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The role of noncognitive traits in undergraduate study behaviours

Liam Delaney[a,d], Colm Harmon[b,d,e], Martin Ryan[c,d,*]

[a] Division of Economics, University of Stirling, Scotland, United Kingdom
[b] School of Economics, University of Sydney, Australia
[c] Higher Education Policy Research Unit, Dublin Institute of Technology, Ireland
[d] Geary Institute, University College Dublin, Ireland
[e] IZA, Bonn, Germany

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ABSTRACT

Undergraduate study behaviours, principally lecture attendance and additional study, are shown to predict better student achievement by many researchers. Despite this, there is not much evidence on the determinants of these behaviours. This is the first paper to explore the determinants of study behaviours across multiple subject areas; and is the first to incorporate students' noncognitive traits into such a model; that the authors are aware of. This enables the formation of policy that can improve academic achievement by encouraging study behaviour. The results show that students' noncognitive traits, in particular conscientiousness and future-orientation, are important determinants of lecture attendance and additional study hours. In fact, there is very little that explains undergraduate study behaviour besides noncognitive traits. Standard economic factors, such as family income, financial aid and parental transfers, are not predictive of study behaviours. Some comments are provided on a potential behavioural economics approach to encouraging study behaviours.

1. Introduction

Undergraduate study behaviours, principally lecture attendance and additional study, are shown to predict better student achievement by many researchers. It has been demonstrated that lecture attendance is an important determinant of academic achievement by Schmidt (1983), Romer (1993), Durden and Ellis (1995), Dolton, Marcenaro, and Navarro (2003), Martins and Walker (2006), Cohn and Johnson (2006), and Arulampalam, Naylor, and Smith (2012), among others. In addition, there is evidence that additional hours of study are positively related to grades, for example: Martins and Walker (2006), Stinebrickner and Stinebrickner (2008), Arulampalam et al. (2012), and Grave (2011). However, despite the existence of these findings, researchers have a very limited knowledge about what factors determine student inputs in the higher education production function. This paper fills that gap by exploring the micro-level determinants of lecture attendance and additional study hours. This enables the formation of policy that can *improve* academic achievement by *encouraging* study behaviour.

Of particular interest is the potential role of students' noncognitive traits. (The nature of these traits is discussed in the following section.) Heckman, Stixrud, and Urzua (2006) demonstrate that better noncognitive traits lead to more years of schooling, and a greater likelihood of college attendance. Therefore, it is probable that better noncognitive traits would lead to more lecture attendance and additional study for those students who progress to higher education. In fact, there is evidence which sug-

* Corresponding author at: Higher Education Policy Research Unit, Dublin Institute of Technology Directorate of Research and Enterprise, 143 Rathmines Road, Dublin 6, Ireland. Tel.: +353 1 402 7504.
E-mail address: martin.ryan@dit.ie (M. Ryan).

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gests that self-control, perseverance, and other aspects of conscientiousness are contributing factors to students' academic success; for example: Wolfe and Johnson (1995), Paunonen and Ashton (2001), Chamorro-Premuzic and Furnham (2003), Duckworth and Seligman (2005), Robbins, Allen, Casillas, Peterson, and Le (2006), Noftle and Robins (2007), and Borghans, Golsteyn, Heckman, and Humphries (2011).[1] In addition, there is evidence that the association between conscientiousness and grades is mediated by positive study habits and attitudes, effort, and prosocial behaviour in the classroom (Almlund, Duckworth, Heckman, & Kautz, 2011). All of this suggests that noncognitive traits should play an important role in determining study behaviours. Furthermore, these traits should be controlled for if one wants to assess the importance of other independent variables (such as financial transfers) as accurately as possible.

Information on lecture attendance and additional study hours was acquired from students' self-reports; the data were collected through a web-survey that the authors designed for an official research project on the seven universities in Ireland. Self-reported variables provide measurement challenges (discussed later in the paper), but also provide some advantages. The use of a web-survey means that analysis can be performed across multiple subject areas relatively easily.[2] This is the first paper to explore the determinants of study behaviour across multiple subject areas; and is the first to incorporate students' non-cognitive traits into such a model; that the authors are aware of. A three-way interaction between subject area, university affiliation and year of enrolment is also included; this can be viewed as an endogenous class-room effect, encapsulating class-room conditions. This means that account is taken of any micro-level factors that have arisen in prior class-room studies. Martins and Walker (2006) is the only other paper to use a control for class-group; that the authors are aware of.[3]

Overall, this paper investigates the determinants of undergraduate study behaviours, with a particular focus on the role of noncognitive traits. After controlling for a wide range of covariates, including student demographics, family background, financial transfers, institutional affiliation and class-room conditions, the authors find that certain noncognitive traits are virtually the only variables which predict greater amounts of study behaviour. Standard economic factors, such as family income, financial aid and parental transfers, are not predictive of study behaviours. This is a noteworthy result; and is not what the authors expected to find when they set about doing this research. The remainder of the paper is organised as follows. The next section presents measures of noncognitive traits; and their use in previous research. The third section reviews the existing research on undergraduate study behaviour. The fourth section outlines the data and the empirical strategy. The fifth section concludes with the results and a discussion, including comments on a potential behavioural economics approach to encouraging study behaviours.

2. Measures of noncognitive traits

Traits are defined as a distinguishing characteristic or quality, of a personal nature. Borghans, Duckworth, Heckman, and ter Weel (2008) distinguish between cognitive and noncognitive traits by using the term *noncognitive* to refer to traits other than those that characterise abstract problem solving.[4] Cunha and Heckman (2007) describe how there are many aspects of noncognitive ability, including perseverance, motivation, time preference, risk aversion, self esteem, self control and preference for leisure. Some authors refer to noncognitive abilities, some refer to noncognitive skills, and others (less formally) refer to personality (traits) when discussing the same idea. This paper proceeds on the basis of using the phrase *noncognitive traits* to refer to any of the above. Discussion on the measurement of noncognitive traits is focused on those traits which feature in this paper. These include personality (specifically, the Big Five personality factors) and economic psychology (specifically, the psychometric elicitation of attitudes towards risk and the future).

The most widely accepted taxonomy of personality traits is the *Big Five* or *Five Factor Model* (Borghans et al., 2008). The Big Five personality factors are as follows: openness, conscientiousness, extraversion, agreeableness and neuroticism. (Neuroticism is sometimes referred to as its opposite: emotional stability.) The Big Five are defined in detail in Appendix A, following the American Psychological Association Dictionary (2007). These personality factors account for substantial variance in life outcomes such as psychological well-being, happiness, family and peer relationships, job performance, career satisfaction, and physical health (Ozer & Benet-Martínez, 2006). Personality assessed early in life is predictive of a wide range of important life outcomes; and the size of the effect of personality on mortality, divorce and occupational attainment is about the same as that of socioeconomic class and intelligence (Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). Conscientiousness is the best predictor of health outcomes (Friedman et al., 1993; Hampson, Goldberg, Vogt, & Dubanoski, 2007; Roberts et al., 2007), academic outcomes (Poropat, 2009), and divorce (Roberts et al., 2007).

