficient represents the change associated with a shift in the variable from 0 to 1. IMD score: the local deprivation index ranges from 0 to 80, in the estimation we have divided the index by 10. The Chi-square test the null hypothesis: all slope parameters in the structural part of the model are 0, and the factor loadings in the measurement part of the model are all 1. Sample weights have been used in all analysis. The values in parentheses represent SE.

*Significant at 10%;

**significant at 5%;

***significant at 1%.

socio-economic family significantly decrease the probability of being NEET; while prior mental health issues increase the likelihood of being NEET.

The diagnostic statistics indicate that the model fits the data well for both genders. Comparative Fit Index is close to the recommended level of 0.90, and root mean square error approximation is below 0.05, as recommended. We can reject the null hypothesis of the chi-squared test that all slope parameters in the structural part of the model are 0, and the factor loadings in

TABLE 4 Parameter estimates of the structural model for $t = 2$ and for $t = 3$

Age (years)	Girls 16 $t = 2$	Girls 18 $t = 3$	Boys 16 $t = 2$	Boys 18 $t = 3$
Dependent variable:	**Cognitive ability**	**NEET**	**Cognitive ability**	**NEET**
Explanatory variables, all from $t - 1$[a]				
Cognitive ability	0.786***	−0.039***	0.808***	−0.038***
	(0.026)	(0.013)	(0.022)	(0.014)
Covariates				
School engagement	0.045**	−0.071	0.080***	−0.109***
	(0.019)	(0.044)	(0.019)	(0.039)
Locus of control	0.106***		0.086***	
	(0.023)		(0.023)	
Household SES:				
Routine/manual	0.384***	−0.188	0.185	−0.218
	(0.112)	(0.148)	(0.123)	(0.140)
Intermediate	0.416***	−0.142	0.334**	−0.375**
	(0.120)	(0.207)	(0.133)	(0.165)
Managerial/professional	0.518***	−0.188	0.301**	−0.260*
	(0.116)	(0.165)	(0.126)	(0.155)
Home ownership	0.161	0.496*	−0.075	0.184
	(0.167)	(0.287)	(0.155)	(0.253)
Lone parent household	−0.090	0.235	−0.102	0.094
	(0.164)	(0.335)	(0.155)	(0.233)
Siblings	0.015	−0.132	0.004	0.001
	(0.065)	(0.118)	(0.071)	(0.131)
Self-assessed health low	−0.307***	0.171	−0.453***	0.073
	(0.117)	(0.207)	(0.167)	(0.330)
Mental health	−0.012	0.008	0.001	0.030*
	(0.025)	(0.018)	(0.025)	(0.016)
Parent thinks YP will continue into education	0.361***	−0.083	0.466***	−0.056
	(0.079)	(0.220)	(0.076)	(0.160)
Parent would like YP to continue into education	0.185**	0.055	0.090	0.074
	(0.089)	(0.248)	(0.074)	(0.155)
YP has University plans	0.377***	−0.129	0.234***	−0.175
	(0.057)	(0.133)	(0.058)	(0.108)

TABLE 4 (Continued)

Age (years)	Girls 16 $t = 2$	Girls 18 $t = 3$	Boys 16 $t = 2$	Boys 18 $t = 3$
Dependent variable:	**Cognitive ability**	**NEET**	**Cognitive ability**	**NEET**
Risky behaviour	−0.127***	0.001	−0.129***	0.031
	(0.031)	(0.045)	(0.033)	(0.030)
Local unemployment rate[a]		0.063***		0.036**
		(0.016)		(0.015)
Ethnicity controls	Yes	Yes	Yes	Yes

Notes: For continuous latent outcome, ability, $t = 2$, standardized coefficients are reported; for continuous covariates, the coefficient represents the change in the dependent variable associated with a 1 SD change in the covariate, and for the binary covariates the coefficient represents the change associated with a shift in the variable from 0 to 1. For the binary outcome, NEET, $t = 3$, we report the unstandardised probit coefficients. Sample weights have been used in all analysis. The values in parentheses represent SE.

[a]With the exception of local unemployment rate, which is contemporaneous.

Abbreviation: YP, young people.

*Significant at 10%;

**significant at 5%;

***significant at 1%.

the measurement part of the model are all significant. Additionally, the individual parameter estimates reported appear to have face validity.

NEET status of the YP depends on not only their individual characteristics and circumstances but also the local labour market conditions. The most relevant local labour market indicator that we use, based on the literature review, is the local youth unemployment rate. Impact of the local youth unemployment rate is over and above the individual and family circumstances. As a robustness check, we explore two other labour market indicators. First, we include the (contemporaneous) average ‘gross weekly earnings of full time employees’, as a control for labour market conditions at the local level. We try two different specifications for this: weekly earnings are included in the model with and without the local youth unemployment rate. In the specification where only weekly earnings are used, the estimated coefficient on weekly earnings is near zero and insignificant. In the specification where we include weekly earnings instead of the youth unemployment rate, for boys the coefficient is still near different from zero, while for girls the coefficient is 0.001 and significant at the 10% level. Qualitatively, all other estimated coefficients, in both specifications, remain the same. Second, instead of the (contemporaneous) local youth unemployment rate we include the (contemporaneous) local adult unemployment rate as a control. We find the coefficient on the local adult unemployment rate to be positive and significant in the NEET equation for both boys and girls. Qualitatively, all other estimated coefficients in the model remain the same.

