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Educational expectations of UK teenagers and the role of socio-economic status and economic preferences

Silvan Häs
University College London

Jake Anders
University College London

John Jerrim
University College London

Nikki Shure
University College London

Young people's decision making process to go to university might depend on both family background and character traits. In this study, we research the association between long-term socio-economic status (SES) during adolescence, economic preferences such as risk attitudes and time preferences, and teenagers' expectations of going to university. Using data on British teenagers from the Millennium Cohort Study we find that higher SES is associated with higher educational expectations. Furthermore, more patient teenagers think it more likely for them to go to university. However, risk attitudes are not associated with educational expectations. All results are robust to including rich sets of background variables, including cognitive measures and school grades. This implies that for the British education system to become more meritocratic and to improve intergenerational mobility, future policies should target the SES gap in educational expectations. Furthermore, improving patience in young people could be a channel through which educational policy helps improve university attendance.

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Highlights

- Young people's socioeconomic background is already known to be associated with their expectations of going to university.
- This paper explores the additional role of individuals' economic preferences (risk and time preferences) and their interplay with the role of socioeconomic status. These economic preferences are elicited using participants' responses to hypothetical games posed in the questionnaire, rather than simply asked about directly.
- We show that while SES and individuals' time preference (i.e. their patience) are associated with expecting to go to university, individuals who are more risk averse are no less likely to expect to go to university. This finding is robust to controlling for a wide set of sociodemographic characteristics and cognitive measures.
- We also show that risk preferences do not predict that, among individuals who report not expecting to go to university, the main reason for this is concerns about money. Again, this is in contrast to the importance of SES and patience.

Why does this matter?

The lack of importance of risk preferences in the formation of university education expectations suggests that Britain's student finance system is successful in buffering the concerns of risk averse individuals about borrowing to fund their studies.

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Silvan Häs*
s.has@ucl.ac.uk

Jake Anders‡
jake.anders@ucl.ac.uk

John Jerrim*
j.jerrim@ucl.ac.uk

Nikki Shure*
nikki.shure@ucl.ac.uk

* UCL Social Research Institute ‡ UCL Centre for Education Policy & Equalising Opportunities

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Keywords: Human capital formation. Educational investments. Risk preferences. Time preferences. Socio-economic status.

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1. Introduction

From educational attainment to lifetime earnings, coming from a family with a low socio-economic status (SES) is often expected to profoundly affect people's lives (Bradley and Corwyn 2002). In the UK, between 20 and 30%[1] of children lived in relative poverty in 2019 (UK Department for Work and Pensions 2020), more than 15% of children were eligible for free school meals – a programme aimed families with low incomes (Office for National Statistics 2020). Furthermore, British children are much more likely to live in a poor household than those in other European countries. According to Eurostat (2020), in 2019, almost 30% percent of children lived in relative poverty in the UK, compared to only 15% and 23% in Germany and France, respectively. Where and how we grow up shapes the way we perceive the world around us, what we deem possible goals worth pursuing and which we expect to remain dreams. In the UK, education is often seen as a key part in social mobility: more equality in education outcomes is expected to lead to more equal society (Great Britain. HM Government 2011). Therefore, the impact socio-economic status has on educational decisions is of great importance to understand social mobility.

Using recent UK specific panel data, we study the relationship between socio-economic background during childhood and adolescence and how this affects young adults' educational expectations. Moreover, we focus on the role economic preferences (risk and time preferences) play in the formation of adolescents' educational expectations. Among adolescents expecting the cohort member not to go to university, we analyse the role the cost of higher education plays in decision making and how this differs between higher and lower SES pupils.

Economic preferences, i.e. risk and time preferences, are the subject of a variety of economic research. Assumptions about risk attitudes are often made in theoretical models (e.g. Eeckhoudt, Gollier, and Schlesinger 2011; Gollier 2001) and time preferences are regularly embedded in inter-temporal models (e.g. Blackorby et al. 1973; Chamberlain and Wilson 2000). The mechanics of how these preferences are formed and what makes some people more risk loving and impatient than others is subject to both experimental and observational studies (Deckers et al. 2015; Neyse, Johannesson, and Dreber 2021; Becker, Enke, and Falk 2020). Some studies examine the link

[1] Depending on measure used.

between socio-economic status and the formation of economic preferences. For example, Deckers et al. (2017) show that seven to nine year old children from lower socio-economic status households are more impatient and more risk-taking compared to their high-SES peers. However, Chowdhury, Sutter, and Zimmermann (2018) find no effect of household SES in the preference formation of children once accounting for parental economic preferences.

Furthermore, economic preferences are considered important factors for decision making. Both risk preferences and time preferences have been shown to be linked to decisions such as smoking and drinking (Anderson and Mellor 2008; Dohmen et al. 2011) as well as criminal behaviour (Becker and Landes 1974; Mesquita and Cohen 1995; McCarthy and Hagan 2001). Risk attitudes may be linked to educational decisions in the UK in the following ways. First, going to university requires most young people to take up a loan of tens of thousands of pounds with uncertain returns on that investment. More risk averse people may be put off by this. Empirically, Belzil and Leonardi (2013) find that in Italy higher risk aversion functions as a deterrent to going to university. Similarly, in a review of the economic literature, Outreville (2015) conclude that more risk averse individuals have lower educational attainment. Following these studies, we would expect more risk averse individuals to have *lower* educational expectations. Conversely, a university education can be viewed as 'insurance' against unemployment and poverty – causing more risk averse individuals to pursue university degrees. Hanushek et al. (2020) and Sunde et al. (2020) find that on average more risk averse societies have higher student achievement, supporting this hypothesis. According to these studies, we would expect risk averse students to think it *more likely* to go to university. The case for the potential impact of time preferences is clearer. Monetary payoffs of a university degree lie in the future, with upfront costs of obtaining a degree in the present. This may lead to more patient individuals to be more likely to go to university (Hanushek et al. 2020) resulting in higher human capital (Sunde et al. 2020). Furthermore, Golsteyn, Grönqvist, and Lindahl (2014) find that more impatient individuals perform worse in school and have lower earnings later in life.

The studies detailed above link SES, risk attitudes and time preferences to different outcomes such as educational attainment. In our study, we focus on educational expectations, in particular how likely 17 year olds think it is they go to university after finishing school. Educational expectations in teenagers are found to have a strong association with actual education decisions later in life

(Jerrim 2011; Anders and Micklewright 2015). Some evidence suggests there might even be a *causal* link between educational expectations and outcomes, meaning that increasing educational expectations directly affects educational outcomes (Morgan 2004). The level of education young people obtain is an important contributor to their opportunities later in life. For instance, lifetime earnings of university graduates in the UK are on average significantly higher than for non-graduates (Blundell et al. 2000; Walker and Zhu 2011, 2013; Belfield et al. 2018; Green, Jin, and Blundell 2016). Higher education further affects health outcomes (Davies et al. 2018) and is considered an important contributor to social mobility both by academics (Jerrim and Macmillan 2015; Gregg et al. 2013) and policy makers (Great Britain. HM Government 2011; Milburn 2012).

As socio-economic status may be linked to the formation of economic preferences, so may educational decisions be influenced by socio-economic status. While parts of the literature focus on the link between SES and educational outcomes, such as going to university (Declercq and Verboven 2015; Crawford et al. 2016), others have focused more on educational expectations – a good predictor of subsequent decisions (Jerrim 2011; Anders and Micklewright 2015; Morgan 2004). Children growing up in low-SES households in the UK are found to have lower educational expectations when controlling for rich background characteristics, including prior attainment (Anders and Micklewright 2015; Jerrim 2011). Moreover, low-SES students are much more likely to lower their expectations after receiving discouraging GCSE results and are less likely to level their expectations up after good results (Anders 2017). While overall educational expectations have been on the rise the UK over the past decades, the SES gap remains rather stable (Schoon 2021).

In this study, we explore how socio-economic household characteristics during childhood and young people's economic preferences (i.e. risk and time preferences) are associated with educational expectations. In the UK, schooling is compulsory until the age of 16. At age 17 – the age group subject to this study – can either continue full-time education in school leading to qualifications such as A-levels, or they can leave school and choose another form of education such as an apprenticeship or further education (FE) colleges. Therefore, at this point the MCS cohort members have already decided whether to stay in school or not and possibly have informed expectations on how likely they are to continue their education at a university. As discussed before, there is strong evidence that educational expectations formed at the age of 14 and 17 are good predictors of future university enrolment (Jerrim 2011; Anders and Micklewright 2015; Anders 2017) and, so, are a good indicator of the educational careers taken a few years later.

Our research contributes to the existing literature in the following ways. First, to the best of our knowledge, this article is the first to study how socio-economic status, economic preferences, and educational expectations are linked in the UK context. An economic decision about whether to go to university or not is likely to be influenced by economic preferences as well as socio-economic status. On the one hand, growing up in a higher income household with well-educated parents (i.e. higher socio-economic status) can shape a child's choices for the future. We expect to see that higher SES pupils have higher educational expectations. Risk attitudes and time preferences may play an important role as well.

Going to university is a commitment of at least three years, costing close to £30,000 in student fees alone. The potential return on the investment lies in the future and is not immediately available. It may not be until university graduates' 30s that an advantage in earnings becomes sizeable. Moreover, even though studies consistently find that getting a university degree increases average lifetime earnings in the UK, especially for women (Blundell et al. 2000; Waltmann et al. 2020; Walker and Zhu 2011, 2013; Belfield et al. 2018), any university-premium heavily relies on career choices (Waltmann et al. 2020; Walker and Zhu 2011; Belfield et al. 2018) and is distributed unevenly within subject (Waltmann et al. 2020). Risk averse individuals might see this as too much of a gamble and might shy away from university education. On the other hand, higher education serving as insurance against unemployment and poverty might attract more risk-averse individuals. Risk aversion may contribute to higher educational achievements (Hanushek et al. 2020; Sunde et al. 2020). However, the link between risk aversion and educational expectations in the UK context of recently increased student fees remains unclear. The narrative for the role time preferences play in the formation of educational expectations is clearer. Impatient people might not want to wait more than 10 years after graduating to see their investment pay off. Hence, we hypothesise that more patient individuals are more likely to expect to go to university.

Second, we use the most recent data from the Millennium Cohort Study (MCS), published in 2020, to research the link between educational expectations and socio-economic status. This adds to evidence from studies such as Anders (2017) and Anders and Micklewright (2015), who use data for teenagers and young adults born in England around 1990, more than 10 years prior to when

MCS cohort members were born. In the meantime, student fees increased steeply from around £3,000 per year to more than £9,000 per year for an undergraduate degree. This step was discussed extensively by the wider public. Many argued the increase in student fees may deter young people from low-income backgrounds from going to university (Wintour et al. 2010; Coughlan 2010; BBC 2010). However, the UK government at the time alongside others argued that the way the student fee system is structured – no up-front payments with loans repaid proportional to earnings – would even reduce the burden on many students (The Independent 2010). This and other factors such as the financial crisis of 2007 may have changed the way socio-economic status is linked to educational expectations. Therefore, adding an updated view on the link between SES and educational expectations contributes to the understanding of educational choices in the UK context.