[1] A meta-analysis by O'Connor and Paunonen (2007) shows *conscientiousness* to be most strongly and consistently associated with students' grade-scores. Associations with grades are substantially smaller for other personality factors, the largest of which is *openness to experience*. One factor sometimes negatively related to grades is extraversion.

[2] Betts and Morell (1999), Dolton et al. (2003), Arcidiacono, Foster, Goodpaster, and Kinsler (2009) and Bandiera, Larcinese, and Rasul (2010) are the only studies to estimate a higher education production function across multiple subject areas; that the authors are aware of.

[3] However, Martins and Walker (2006) conduct their analysis within one subject area; they define class-group as the combination of academic year, module (within the subject of Economics) and teaching assistant. Also, Martins and Walker (2006) is focused on the determinants of student achievement; whereas this paper is focused on the determinants of study behaviours.

[4] Heckman and Rubinstein (2001) identify the importance of noncognitive traits for contemporary economic research. They observe that some high school equivalency recipients earn less than high school dropouts, despite the fact that those high school equivalency recipients have higher cognitive skills. They attribute this to the negative noncognitive attributes of the equivalency recipients.

The term *Big Five* is introduced by Goldberg (1981) and is modelled with a personality inventory by Costa and McCrae (1985). The Big Five structure does not imply that personality differences can be reduced to only five traits. Rather, these five dimensions represent personality at the broadest level of abstraction, and each dimension summarises a large number of distinct, more specific personality characteristics (John & Srivastava, 1999). The Big Five are commonly measured using the *Ten Item Personality Inventory*, as developed by Gosling, Rentfrow, and Swann (2003). When presented with the Ten Item Personality Inventory (TIPI), survey respondents rate how characteristic each of ten statements is of their own behaviour on a scale from 1 (disagree strongly) to 7 (agree strongly). Appendix B describes in detail the ten statements, the respondent instructions and the scoring mechanism that produce the Big Five factors from the TIPI; it operates on a scale of 2–14 for each personality factor. Higher scores on the scale indicate higher levels of the personality factor in question. Gosling et al. (2003) report that the TIPI reaches adequate levels in terms of: (a) convergence with widely used Big Five measures in self, observer and peer reports, (b) test re-test reliability, (c) patterns of predicted external correlates, and (d) convergence between self and observer ratings. On the basis of these tests, Gosling et al. (2003) suggest the use of a 10 item measure in situations where very short measures are needed.

Measurement of attitude to risk is examined by Bonin, Dohmen, Falk, Huffman, and Sunde (2007) using a question that asks about *willingness to take risks* on an 11 point scale. The question reads as follows: "Please indicate on a scale of 0–10, how willing you are to take risks in general, where 0 indicates unwilling to take risks and 10 indicates fully prepared to take risks." Bonin et al. (2007) investigate whether risk preferences explain how individuals are sorted into occupations with different earnings variability. They use data from the German Socio-Economic Panel; and as a measure of earnings risk, they use the cross-sectional variation in earnings that is left unexplained by human capital in a Mincerian wage regression. By relating this earnings risk to the subjective measure of risk preference in the survey, they demonstrate that individuals with a lesser willingness to take risks are more likely to be sorted into occupations with low earnings risk.

Dohmen et al. (2011) report that a subjective elicitation of attitude to risk, such as that used by Bonin et al. (2007), predicts behaviour across multiple domains; but that a standard lottery measure does not. Again using a similar subjective measure to Bonin et al. (2007), Jaeger et al. (2010) find that individuals who are more willing to take risks are more likely to migrate between German labour market districts. Daly, Delaney, and McManus (2010) show that *risk-willingness* is a robust predictor for students to increase their debt, after controlling for students' personality, consideration of future consequences and other covariates.

Measurement of future-orientation is examined by Strathman, Gleicher, Boninger, and Edwards (1994) using a scale which approximates to economists' understanding of *present-biased preference*. More particularly, this scale is used to measure individuals' *consideration of future consequences* (CFC). The CFC contains twelve statements reflecting an individuals' tendency to consider the immediate and future consequences of their behaviour. Five statements in the CFC reflect a concern with future consequences (e.g. *I consider how things might be in the future, and try to influence those things with my day to day behaviour*) while the remaining seven statements reflect a concern with immediate consequences (e.g. *My behaviour is only influenced by the immediate outcomes of my actions*). Respondents rate how characteristic each statement is of their own behaviour on a scale from 1 (extremely uncharacteristic) to 5 (extremely characteristic).

Appendix C describes in detail the statements, respondent instructions and scoring mechanism that produces the CFC; it normally operates on a scale of 12–60. Higher scores on the scale indicate higher levels of future-orientation. Strathman et al. (1994) use data from 7 samples of college students to show that the CFC has acceptable reliability and validity. Daly, Delaney, and Harmon (2009) demonstrate that the CFC is associated with financial discounting. The scale is also associated with high levels of self-reported impulsive buying tendencies (Verplanken & Herabadi, 2001) and temporal discounting (Kirby, Petry, & Bickel, 1999).

3. Existing research on study behaviour

Some of the noncognitive traits described in the previous section have a prospective relationship with study behaviour. Students are less likely to attend their lectures if they perceive that they can pass without attending (Massingham & Herrington, 2006). This could be explained by students' willingness to take risks. There is a correlation between CFC scores (consideration of future consequences) and academic achievement, as demonstrated by Joireman (1999) and Peters, Joireman, and Ridgway (2005). Given this, one might expect there to be a correlation between future-orientation and the extent of undergraduate engagement with the study process. With respect to personality factors, conscientiousness is strongly and consistently associated with academic achievement; openness to experience is positively associated to achievement; and extraversion is sometimes negatively related to achievement (O'Connor & Paunonen, 2007). Kaufman, Agars, and Lopez-Wagner (2008) and Borghans et al. (2011) show that students' conscientiousness is a strong predictor of higher grades. Furthermore, there is evidence that the association between conscientiousness and grades is mediated by positive study habits and attitudes, effort, and pro-social behaviour in the classroom (Almlund et al., 2011). All of this suggests that conscientiousness might predict undergraduate study behaviours. Openness to experience might be positively related to study behaviours; extraversion might be negatively related.

Carneiro and Heckman (2002) demonstrate that long-term factors, such as the fostering of cognitive and non-cognitive traits, are more important than short-term credit constraints in the determination of post-secondary schooling attainment. Given these findings, one might expect noncognitive traits to be more important than credit

constraints in undergraduates' engagement with the study process. On the likely effect of parental transfers on study behaviours, Bodvarsson and Walker (2004) find that students receiving cash transfers from their parents failed their courses more often than self-financed students, were at higher risk of being placed on academic probation, and achieved lower grades. This suggests that parental transfers may discourage students from engaging with the study process.