5.2 | Indirect effects

Table 5 presents the indirect effects for some of the variables, from $t = 0$ and $t = 1$, on NEET status. While the indirect effects, on NEET status, of all variables in the model can be calculated,

TABLE 5 Indirect effects derived from the structural model

Variable	Girls Coefficient	Girls SE	Boys Coefficient	Boys SE
Dependent variable: NEET, Y_3 ($t = 3$)				
Cognitive ability, θ_0 ($t = 0$)	−0.091***	0.031	−0.078***	0.029
Cognitive ability, θ_1 ($t = 1$)	−0.036***	0.012	−0.033***	0.012
School engagement ($t = 1$)	−0.006*	0.003	−0.009**	0.004
Locus of control ($t = 1$)	−0.014***	0.005	−0.010**	0.004
YP has University plans ($t = 1$)	−0.051***	0.019	−0.026**	0.012
Parent thinks YP will continue into education ($t = 1$)	−0.049***	0.019	−0.053***	0.021
Parent would like YP to continue into education ($t = 1$)	−0.025**	0.015	−0.010	0.009
Risky behaviour ($t = 1$)	0.010***	0.004	0.009**	0.004

Note: In the table we report the unstandardised coefficients.
*Significant at 10%;
**significant at 5%;
***significant at 1%.

we focus here on a small set of covariates. Given the significant self-productivity of ability, and the significant impact of ability at age 16 in reducing the risk of NEET status at age 18, variables significantly associated with increased skill accumulation in early adolescence can be expected to have a significant indirect effect on NEET status. Hence we focus on school engagement, locus of control, aspirations and risky behaviour; further these variables are more amenable to being improved through targeted interventions.

For both girls and boys, cognitive ability in childhood ($t = 0$) and early adolescence ($t = 1$) are significantly associated with a lower probability of being NEET post compulsory education; with the impact of earlier cognitive ability (at $t = 0$) being higher. School engagement at $t = 2$ has a significant direct impact on NEET status for boys but not for girls, as seen from results reported in Table 4, however, via ability, school engagement at $t = 1$ has a significant indirect impact on NEET status for both girls and boys. Similarly, locus of control at $t = 1$ has an indirect impact on NEET status for both boys and girls. Risky behaviour, at $t = 1$, of YP has a significant indirect impact on NEET status, via past ability, despite having no significant direct impact on NEET status. Impact of risky behaviour on increasing the probability of being NEET is bigger for girls and almost the same size for boys, relative to the protective impact of school engagement on becoming NEET.

The aspirations of the YP and what their parent think (predict) they would do, at $t = 1$, are significantly associated with a reduced risk of being NEET, indirectly via their impact on past ability, even though these variables have no direct impact on being NEET. For girls the indirect impact of YP's aspirations at $t = 1$ on the probability of being NEET is of much higher magnitude relative to the impact of cognitive ability of girls at $t = 1$. For boys it is the indirect impact of aspirations of parents, what they think the YP will do, which has bigger magnitude, relative to cognitive ability of boys at $t = 1$. Preferences of parents, that is, what parent would like the YP to do has an indirect impact on NEET status only for girls; preferences of parents has neither a direct nor an indirect significant effect on NEET status for boys.

5.3 | Predicted probabilities

To get a sense of what the estimated coefficients (both direct and indirect) from the structural model mean and what the relative contribution of the various factors is to the probability of being NEET, we predict the probability for being NEET for a few scenarios using our estimated model. These are reported in Table 6, separately for girls and boys. The predicted probability of being NEET, if all explanatory variables are at their gender-specific mean value is 2.43% for girls and 11.21% for boys (row (1) of Table 6). The mean probability predicted from the model is closer to the raw probability for boys (which is 10.1%), but lower for girls (which is 6.6%).

Of more interest to us are the marginal effects of the covariates, that is, how the predicated probability of being NEET changes for a small change in the covariate of interest, say cognitive ability of the young person, holding all other covariates fixed at their average value (which fixes the scale factor in the probit model). However, as a number of our covariates are categorical their average values have no practical interpretation. For example, while 20.3% of girls at $t = 2$ come from lone parent households, using 0.203 to represent the 'average' girl in the sample has little meaning. Instead we use the maximum and minimum values of the categorical control values to create two cases: the least-likely to be NEET and the most-likely to be NEET. This helps us fix the scale factor meaningfully; using these two cases, we can then obtain the marginal effects for covariates of interest. For a full discussion of obtaining the marginal effects in probit models in the presence of categorical control variables see Wooldridge (2020, chapter 17).

The hypothetical YP who is least-likely to be NEET in terms of the categorical variables does not report low self-assessed health, has no risk factors, has university plans, has parents who think and would like YP to continue in education, and comes from a two parent household with 'managerial or professional' SES, and own their home. The YP who is most-likely to be NEET, on the other hand, reports low self-assessed health, engages in one risky behaviour (this is the median risky behaviour in our analysis sample), has no university plans, has parents who neither think nor would like the YP to continue in education, and comes from a single parent household with 'long-term unemployed' SES, and rent their home. For both of these extreme cases, ethnicity is fixed at white, as this is the dominant group in our sample (and in the English population); making across ethnicity comparisons is beyond the scope of this paper.

