Why Are Extraverted Young Men Less Likely to Receive Higher Education? Evidence from Hungary

Zsombor Cseres-Gergely* and Gábor Kézdi**

Abstract

Using a unique longitudinal survey from Budapest, Hungary, this paper analyzes the role of extraversion in studying towards higher education and working. Extraversion is found to have no effect on higher education for young women but a significant negative effect for young men. Results from a more structural model suggest that, conditional on IQ and various measures of other personality traits, as well as past schooling experience and past behavioral problems, more extraverted men expect lower returns to higher education. These results are new in the literature and are unlikely to be caused by the specificity of the survey.

Keywords: college enrollment, non-cognitive skills, Big Five, extraversion, returns to traits

JEL codes: I210, J240

1 Introduction

Whether and how personality traits affect labor market outcomes has become a focus of active research in education and labor economics recently. The role of cognitive skills, often measured by IQ, has been recognized since at least Mincer (1958) and Mincer (1974). Economists' interest in other personality traits, often labeled as non-cognitive skills, is more recent. Bowles et al. (2001), Heckman and Rubinstein (2001), Heckman et al. (2006) emphasize the importance of non-cognitive skills in wage formation. While new in

* Institute of Economics, Hungarian Academy of Sciences and Central European University.
Address: Budaörsi út 45. 1112 Budapest, Hungary. E-mail: zgergely@mtakti.hu
Corresponting author. Tel.:+36308164261. Fax: +36 1 319-3136
** Central European University and Institute of Economics, Hungarian Academy of Sciences.
Address: Nádor u. 9, 1051 Budapest, Hungary. E-mail address: kezdig@ceu.hu

economics, personality traits have been the focus of an entire field within psychology for decades. A recent paper by Borghans et al. (2008) has called for more systematic research on non-cognitive traits by a incorporating more results of psychology research.

The broad question in this area is which personality traits are important for which outcome and why. From the economists' point of view, perhaps the most important outcome is labor market success. The role of personality is mediated through educational attainment in two possible ways: educational choice (and attainment) may be caused by personality traits, and/or education may cause those traits to develop (Carneiro and Heckman, 2003). The effects on labor market outcomes and education are therefore of foremost interest. In terms of traits, a wide range of measures have been analyzed, from self-esteem and locus of control (Heckman et al, 2006) to social adjustment (Carneiro et al, 2006). At the same time, psychology research converged on the importance of the Big Five personality classification. The five dimensions established are: extraversion/introversion; friendliness/hostility; conscientiousness/impulsivity; emotional stability/neuroticism; and openness to experience. It is important to learn more about the role of the Big Five traits as established in psychology in the domains important for economists, by using the appropriate methods used by economists (Borghans et al, 2008).

This paper focuses on one, and perhaps the most influential, of the Big Five personality traits, extraversion. In particular, we look at the gender differences in the relationship of extraversion in enrollment into higher education. Extraversion is the tendency to enjoy human interactions and to be enthusiastic, talkative, assertive, and gregarious. Gender differences in personality have been analyzed in the psychology literature (see, e.g. Costa et al, 2001), and gender differences in educational and labor market outcomes have been the focus of a large economics literature (see, e.g. Altonji and Blank, 1999). At the same time, gender differences in the returns to personality traits have been less often analyzed. An exception is Jacob (2002) who shows that not only have boys significantly more behavioral problems in high school, but these problems have a more negative effect on boys than on girls in terms of college enrollment. These effect are found to persist even after controlling for a series of family background variables. We know of no study that looked at gender differences in the role of extraversion in educational and labor market outcomes.

In order to answer our question, we make use of the Budapest Longitudinal Survey of Child

Development (BLSCD). The BLSCD is a unique longitudinal dataset that collects detailed information on a few hundred respondents from their birth through age 22. Although the number of relevant observations is relatively low at around 320, the richness of the survey enables us to improve upon existing studies in measuring cognitive and non-cognitive skills and to remedy some of the endogeneity problems, based on the longitudinal dimension.