Lang, Joyce, Conaty, and Kelly (2008) report results from a survey on first year Accounting students at an Irish university. They find that class attendance is positively affected by female gender and by students' interest in their subject area. The existence of a gender difference is also reported by Arulampalam et al. (2012); they show that females miss fewer classes than males. In addition, Arulampalam et al. (2012) report that overseas students miss more classes compared to domestic students. Lassibille, Gomez, and Paul (2001) show that study hours are positively affected by female gender; and they produce evidence that students living at home do more hours of study. Bratti (2002) investigates differences across U.K. universities in life sciences students' academic achievement. After including a range of controls related to the quality of students, Bratti (2002) finds significant differences across universities in students' degree performance. This suggests that the institution students attend might be important. Lang et al. (2008) find that class attendance is significantly affected by quality of teaching and the availability of notes.[5] Grabe, Christopherson, and Douglas (2005) show that the availability of lecture notes is associated with lower attendance rates. In several studies, a reason reported by students for non attendance is poor quality of lectures (Clay & Breslow, 2006; Dolnicar, 2005; Friedman, Rodriguez, & McComb, 2001; Kottasz, 2005; Massingham & Herrington, 2006; Romer, 1993). Arulampalam et al. (2012) report that students' attendance is associated with more favourable evaluations of the class tutor.

Finally, the logistics associated with a lecture can also have an effect on attendance. The size of the class can influence students because their absence is more likely in subjects with large enrolments (Friedman et al., 2001). Grise and Kennedy (2003) show that students perceive smaller theatres to allow for greater interaction between lecturers and students. Students may be less attentive in larger classes, or may compensate for larger classes by exerting more effort outside of lecture times (Bolander, 1973; Feldman, 1984; McConnell & Sosin, 1984). Instructors may be better able to identify the ability and interests of the median student in smaller classes, or be more able to answer students' questions directly (Bandiera et al., 2010). The time of day is another factor; Arulampalam et al. (2012) find that tutorial absence is higher for the 9am class and, to a lesser extent, for all morning classes. The optimum time for scheduling lectures is between 10 am and 3 pm, according to Devadoss and Foltz (1996). Attendance is also shown to decline as the semester progresses (Moore, 2004; Rodgers, 2001). Finally, Kirby and McElroy (2003), using a sample of first year Economics students at an Irish university, show that class attendance is affected by travel time to university, and by the hours that students spend working in a part-time job. Kottasz (2005) reports that students explain absences as being the result of transport problems.

[5] Quality of teaching and the availability of notes are class-room characteristics separate to but perhaps affected by institutional factors.

4. Data and empirical strategy

4.1. Data

Round 2 of the Irish University Study (henceforth *IUS Round 2*) is examined in this paper. This is a large scale web survey that was designed by the authors to elicit feedback from students attending the seven universities in Ireland. The data for IUS Round 2 were collected during spring 2009; the field work received 4770 responses, which equates to a response rate of 20%.[6] 24,000 students were contacted by their institution using a sampling strategy based on the Irish university population for the academic year 2006/2007; this was the most recent year that figures were available for, at the time of going to the field.[7] Given the requirement for a sample of a certain size (based on the size of its student population), each university randomly selected the corresponding number of individuals from their administrative records.[8]

A monetary incentive was offered to students to participate in the survey, and each university issued two reminders about the invitation to participate. A valid concern is whether respondents selected into the survey. It may be the case that *conscientious* students self-selected to some extent. On balance, it is impossible to ascertain if students filled out the survey because of their conscientiousness, or because of the incentive.[9] Robustness checks between the data from the *Irish Universities Study* and the data available for the population of Irish university students are presented in Appendix D (across gender, institution and area of study). Overall, on several observables,

[6] Because measurement of the relationship between non-response and survey-accuracy is complex and expensive, few studies have provided empirical evidence to document the consequences of lower response rates, until recently. These studies challenge the idea that a lower response rate means lower survey-accuracy. Vissner, Krosnick, Marquette, and Curtin (1996) and Scott, Kennedy, Dimock, Best, and Craighill (2006) show that surveys with low response rates are not necessarily low in validity. Holbrook, Krosnick, and Pfent (2007) assess whether lower response rates are associated with less representativeness (of a sample). Holbrook et al. find that surveys with much lower response rates are only minimally less accurate. As a result of these recent findings (Holbrook et al., 2007; Scott et al., 2006), the authors argue that a low response rate does not necessarily mean lower survey accuracy.

[7] Information about the population of university students in Ireland is taken from the website of the Irish Higher Education Authority (HEA): http://www.hea.ie/en/statistics.

[8] This was done by randomly generating a unique decimal number between 0 and 1 for every undergraduate and postgraduate student. Those who had the lowest random numbers were selected.

[9] Furthermore, not all students who filled out the survey are equally conscientious. Fig. 2 shows that while most students view themselves as being conscientious; there is variation: some students view themselves to be much more conscientious in comparison to others.

Table 1
Summary statistics: IUS Wave 2.

Variable	Form	Scale	Mean	Std. Dev.	*N*
Student's percentage of lectures attended	Cont.	0–100	81.25	17.76	2502
Student's hours of study	Interval	0–61+	03.03	1.43	2438
Monthly income from family (€)	Cont.	0–900	210.0	213.4	2339
Monthly income from state (€)	Cont.	0–500	50.40	116.3	2363
Student's age	Cont.	17–50	21.10	4.20	2843
Whether the student is male	Binary	0–1	0.36	0.48	2867
Student's year of enrolment	Category	0–6	2.27	1.10	2863
Whether father has some higher education	Binary	0–1	0.46	0.49	2608
Family income in brackets of €20,000	Interval	0–140K+	4.01	2.43	2711
Student's willingness to take risks	Cont.	0–10	6.49	1.75	2581
Student's future-orientation	Cont.	5–20	12.30	2.44	2561
Student's openness	Cont.	2–14	10.76	2.10	2581
Student's conscientiousness	Cont.	2–14	10.26	2.61	2580
Student's extraversion	Cont.	2–14	9.20	2.74	2580
Student's agreeableness	Cont.	2–14	9.79	2.23	2580
Student's emotional stability	Cont.	2–14	6.65	2.76	2579

the sample is aligned to its underlying population. Any self-selection (that might occur) is driven by variables that the authors cannot observe.

Analysis is restricted to observations where students are enrolled in full-time courses; this is because part time students are a characteristically different group. In addition, the sample is restricted to full time undergraduates because postgraduates are also a characteristically different group. Summary statistics relating to the analytical sample are presented in Table 1; $n = 2867$. This figure can be compared with the *N* column in Table 1 to indicate the extent of missing values. The most missing values arise for the financial support variables: approximately 18% of the analytical sample. However, on average, missing values are only present for approximately 10% of the analytical sample. Finally, there are no meaningful differences between the summary statistics for the study-sample and the summary statistics for the analytical sample.

Lecture attendance is measured as the self-reported percentage of lectures that are attended by each student. Students are asked: *What percentage of your lectures do you attend, on average?* Approximately 12% of students claim to attend all of their lectures. 47% of students claim to attend 80% or more of their lectures. 67% of students claim to attend 50% or more of their lectures. Overall, the mean-level of *percentage lectures attended* is 81%. This is a self reported behaviour; and there are reasonable grounds to suspect that it is over-stated due to the presence of *social desirability bias*.[10] This is a term used to describe the tendency of respondents to reply in a manner that will be viewed favourably by others; see Bound, Brown, and Mathiowetz (2001) for a discussion. Bertrand and Mullainathan (2001) also discuss the problem; they provide the example that roughly 25% of nonvoters report having voted immediately after an election. According to Bound et al. (2001), questions for which the source of the measurement error is related to social desirability bias often call for the use of questionnaire modes that provide the respondent with a greater sense of confidentiality or anonymity. The web-survey used to collect the data for this paper assured students about both confidentiality and anonymity at the start of the questionnaire.