The least-likely and the most-likely cases are artificial. In the analysis sample there are no young men or young women who satisfy the most-likely case; and there are 578 YP (317 females and 261 males) who satisfy the least-likely case, and of these, 5.4% (17) young women and 3.8% (10) young men are NEET. For both of these extreme cases, if we keep the latent cognitive ability, and all other continuous (observed and latent) explanatory variables, such as school engagement, siblings in the household, mental health and local unemployment rates, at their mean values for $t = 2$, the probability of being NEET for the least-likely case (given in row (2) of Table 6) is 2.59% for girls and 10.11% for boys, as opposed to 4.56% and 19.91% in the most-likely case (row (3) of Table 6).

Next, focusing on the most-likely to be NEET case, we change one individual predicator at a time to see how the predicted probabilities respond, and where relevant link them to the various policy initiatives and interventions. Changing one predictor at a time follows from the ceteris paribus assumption inherent in calculating the marginal effects, and as a result ignores the correlation among the predictors (Wooldridge, 2020, chapter 17). There is a discussion in the literature over investments in early childhood versus in adolescent years, with evidence of more benefits to earlier investment (Heckman & Carneiro, 2003). However, all the interventions we discuss

TABLE 6 Predicted probabilities (%) of being not in education, employment or training (NEET) under different scenarios

		Girls			Boys		
		Probability	Absolute effect*	Relative effect*	Probability	Absolute effect*	Relative effect*
(1)	At mean values	2.43			11.21		
(2)	Least-likely case	2.59			10.11		
(3)	Most-likely case	4.56			19.91		
(4)	Most-likely case with 1-SD increase in cognitive ability	3.40	−1.16	−25.38	16.93	−2.98	−14.95
(5)	Most-likely case with 1-SD increase in school engagement	3.92	−0.64	−14.12	16.99	−2.91	−14.63
(6)	Most-likely case with 1-SD increase in locus of control	4.43	−0.13	−2.95	19.64	−0.27	−1.35
(7)	Most-likely case with YP has university plans	3.46	−1.11	−24.23	15.39	−4.52	−22.72
(8)	Most-likely case with YP has university plans and parents think YP will continue into education	2.87	−1.70	−37.17	14.09	−5.82	−29.24
(9)	Least-likely case with 1-SD increase in local unemployment	3.98	1.38	53.44	11.94	1.83	18.06
(10)	Most-likely case with 1-SD increase in local unemployment	6.71	2.15	47.08	22.73	2.82	14.17

Notes: (1) Probability of being NEET at the gender-specific mean of all variables. (2) Lest-likely case: young people (YP) is White, does not report low self-assessed health, has no risk factors, has university plans, has parents who think and would like YP to continue in education, and comes from a household with 'managerial or professional' SES, own home, and two-parents. Continuous variables (ability, siblings in the household, mental health and local unemployment rate) are at their mean value. (3) Most-likely case: YP is White, reports low self-assessed health, engages in one risky behaviour (this is the median risky behaviour), has no university plans, has parents who neither think nor would like the YP to continue in education, and comes from the household with 'long-term unemployed' SES, rented home, and single parent. Continuous variables (ability, siblings in the household, mental health and local unemployment rate) are at their mean value. (4) Most-likely case with 1-SD increase in cognitive ability at $t = 2$. (5) Most-likely case with 1-SD increase in school engagement at $t = 2$. (6) Most-likely case with 1-SD increase in locus of control at $t = 1$. (7) Most-likely case, but YP has university plans at $t = 2$. (8) Most-likely case, YP has university plans and parents think the YP will continue in education at $t = 2$. (9) Least-likely case with 1-SD increase in gender-specific local unemployment rate. (10) Most-likely case with 1-SD increase in gender-specific local unemployment rate.
[a]Absolute and relative effects: for rows (4) to (7) and rows (9) and (10) effects are from the case in row (3); for row (8) effects are from case in row (2).

below are targeted towards adolescents, with evidence suggesting that while costs, relative to benefits, are higher in later investments, they are not ineffectual; see Grossman and Tierney (1998) and Kahne and Bailey (1999) for two such successful programmes targeted towards youth in the United States.

There have been various policy initiatives to boost the academic standards of the poor performing students. Often these take the form of remedial educational programmes with increase in instruction times for underachieving students; see Lavy and Schlosser (2005) for Israel, Machin et al. (2010) for England, and García-Pérez and Hidalgo-Hidalgo (2017) for Spain. The first simulation we undertake is to see what would happen to the probability of being NEET if we increase the average cognitive ability, across the entire sample of NEET and not NEET, θ_2 by 1 SD. The probability of being NEET for the most-likely girls and boys, given in row (4), falls to 3.40% and 16.93%, respectively, with effect size relative to row (3) of 25.38% and 14.95%, respectively.

Along with initiatives to increase cognitive ability of YP, a number of policy interventions have also focused on increasing their non-cognitive abilities, with the aim of promoting positive behaviours and skills. These interventions include, but are not limited to, mentoring, service learning (connecting community activities such as volunteering to classroom learning), outdoor adventure and social and emotional learning (SEL) programmes. While most of these interventions target more than one dimension of non-cognitive skills of YP, outdoor adventure programmes have been found effective in increasing locus of control, and service learning and SEL programmes have been found effective in increasing school engagement. See Heckman and Kautz (2014) and Gutman and Schoon (2013) for a review of such programmes and effectiveness of different interventions on a range of non-cognitive skills.