In this study, we look at the unconditional associations of socio-economic status, risk attitudes, and time preferences on educational expectations, as well as the associations conditional on a rich set of background variables. Throughout all methods applied in our analyses, we find that both long-term socio-economic status and time preferences at age 17 matter in the formation of educational expectations: more patient cohort members with higher SES are more likely to expect to go to university than impatient cohort members with lower SES. Risk attitudes, on the other hand, are not associated with the expectation of going to university. Including control variables such as cognitive scores reduces the size of our estimates. However, regardless of model choice, we find a very robust and substantial influence both SES and patience have on the expectations to go to university.

The remainder of this paper is structured as follows. In Section 2, we introduce the data and describe how we recoded variables of interest. This includes a discussion of attrition bias and missing data as issues for the representativeness of the MCS cohort for the generation of young adults in the UK. Section 3 introduces the methods we use to analyse the data. In Section 4, we discuss the results of these analyses. Last, in Section 5, we summarise the findings of this paper, arising questions for future research, and potential implications of our findings for policy making.

2. Data

To answer the research questions, we conduct secondary data analysis of the Millennium Cohort Study (University of London, Institute of Education, Centre for Longitudinal Studies 2017b, 2017d, 2017e, 2017c, 2017a, 2019, 2020), a longitudinal survey following a representative sample of approximately 19,000 children born in the UK around 2001. As of the time of writing this article, MCS data has been collected and published in seven sweeps at age one, three, five, seven, 11, 14 and 17. The data contains rich information provided by parents, teachers, and cohort members themselves.

2.1 Educational expectations

Of greatest interest for this study are educational expectations reported by cohort members at age 17. Cohort members are asked to report the likelihood with which they expect to go to university on a percentage scale from 0% (not at all likely) to 100% (sure to go to university). The probability scale might be preferable to the verbal scales often used in these types of questionnaires: the interpretation of what is likely and what is not might vary between individuals and between questions and is at the same time unnecessarily coarse, not allowing for more nuanced expressions of expectations (Manski 2004).

Figure 1 shows the distribution of cohort members' educational expectations. The histogram shows the expectation of going to university in 10 bins. One can see a concentration at the bottom of the distribution close to 0%. This is likely the group of 17 year olds who are very certain that they will not be going to university and that potentially have made alternative plans already. Unsurprisingly, at around 50% there is another spike in observations. The third spike is in the 90-100% bin, consisting of those adolescents who are very sure that they will go to university.

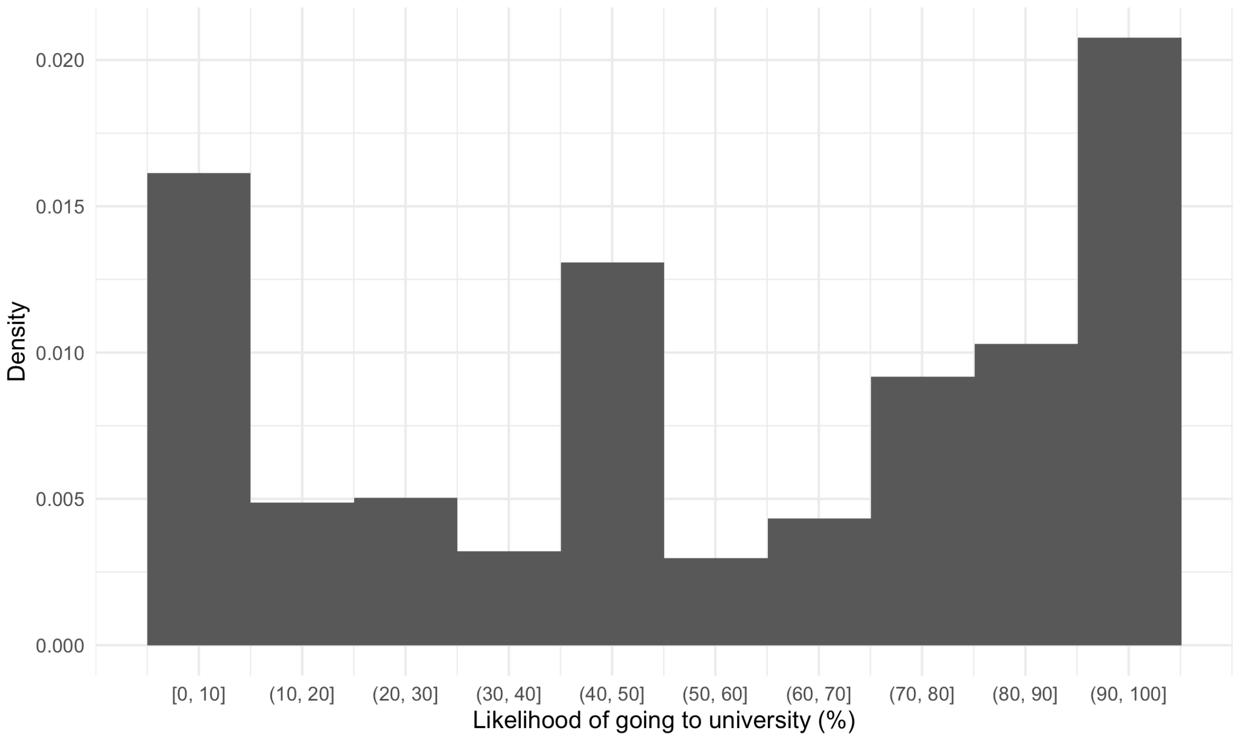

Figure 1. Histogram of educational expectations at age 17

Notes: Number of observations: 6,382. Average educational expectation (weighted): 56%. Educational expectations as observed in MCS age 17 sweep. A total of 10 bins closed to the right, hence the estimated chance of 50% falls in the 40-50% bin. Inverse probability weights applied.

Additionally, cohort members reporting a value below 100% are asked what would be the main reason not to go to university, for example that their family cannot afford it. In this study, we use this information to understand better why cohort members are not sure they will or certain they will not go to university. Figure 2 shows the distribution of educational expectations in those cohort members who say money would be the main reason for them not to attend university, and those who mention other reasons. Educational expectations are very similar between 17 year olds who report financial constraints as a reason not to go to university and those who do not. However, financially constraint pupils are less likely to have very low educational expectations. This is possibly as low ability pupils might list poor grades no interest in further education as the main reason not to go to university, whereas higher ability pupils' reason not to attend might be more likely for money reasons.

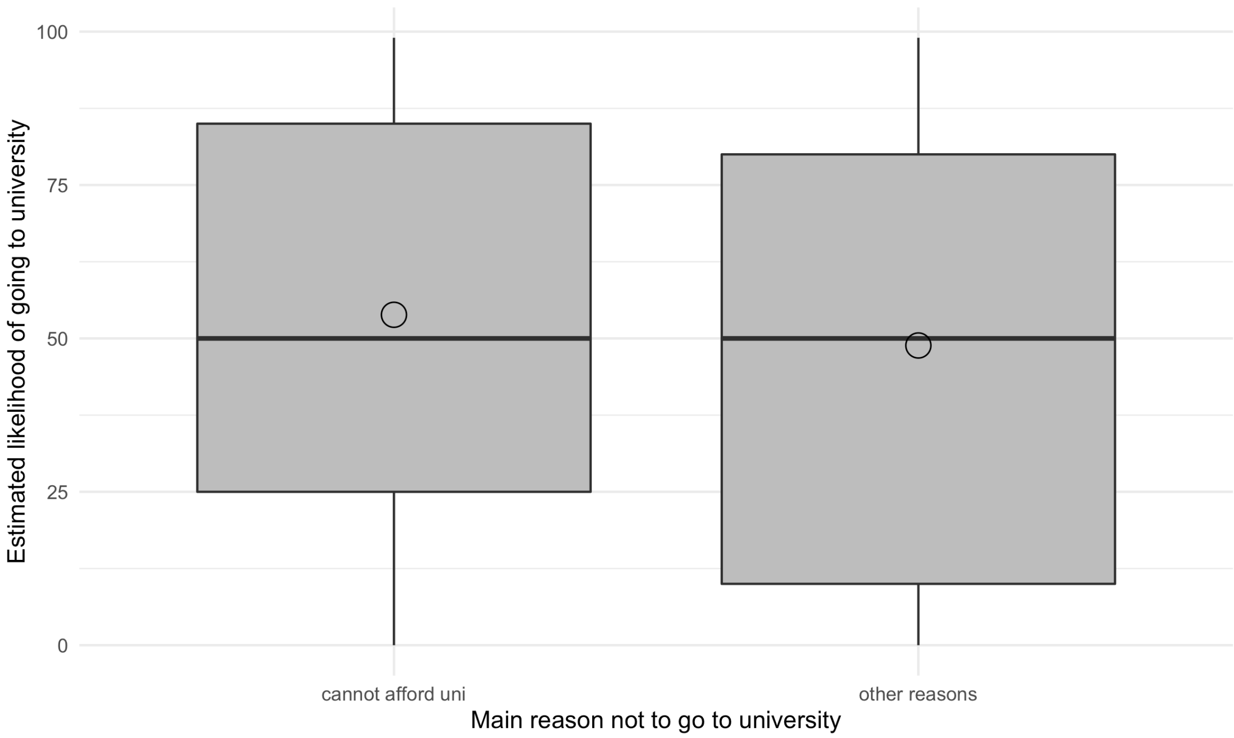

Figure 2. Boxplot of educational expectations by main reason not to go to university

Notes: Number of observations: 5,307 Inverse probability weights applied.

2.2 Economic preferences

Risk preferences are measured at the age 17 sweep by asking cohort members to choose between a hypothetical game in which they would win £240 with 50% chance or nothing, and a hypothetical payout between £132 and £24. The lower the safe payout cohort members choose over the bet, the more risk averse they are. Time preferences at age 17 are measured in a similar way by giving the alternative between a certain hypothetical payout of £50 in two months time and a hypothetical payout between £50 and £150 in four months time. This measures the level of *impatience* the cohort member shows. If the cohort member is very patient and does not mind waiting for the money and additional two months, they might choose £50 or £52 in four months over £50 in two months. The higher the amount that needs to be offered such that the cohort member prefers to wait another two months, the more impatient they are.

The obvious caveat of measuring economic preferences without actual payouts is that people might report a certain (potentially more risk loving, more patient) preference than if they were actually confronted with a question such as the ones described above in real life with real money. However, in a literature review, Camerer et al. (1999) find that monetary incentives barely change economic preferences, mainly reducing the variance of the measurements, not the mean. In the case of risk attitudes, some of the reviewed studies suggest subjects becoming more risk averse when real money is involved. Similarly, the measurement of time preferences appears not to be affected by monetary rewards (Madden et al. 2004). Another shortcoming of the way economic preferences are measured in the MCS is that the measure for risk aversion is less sophisticated than the widely applied one proposed by Holt and Laury (2002), although similar to Eckel and Grossman (2008). Moreover, risk and time preferences are only observed at one point in time while studies such as Deckers et al. (2017) use an average of multiple measures, further increasing the accuracy of the measure. Lastly, the external validity of economic preferences measured in survey or laboratory settings appears to be limited and at best weakly linked to outcomes hypothesised to correlate with risk or time preferences such as smoking (Galizzi and Miniaci 2016).