Additional study hours are measured using the following question: *How many hours per week do you spend on average on personal study time?* Respondents give their answer in a grid comprised of hours (per week), categorised as follows: 0, 1–5, 6–10, 11–15, 16–20, 21–30, 31–40, 41–50, 51–60, and 61+. An interval plot (Fig. 1) shows the frequency of students reporting their additional study time in each category. As Stinebrickner and Stinebrickner (2004) note, reporting error from retrospective questions of this sort can be non-trivial. An alternative approach would have been to collect information about a single time period using a time diary. However, this information would have been compromised by the presence of variation in study time across days in the year (Stinebrickner & Stinebrickner, 2004). The main concern about the measure used in this paper is that survey respondents may have framed their answers around the week of the survey, rather than the *average week*. To control for this, a variable is included which indicates the actual week that the survey

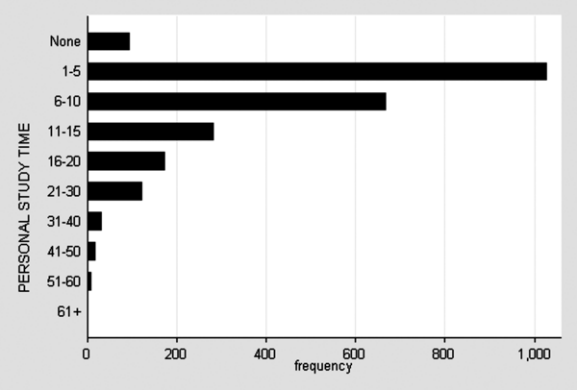

Fig. 1. Additional study hours per week Irish Universities Study.

[10] Students may be attending more of their lectures in the recession than they would in better economic conditions. University students in the UK studied for 2 h and 12 min more (per week) in 2009 than they did in 2007, according to the Higher Education Policy Institute (Bekhradnia, 2009).

was completed.[11] This alleviates concerns about the retrospective nature of the question on hours studied per week.

The independent variables are grouped into four themes: (i) transfers to students, (ii) students' family background (and student characteristics such as age and gender), (iii) institutional effects, and (iv) students' noncognitive traits. Financial transfers include finance received from students' parents (€210 per month, on average), and finance received from the state (€50 per month, on average).[12] Finance received from students' parents is the sum of direct transfers and indirect payments on the behalf of students. The family background variables are as follows: whether the student's father has some higher education and the family income of the student. The family income variable is top-coded at €200,000+. The uppermost category of the family income variable accounts for 3.43% of the sample. The course year that the student is enrolled in is also included, as well as students' age and gender (whether the student is male). 36% of students are male, 46% of students' fathers have some higher education, and average family income is in the range of €60,000–80,000. Students' average age is 21, and the average year of enrolment is 2.[13]

Noncognitive traits are measured by willingness to take risks (on a scale of 0–10), consideration of future consequences (on a scale of 5–20) and the Ten Item Personality Inventory (on a scale of 2–14 for each of the five personality factors).[14] In total, there are seven variables relating to students' noncognitive traits: ranging from a continuous scale of 11 points to a continuous scale of 15 points. In other words, the numeric form of the seven noncognitive traits is relatively similar. A series of histograms in Fig. 2 illustrates the seven traits. It can be seen that the biggest skews are towards students viewing themselves as conscientious (dependable and self disciplined; not disorganised and careless); and students viewing themselves not to be neurotic (not being anxious or easily upset; but being calm and emotionally stable).

4.2. Empirical strategy

The determinants of lecture attendance and additional study hours are estimated using the following cross-sectional specification:

$$Y_{ij} = \alpha_i + \beta_1 transfers_{ij} + \beta_2 family_{ij} + \beta_3 college_{ij} + \beta_4 noncog_{ij} + \mu_{ij} \quad (1)$$

where Y_{ij} is lecture attendance or additional study for student i at university j; $transfers_{ij}$ is a matrix of parental transfer variables; $family_{ij}$ is a matrix of family background variables (and student demographics); $college_{ij}$ is a matrix of institutional or class-room effects; and $noncog_{ij}$ is a matrix of variables relating to students' non-cognitive traits. The seven variables relating to noncognitive traits are standardised using z-scores. Lecture attendance is modelled using robust ordinary least squares (OLS) regression; clustered by university in order to avoid under estimation of the standard errors. Additional study hours are modelled using interval regression.

An important consideration is that some students are enrolled in courses related to science, engineering, technology and maths (STEM); and others are enrolled in non-STEM subjects. This distinction is important because STEM students are required to attend more lectures than non-STEM students. By extension, STEM students have less time for additional study, compared to non-STEM students.[15] Given this, the main specification controls for whether a student is enrolled in a STEM course or not. There may be some concern at the inclusion of this subject area control: due to it being (mostly) a *choice variable*.[16] To allay this concern the authors have experimented with a specification that leaves out the subject area control; this omission make no difference to the overall pattern of results.

Information on time spent working and commuting is not used in the main specification, due to concerns about endogeneity. However, if these variables are included, there is no change in the overall pattern of results. It is also possible to include a number of satisfaction variables: satisfaction with quality of lecture content, satisfaction with clarity of teaching, satisfaction with timetabling of classes and satisfaction with class size. However, these satisfaction variables are highly subjective and are also endogenous to study behaviour; and for these reasons they are excluded from the main specification. If these variables are included, there is no change to the overall pattern of results.

A potential source of reverse causality is the possible effect of study behaviour on parental transfers. (Parental transfers are treated as exogenous to study behaviours in the main specification). To address this concern the authors

[11] This can be thought of as "proximity to exam-time"; and was categorised by equal spacing of time (3 weeks for each category).

[12] Finance received from the state is known in Ireland as the higher education maintenance grant; it comes with fee-remission, which was very salient when tuition fees were charged in Ireland prior to 1997. However, there remains an annual registration fee for Irish students (currently €1500), which is covered by the remission. The grant, as it is colloquially known, is never more than €3342 per annum and is often closer to €1370, depending on how far the student lives away from college. To qualify for the full grant, the (pre-tax) family income of the student must be no more than €41,110. There are slightly higher thresholds for larger numbers of children. In addition, reduced grant payments are available up to a family income threshold of €51,380. However, in the band below this upper threshold (that is, €51,380), only the students' registration fee is paid (and there is no maintenance support).

[13] Most courses are 3–4 years in duration; a small number (such as Medicine) last 6 years.

[14] The CFC normally operates on a scale of 12–60. However, the authors used a four item version instead of a twelve item version, which results in the scale of 5–20.

[15] There is also a common belief that the sciences and maths grade harder than the social sciences, which in turn grade harder than the humanities (Achen & Courant, 2009).