In view of these programmes looking to raise non-cognitive skills of YP, we look at what happens to the probability of being NEET for the most-likely case, if we increase the average school engagement. The direct impact of increasing school engagement by 1SD is to decrease the probability of being NEET (row (5)), for both girls and boys. For boys, the effect size of increasing school engagement is similar to raising their cognitive ability. We also look at the impact of increasing locus of control by 1 SD (row (6)), recall that locus of control impacts NEET status only indirectly in our model via cognitive ability. While increasing locus of control does reduce the probability of being NEET for the most-likely cases, the effect sizes are quite small.

Lower aspirations in white children, especially boys, coming from workless households is associated with a range of adverse outcomes (Berrington et al., 2016) and is of specific policy concern in the United Kingdom (House of Commons, 2021). We next consider a scenario where the YP has aspirations to go to university, but is otherwise identical to the most-likely case in row (3). The probability of being NEET, given in row (7), drops to 3.46% (effect size 24.23%) for girls and 15.39% (effect size 22.72%) for boys. The relative effect of the YP having and not having aspirations is almost the same as the relative effect of a 1 SD improvement in average cognitive ability for girls, and much larger for boys. If we further add parental aspirations to this, then effect size, given in row (8), is even larger.

Local unemployment rates have a significant relationship with NEET status in our model, further, YP are known to be disproportionately impacted by economic recessions (Bell & Blanchflower, 2011); the recent recession as a result of COVID-19 pandemic has also seen a large increase in youth unemployment rates (Costa Dias et al., 2020). We use our estimates to predict the probability of being NEET if the gender-specific local youth unemployment rate increases by 1 SD. For girls, this would mean the average local unemployment going up from 13.57% to 16.6%, and for boys from 17.44% to 20.16%. In the 2008–2009 recession that the United Kingdom faced, youth unemployment rate was 18.9%, so these increases are not unrealistic. A 1 SD increase in the local unemployment rate increases the probability of being NEET for both the least-likely and the most-likely cases, as shown in the last two rows of Table 6. The absolute effect of this is larger for the most-likely cases, but the relative effect is larger for the least-likely cases, with the effect sizes exceeding that of a 1 SD increase in past ability.

6 | CONCLUDING DISCUSSION

This paper used a dynamic latent factor model to investigate the determinants of NEET status among adolescents in the UK. Two main contributions of our work are, first, in modelling the educational progress over multiple periods through the life of the young person, up to the completion of compulsory schooling. By taking into account this progression, we can determine the direct and indirect impacts of different determinants of NEET status, and the stages in the life of the YP when each determinant is important. Our second contribution is in bringing together within one framework various determinants of NEET status, such as educational achievements, non-cognitive skills, family socio-economic factors, aspirations, mental health and local labour market conditions. We then use the estimated coefficients from our model to calculate the probability of being NEET under different policy relevant scenarios.

While the longitudinal nature of the data (LSYPE) and the modelling approach used in this paper allow us to conduct the analysis it comes with some limitations. First, a substantial proportion of the initial survey sample is dropped from the analytic sample through attrition and item non-response. To an extent, this is a common issue faced when undertaking longitudinal analyses, and any inferences made with respect to the general adolescent population must be interpreted with care. Second, LSYPE is limited in the measures it has to capture non-cognitive skills. LSYPE is the first UK national survey for many years to follow a group of English adolescents, born in 1990, through much of their secondary education and into early adulthood. The one before this was the British Cohort Study, which followed children born in 1970, who completed compulsory education in 1986. The next one is the Millennium Cohort Study, which is following children born in 2000 and its latest available data only cover up to compulsory years of education. Thus, LSYPE is the only data source that currently exists that is relevant to this research question.

Consistent with the literature, we find that both cognitive and non-cognitive skills play a substantial role in protecting or exposing individuals to the risk of being NEET. Further, the YP's individual characteristics and family environment all matter for NEET status, as suggested in the literature. However, our findings also suggest that the impact of most of these determinants is largely indirect through accumulation of cognitive ability, and not necessarily direct. For example, school engagement of the YP raises their academic achievement and hence indirectly lowers the probability of being NEET for both boys and girls; however, its direct impact on NEET status is for boys only. Similarly, while household socio-economic status is important for educational progress and achievements over time, for both girls and boys, it has no direct bearing on NEET status for girls; and the impact of engagement of the YP in risky behaviour on NEET status is entirely indirect. This is an important finding, which provides greater insight and understanding into the mechanism determining NEET status.

YP's own aspirations and their plans for university have both a direct and an indirect impact on the likelihood of them becoming NEET, thus helping them in 'beating the odds'. However, parental aspirations impact NEET status mostly indirectly, via educational progress. Local labour markets, as captured by the local youth unemployment rates, remain significant in explaining and predicting NEET status; our simulations with local unemployment rates indicate that high youth unemployment rates have a large adverse impact on YP. Our predicted probabilities further suggest that the effect raising aspirations of the YP and worsening the local youth unemployment rates have on the likelihood of the YP being NEET could be as large as boosting their skills.