The next paragraphs describe how we create a measure for risk and time preferences from the survey data of the MCS.

2.2.1 Risk preferences

The MCS variable measuring risk attitudes is designed as follows. Cohort members are asked to state their preference between a bet – winning £240 with 50% chance and nothing in the remaining 50% of cases – and a safe payout between £132 and £24, decreasing in steps of 12. Once a cohort member prefers the bet over the safe payout, this value measures their attitudes towards risk.

To clarify this, it is important to understand the concept of risk aversion frequently used by economists. If one were to repeat the above-described bet (50% chance to win £240) many times, one would expect to win on average £120 each round. This is the *expected value* of the bet. This can be more formally expressed as the expected value of a bet, b, in which one gains a high prize, g, with probability p_g and one loses gaining the low prize, l, with probability p_l:

$$\mathrm{E}(b) = p_g \cdot g + \underbrace{\left(1 - p_g\right)}_{p_l} \cdot l. \tag{1}$$

While this is a useful concept in general, it does not describe human preferences in a single-round bet very well. As a solution, we use the Von Neumann–Morgenstern expected utility framework, in which individuals maximise their expected utility rather than the expected value. In the case of a concave utility function, this means that the difference between a prize of £10 and a prize of £110 results in a larger difference in utility from the prizes as the difference between prizes of £1,000 and £1,100.

In the context of the question being asked to cohort members to state their preference between a bet and a safe payment, they reveal something about their risk attitudes. This can be formalised as follows. Each cohort member i with utility function u_i can decide between a 50% chance to gain £240 or to take the safe payout s. If the expected utility of the bet is higher than the utility of the safe payout, the cohort member would choose the bet, otherwise the safe payout:[2]

$$u_i(s) \lesseqgtr 0.5 \cdot u_i(£240) + 0.5 \cdot u_i(0). \tag{2}$$

The more risk-averse an individual is, the smaller the safe payout, s, they would accept. Hence, we use information from this question asked to cohort members in the Age-17 MCS sweep to measure the degree of risk aversion. The lower the safe payout they would prefer over the 50-50 bet, the more risk averse the cohort member.

To create a meaningful variable from this survey data in order to conduct regression analyses, we quantify the level of risk aversion an individual expresses. Galizzi and Miniaci (2016) highlight that risk aversion is unlikely to linearly follow the value of the safe payout an individual chooses. Therefore, based on Galizzi and Miniaci (2016), we assume each expected utility maximising individual to have constant relative risk aversion (CRRA), with the isoelastic utility function

$$u_i(M) = \begin{cases} \dfrac{M^{(1-r_i)} - 1}{1 - r_i} & \text{for } r_i \neq 1 \\ \ln(M) & \text{for } r_i = 1, \end{cases} \tag{3}$$

where M represents a monetary prize and r_i represents the individual risk attitudes. An individual is risk averse for $r_i > 0$ and risk-taking for $r_i < 0$.

Using this utility function, we compute lower and upper bounds of r for each choice between lottery and safe payout. Table 1 the lower and upper bounds of r, r_l and r_u, for which an individual

[2] Often this representation includes the individual's wealth level, w_i, as part of the utility function. For reasons of simplicity and as this wealth level is often to be assumed to be 0 in applied research, we do not include it in the equation.

would choose the lottery of a 50% chance of £240 and 50% chance of £0 over the safe payout presented in the first column. The second column shows the difference in expected value between the lottery and the safe payout, negative values indicating the lottery has a lower expected value than the safe payout and positive values indicating the lottery having a larger expected value than the safe payout.

Table 1. Risk attitudes measured in the MCS

Smallest safe payout preferred over lottery	r_l	r_u
£132 $\prec$ lottery	$-\infty$	-0.16
£120 $\prec$ lottery $\prec$ £132	-0.16	0
£108 $\prec$ lottery $\prec$ £120	0	0.13
£96 $\prec$ lottery $\prec$ £108	0.13	0.24
£84 $\prec$ lottery $\prec$ £96	0.24	0.33
£72 $\prec$ lottery $\prec$ £84	0.33	0.42
£60 $\prec$ lottery $\prec$ £72	0.42	0.49
£48 $\prec$ lottery $\prec$ £60	0.49	0.56
£36 $\prec$ lottery $\prec$ £48	0.56	0.63
£24 $\prec$ lottery $\prec$ £36	0.63	0.69
lottery $\prec$ £24	0.69	∞

Notes: Each row represents the choice between a safe payout and the bet of winning £240 with 50% chance and £0 otherwise. Individuals with $r_l \leq r_i \leq r_u$ choose the lottery over the safe bet presented in the respective row.

In order to obtain a single value r_i for each cohort member instead of only assigning them to the intervals $[r_l, r_u]$, we run an interval regression. For this, we use a set of background variables X_i. The point estimates of the predicted values from the interval regression, r^{int}, possibly fall outside of the observed interval, $[r_l, r_u]$. To avoid this, we draw n times from the normal distribution $\mathcal{N}\left(r_i^{int}, se_i^{2^{int}}\right)$, where se_i^{int} denotes the standard error of the point estimates from the interval regression. Then we discard all values that fall outside the interval $[r_l, r_u]$. To estimate r_i, we then take the mean of the remaining values. In case all of the n drawn values fall above or below $[r_l, r_u]$, we estimate r_i to be equal to r_u or r_l, respectively.

In our own simulation studies, this approach has considerably improved the correlation between the estimated and real (observed only in intervals) risk attitudes parameter. While taking predicted values from an interval regression only is very useful in case of a strong correlation between the grouped outcome variable and the explanatory variables, the predictions become less accurate the weaker this link becomes.

2.2.2 Time preferences

The MCS also contains information about cohort members' time preferences, i.e. how much the cohort member prefers a payout to be sooner rather than later. The time preference measure is constructed as follows. Each cohort member is asked whether they would prefer a safe payout of £50 in two months time or a safe payout in four month time of $£(50 + x)$, where $x \in \{0,2,5,10,20,30,40,50,70,100\}$. The higher the extra payout necessary for the cohort member to prefer the payout in four months over the payout in two months, the stronger the *present bias* or *impatience*. Note that both payouts being set in the future avoids methodologically difficulties around time-inconsistent preferences (for an in-depth discussion of different measures for time preferences, see Cohen et al. 2020).

To translate each cohort member's survey answers into a measure of time preferences, we choose a framework based on Samuelson's classical discounted utility model (Samuelson 1937). In this framework, each individual has a *discount rate*, δ_i, with which they discount their utility of future monetary payouts. More formally, the cohort member prefers a payout in two months of 50£ over a payout in four months of $£(50 + x)$ if the following holds:

$$\begin{array}{rrl} 3 & \delta_i u_i(£50) & > \delta_i^2 u_i(£50 + x) \\ \Leftrightarrow & u_i(£50) & > \delta_i u_i(£50 + x). \end{array} \tag{4}$$

In order to estimate an individual's inter-temporal discount rate, δ_i, additional assumptions about the utility function, u_i, are needed. It is common in the literature to assume utility to be linear in the monetary payout (Lawyer et al. 2010; Cohen et al. 2020). However, this would not be in line with the concave utility function assumed to estimate risk attitudes as discussed in Section 2.2.1.

Therefore, in line with Ubfal (2016), we use the previously estimated cohort members' risk attitudes, r_i, which constitutes the curvature of the individual's utility function. Based on the estimated utility function, u_i, we estimate the individual inter-temporal discount factor, δ_i.

Similar to the MCS measurement of risk preferences detailed in Section 2.2.1, time preferences are measured in 10 categories. For each cohort member, i, we calculate the range of plausible discount factors, $\delta_i \in [\delta_{i,l}, \delta_{i,u}]$, that would result in the observed choice of x. Based on these estimated intervals, we estimate a single individual discount factor, δ_i, using the interval regression approach described above.

2.3 Socio-economic status

Household SES is a central component of many studies in educational economics (Boneva and Rauh 2017; Croll 2008; Declercq and Verboven 2015; Duarte, Ferrando-Latorre, and Molina 2018; Kajonius and Carlander 2017; Polidano, Hanel, and Buddelmeyer 2013; Ratshivhanda and Guvuriro 2018; Taylor and Yu 2009). Often researchers have to rely on available proxy measures for SES, such as the number of books at home (Yang Hansen, Rosén, and Gustafsson 2011; Wößmann 2005; Quintelier and Hooghe 2013). However, the MCS data we use for this study is rich in background variables and contains all the main measures of SES discussed by Galobardes, Lynch, and Smith (2007): parental education, (last held) occupation, permanent income and wealth. Moreover, additional indicators (e.g. eligibility for free school meals) are available (see Jerrim 2020 for a detailed discussion on the relationship between different proxy-measures of socio-economic status and Hobbs and Vignoles 2010 for a discussion of free school meals and family income).

For this study, we measure socio-economic status in two different ways. First, we use a set of variables capturing different aspects of a household's socio-economic status. This includes a household's permanent income, income volatility, housing situation, number of worklessness spills, single parenthood, and highest parental education. Using this approach, the individual contribution of each SES dimension to the outcomes of interest can be measured. However, multicollinearity between the different SES indicators as well as with control variables might make it difficult to disentangle the effect sizes of each variable, thwarting a clear interpretation of the results.

In a second approach, we combine all of the aforementioned relevant measures for socio-economic status into a single index. While now we cannot distinguish between the different contributors of SES, having a single indicator allows for a more direct interpretation of the results. The method we use to construct this index is principal component analysis. This technique is fully data-driven and identifies the dimension in the dataset which explains most of the variance (and subsequently dimensions with smaller contributions to overall variance). We the use the dimension explaining the largest amount of variance, i.e. around 56%, in the above mentioned variables.

2.4 Background variables

The Millennium Cohort Study is a rich survey dataset with hundreds of data points measuring different aspects of the household cohort members grow up in. By including this information, we aim at reducing any potential bias in our estimates as well as possible. In the following, we discuss which household characteristics we use as control variables and how we include them in our subsequent analyses.

Demographics

As demographic variables, D, we consider a set of background variables. For one, the region in which the cohort member lives. In case this changes over the course of the MCS, we choose the region in which the cohort member has lived for the majority of MCS sweeps. Next, the MCS consists of a sampling stratum – advantaged or disadvantaged neighbourhood and ethnic minority neighbourhood (England only). While every cohort member we include in our analysis has to participate in the age 17 sweep, we control for the number of sweeps missed up until that point. Furthermore, we include some cohort member specific characteristics about their gender or sex and their ethnicity.