[16] Entry to a programme leading to an honours bachelor degree is determined by students' performance in the Leaving Certificate (Leaving Cert.), which is the senior state examination at the end of secondary school in Ireland. Entry is based on the "points system" in which the more advanced papers get higher points. Points are awarded for the six examinations in which a student performs best. Entry is through a centralised application system – the Central Applications Office (CAO). A total of ten higher education courses may be chosen in order of preference. Each applicant is given a place in the highest of his course preferences in which his merit rating will allow.

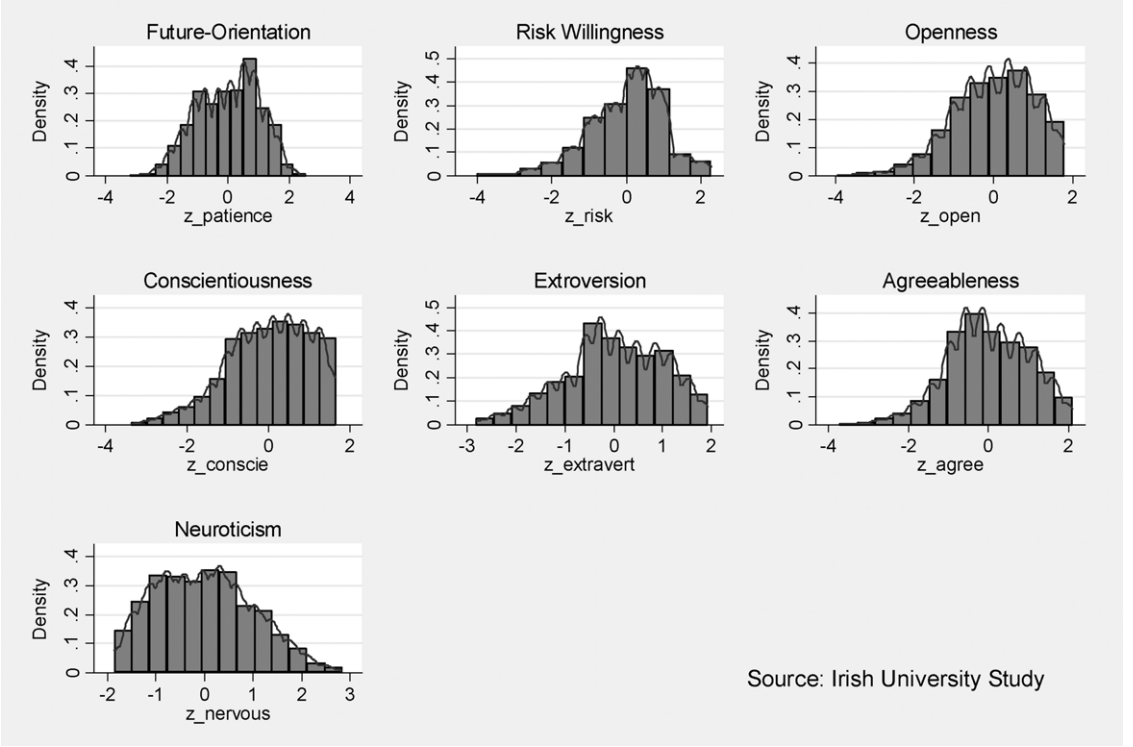

Fig. 2. Standardised comparison of noncognitive traits.

Source: Irish University Study.

have experimented with a specification that leaves out the parental transfer variable; this omission makes no difference to the overall pattern of results. Finally, another potential source of reverse causality is the possible effect of study behaviour on noncognitive traits. An argument against this possibility is the strong case for the stability of noncognitive traits (Borghans et al., 2008).

In addition, it is argued here that students' noncognitive traits should be largely stable by the time they enter higher education. Cunha, Heckman, Lochner, and Masterov (2006) explain how skill begets skill through a multiplier process. Skill attainment at one stage of the life cycle raises skill attainment at later stages of the life cycle (self-productivity). Early investment facilitates the productivity of later investment (complementarity). Remediation of inadequate early investments is difficult and very costly as a consequence of both self-productivity and complementarity (Cunha et al., 2006). Therefore, there should be a limited expectation for the presence of instability in college students' noncognitive traits.

Finally, while *starting* college may impact on students' noncognitive traits to some extent, there is a mean-level in cohort traits; and it is argued here that this is mostly stable over the (relatively) short duration of undergraduate enrolment. Rivkin, Hanushek, and Kain (2005) make the assumption that some noncognitive traits (such as motivation and personality factors) do not change during the school years considered for their model of academic achievement.[17] Cobb-Clark and Schurer (2011) demonstrate that personality (as measured by the Big Five) is stable over a four-year period.[18]

5. Results and discussion

5.1. Results

Columns 1 and 3 (Table 2) show the full specification, including noncognitive traits, for the lecture attendance and study-hours equations, respectively. Columns 2 and 4 (Table 2) omit the noncognitive traits. This allows one to see clearly the effect of including noncognitive traits in the empirical model. It can be seen that the inclusion of noncognitive traits does not change the results in any systematic way. The only difference in the more parsimonious specification (columns 2 and 4) is that the negative coefficient on being male becomes larger.

In general (across all specifications), males are less likely to attend their lectures, but are no less likely to do additional hours of study. Being in a later year of one's

[17] Rivkin et al. (2005) also make the assumption that cognitive ability does not change during the school years considered for their model of academic achievement.

[18] Average personality changes are small and do not vary substantially across age groups. Personality can be modeled as a stable input into many economic decisions (Cobb-Clark & Schurer, 2011).

Table 2
Determinants of percentage lecture attendance and additional study hours.

	(1) % lecture attendance	(2) % lecture attendance	(3) Additional study	(4) Additional study
Log(Monthly income from family)	0.195	0.168	−0.007	−0.006
	(0.209)	(0.206)	(0.087)	(0.089)
Log(Monthly income from state)	0.096	0.052	−0.007	0.001
	(0.177)	(0.224)	(0.094)	(0.096)
Whether the father has higher ed.	0.799	0.253	0.379	0.294
	(0.897)	(0.987)	(0.392)	(0.400)
Family income: brackets of	−0.193	−0.246	0.003	0.006
€20,000	(0.185)	(0.210)	(0.086)	(0.087)
Student's age	0.493***	0.553***	0.335***	0.375***
	(0.078)	(0.087)	(0.046)	(0.047)
Whether the student is male	−3.368**	−4.413**	0.503	−0.015
	(1.364)	(1.481)	(0.397)	(0.381)
Student's year of enrolment	−0.377	−0.107	1.585***	1.656***
	(0.281)	(0.340)	(0.166)	(0.170)
Whether student is in the STEM	1.019	1.332	−0.530	−0.532
area	(0.927)	(1.002)	(0.399)	(0.407)
The week the survey is conducted	−1.200**	−1.539**	−0.226	−0.298
	(0.339)	(0.471)	(0.187)	(0.191)
Student's future-orientation	2.695***		1.959***	
	(0.673)		(0.338)	
Student's willingness to take risks	−1.229*		−0.300	
	(0.541)		(0.292)	
Student's openness	−1.078		0.729**	
	(0.636)		(0.359)	
Student's conscientiousness	7.444***		1.838***	
	(0.658)		(0.282)	
Student's extraversion	−0.677		0.065	
	(0.544)		(0.269)	
Student's agreeableness	0.869*		0.272	
	(0.370)		(0.300)	
Student's neuroticism	0.551		0.509**	
	(0.429)		(0.228)	
Constant	73.324***	75.676***	2.909**	3.734***
	(2.717)	(2.697)	(1.359)	(1.381)
Observations	2502	2502	2435	2435
Log-likelihood			−5053.9	5114.3
R-Squared	0.162	0.060		