While our findings highlight the key predictors of NEET status, it is important to stress that from a policy perspective the individual predictors cannot be considered in isolation. For example, there is evidence from interventions that target non-cognitive ability with the aim of improving the cognitive abilities of YP (Holmlund & Silva, 2014; Martins, 2010), highlighting the complementarity between cognitive and non-cognitive skills. Furthermore, non-cognitive skills encompass a range of skills including, but not limited to, personality traits, character skills, soft skills, psychological capital and socio-emotional skills; these skills are inter-related and need to be developed in combination to have any impact on long-term outcomes of YP (Gutman & Schoon, 2013; Poropat, 2009). Finally, the decisions made by the YP at the end of compulsory education depend on not only their individual characteristics and circumstances but also on the macroeconomic conditions and the institutions governing the school-to-work transitions.

The institutions governing school-to-work transition include, but are not limited to, Active Labour Market Polices (ALMP) and Vocational Education and Training (VET) programmes (Caroleo et al., 2020). The importance of the macroeconomic conditions on youth unemployment has been highlighted by the impact of the policy responses to the Covid-19 pandemic on the labour market. The various lockdown measures impacted sectors such as hospitality, tourism and retail, and in the United Kingdom these sectors employ a third of all full-time employees aged under 25 (Joyce & Xu, 2020). With respect to the institutions, there has been a policy change in the United Kingdom, where since 2015, all YP must continue with education, job, or apprenticeship, until they are 18 years old. However, despite the policy change formal academic education has dominated in government funding, at the costs of VET programmes, which remain poorly funded or standardised (Britton et al., 2020); and evidence suggest that while ALMP help older individuals (20–24 year olds), they are less effective for younger individuals (16–18 year olds) for whom VET programmes are more successful (Speckesser et al., 2019). In our paper, we do not look at the role of ALMP and VET programmes as this would require carrying out a cross cohort analysis. Nevertheless, taken at face value, our findings suggest that, while policy makers need to continue the focus on raising the ability of the YP to improve their life-chances, fostering the aspirations of YP and protecting a healthy labour market for them may be equally, if not more, important.

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REFERENCES

Ackerman, P.L. & Heggestad, E.D. (1997) Intelligence, personality, and interests: evidence for overlapping traits. *Psychological Bulletin*, 121, 219–245.

Almlund, M., Duckworth, A.L., Heckman, J. & Kautz, T. (2011) Personality psychology and economics. In: Hanushek, E.A., Machin, S., & Wessmann, L. (Eds.) *Handbook of the economics of education*, vol. 4. Elsevier: Amsterdam, pp. 1–181.

Anders, J. (2012) *Using the longitudinal study of young people in England for research into higher education access* (Department of Quantitative Social Science Working Paper No. 12-13). December 2012 (No. 12-13). London.

Avey, J.B., Reichard, R.S., Luthans, F. & Mhatre, K.H. (2011) Meta-analysis of the impact of positive psychological capital on employee attitudes, behaviors, and performance. *Human Resource Development Quarterly*, 22, 127–152.

Bell, D.N. & Blanchflower, D.G. (2011) Young people and the great recession. *Oxford Review of Economic Policy*, 27(2), 241–267.

Berrington, A., Roberts, S. & Tammes, P. (2016) Educational aspirations among UK young teenagers: exploring the role of gender, class and ethnicity. *British Educational Research Journal*, 42(5), 729–755.

Björklund, A. & Salvanes, K.G. (2011) Education and family background: Mechanisms and policies. In: Hanushek, E., Machin, S. & Woessmann, L. (Eds.) *Handbook of the economics of education*, Vol. 3, 3rd edition, Elsevier: Amsterdam, pp. 201–247.

Black, S.E., Devereux, P.J. & Salvanes, K.G. (2005) The more the merrier? The effect of family size and birth order on children's education. *Quarterly Journal of Economics*, 120, 669–700.

Bradley, S. & Lenton, P. (2007) Dropping out of post-compulsory education in the UK: an analysis of determinants and outcomes. *Journal of Population Economics*, 20(2), 299–328.

Bradley, R.H., Corwyn, R.F., McAdoo, H.P. & García Coll, C. (2001) The home environments of children in the United States part I: Variations by age, ethnicity, and poverty status. *Child Development*, 72(6), 1844–1867.

Britton, J., Farquharson, C., Sibieta, L. & Waltmann, B. (2020) *Annual report on education spending in England*, (Institute for Fiscal Studies (IFS), Report R183). https://www.ifs.org.uk/publications/15150.

Brooks-Gunn, J., Klebanov, P.K. & Duncan, G.J. (1996) Ethnic differences in children's intelligence test scores: Role of economic deprivation, home environment, and maternal characteristics. *Child Development*, 67(2), 396–408.

Brunello, G. & Schlotter, M. (2011) *Non cognitive skills and personality traits: labour market relevance and their development in education & training systems* (IZA discussion paper 5743).

Cameron, S. & Heckman, J. (1998) Life cycle schooling and dynamic selection bias: Models and evidence for five cohorts of American males. *The Journal of Political Economy*, 106(2), 262–333.

Cameron, S. & Heckman, J. (2001) The dynamics of educational attainment for black, Hispanic, and white males. *Journal of Political Economy*, 109(3), 455–499.

Carneiro, P., Crawford, C. & Goodman, A. (2007) The impact of early cognitive and non-cognitive skills on later outcomes. (CEE Discussion Paper 0092).

Caroleo, F.E., Rocca, A., Mazzocchi, P. & Quintano, C. (2020) Being NEET in Europe before and after the economic crisis: an analysis of the micro and macro determinants. *Social Indicators Research*, 149, 991–1024.