Parental health

Whether or not cohort members think they will go to university may be influenced by household environment other than SES. For example, if parents have health issues, this affects the decision making process and, therefore, educational expectations. When controlling for parental health, we construct two variables. First, each carer is asked to assess their personal health level, ranging from 'poor' to 'excellent'. In the first two sweeps, health is measured in four categories, the remaining sweeps provide five categories to choose from. To ensure comparability across sweeps, we assign value 1 for the lowest category, poor, and 5 for the highest category, excellent, and fit the additional categories in between spaced equally. More formally, we construct the parental health measure as follows. To account for parental health in household i, we create the long-term health score, $\mathcal{H}_i$, from the health levels all carers in the household report, $h_{i,t}^j$, where $j \in \{m, p\}$ denotes main carer and their partner, respectively, and $t \in \{1,2,\dots,7\}$ denotes the sweep. We divide the household's total health score by the total number of household observations, i.e. $\mathcal{I}(i,j,t)$ takes the value 1 if for household i, carer j and sweep t the health level is observed, and 0 otherwise. Hence:

$$\mathcal{H}_i = \frac{\sum_t \sum_j h_{i,t}^{j}}{\sum_t \sum_j \mathcal{I}\,(i,j,t)} \tag{5}$$

Therefore, the highest household health level in this measure is 5 and the lowest possible value is 1. The second health variable is smoking behaviour which indicates whether or not the household ever was a smoking household during the course of the MCS.

Educational investments

Parents can invest their time and money in their child's education. These investments vary substantially depending on age, ranging from childcare and reading to the child for young children to homework help and fee-paying schools for older kids. To account for these investments, we use a set of variables from across sweeps and conduct a principal component analysis to create a separate time investments and monetary investments variable.

Cohort member's cognitive ability

Throughout the MCS, cohort members are assessed in terms of their cognitive ability. In the MCS, these scores are collected from the age of three onwards, with every sweep containing age-appropriate cognitive measures. Furthermore, they cover a wide range of abilities ranging from vocabulary to pattern recognition and numeric skills. In order to create a single overall cognitive ability score for cohort members, A_i^{CM} we proceed as follows. First, we take the so-called standard scores or T-scores which take into account the individual cohort member's age at the time of testing as age varies considerably within each MCS sweep. Second, we standardise each of the ten scores to have mean 0 and standard deviation 1, which ensures that in creating a composite score we do treat the information provided by each score equally. Third, we impute missing values. Some cohort members do not participate in all of the cognitive assessments. We compute the quantile a cohort member falls into in those cognitive assessments observed. For each cohort member with missing values we then impute the score consistent with the observed quantile. In a final step, we use the standardised and imputed scores and perform a principal component analysis. As a composite cognitive score, A_i^{CM}, we use the first principal component, which alone explains around 50% of the variance in the ten cognitive measures.

Strengths and Difficulties

Each MCS sweep from age three onwards contains the Strengths and Difficulties Questionnaire (SDQ). In these questionnaires, four categories are assessed: emotional symptoms, conduct problems, hyperactivity, and peer relationship problems. In each of these four categories, ten points can be scored with higher scores indicating more difficulties. The sum of these four categories is reported as total difficulties. We construct our SDQ score to be the average of total difficulties scored over the course of the MCS.

2.5 Missing data

The age 17 sweep of the MCS takes place approximately 16 years after the interviews for the first sweep. During this time, a considerable proportion of cohort members have dropped out of the MCS, so-called ‘attrition’ or ‘mortality’. Therefore, while the MCS was originally designed to be representative of the population of children born in the UK in the year 2001, this does not naturally hold for those cohort members still participating in the study in 2018. In previous cycles up until the age 14 sweep, the MCS data contained weights accounting for both survey design (some demographics were ‘oversampled’) and attrition. These weights, however, are not available for the age 17 sweep.

Another source of missing data at age 17 is due to multiple questionnaires being administered to both the household (e.g. parents) and the cohort member. While a household can be responsive in general, the cohort member may have decided not to take part in the questionnaire themselves or to skip certain questions, resulting in missing data for educational expectations or economic preferences.

Third, some households may skip one or more sweeps before being responsive again at the age 17 sweep. This does not affect our analyses in principle, but this requires me to exclude these sweeps for the computation of aggregate measures for SES, parental health, cohort members’ cognitive ability, and more.

We address these sources of missing data in different ways. The previously mentioned missing data in sweeps prior to the age 17 sweep is the least problematic. As described previously, we can often simply exclude these measures from the calculation of average measures such as health or permanent income. For composite measures based on the principal components of multiple variables, missing values need to be imputed. Depending on variables, we either use the mean, mode (i.e. most commonly observed category), or – in case of cognitive scores – our imputing based on the relative performance in observed sweeps.

We address missing values from attrition and non-response to questions the same way using inverse probability weights (IPWs). To construct these IPWs, we indicate whether a cohort member present at a previous sweep is used in our final analysis or not. Then, we calculate the propensity with which a MCS cohort member is part of our final sample, given observed background characteristics. This is done using the predicted values from a logistic regression. We then take the inverse of these predicted probabilities. Finally, to ensure our final sample is representative as possible of children born in the UK in 2001, we combine the inverse probability weights with the original sampling weights provided with the MCS. If not stated otherwise, we use these weights in all descriptive statistics as well as regression analyses, ensuring our results are representative of young people in the UK.

2.6 Descriptive statistics

After removing all cohort members that are not present at the age 17 sweep or have missing values in either socio-economic status, risk attitudes, time preferences or educational expectations, a total of 6,382 observations remain for further analysis.

First, we look at the outcome variables of interest. The main outcome variable is educational expectations in the MCS age 17 sweep. Recall that 'educational expectations' refers to cohort members reporting their estimate of how likely they think it is that they go to university on a 0 to 100 percentage scale. As previously shown in Figure 1, the distribution of educational expectations is particularly heavy around 0%, 50%, and 100%.

A total of 5,307 cohort members reporting educational expectations below 100% answered questions about the possible reasons for them not to attend university. Of these cohort members, around 13% report the *main* reason for them not to go to university would be that they or their family cannot afford that. The distribution of educational expectations among financially constrained pupils is very similar to that among pupils who name other reasons as the main reason not to go to university. For more details, see Figure 2.

Table 2 shows descriptive statistics for all variables included in our analysis as explanatory variables of interest or control variables. In creating this table, we apply the combined sampling and inverse probability weights (see above and Appendix 7 for a detailed discussion on the construction of weights). As the variables measuring SES, educational investments, and cognitive aptitude are constructed using a principal component analysis, the distribution of these variables, including their mean, do not allow for any meaningful interpretation. These variables are included in the descriptive table in their original form but are being standardised (mean 0, standard deviation 1) for further analysis.

Table 2. Descriptive statistics

Variable	mean	sd	min	max
SES[a]	0.328	1.758	-4.7	3.784
r (risk preference)	0.224	0.313	-0.344	0.853
δ (impatience)	0.75	0.207	0.168	1.12
Region				
South East	14.7%			
London	11%			
North West	10.9%			
East of England	10.4%			
Yorkshire and the Humber	8.5%			
South West	8.4%			
West Midlands	8%			
East Midlands	7.3%			
North East	3.5%			
Scotland	8.8%			
Wales	5.1%			
Northern Ireland	3.5%			
Sex (cohort member)				
Male	51.1%			
Female	48.9%			
Ethnicity (cohort member)				

White	87.4%			
Pakistani & Bangladeshi	4%			
Indian	1.9%			
Black	2.5%			
Mixed	3.1%			
Other	1.2%			
Number of Sweeps (until age 14)	5.729	0.591	2	6
Parental health score	3.722	0.656	1.19	5
Ever smoking household				
Yes	53%			
No	47%			
Monetary investments[a]	0.132	1.451	-0.901	8.081
Time investments[a]	0.017	1.518	-5.623	3.211
Strengths and Difficulties	8.148	4.683	0	31.5
Cognitive aptitude score[a]	0.199	2.157	-9.376	6.857

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied.

[a]Composite variables created by principal component analysis.

The economic preferences variables – risk attitude and time preferences – need to be interpreted in the context of their economic meaning. Recall that from Equation 3, r is defined as follows:

$$u_i(M) = \begin{cases} \dfrac{M^{(1-r_i)} - 1}{1 - r_i} & \text{for } r_i \neq 1 \\ \ln(M) & \text{for } r_i = 1. \end{cases} \tag{6}$$

Negative values of r result in a convex function resulting in risk seeking behaviour. Conversely, positive r corresponds with a concave utility function causing risk aversion. Hence, the average value of r measured in the MCS of 0.22 corresponds to moderate risk aversion. In the context of the lottery choice given in the questionnaire, this level of risk aversion would make the average cohort member indifferent between a 50% chance of £240 or a safe payout of £98.

Further, recall that the time preference measure, δ, was introduced in Equation 4 as follows:

$$\delta_i = \frac{u_i(£50)}{u_i(£50 + x)}, \tag{7}$$

where x is the amount needed to make a cohort member with discount factor δ_i indifferent between receiving £50 in two months time or £50 plus x in four months' time. For the average cohort member, this discount factor is 0.75. Also using the average r of 0.22, this means that such an individual is indifferent between £50 in two months and £71 in four months.

For more information about the distribution of risk attitudes and time preferences in the MCS sample, see Appendix 6.

3. Methods

In this section, we introduce the methods we use to understand the associations between socio-economic status and economic preferences with educational expectations.

The key variable of interest, long-term socio-economic status, is essentially a time-invariant construct: as we are interested in the association between SES during childhood on educational expectations at age 17, this variable does not change over time. The other key explanatory variables, risk attitudes and time preferences, are measured at age 17. Therefore, the methods we apply to understand the formation of educational expectations reflect the nature of socio-economic status and isolate the role SES and economic preferences play conditional on a rich set of control variables.

Thanks to the detailed information provided in the MCS, our estimates account for many often unobserved factors, including parental health, education, income, home ownership, the cohort members' cognitive performance, sex, ethnicity and more. In the remainder of this section, we introduce the methods we apply to measure the association between socio-economic status, economic preferences and educational expectations.

3.1 Unconditional associations

The methods detailed below aim to measure the association between socio-economic status, risk attitudes, and time preferences, on the one hand, and educational expectations on the other hand. To do so, we start by focussing on each of the three explanatory variables of interest at a time, not yet including any background characteristics. These correlations serve as a benchmark.