Standard errors in parentheses.
Note: In the first and second columns lecture attendance is modelled using robust OLS regression, where the standard errors are clustered by university. In the third and fourth columns study hours are modelled using interval regression. The seven variables relating to noncognitive traits are standardised using *z*-scores. Where they apply, control variables for missing value adjustment and institutional fixed effects are not shown in the results. Outliers and missing values are adjusted *only* for independent variables.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

course makes no difference for lecture attendance, but does predict more additional study hours. Besides age, gender and year of enrolment, the main determinants of lecture attendance and additional study are the following set of noncognitive traits: conscientiousness, future-orientation, willingness to take risks, agreeableness, openness to experience, and neuroticism.[19] Conscientiousness and future-orientation are the only traits which affect both study behaviours.

It makes sense that those students who are more willing to take risks are less likely to attend their lectures. Risk-preferring students could miss out on the illustration of exam style questions by instructors, or other information relating to the structure of exam papers.[20] Students who are more agreeable (that is, those who have a tendency to act in a cooperative, unselfish manner) are more likely to attend their lectures. Students with higher levels of neuroticism (that is, those who are more prone to psychological distress) are more likely to do additional hours of study.

[19] Instead of looking at whether the father has some higher education, the authors also examined whether the mother has some higher education; as well the sum of parental education. None of these alternatives produce a statistically significant result in explaining lecture attendance. However, if mothers have some college education, then students are more likely to do additional hours of study. Father's education is used in the main specification as it is considered to pick up more of the social background for the household that each student comes from.

[20] Even if they could get this information from their friends who did attend, there is no guarantee that it would be fully accurate.

Finally, students who are more open to experience (that is, those who are more open to new aesthetic, cultural, or intellectual experiences) are more likely to do additional hours of study.

Conscientiousness is usually predictive of higher grade scores (O'Connor & Paunonen, 2007); and it predicts more of both study behaviours in the results of this paper. However, openness to experience is usually predictive of lower grade scores (O'Connor & Paunonen, 2007); but it predicts more hours of additional study in the results of this paper. Finally, extraversion is negatively related to grade scores in other studies (O'Connor & Paunonen, 2007); but it predicts neither of the study behaviours according to the results of this paper. This suggests that some noncognitive traits may operate differently in how they affect study behaviours, compared to how they affect academic achievement.

Focusing on the noncognitive traits which affect both study behaviours, one standard deviation increase in students' conscientiousness increases lecture attendance by approximately 7.4%; and increases study time by almost 2 h. One standard deviation increase in students' future-orientation increases lecture attendance by approximately 2.7%, and increases study time by almost 2 h.[21] Overall, the biggest effects on students' engagement with the study-process arise from being conscientious (that is, dependable and self disciplined; not disorganised and careless) and being future-orientated. In addition, these are the only noncognitive traits which affect both study behaviours. However, it is also notable that students who are more willing to take risks are less likely to attend their lectures, all else considered.

It might be the case that the effect of noncognitive traits differs throughout the distribution of lecture attendance. To allow for this, lecture attendance is modelled using quantile regression in Appendix E. The results are broadly similar when quantile regression is applied. As the behaviours of lecture attendance and additional study are intuitively related, bivariate regression analysis is applied to a joint specification[22]; the results of this analysis can be seen in Appendix F. Bivariate regression makes no difference to the overall pattern of results. Appendix G shows results from an analysis which includes a three-way interaction between subject area, university affiliation and year of enrolment. This interaction can be viewed as an endogenous class room effect, encapsulating class room characteristics and conditions. The effects of students' conscientiousness and future orientation are robust to the inclusion of controls for classroom conditions.[23]

5.2. Discussion

The results in this paper show that noncognitive traits, in particular conscientiousness and future-orientation, are important determinants of lecture attendance and additional study. In fact, there is very little that explains undergraduate study behaviour besides noncognitive traits. After controlling for a wide range of covariates, including students' traits; the results show that standard economic factors, such as family income, financial aid and parental transfers, are not predictive of study behaviours. However, as measurement of family income (and financial transfers) is prone to error, further research should attempt to replicate the findings in this paper. While causal identification of transfers requires further attention, it may be the case that noncognitive traits are more important than financial constraints in the determination of study behaviours. However, it is important to remember that financial constraints might still be important in relation to student welfare. That is, while financial constraints may not stop students attending lectures and doing additional hours of study, there may be other costs to attending/studying that are associated with having less financial resources (such as higher levels of stress).

It is worth noting that students in a later year of their course are more likely to do additional hours of study, after controlling for their noncognitive traits, and a range of other factors including their age. This behaviour could be a response by students to the end loading of their overall assessment towards the final and penultimate years of their study. The incentives in some Irish universities have changed in recent years as some weighting has been applied to the penultimate year of study; however, the majority of courses are still heavily weighted towards the final year. Any incentives that discourage students from smoothing their academic engagement over the entire duration of their studies can be viewed as sub-optimal; especially in light of the demonstrated advantage for students in being more future-orientated and conscientious. Overall, it would be preferable to allocate an equal weight to each year of study, in relation to what determines students' final mark.

One might wonder if there is a case for a mandatory attendance policy, given that students are more likely to miss their lectures if they are less conscientious and less future-orientated.[24] According to a meta-analysis by Crede, Roch, and Kieszczynka (2010), mandatory attendance policies have a small positive impact on grades. However, there is much debate on what incentives or penalties are appropriate in this regard, as penalising students for not showing up can be seen as *double jeopardy*: that is, students would

[21] Considering the other noncognitive traits, one standard deviation increase in students' willingness to take risks decreases their lecture attendance by more than 1%. One standard deviation increase in agreeableness increases lecture attendance by almost 1%. One standard deviation increase in openness increases study time by a considerable part of 1 h. One standard deviation increase in neuroticism increases study time by approximately 1 h.

[22] The number of additional study hours is treated as a continuous variable for this exercise.

[23] As year of enrolment is part of the three-way interaction, its effect on additional study hours becomes statistically insignificant.

[24] Mandatory attendance policies are rare – in the UK and Ireland at least (Allen & Webber, 2010).

be likely to get lower grades as well as being affected by an attendance-penalty.[25] One possibility is to *encourage* at-risk students to attend their lectures; rather than penalising students for not attending. This would be a similar approach to the ideas suggested by Thaler and Sunstein (2003) in their examination of the relationship between behavioural economics, public policy and paternalism. Thaler and Sunstein (2003) develop the terminology of *libertarian paternalism* to demonstrate that paternalism does not always have to involve coercion; they say: "we emphasise the possibility that in some cases individuals make inferior choices, choices that they would change if they had . . . no lack of willpower". Libertarian paternalism is defined as an approach that "preserves freedom of choice but that authorises . . . institutions to steer people in directions that will promote their welfare" (Thaler & Sunstein, 2003).