Chetty, R., Hendren, N. & Katz, L.F. (2016) The effects of exposure to better neighborhoods on children: new evidence from the moving to opportunity experiment. *American Economic Review*, 106(4), 855–902.

Coelli, M.B., Green, D.A. & Warburton, W.P. (2007) Breaking the cycle? The effect of education on welfare receipt among children of welfare recipients. *Journal of Public Economics*, 91(7-8), 1369–1398.

Coles, B., Godfrey, C., Keung, A., Parrot, S. & Bradshaw, J. (2010) Estimating the life-time cost of NEET: 16-18 year olds not in education, employment or training. Research conducted for the audit commission, July 2010. http://php.york.ac.uk/inst/spru/pubs/ipp.php?id=1776

Cornaglia, F., Crivellaro, E. & Mcnally, S. (2015) Mental health and education decisions. *Labour Economics*, 33, 1–12.

Costa Dias, M., Joyce, R. & Keiller, A.N. (2020) COVID-19 and the career prospects of young people. Institute for Fiscal Studies (IFS), Briefing Note, 299.

Crawford, C., Duckworth, K., Vignoles, A. & Wyness, G. (2011) *Young people's education and labour market choices aged 16/17 to 18/19*. London: Department of Education.

Crawford, C., Dearden, L. & Greaves, E. (2014) The drivers of month-of-birth differences in children's cognitive and non-cognitive skills. *Journal of the Royal Statistical Society Series A*, 177(4), 829–860.

Cunha, F. & Heckman, J. (2007) The technology of skill formation. *American Economic Review*, 97(2), 31–47.

Cunha, F. & Heckman, J. (2008) Formulating, identifying and estimating the technology of cognitive and non-cognitive skill formation. *Journal of Human Resources*, 43(4), 738–782.

Cunha, F., Heckman, J.J., Lochner, L. & Masterov, D.V. (2006) Interpreting the evidence on life cycle skill formation. In: Hanushek, E.A. & Welch, F. (Eds.) *Handbook of the economics of education*. Amsterdam: North-Holland, pp. 697–812.

Cunha, F., Heckman, J. & Schennach, S. (2010) Estimating the technology of cognitive and non-cognitive skill formation. *Econometrica*, 78(3), 883–931.

De Luca, G., Mazzocchi, P., Quintano, C. & Rocca, A. (2020) Going behind the high rates of NEETs in Italy and Spain: the role of early school leavers. *Social Indicators Research*, 151(1), 345–363.

Del Bono, E., Ermisch, J. & Francesconi, M. (2012) Intrafamily resource allocations: a dynamic structural model of birth weight. *Journal of Labor Economics*, 30(3), 657–706.

Department for Education. (2013) About LSYPE. Retrieved from: https://www.education.gov.uk/ilsype/workspaces/public/wiki/Welcome/LSYPE

Dickerson, A. & Jones, P. (2004) Estimating the impact of a minimum wage on the labour market behaviour of 16 and 17 year olds.

Dickerson, A., Morris, D. & McDool, E. (2020) Post-compulsory education pathways and labour market outcomes. Research Discussion Paper 026. London: Centre for Vocational Education Research.

Ding, W., Lehrer, S.F., Rosenquist, J.N. & Audrain-McGovern, J. (2009) The impact of poor health on academic performance: New evidence using genetic markers. *Journal of Health Economics*, 28(3), 578–597.

Duckworth, K. & Schoon, I. (2012) Beating the odds: exploring the impact of social risk on young people's school-to-work transitions during recession in the UK. *National Institute Economic Review*, 222(1), R38–R51.

Duckworth, A.L. & Yeager, D.S. (2015) Measurement matters: Assessing personal qualities other than cognitive ability for educational purposes. *Educational Researcher*, 44(4), 237–251.

Eckstein, Z. & Wolpin, K. (1999) Why youths drop out of high school: the impact of preferences, opportunities, and abilities. *Econometrica*, 67(6), 1295–1340.

Egan, M., Daly, M. & Delaney, L. (2015) Childhood psychological distress and youth unemployment: Evidence from two British cohort studies. *Social Science & Medicine*, 124, 11–17.

Falch, T. & Strøm, B. (2013) Schools, ability, and the socioeconomic gradient in education choices. *The Journal of Socio-Economics*, 43, 49–59.

Feinstein, L., Lupton, R., Hammond, C., Mujtaba, T., Salter, E. & Sorhaindo, A. (2008) *The public value of social housing: a longitudinal analysis of the relationship between housing and life chances*.

Fletcher, J. (2008) Adolescent depression: diagnosis, treatment, and educational attainment. *Health Economics*, 1235(2007), 1215–1235.

Foley, K., Gallipoli, G. & Green, D.A. (2014) Ability, parental valuation of education, and the high school dropout decision. *Journal of Human Resources*, 49(4), 906–944.

Fredricks, J.A., Blumenfeld, P.C. & Paris, A.H. (2004) School engagement: Potential of the concept, state of evidence. *Review of Educational Research*, 74, 59–109.

Gan, L. & Gong, G. (2007) *Estimating interdependence between health and education in a dynamic model (No. w12830)*. National Bureau of Economic Research.

García-Pérez, J.I. & Hidalgo-Hidalgo, M. (2017) No student left behind? Evidence from the Programme for School Guidance in Spain. *Economics of Education Review*, 60, 97–111.