We estimate these correlations using a linear regression with educational expectations as the dependent variable and SES, risk attitudes, and time preferences, respectively, as sole explanatory variables:

$$\begin{aligned}
EduExp_i &= \beta_0^{SES} && +\beta_1\, SES_i &&&&&& +\epsilon_i^{SES} \\
EduExp_i &= \beta_0^{r} &&&& +\beta_2\, r_i &&&& +\epsilon_i^{r} \\
EduExp_i &= \beta_0^{\delta} &&&&&& +\beta_3\, \delta_i && +\epsilon_i^{\delta}
\end{aligned} \tag{8}$$

Next, we aim to understand better how these three explanatory variables interact in their association with educational expectations. We do so by using linear regressions combining pairs of two explanatory variables as well as all three explanatory variables and examining how the associations are impacted by different combinations.

$$\begin{aligned}
EduExp_i &= \beta_0 && +\beta_1\, SES_i && +\beta_2 r_i &&&& +\epsilon_i \\
EduExp_i &= \beta_0 && +\beta_1\, SES_i &&&& +\beta_3 \delta_i && +\epsilon_i \\
EduExp_i &= \beta_0 &&&& +\beta_2 r_i && +\beta_3 \delta_i && +\epsilon_i \\
EduExp_i &= \beta_0 && +\beta_1\, SES_i && +\beta_2 r_i && +\beta_3 \delta_i && +\epsilon_i
\end{aligned} \tag{9}$$

3.2 Conditional Associations

From the correlation analysis, we move on to include further background variables to control for various individual and household characteristics. This is to measure the association between the three explanatory variables of interest – socio-economic status, risk attitudes, and time preferences – and the cohort members' educational expectations as accurately as possible, eliminating all observable confounders.

Table 3 shows which groups of variables are included in each model. There are four groups of control variables we consider. First, demographic information containing country and deprivation, region as well as the cohort members' sex and ethnicity. Second, parental health is constructed as detailed in Section 2. Third, educational investments, consisting of two composite measures, one for monetary and one for time investments. Fourth, a behavioural score based on the strength and difficulties questionnaire and a cognitive score based on a combination of all cognitive assessments – both between age three and 14.

Model M1 contains just the main explanatory variables (SES, risk attitudes, time preferences) and demographic information. Next, in model M2 we add parental health, educational investments are included in model M3. Finally, in model M4 we add both behavioural and cognitive scores.

Table 3. *Overview of regression analyses*

		Model		
Control		M1	M2	M3
Demographics	D	x	x	x
Region				
Stratum				
Sex				
Ethnicity				
MCS sweeps missed				
Parental Health	H	x	x	x
Average health score				
Smoking habits				
Educational Investments	I	–	x	x
Time investments				
Monetary investments				
Behavioural and cognitive scores	C	–	–	x
SDQ score				
Composite cognitive scores				

Hence, the regression models look as follows:

$$EduExp_i = \underbrace{\beta_0 + \beta_1 \mathrm{SES_i} + \beta_2 \mathrm{r_i} + \beta_3 \delta_\mathrm{i} + \gamma_1 \mathrm{D_i} + \gamma_2 \mathrm{H_i}}_{\mathrm{M1,M2,M3}} \underbrace{+\gamma_3 \mathrm{I_i}}_{\mathrm{M2,M3}} \overbrace{+\gamma_4 \mathrm{C}}^{\mathrm{M3}} + \epsilon_\mathrm{i} \tag{10}$$

For a less biased estimation of β_1, β_2 and β_3, the error term, ϵ, needs to have little correlation with the outcome variable, given all included explanatory variables. Therefore, model M3 can be expected to have smallest bias since a wide range of external, household, and individual characteristics are covered. However, factors not included in our analysis such as an individual's general motivation, the ability to translate cognitive aptitude into school grades[3], or how much an individual enjoys learning new things, may lead to the error term to be correlated with the outcome

[3] See Appendix 8 for regression results including GCSE grades for a subset of English students.

variable. Therefore, it is important to note that despite the rich set of background data included, we do not make causal claims.

Furthermore, we look at what socio-economic status, risk attitudes and time preferences *add* to the formation of educational expectations between the age of 14 and 17. We do this by controlling for educational expectations at age 14:

$$\mathrm{EduExp}_i^{\mathrm{age17}} = \beta_0 + \beta_1 \mathrm{SES}_i + \beta_2 r_i + \beta_3 \delta_i + \underbrace{\gamma X_i}_{see\ M3} + \rho \mathrm{EduExp}_i^{\mathrm{age14}} + \epsilon_i \tag{11}$$

By conditioning the educational expectations at age 17 on educational expectations observed at age 14, we can draw inferences on whether SES, risk attitudes and time preferences play a role beyond the age of 14. We refer to this as model M4.

Finally, in model M5 we alter the model specifications of M3 (all control variables, no educational expectations at age 14) by replacing the SES measure constructed as described in Section 2 with its individual components. This is to better understand which element of socio-economic status might be most important in explaining differences in educational expectations. These elements are permanent income, income volatility, proportion of time the household lives in a owned home instead of renting, proportion of time the household is workless or a single-carer household, and highest parental education level. Model M5 also serves as a robustness checks for the association between economic preferences and educational expectations. In case the composite SES variable omits the correlation between risk or time preferences and one of the SES contributors, this can be detected in model M5.

Robustness checks

As shown in the histogram in Figure 1, educational expectations are concentrated at the margins at 0% and 100%. The linear models introduced above do not take into account the censored nature of the data and allow for predicted values to fall outside the 0–100 percent range. Therefore, we present the result from a Tobit model in Table 11 (Appendix 8) as a robustness check. Furthermore, for English pupils, we include GCRE exam results as a control variable in robustness checks in Table 12. Last, we use simplified binary measures for risk attitudes and time preferences based solely on the MCS variables and not on the estimated shape of cohort members' utility functions (Table 13).

3.3 Reasons not to go to university

All cohort members who report educational expectations below 100% are then asked what their main reason not to go to university is. As this variable is binary, we estimate which of the explanatory variables – SES, risk attitudes, and time preferences – are associated with naming the cost of university education as the main reason not to go to university using three different logistic regressions:

$$logit(Reason_i) = \underbrace{\beta_0 + \beta_1 SES_i + \beta_2 r_i + \beta_3 \delta_i}_{R1,R2,R3} \overbrace{+\gamma_1 D_i + \gamma_2 H_i + \gamma_3 I_i + \gamma_4 C}^{R2,R3} \underbrace{+\xi EduExp_i}_{R3} + \epsilon_i \quad (12)$$

As the above equation shows, in the base Model R1 we include all three explanatory variables of interest – SES, risk attitudes, and time investments. Model R2 further contains all background variables as also controlled for in Model M4. Finally, in Model R3 we also control for educational expectations. As mentioned in Section 2.6, educational expectations in those cohort members who mention monetary reasons as the main reason not to go to university tend to be higher than in cohort members who do not mention monetary reasons.

4. Results

4.1 Unconditional associations

First, we begin the analysis of the association between socio-economic status, risk attitudes and time preferences with educational expectations by exploring correlations. This is to understand how each individual explanatory variable relates to the likelihood with which 17 year olds think they go to university (model C1 – C3). Building on this, we explore how these associations change once we account for other explanatory variables (model C4 – C7).

Table 4 shows models C1, C2 and C3 in which we regress each explanatory variable individually on educational expectations without controlling for any background characteristics. Model C1 shows a clear positive correlation between socio-economic status and educational expectations. An increase in SES of one standard deviation is associated with an increase in educational expectations of more than nine percentage points. This relationship is significant at the 0.1% level.

Furthermore, SES alone – not accounting for any other background characteristics – explains more than 8% of the variance in educational expectations among cohort members. Model C2 estimates there to be no statistically significant relationship between risk attitudes and educational expectations. However, the estimates from Model C3 suggest that patience (larger δ) as positively associated with educational expectations ($p < 0.001$). In particular, if delta increases by 0.2 (around one standard deviation), this correlates with an increase in educational expectations of almost five percentage points.

Table 4. Unconditional associations of SES, risk attitudes and time preferences with educational expectations

Variable	C1	C2	C3
SES	9.413***		
	(0.666)		
Risk attitudes r		-1.217	
		(1.957)	
Time preferences δ			24.58***
			(2.795)
R^2	0.084	0.000	0.019
Standard errors in parentheses			
$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$			

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

Next, Table 5 shows models C4 – C7. In these, we regress different combinations of two explanatory variables on educational expectations (C4 – C6) and all three explanatory variables together (C7). Again, we do not control for any background characteristics. In these different models, both SES and time preferences remain strongly and significantly associated with educational expectations. Again, risk attitudes are not significantly associated with educational expectations with the expectation of Model C6, in which only risk and time preferences were regressed on educational expectations. The magnitudes of these associations are similar but smaller to the ones shown in Table 4.

Table 5. Bivariate associations of SES, risk attitudes and time preferences with educational expectations

Variable	C4	C5	C6	C7

SES	9.419***	9.040***		8.978***
	(0.667)	(0.675)		(0.678)
Risk attitudes r	0.419		-5.585**	-3.005
	(1.779)		(2.024)	(1.847)
Time preferences		19.28***	26.68***	20.45***
		(2.497)	(2.939)	(2.614)
R^2	0.084	0.095	0.021	0.096

Standard errors in parentheses
$* \, p < 0.1$, $** \, p < 0.05$, $*** \, p < 0.01$

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

Overall, these results indicate a potential link between socio-economic status and economic preferences – in particular time preferences – and educational expectations. The analysis using different subsets of the three explanatory variables has also shown that SES and time preferences are independently correlated with educational expectations with both regression coefficients decreasing only slightly when regressed in combination.

4.2 Conditional associations

In the following, we present the results from our regression analyses when including control variables. As detailed in Section 3, we begin by stepwise adding more background information in models M1 until M3. Table 6 shows the estimates for the associations between SES, risk attitudes, and time preferences with educational expectations, adding demographical, health, educational investment, and cognitive and behavioural scores.

In all four models, socio-economic status and time preferences are statistically significantly associated with educational expectations at the 0.1% level, while no link can be measured for risk attitudes. In Model M1, an increase in SES by one standard deviation is estimated to be linked to 9.5 percentage points higher educational expectations. When including parental health and educational investments (Model M2), the point estimate goes down to around eight percentage points. Similarly, increasing the time preference parameter, δ, by 0.1 (around half a standard deviation) increases educational expectations by 1.6 percentage points (M1 & M2). However, when including cognitive ability and behavioural issues in the analysis, the point estimate for the association of socio-economic status is reduced by more than half to around four percentage points for a standard deviation increase in SES. The change in our estimate for time preferences is less pronounced: the association measured in M3 estimates that an increase in δ (more patient) by one standard deviation increases educational expectations by 2.5 percentage points.

Previous research has shown that economic preferences are correlated with cognitive ability (Dohmen et al. 2010). Therefore, observing the association between patience and educational expectations change when including cognitive measures is unsurprising. Dohmen et al. (2010) find ability pupils to be more patient. Also, universities select students based on their ability such that high ability students are more likely to meet the criteria to enter higher education. Hence, when including only economic preferences as a regressor and not cognitive ability as a control variable, this would overestimate the association between economic preferences and educational expectations.