Nonetheless, one might wonder how it would be possible to encourage (or nudge) at-risk students to attend their lectures; in particular, how to identify at-risk students. However, there are recent technological advances which substantially ease the burden of collecting attendance data (Crede et al., 2010). Smart-card technology is available explicitly for the use of measuring student attendance; and there are new electronic systems which are being used to detect the ID cards students are carrying as they enter classrooms at Arizona University, and at one Irish institution of higher education. Therefore, it is possible to inform students about the number of lectures that they have missed. Future research should investigate this behavioural economics approach to encouraging lecture attendance using experimental methods.

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[25] Stephenson and Deere (1994) argue that lecture attendance should not be mandatory for the following reasons: students are missing the least productive classes, a captive audience is not an ideal learning environment, students should be allowed to maximise utility, attendance policies are difficult to implement.

Appendix A. The Big Five personality factors defined

The Big Five personality factors (American Psychological Association Dictionary, 2007)

Factors	Definition of factor
Openness to experience	The tendency to be open to new aesthetic, cultural, or intellectual experiences.
Conscientiousness	The tendency to be organised, responsible, and hardworking.
Extraversion	An orientation of one's interests and energies towards the outer world of people and things rather than the inner world of subjective experience; characterised by positive affect and sociability.
Agreeableness	The tendency to act in a cooperative, unselfish manner.
Neuroticism	Neuroticism is a chronic level of emotional instability and proneness to psychological distress. Emotional stability is predictability and consistency in emotional reactions, with absence of rapid mood changes.

Appendix B. Ten Item Personality Inventory

http://homepage.psy.utexas.edu/HomePage/Faculty/Gosling/scales_we.htm#Ten%20Item%20Personality%20Measure%20%28TIPI%29

Respondent instructions:
Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.
1 = disagree strongly
2 = disagree moderately
3 = disagree a little
4 = neither agree nor disagree
5 = agree a little
6 = agree moderately
7 = agree strongly

Statements: I see myself as:
1. Extraverted, enthusiastic.
2. Critical, quarrelsome.
3. Dependable, self-disciplined.
4. Anxious, easily upset.
5. Open to new experiences, complex.
6. Reserved, quiet.
7. Sympathetic, warm.
8. Disorganised, careless.
9. Calm, emotionally stable.
10. Conventional, uncreative

"R" denotes reverse-scored items:
Extraversion: 1, 6R; agreeableness: 2R, 7; conscientiousness: 3, 8R; emotional stability: 4R, 9; openness to experiences: 5, 10R.

Scoring:
1. Recode the reverse-scored items (i.e., recode a 7 with a 1, a 6 with a 2, a 5 with a 3, etc.). The reverse scored items are 2, 4, 6, 8, and 10.
2. Take the AVERAGE of the two items (the standard item and the recoded reverse-scored item) that make up each scale.
Example using the Extraversion scale: A participant has scores of 5 on item 1 (Extraverted, enthusiastic) and 2 on item 6 (Reserved, quiet). First, recode the reverse-scored item (i.e., item 6), replacing the 2 with a 6. Second, take the average of the score for item 1 and the (recoded) score for item 6. So the TIPI Extraversion scale score would be: (5 + 6)/2 = 5.5.

Appendix C. Consideration of Future Consequences Scale

http://web.missouri.edu/~strathmana/CFC%20%20English.pdf

Respondent instructions:
For each of the statements below, please indicate whether or not the statement is characteristic of you. If the statement is extremely uncharacteristic of you (not at all like you) please fill-in a "1" on the answer sheet; if the statement is extremely characteristic of you (very much like you) please fill-in a "5" on the answer sheet. And, of course, use the numbers in the middle if you fall between the extremes. Please keep the following scale in mind as you rate each of the statements below.
1 = extremely uncharacteristic
2 = somewhat uncharacteristic
3 = uncertain
4 = somewhat characteristic
5 = extremely characteristic

Statements:
1. I consider how things might be in the future, and try to influence those things with my day to day behaviour.
2. Often I engage in a particular behaviour in order to achieve outcomes that may not result for many years.
3. I only act to satisfy immediate concerns, figuring the future will take care of itself.
4. My behaviour is only influenced by the immediate (i.e., a matter of days or weeks) outcomes of my actions.
5. My convenience is a big factor in the decisions I make or the actions I take.
6. I am willing to sacrifice my immediate happiness or well-being in order to achieve future outcomes.
7. I think it is important to take warnings about negative outcomes seriously even if the negative outcome will not occur for many years.
8. I think it is more important to perform a behaviour with important distant consequences than a behaviour with less-important immediate consequences.
9. I generally ignore warnings about possible future problems because I think the problems will be resolved before they reach crisis level.
10. I think that sacrificing now is usually unnecessary since future outcomes can be dealt with at a later time.
11. I only act to satisfy immediate concerns, figuring that I will take care of future problems that may occur at a later date.
12. Since my day to day work has specific outcomes, it is more important to me than behaviour that has distant outcomes.

Scoring:
Generally, the CFC Scale is scored so that higher numbers indicate a greater consideration of future consequences. To do this, items 3, 4, 5, 9, 10, 11, and 12 should be reverse-scored. This can be done by creating a new variable which is "6-response" for each of the reverse-scored items. These seven new variables should then be summed along with the five items which need not be reversed (items 1, 2, 6, 7, and 8).

Appendix D. IUS (survey) data versus HEA (population) data

	IUS data set	HEA (2009)
Gender		
Male	37%	43%
Female	63%	57%
University		
DCU	6%	9%
NUIG	12%	16%
NUIM	12%	8%
TCD	19%	15%
UCC	20%	18%
UCD	24%	23%
UL	7%	12%
Subject		
Education	2%	4%
Humanities & Arts	23%	25%
Social Science	11%	7%
Business	11%	13%
Law	4%	6%
Science	16%	12%
Maths	3%	1%
Computing	3%	3%
Engineering	7%	8%
Agriculture	2%	2%
Health	15%	18%
Sport	0%	0%
Other	3%	2%