Goldberg, D.P. & Williams, P. (1988) In: Goldberg, D.P. & Williams, P. (Eds.) *A User's Guide to the General Health Questionnaire*. Windsor: NFER-Nelson.

Goldin, C., Katz, L.F. & Kuziemko, I. (2006) The homecoming of American college women: The reversal of the college gender gap. *Journal of Economic Perspectives*, 20(4), 133–156.

Goldman-Mellor, S., Caspi, A., Arseneault, L., Ajala, N., Ambler, A., Danese, A. et al. (2016) Committed to work but vulnerable: Self-perceptions and mental health in NEET 18-year olds from a contemporary British cohort. *Journal of Child Psychology and Psychiatry*, 57(2), 196–203.

Goodman, A., Gregg, P. & Washbrook, E. (2011) Children's educational attainment and the aspirations, attitudes and behaviours of parents and children through childhood. *Longitudinal and Life Course Studies*, 2(1), 1–18.

Goodman, A., Joshi, H., Nasim, B. & Tyler, C. (2015) *Social and emotional skills in childhood and their long-term effects on adult life*. London: Institute of Education.

Goux, D., Gurgand, M. & Maurin, E. (2017) Adjusting your dreams? High school plans and dropout behaviour. *The Economic Journal*, 127(602), 1025–1046.

Gregg, P. (2001) The impact of youth unemployment on adult unemployment in the NCDS. *The Economic Journal*, 111(475), 626–563.

Gregg, P. & Tominey, E. (2005) The wage scar from male youth unemployment. *Labour Economics*, 12(4), 487–509.

Grossman, M. (2006) Ch. 10 Education and nonmarket outcomes. In: E. Hanushek, & F. Welch (Eds.) *Handbook of the economics of education*, vol. 1, Amsterdam: Elsevier, pp. 577-633.

Grossman, J.B. & Tierney, J.P. (1998) Does mentoring work? An impact study of the big brothers big sisters program. *Evaluation Review*, 22(3), 403–426.

Gutman, L.M. & Schoon, I. (2013) The impact of non-cognitive skills on outcomes for young people: Literature review. Education Endowent Foundation, London, Available at: https://discovery.ucl.ac.uk/id/eprint/10125763/ [Accessed 2nd October 2022].

Hao, L., Hotz, V.J. & Jin, G.Z. (2008) Games parents and adolescents play: Risky behaviour, parental reputation and strategic transfers. *The Economic Journal*, 118(528), 515–555.

Hawkes, D. & Joshi, H. (2012) Age at motherhood and child development: Evidence from the UK millennium cohort. *National Institute Economic Review*, 222(1), R52–R66.

Heckman, J. & Carneiro, P. (2003) *Human capital policy*. National Bureau of Economic Research, WP No. 9495.

Heckman, J.J. & Kautz, T. (2012) Hard evidence on soft skills. *Labour Economics*, 19(4), 451–464.

Heckman, J. & Kautz, T. (2014) Fostering and measuring skills: Interventions that improve character and cognition. In: Heckman, J., Humphries, J.E. & Kautz, T. (Eds.) *The Myth of Achievement Tests: The GED and the Role of Character in American Life*. Chicago, IL: University of Chicago Press, pp. 341–430.

Heckman, J.J., Stixrud, J. & Urzua, S. (2006) The effects of cognitive and non-cognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, 24(3), 411–482.

Heckman, J.J., Humphries, J.E. & Veramendi, G. (2018) The nonmarket benefits of education and ability. *Journal of Human Capital*, 12(2), 282–304.

Holmlund, H. & Silva, O. (2014) Targeting noncognitive skills to improve cognitive outcomes: Evidence from a remedial education intervention. *Journal of Human Capital*, 8(2), 126–160.

House of Commons Education Committee Report. (2021) The forgotten: how White working-class pupils have been let down, and how to change it. HC 85. https://committees.parliament.uk/publications/6364/documents/70802/default/

Jerrim, J. (2011) *Disadvantaged children's "low" educational expectations: Are the US and UK really so different to other industrialised nations? No. 11-04*. Department of Quantitative Social Science-UCL Institute of Education, University College London.

Joyce, R. & Xu, X. (2020) *Sector shutdowns during the coronavirus crisis: which workers are most exposed?* Institute for Fiscal Studies (IFS), Briefing Note BN278. https://www.ifs.org.uk/publications/14791.

Kahne, J. & Bailey, K. (1999) The role of social capital in youth development: the case of "I Have a Dream" programs. *Educational Evaluation and Policy Analysis*, 21(3), 321–343.

Kalil, A., Ryan, R. & Corey, M. (2012) Diverging destinies: Maternal education and the developmental gradient in time with children. *Demography*, 49(4), 1361–1383.

Khattab, N. (2015) Students' aspirations, expectations and school achievement: What really matters? *British Educational Research Journal*, 41(5), 731–748.

Lagravinese, R., Liberati, P. & Resce, G. (2020) The impact of economic, social and cultural conditions on educational attainments. *Journal of Policy Modeling*, 42(1), 112–132.

Lavy, V. & Schlosser, A. (2005) Targeted remedial education for underperforming teenagers: Costs and benefits. *Journal of Labor Economics*, 23(4), 839–874.

Lazarus, A. & Khattab, N. (2018) The unobserved power of context: Can context moderate the effect of expectations on educational achievement? *Ethnicities*, 18(4), 541–570.