Table 6. Conditional associations of SES, risk attitudes, and time preferences with educational expectations at age 17

Variable	M1	M2	M3
SES	9.492***	8.194***	3.914***
	(0.719)	(0.700)	(0.617)
Risk attitudes r	-3.217	-2.838	-1.783
	(1.766)	(1.721)	(1.602)
Time preferences δ	16.04***	15.55***	12.58***
	(2.581)	(2.549)	(2.320)
Demographics	x	x	x
Parental Health	x	x	x
Educational Investments	–	x	x
Behavioural and cognitive	–	–	x
R^2	0.195	0.205	0.288

Standard errors in parentheses
$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

Figure 3 shows the relationship between SES, time preferences and predicted educational expectations as modelled in M3. Assuming a hypothetical average individual with the most common background characteristics – White, female, from an advantaged neighbourhood in the South-East of England – we show the predicted educational expectations (y-axis) for different time preferences x-axis) and SES levels (lines). The solid red line represents cohort members from a high SES background (75th percentile), the green dashed line shows predicted values for median-SES, the dotted blue line represents low SES (25th percentile). This figure highlights the strong difference in educational expectations depending on SES level and time preferences. All three lines show how educational expectations increase in levels of patience. More patient cohort members from a medium-SES background are predicted to fully compensate for their SES disadvantage if their time preference, δ, increases by 0.1 – equivalent to half a standard deviation. On the other hand, high-SES individuals with very low δ (i.e. very impatient) at around the 10th percentile are predicted to have almost the same educational expectations as very patient (90th percentile) cohort members from low-SES backgrounds.

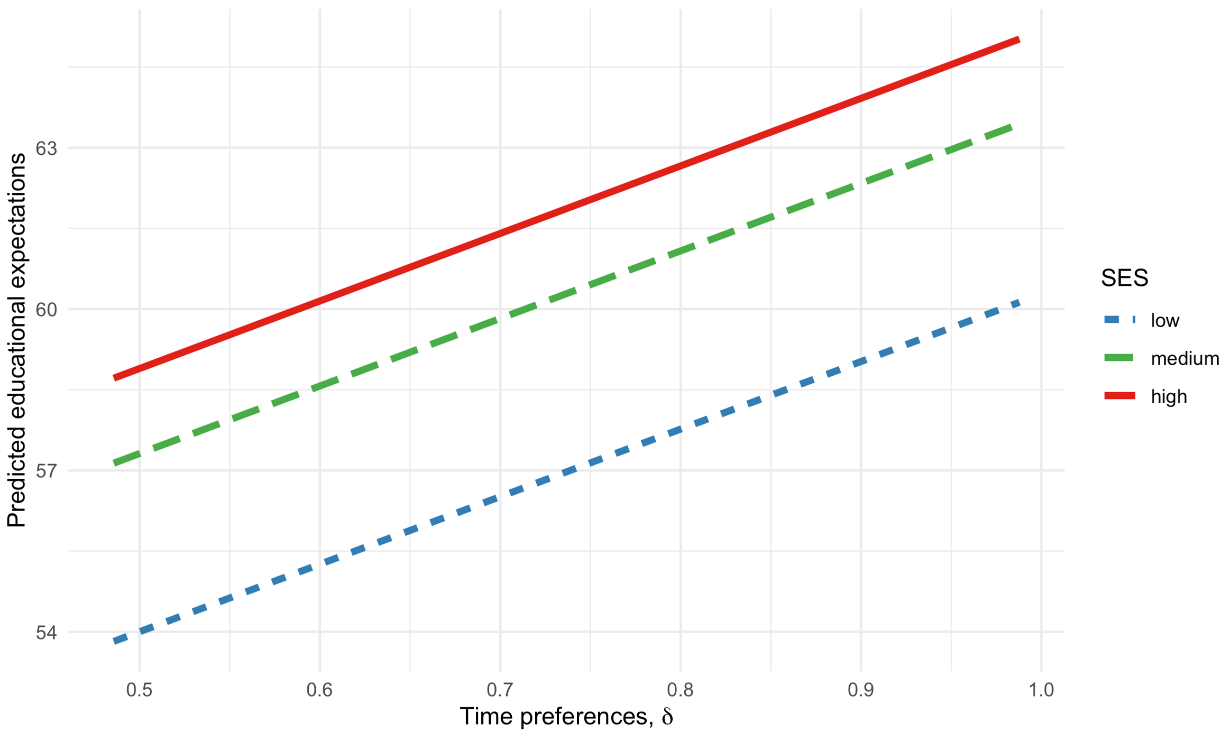

Figure 3. Predicted educational expectations by time preferences and SES

Notes: Predicted educational expectations computed for a White, female cohort member from an advantaged neighbourhood in the South-East of England, non-smoking household. Low, medium, and high SES corresponds to 25th percentile, median, and 75th percentile, respectively. All other variables held at average.

Next, in order to better understand the impact SES and economic preferences have on the formation of educational expectations, we control for educational expectations at age 14. In Table 7, we present the results from Model M3 for those 5,884 cohort members for whom we observe educational expectations at age 14 and 17, as well as the results from Model M4. Our results indicate that SES and time preferences are associated with educational expectations at age 17 even when controlling for educational expectations at age 14. In particular, consider an example with two cohort members who have the same educational expectations at age 14 and have identical other background characteristics. The only difference being that cohort member A has a socio-economic status of one standard deviation higher than cohort member B. Our results suggest that at age 17, A estimates the likelihood of going to university to be around 2.7 percentage points higher than B's estimate. Similarly – all other things equal – a one standard deviation more patient individual with same educational expectations at age 14 estimates the likelihood of going to university at age 17 at 2.2 percentage points higher than a more impatient individual.

Table 7. Conditional associations with educational expectations at age 17 controlling for educational expectations at age 14

Variable	M3	M4
SES	3.850***	2.653***
	(0.664)	(0.676)
Risk attitudes r	-1.164	-0.753
	(1.752)	(1.649)
Time preferences δ	12.04***	10.82***
	(2.501)	(2.338)
Educational expectations at age 14		0.475***
		(0.0206)
R^2	0.293	0.399
Standard errors in parentheses		
$* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$		

Notes: Number of observations: 5,884. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

Last, we examine the individual contribution of each component of the composite SES indicator. Recall that the SES measure is a composite measure consisting of permanent income, income volatility, home ownership, worklessness, single-parenthood and parental education. Table 8 shows the association of economic variables (1), worklessness and single parenthood (2), parental education (3) and a combination of all of these (4) with educational expectations. Across these regressions, different variables show to be statistically significant at times. The pattern visible in

(1), (2), and (3) is that income, living in a two-parent household, and high education are positively associated with higher educational expectations. However, the estimates in (4) can be misleading due to the strong correlation between them (multi-collinearity). Therefore, we show the F-statistic for a test of joint significance at the bottom of the regression table. In all four models, we find that the SES measures included are highly significantly associated with educational expectations at age 17. Furthermore, regardless of which SES measures are included, our estimates for the economic preferences measures are robust.

Table 8. Conditional associations of SES components and economic preferences with educational expectations

Variable	(1)	(2)	(3)	(4)
Permanent income (log)	14.97***			15.07***
	(2.043)			(2.471)
Income volatility	0.0168			-0.336
	(0.563)			(0.561)
Home ownership rate	-2.576			-0.840
	(1.569)			(1.624)
Worklessness rate		2.782		11.27***
		(2.197)		(2.770)
Single-carer rate		-		-3.034
		(2.212)		(2.291)
Overseas qual only			-0.983	-1.099
			(4.916)	(4.833)
NVQ level 1			-1.891	-1.656
			(4.223)	(4.121)
NVQ level 2			-4.122	-4.322
			(3.523)	(3.648)
NVQ level 3			0.126	-0.992
			(3.644)	(3.864)
NVQ level 4			5.425	2.450
			(3.229)	(3.434)
NVQ level 5			8.845**	4.405
			(3.328)	(3.602)
Risk attitudes r	-1.792	-1.802	-2.032	-1.713
	(1.604)	(1.592)	(1.606)	(1.607)
Time preferences δ	12.70***	13.03***	12.62***	12.29***

	(2.297)	(2.333)	(2.353)	(2.280)
R^2	0.293	0.283	0.292	0.302
F-statistic (joint test of SES	24.51	5.92	12.45	12.35
$Prob > F$	0.0000	0.0029	0.0000	0.0000

Standard errors in parentheses
$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

Robustness checks

Robustness checks indicate that both changing the model specifications to a Tobit model as well as including GCSE results as control variables reduces point estimates for SES and time preferences, but both remain statistically significant. Similarly, using a categorised measure for risk attitudes and time preferences does not alter our estimates for SES. Furthermore, there remains no association between risk attitudes and educational expectations and a positive relationship for time preferences.

4.3 Reasons not to go to university

All cohort members reporting to be less than 100% sure to go to university are asked what their main reason for not attending university would be. Possible answers include not having good enough grades, preferring to get a job, or that they and their family cannot afford to pay for a university education. Around 13% of cohort members say the main reason for them not to go to university would be money.

Table 9 shows the estimates of the association between SES, risk attitudes and time preferences with the likelihood for cohort members to mention money as the main reason for them not to attend university. In R1, not controlling for any background characteristics, we find that cohort members with one standard deviation higher SES are 2.7 percentage points less likely to report money as their main reason. Furthermore, we observe a statistically significant ($p < 0.05$) positive association between patience (higher δ) and money being the main reason not to attend university. In R2, we control for all observed background characteristics. In this model, we estimate the association between SES and reasons not to attend university to be around -2.1. Our estimate for time preferences is not statistically significant in this model. Lastly, Model R3 controls for educational expectations at age 17. Again, an increase in SES of one standard deviation is associated with a decrease in the likelihood to report monetary reasons as the main cause not to attend university of 2.5 percentage points.

Table 9. Main reason not to attend university

Variable	R1	R2	R3
SES	-0.0276***	-0.0211**	-0.0251**
	(0.00597)	(0.00762)	(0.00767)
Risk attitudes r	-0.00100	-0.00229	-0.0000862
	(0.0199)	(0.0195)	(0.0197)
Time preferences δ	0.0666*	0.0489	0.0384
	(0.0298)	(0.0299)	(0.0298)
Educational expectations (age 17)			0.000998***
			(0.000189)
Demographics	–	x	x
Parental Health	–	x	x
Educational Investments	–	x	x
Behavioural and cognitive scores	–	x	x
Standard errors in parentheses			
$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$			

Notes: Number of observations: 5,307. All reported coefficients are average marginal effects. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis.

In summary, these results indicate that adolescents from a lower SES background are significantly more likely to expect not to go to university for financial reasons. This holds true even when controlling for cognitive and behavioural scores and other background characteristics. The point estimates suggest that lowering SES by one standard deviation makes in 2–3 percentage points more likely for money to play a role in university attendance. In the context of only around 13% of 17 year olds naming financial reasons as their main reason, low SES is a very strong predictor of money being an important factor in educational decisions. While not entirely unexpected as SES is hugely associated with household income and wealth, this result highlights that money is a key factor in keeping disadvantaged children from pursuing a university education.