Appendix E. Quantile regression analysis: percentage lecture attendance

	(1) OLS	(2) 25th percentile	(3) Median	(4) 75th percentile
Log(Monthly income from family)	0.195	0.292	−0.041	−0.131
	(0.164)	(0.270)	(0.164)	(0.114)
Log(Monthly income from state)	0.096	0.232	0.136	−0.033
	(0.178)	(0.289)	(0.178)	(0.125)
Whether the father has higher ed.	0.799	1.806	−0.142	−0.103
	(0.738)	(1.202)	(0.741)	(0.519)
Family income: brackets of €20,000	−0.193	−0.073	−0.162	−0.159
	(0.161)	(0.262)	(0.161)	(0.118)
Student's age	0.493***	0.686***	0.417***	0.168***
	(0.088)	(0.147)	(0.087)	(0.061)
Whether the student is male	−3.368***	−3.626***	−2.139***	−0.928*
	(0.747)	(1.206)	(0.750)	(0.525)
Student's year of enrolment	−0.377	−0.946*	−0.002	0.218
	(0.313)	(0.513)	(0.314)	(0.221)
Whether student is in the STEM area	1.019	2.818**	1.336*	0.027
	(0.753)	(1.225)	(0.757)	(0.516)
The week the survey is conducted	−1.200***	−1.452**	−1.279***	−0.652***
	(0.350)	(0.576)	(0.350)	(0.239)
Student's future-orientation	2.695***	2.658**	2.867***	2.248***
	(0.639)	(1.041)	(0.642)	(0.437)
Student's willingness to take risks	−1.229**	−1.222	−1.189**	−0.624
	(0.554)	(0.899)	(0.555)	(0.402)
Student's openness	−1.078	−1.189	−0.870	−0.616
	(0.674)	(1.085)	(0.673)	(0.480)
Student's conscientiousness	7.444***	9.615***	7.134***	4.857***
	(0.536)	(0.864)	(0.538)	(0.377)
Student's extraversion	−0.677	−0.841	−0.466	0.159
	(0.507)	(0.843)	(0.508)	(0.358)
Student's agreeableness	0.869	0.856	0.804	0.807**
	(0.566)	(0.938)	(0.567)	(0.385)
Student's neuroticism	0.551	0.985	0.274	0.558*
	(0.429)	(0.702)	(0.431)	(0.300)
Constant	73.324***	60.786***	79.178***	90.700***
	(2.570)	(4.278)	(2.570)	(1.777)
Observations	2502	2502	2502	2502
R-Squared	0.162			

Standard errors in parentheses.

Note: The seven variables relating to noncognitive traits are standardised using *z*-scores. Where they apply, control variables for missing value adjustment and institutional fixed effects are not shown in the results. Outliers and missing values are adjusted *only* for independent variables.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Appendix F. Bivariate regression analysis

	(1) % lecture attendance	(2) Additional study	(3) % lecture attendance	(4) Additional study
Log(Monthly income from family)	0.217	−0.001	0.201	−0.001
	(0.166)	(0.013)	(0.175)	(0.014)
Log(Monthly income from state)	0.102	0.004	0.068	0.006
	(0.180)	(0.014)	(0.190)	(0.015)
Whether the father has higher ed.	0.838	0.066	0.309	0.053
	(0.747)	(0.060)	(0.788)	(0.062)
Family income: brackets of €20,000	−0.180	0.003	−0.225	0.004
	(0.164)	(0.013)	(0.172)	(0.013)
Student's age	0.489***	0.054***	0.552***	0.061***
	(0.088)	(0.007)	(0.093)	(0.007)
Whether the student is male	−3.505***	0.061	−4.526***	−0.020
	(0.755)	(0.061)	(0.750)	(0.059)
Student's year of enrolment	−0.456	0.262***	−0.180	0.275***

Appendix F. (*Continued*)

	(1) % lecture attendance	(2) Additional study	(3) % lecture attendance	(4) Additional study
	(0.316)	(0.026)	(0.334)	(0.026)
Whether student is in the STEM area	1.144	−0.050	1.451*	−0.051
	(0.760)	(0.061)	(0.801)	(0.063)
The week the survey is conducted	−1.219***	−0.042	−1.582***	−0.055*
	(0.357)	(0.029)	(0.376)	(0.029)
Student's future-orientation	2.854***	0.333***		
	(0.645)	(0.052)		
Student's willingness to take risks	−1.205**	−0.026		
	(0.558)	(0.045)		
Student's openness	−1.300*	0.117**		
	(0.684)	(0.055)		
Student's conscientiousness	7.352***	0.302***		
	(0.539)	(0.043)		
Student's extraversion	−0.661	0.001		
	(0.512)	(0.041)		
Student's agreeableness	0.951*	0.047		
	(0.572)	(0.046)		
Student's neuroticism	0.480	0.080**		
	(0.434)	(0.035)		
Constant	73.306***	1.256***	75.554***	1.399***
	(2.590)	(0.209)	(2.717)	(0.213)
Observations	2430	2430	2430	2430
R-Squared	0.164	0.168	0.061	0.118

Standard errors in parentheses.

Note: Columns 1 and 2 are estimated jointly (with noncognitive traits). Columns 3 and 4 are estimated jointly (without noncognitive traits). Additional study hours are treated as a continuous variable for the purpose of bivariate regression analysis. The seven variables relating to noncognitive traits are standardised using *z*-scores. Where they apply, control variables for missing value adjustment and institutional fixed effects are not shown in the results. Outliers and missing values are adjusted *only* for independent variables.

* $p < 0.1$

** $p < 0.05$.

*** $p < 0.01$.

Appendix G. The inclusion of classroom controls

	(1) % lecture attendance	(2) % lecture attendance	(3) Additional study	(4) Additional study
Log(Monthly income from family)	0.204	0.165	−0.003	−0.006
	(0.164)	(0.172)	(0.087)	(0.089)
Log(Monthly income from state)	0.074	0.032	−0.020	−0.011
	(0.178)	(0.188)	(0.094)	(0.096)
Whether the father has higher ed.	1.081	0.512	0.277	0.180
	(0.742)	(0.779)	(0.392)	(0.401)
Family income: brackets of €20,000	−0.161	−0.209	0.011	0.023
	(0.162)	(0.170)	(0.086)	(0.087)
Student's age	0.509***	0.570***	0.324***	0.365***
	(0.088)	(0.092)	(0.046)	(0.047)
Whether the student is male	−2.702***	−3.576***	0.573	0.130
	(0.762)	(0.759)	(0.403)	(0.390)
Student's year of enrolment	−12.164**	−12.712**	−1.445	−1.493
	(5.768)	(0.000)	(2.996)	(3.070)
Whether student is in the STEM area	−35.415**	−35.562**	−6.230	−5.870
	(15.661)	(16.504)	(8.280)	(8.488)
The week the survey is conducted	−1.256***	−1.594***	−0.251	−0.334*
	(0.351)	(0.369)	(0.187)	(0.191)
Student's future-orientation	2.455***		1.913***	
	(0.641)		(0.339)	
Student's willingness to take risks	−1.144**		−0.222	
	(0.556)		(0.292)	
Student's openness	−1.106		0.598*	
	(0.679)		(0.360)	
Student's conscientiousness	7.327***		1.923***	
	(0.538)		(0.282)	
Student's extraversion	−0.800		0.114	
	(0.508)		(0.268)	

Appendix G. (*Continued*)

	(1) % lecture attendance	(2) % lecture attendance	(3) Additional study	(4) Additional study
Student's agreeableness	0.670		0.227	
	(0.567)		(0.299)	
Student's neuroticism	0.635		0.465**	
	(0.429)		(0.227)	
Constant	81.760***	86.747***	4.199	5.107
	(11.754)	(12.378)	(6.105)	(6.252)
Observations	2502	2502	2435	2435
R-Squared	0.191	0.098		

Standard errors in parentheses.

Note: The seven variables relating to noncognitive traits are standardised using *z*-scores. Where they apply, control variables for missing value adjustment and institutional fixed effects are not shown in the results. Outliers and missing values are adjusted *only* for independent variables.

* $p < 0.1$

** $p < 0.05$.

*** $p < 0.01$.

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