LSYPE. (2011) Users guide to the datasets, department of education. http://doc.ukdataservice.ac.uk/doc/5545/mrdoc/pdf/5545lsye_user_guide_wave_1_to_wave_7.pdf

Luthans, F. & Youssef-Morgan, C.M. (2017) Psychological capital: An evidence-based positive approach. *Annual Review of Organizational Psychology and Organizational Behavior*, 4, 339–366.

Machin, S., Telhaj, S. & Wilson, J. (2006) The mobility of English school children. *Fiscal Studies*, 27(3), 253–280.

Machin, S., McNally, S. & Meghir, C. (2010) Resources and standards in urban schools. *Journal of Human Capital*, 4(4), 365–393.

Martins, P.S. (2010) *Can targeted, non-cognitive skills programs improve achievement? Evidence from EPIS*. IZA Discussion Papers 5266.

Mendolia, S. & Walker, I. (2014) *Do NEETs need grit?* IZA Discussion Paper No. 8740.

Mendolia, S. & Walker, I. (2015) Youth unemployment and personality traits. *IZA Journal of Labor Economics*, 4(1), 19.

Meschi, E., Swaffield, J. & Vignoles, A. (2019) The role of local labour market conditions and pupil attainment on post-compulsory schooling decisions. *International Journal of Manpower*, 40(8), 1482–1509.

Mroz, T. & Savage, T. (2006) The long-term effects of youth unemployment. *Journal of Human Resources*, 41(2), 259–293.

Müller, S., Riphahn, R.T. & Schwientek, C. (2016) Paternal unemployment during childhood: causal effects on youth worklessness and educational attainment. *Oxford Economic Papers*, 69(1), 213–238.

Muthén, B. (2011) *Applications of causally defined direct and indirect effects in mediation analysis using SEM in Mplus*. Unpublished working paper, www.statmodel.com.

OECD. (2015) *Skills for social progress: the power of social and emotional skills*, OECD Skills Studies, OECD Publishing, Paris. https://doi.org/10.1787/9789264226159-en.

OECD. (2018) *Education at a Glance 2017: OECD indicators*, http://www.oecd.org/education/education-at-a-glance

ONS. (2021) *Quarterly estimates for young people (aged 16 to 24 years) who are not in education, employment or training (NEET) in the UK*.

Oreopoulos, P. & Petronijevic, U. (2013) Making college worth it: a review of the returns to higher education. *The Future of Children*, 23(1), 41–65.

Oreopoulos, P. & Salvanes, K. (2011) Priceless: The nonpecuniary benefits of schooling. *The Journal of Economic Perspectives*, 24(1), 159–184.

Petrongolo, B. & San Segundo, M.J. (2002) Staying-on at school at 16: the impact of labor market conditions in Spain. *Economics of Education Review*, 21(4), 353–365.

Polidano, C., Tabasso, D. & Tseng, Y.P. (2015) A second chance at education for early school leavers. *Education Economics*, 23(3), 358–375.

Poropat, A.E. (2009) A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, 135, 322–338.

Rotter, J. (1966) Generalised expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and Applied*, 80(1), 1–28.

Schmillen, A. & Umkehrer, M. (2017) The scars of youth: Effects of early-career unemployment on future unemployment experience. *International Labour Review*, 156(3-4), 465–494.

Schoon, I. (2014) Parental worklessness and the experience of NEET among their offspring: Evidence from the Longitudinal Study of Young People in England (LSYPE). *Longitudinal and Life Course Studies*, 6(6), 129–150.

Schoon, I. & Heckhausen, J. (2019) Conceptualising individual agency in the transition from school to work: A social-ecological developmental perspective. *Adolescent Research Review*, 4(2), 135–148.

Schoon, I. & Lyons-Amos, M. (2017) A socio-ecological model of agency: The role of structure and agency in shaping education and employment transitions in England. *Journal of Longitudinal and Lifecourse Studies*, 8(1), 35–56.

Speckesser, S.S., Carreras, F.J.G. & Sala, L.K. (2019) Active labour market policies for young people and youth unemployment: An analysis based on aggregate data. *International Journal of Manpower*, 40(8), 1510–1534.

Stroud, P. (2010) *Social housing: a launchpad, not a destination*. York: Joseph Rowntree Foundation.
Suhrcke, M. & de Paz Nieves, C. (2011) *The impact of health and health behaviours on educational outcomes in high-income countries: a review of the evidence*. Copenhagen: WHO Regional Office for Europe.
Todd, P.E. & Wolpin, K.I. (2003) On the specification and estimation of the production function for cognitive achievement. *The Economic Journal*, 113(485), F3–F33.
Todd, P.E. & Wolpin, K.I. (2007) The production of cognitive achievement in children: Home, school, and racial test score gaps. *Journal of Human Capital*, 1(1), 91–136.
Weel, B.T. (2008) The non-cognitive determinants of labor market and behavioral outcomes: Introduction to the symposium. *The Journal of Human Resources*, 43(4), 729–737.
Wooldridge, J. (2020) *Introductory econometrics: a modern approach*, 7th edition. Bosto, MA: Cengage Learning.
Yates, S., Harris, A., Sabates, R. & Staff, J. (2011) Early occupational aspirations and fractured transitions: a study of entry into 'NEET'status in the UK. *Journal of Social Policy*, 40(3), 513–534.

SUPPORTING INFORMATION

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