However, we do not find risk attitudes and time preferences to be associated with money as the main reason not to attend university. The absence of an association between risk attitudes and ‘money as reason’ contrasts the narrative that more risk averse individuals prefer to avoid student fees and therefore do not go to university. Together with previous results, risk aversion appears to be neither associated with educational expectations nor the reasoning not to go to university. This indicates that the student financing system in the UK may be successful at buffering concerns of financial risks associated with student fees. However, as both risk and time preferences are measured using only one set of questions, measurement error and resulting attenuation bias could be driving this result.

The mechanism via which time preferences are expected to influence behaviour is through *impatience*: high valuation of present utility compared to future utility. On the other hand, financial concerns about the cost of higher education are not related to the timing (after graduation) of the reward (higher earnings). Hence, finding no association between impatience and financial concerns around attending university – conditional on individual and household background characteristics – is in line with our hypotheses.

5. Conclusion

Overall, our results paint a clear picture: the socio-economic status in which a young person grows up as well as the level of patience are strongly associated with educational expectations; however, risk attitudes don’t contribute to the formation of educational expectations. The magnitude of these associations suggests that both SES and patience are major contributors to the belief of going to university and may subsequently result in the decision of going to university. This holds true even when controlling for comprehensive cognitive measures from age three until 14. Hence, given all observable characteristics, including economic preferences, SES matters; and given all observable characteristics, including SES, patience matters. Furthermore, we observe that lower SES cohort members are substantially more likely to report the money as the main reason keeping them from going to university. Moreover, our finding that risk aversion is not linked to lower educational expectations due to financial concerns indicates that the UK student financing system may successfully buffer financial concerns around student fees.

The main limitation of this study is that – despite the rich set of control variables – the causal link remains somewhat questionable. Partly, this is due to the nature of measures such as SES. Socio-economic status is likely to not change much during adolescence for many people. Therefore, we cannot meaningfully apply econometric methods exploiting differences in SES. Similarly, economic preferences may be formed through a long period in childhood and adolescence and be relatively fixed at the age of 17. Furthermore, despite the background information we can rely on for our analysis being very detailed and comprehensive, certain possible confounders are not part of our analysis. Another shortcoming of this research is that – despite the likely link between educational expectations and future decision making – we cannot observe actual educational decisions, yet. Only in a few years time will MCS data be able to verify if the link we observe between SES and impatience with educational expectations prevails into the decision of whether or not to go to university.

As our results are robust against several model specifications in our analyses, it is reasonable to assume that improving SES during childhood also improves educational expectations – even if it doesn't have an impact on any other factors such as cognitive ability. Similarly, making an individual more patient alone contributes to higher educational expectations. Assuming that this results in lower SES and more impatient youths to be less likely to apply for university after finishing school, this has some potential implications for policy makers to reduce the gap in university attendance.

One possible reason for lower educational expectations in low SES individuals is the lack of role models. If neither their parents nor their friends' parents went to university, this in itself might be a deterrent. Mentoring initiatives in which university students peer up with disadvantaged children can effectively help young people find their path in post-secondary education (Resnjanskij et al. 2021). One channel through which this mentoring programme improves low-SES pupils' educational outcomes is by making them more patient. Raising awareness of both teachers and parents to address the benefits of considering future improvements in quality of life might further contribute to improving educational attainment of otherwise equally capable but more impatient young people. However, as low SES cohort members themselves more regularly report money as an important contributing factor in their educational decisions, improving the (perceived) affordability of a university education may help further decrease the gap in educational expectations between low and high SES individuals.

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Appendices

A. Additional descriptives

A.1 Risk attitudes and time preferences

To better understand how risk attitudes and time preferences are distributed, Figures 4 and 5 show histograms of the distribution of these variables. Figure 4 shows the distribution of risk attitudes measured in the coefficient r. Values below 0 indicate risk-loving attitudes, values around 0 indicate risk-neutrality, more positive values indicate more risk-averse attitudes. Only a small subgroup of observations falls in the 'risk loving' category. Similarly, very few observations correspond with highly risk-averse preferences. The vast majority of observations falls in moderately risk averse categories. Figure 5 shows the distribution of the inter-temporal discount factor, δ, measuring time preferences. Smaller values mean future payouts are discounted strongly and present payouts are preferred – i.e. impatience. Larger values indicate more patient preferences. The histogram indicates that very few cohort members are very impatient at the left tail of the distribution. Most observations correspond with moderate to low impatience.

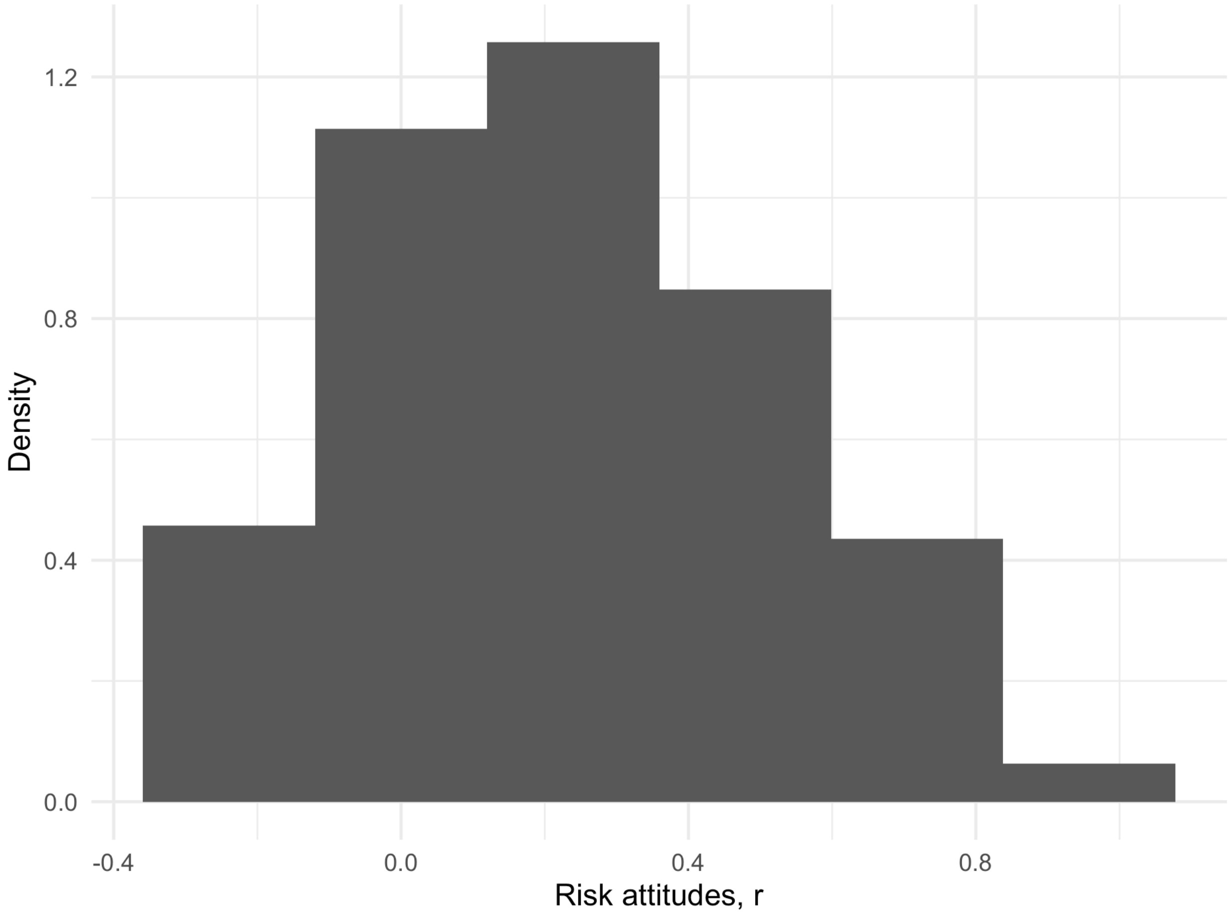

Figure 4. *Risk attitudes*

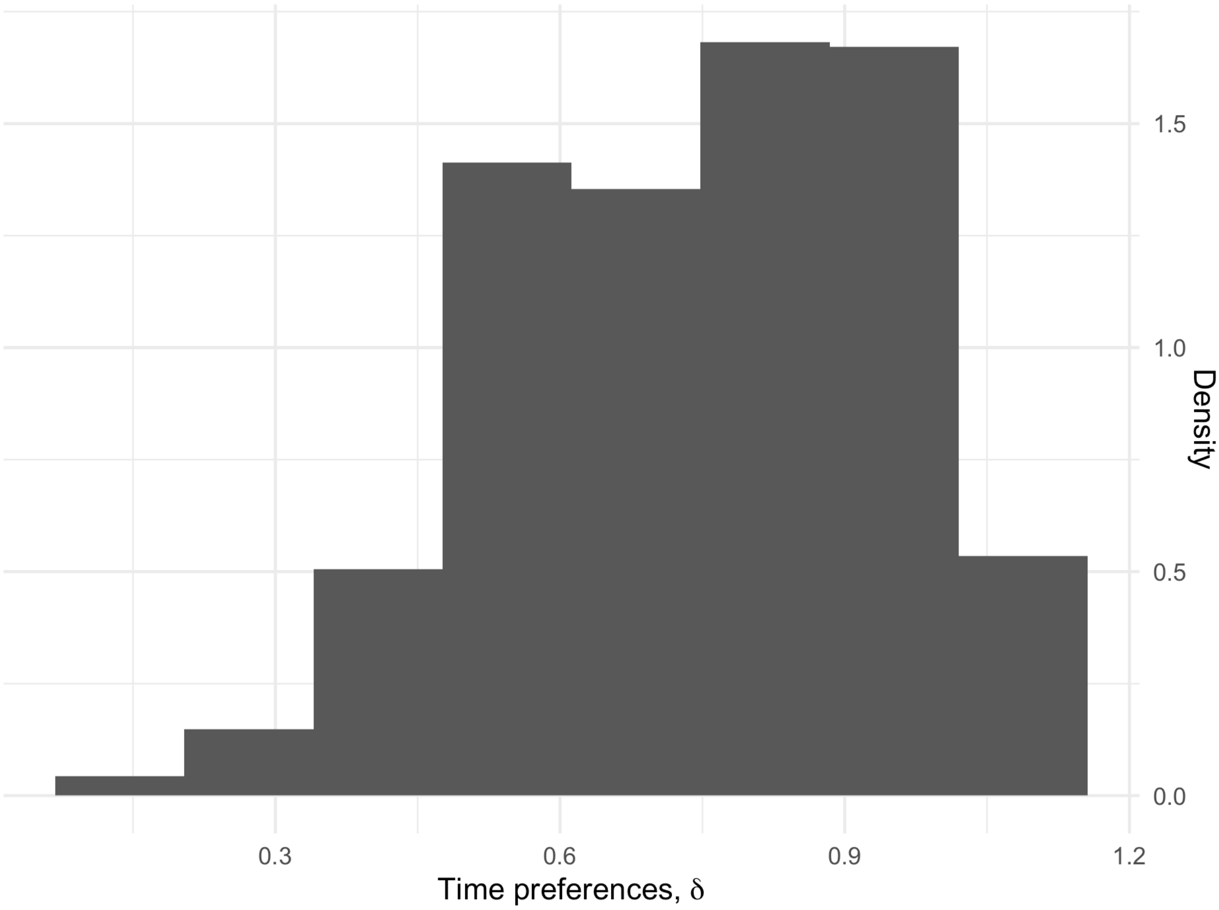

Figure 5. Time preferences

Notes: Number of observations: 6,382. Left: Risk attitudes as utility function coefficient, r. Negative values indicate risk loving; $r = 0$ indicates risk-neutrality; positive values indicate risk-aversion. Right: Time preferences as discount factor, δ. Smaller values represent higher impatience, larger values represent more patient attitudes. Sampling weights and inverse probability weights applied

B. Weights

As described in Section 2, the MCS data suffers from attrition and non-response, which we address by updating the original MCS sample weights. We do this by first computing the probability that an individual cohort member is responsive until age 17, given observations on sex, ethnicity, parental education, income, health, and other factors. These predicted probabilities from a logistic regression model are then inverted to become inverse probability weights (IPWs), which can then be combined with the original sampling weights provided with the MCS data. In an alternative approach, we use the age 14 weights provided with the MCS data and update these weights using the inverse probability weights derived from probability to continue participation between ages 14 and 17.

The key difference between these two approaches is that the former relies on the sample weights only which account for larger sample sizes in different strata. These strata are a combination of country (England, Scotland, Wales, Northern Ireland) and whether or not an area is considered advantaged, disadvantaged or with a large share of the population being ethnic minorities (England only). The second approach uses MCS weights up until age 14, which are designed to account for attrition. These weights are then updated to account for those cohort members present at age 14 that are not part of our final sample at age 17.

In order to choose which weight performs better, we evaluate the weights as follows. As a metric of our comparison, we focus on variables observed at the first MCS sweep (age one) only. These variables are cohort members' sex and ethnicity, their parents' age, education, income, housing situation, health, single parenthood, and household worklessness. The original sample weights are then applied to all observations available at the age one sweep, the weights designed to be applied to our final sample are applied only to those cohort members that are part of the final sample at age 17.

Table 10 shows descriptive statistics of the aforementioned variables. The first column shows the mean and proportions when applying the sample weights to the full sample. In the second and third column, we focus on the subsample that we use for our analyses in the main body and apply the weights calculated as detailed above. In particular, the second column shows results for the weights based on a combination of the MCS sample weights and inverse probability weights based on non-response patterns between the age one and age 17 sweeps. The third column shows descriptive statistics when applying weights based on the MCS weights at age 14 – already including non-response adjustments – combined with inverse probability weights based on non-response patterns between age 14 and age 17. Overall, applying the weights we use for our analyses ('final weights') results in nearly identical descriptive statistics as if the full sample at age one was used. When the alternative weights based on the non-response adjusted sample weights at age 14 are used, the descriptive statistics diverge substantially. In particular, the alternative weights over-represent Pakistani and Bangladeshi as well as Black and Black British ethnic groups. Furthermore, low-income, renting, low education households are given too much weight. The use of the alternative weights leads to an overestimation of single-parenthood, household worklessness as well as parents with bad health.

In order to ensure representativeness of our results for children born in the UK around 2001, we use the final weights as they best recover the distribution of key background variables at age one, compared to the use of the weights based on the MCS non-response adjusted weights at age 14.

Table 10. Descriptive statistics at age one using non-response weights

Variable	Category	Sample	Final	Alternative
Sex	Male	51.3%	51%	52.2%
	Female	48.7%	49%	47.8%
Ethnicity	White	87.7%	87.6%	84%
	Pakistani &	3.8%	4%	5.3%
	Indian	1.8%	1.9%	2%
	Black	2.5%	2.5%	4.2%
	Mixed	3.1%	3%	3.1%
	Other	1.1%	1%	1.4%
Income	–	325.1	323.6	286.2
Housing	Own	63.5%	63%	53.4%
	Rent	30.5%	30.6%	39.1%
	Living with parents	3.8%	3.9%	4.8%
	Shared equity	0.4%	0.4%	0.4%
	Other	1.8%	2%	2.3%
Education	None of these	12.1%	11.8%	18.1%
	Overseas qual only	2.4%	2.2%	2.9%
	NVQ level 1	8.2%	8.2%	9.6%
	NVQ level 2	29.6%	28.9%	30.4%
	NVQ level 3	14.2%	13.5%	12.4%
	NVQ level 4	29.8%	31.4%	23.8%
	NVQ level 5	3.8%	3.9%	2.8%
Education	None of these	10.2%	10.3%	13.8%
	Overseas qual only	2.8%	2.8%	3.3%
	NVQ level 1	6.7%	6.3%	7.3%
	NVQ level 2	27%	26.9%	28.1%
	NVQ level 3	15.5%	15.8%	15.7%
	NVQ level 4	31.5%	31.6%	26.7%
	NVQ level 5	6.3%	6.3%	5.1%
Single	Two-carer	86.1%	85.7%	81.8%
	Single-carer	13.9%	14.3%	18.2%
Workless	Not workless	83.4%	82.6%	77.5%
	Workless	16.6%	17.4%	22.5%
Age (mother)	–	29.7	30.1	28.9
Age (father)	–	33.1	33.3	32.6

Health (mother)	Poor	2.6%	2.5%	3.7%
	Fair	13.7%	13%	14.7%
	Good	52%	51.7%	52.6%
	Excellent	31.7%	32.8%	29%
Health (father)	Poor	2.1%	2.4%	3%
	Fair	12.8%	12.2%	13.8%
	Good	51.6%	51.7%	51.5%
	Excellent	33.4%	33.7%	31.7%

C. Robustness checks

To account for the left and right censored nature of the outcome variable (educational expectations fall between 0 and 100%), we use a Tobit model as robustness check of Model M3. In this model, we include the explanatory variables of interest – SES, risk attitudes, and time preferences – as well as demographic, health, educational investment and cognitive control variables. The Tobit model's regression coefficients cannot be directly compared with regression coefficients from a linear regression. In Table 11, we, therefore, show both the Tobit estimates as well as the corresponding marginal effects. Furthermore, we present the results from model M3 as a reference. The estimates for both the regression coefficients of SES and time preferences are statistically significant in the Tobit specification, while risk attitudes are not statistically associated with educational expectations. This is consistent with the estimates from Model M3. The magnitude of the associations according to the marginal effects is slightly lower in the Tobit specification compared to the linear model. However, this difference is not statistically significant and falls within approximately one standard error of the estimated values.

Table 11. Robustness check for Model M3 using a Tobit regression

Variable			
SES	5.303***	3.662***	3.914***
	(0.929)	(0.631)	(0.617)
Risk attitudes	-1.459	-1.008	-1.783
	(2.224)	(1.536)	(1.602)
Time	14.64***	10.11***	12.58***
	(3.266)	(2.247)	(2.320)
Standard errors in parentheses			
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$			

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis. All estimates are obtained *controlling for demographics, parental health, educational investments, and behavioural and cognitive scores.*

Next, we include GCSE maths and English grades in the analysis to observe the impact feedback about chances of going to university through school grades has on our estimates. As GCSE grades are obtained and comparable within England but not in the devolved nations, we limit our analysis to English pupils only. Furthermore, as GCSE grades were changed from letter grades to numerical grades around the time that cohort members took GCSEs, we recoded letter grades to their numeric equivalents. While previous analyses maintained a sample size of around 6,000 pupils, our analysis being limited to English students and those pupils who disclose their grades further reduces the sample size to 3,380. We use adjusted weights accounting for this further reduction in sample size.

The estimates shown in Table 12 indicate that accounting for GCSE grades reduces the link between SES and educational expectations by half. Similarly, the point estimate for time preferences is reduced by 1/3. Both associations remain statistically significant at the 5 and 1% levels, respectively. Both maths and English grades have a strong positive relationship with educational investments, while the estimate for the cognitive score becomes insignificant once GCSE grades are included. This result indicates that academic feedback via grades is very important to pupils in assessing their future educational options. However, even when including GCSE grades, both low SES and impatience as predictors for lower educational expectations prevail.

Table 12. Robustness check for Model M3 including GCSE grades in English and mathematics

Variable		
SES	3.979***	1.958*
	(0.802)	(0.815)
Risk attitudes	0.298	-0.106
	(2.282)	(2.129)
Time	12.55***	8.591**
	(3.254)	(3.193)
Cognitive	9.439***	0.931
	(0.831)	(1.077)
GCRE Maths		4.189***
		(0.475)
GCRE English		6.203***
		(0.488)
R^2	0.255	0.360

Standard errors in parentheses
$* p < 0.1$, $** p < 0.05$, $*** p < 0.01$

Notes: Number of observations: 3,380. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis. All estimates are obtained controlling for demographics, parental health, educational investments, and behavioural and cognitive scores.

Finally, we test if our results are robust against the specification of risk attitudes and time preferences. In the main body of this study, we used economic theory on the shape of the utility function to derive estimates for risk attitudes, r, and time preferences, δ. As a robustness check, we create categorised variables for risk aversion and patience, both with categories 'low', 'medium', and 'high'. Around 21% of observations are classified as 'low risk aversion', 46% as 'medium', and 33% 'high'. Similarly, 18% fall into the category 'very impatient', 48% are 'moderately patient', and 34% 'very patient'. As shown in Table 13, the estimate for the association between SES and educational expectations does not change significantly when categorised economic preferences are used instead of the economic preferences constructed in the main body of this study. Furthermore, just as with the continuous variable measuring risk preferences, r, the categorised variable shows no association between risk preferences and educational expectations. Last, time preferences continue to be statistically significantly associated with educational expectations. In particular, cohort members falling into the most patient category report educational expectations around 5.5 percentage points higher compared to those in the most impatient category.

Table 13. Robustness check for Model M3 using categorised risk attitudes and time preferences

Variable		
SES	3.914***	3.948***
	(0.617)	(0.617)
Risk attitudes	-1.783	
	(1.602)	
medium		1.586
		(1.230)
high		1.434
		(1.275)
Time	12.58***	
	(2.320)	

medium		2.612
		(1.484)
high		5.548***
		(1.605)
R^2	0.288	0.286

Standard errors in parentheses
$* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$

Notes: Number of observations: 6,382. Inverse probability weights and sample weights applied. SES variable standardised prior to analysis. All estimates are obtained controlling for demographics, parental health, educational investments, and behavioural and cognitive scores.

@cepeo_ucl

ucl.ac.uk/ioe/cepeo