Our main results are coming from a stylized model of higher education attainment, empirically estimated using a multinomial probit specification. We show that besides the strong and gender-neutral effect of cognitive scores, the extroversion measure reduces the probability of higher education attainment of young men in a robust fashion, but the same is not true for women. By using proxies for the cost of higher education in terms of personality traits, we can separate the cost effect of past behavioral problems from the current effect of personality traits. Our results suggest that extraversion lowers the returns on the labor market for men, rather than raising the costs of education.

2 Data

The data we use is coming from the Budapest Longitudinal Survey of Child Development (BLSCD hereafter) of the Institute of Psychology, Hungarian Academy of Sciences. The BLSCD is an ongoing panel survey that collects detailed information on respondents from their birth through age 22 (as of now). The sample of the survey is a subsample of a demographic research project of the Hungarian Statistics Office and is representative for all children born between January 1st 1982 and September 30th 1983 in Budapest, Hungary. The original sample covered 482 newborns. Sampling was based on a quota procedure. Districts were selected first and families were selected second so that they represent the socio-economic diversity of Budapest.

The original sample was followed through six phases of data collection. Wave 1 was administered when the baby was 3 months old, wave 2 at the age of 3, wave 3 at around age 6, just before enrolment into primary school, wave 4 at the age of 8, and wave 5 at the age of 12. The project did not get funding for the following ten years until wave 6 was administered at age 22 (in year 2005). Data quality was kept high by working with the same interviewers throughout the 22 years of the survey. Out of the 482 families in the original sample, 68 opted out before wave 1. In practice, therefore, BLSCD started with 414 newborns (86 per cent). Of them, 354 (86 per cent) were interviewed in wave 6 at age 22. Attrition is relatively low but it is unlikely to be random. There is no detailed study on attrition and nonresponse in the survey.

The representativeness of the survey is difficult to account for as most of the data is unique. But basic demographics we can compare to national representative survey data. For such comparison, we use the four quarterly cross-sectional samples of Hungarian Labor Force Survey (HLFS) of 2004, and look at those who were 22 years old and lived in Budapest. Unfortunately, city of birth is not known in the HLFS thus the comparison is necessarily biased by migration into the city. Since quite a few BLSCD individuals migrated out of Budapest, for this comparison we restrict the sample to the 294 individuals who lived in Budapest in wave 6. In terms of variables, we look at employment and enrollment to higher education, previous schooling and gender.

Table 1 here.

Table 1 shows that by and large, BLSCD participants seem to be more likely to be enrolled in higher education and more educated. This means that the sample might be biased towards more able individuals. The extent of the bias is hard to assess because of the imperfect nature of the comparison.

The BLSCD dataset is very rich. It contains detailed interviews with both parents at birth and a battery of psychological tests. Home environment and parenting practices are also measured in detail. Child development tests were administered at age 2 and 6, and cognitive tests are available for age 6, 8, and 22. Wave 5 (age 12) is less rich in psychology tests but it includes detailed questionnaires of how schoolteachers and parents see the child subjectively. Wave 6 (age 22) again contains cognitive tests and measures of personality.

The dataset is not publicly available, and in a large part stored only on paper. The information available to us is a small subset of the universe recorded in the survey. Labor market participation and history is recorded for every individual. We observe a measure of age 22 cognitive capacity (Raven IQ score) as well as age 22 personality measures (Big Five scores for openness, conscientiousness, extraversion agreeableness and neuroticism). We also have parents' educational attainment (measured for both parents at the birth of the child), and the child's IQ score measured at age 5 (Binet). School grades from grade 1 through grade 12 are available, and we use grade point averages calculated from them. Finally, parents and schoolteachers assessed the child's behavioral problems at age 12, in an independent way.

The focus of this paper is higher education. The estimation sample was therefore restricted to those who could potentially study in higher education. In Hungary, as in many continental European countries, a maturity examination must be passed in order to apply to college. Such exams are administered at the end of grade 12 in secondary schools. Vocational training schools are of 11 grades, and they do not administer such examinations themselves, but graduates can enroll into short courses and take the examination afterwards. All with at least 11 grades of education (and with non-missing educational attainment data) were retained for the analysis. The estimation sample consists of 312 individuals.
Table 2 summarizes the variables used in the analysis, separately for females and males.

Table 2 here.

3 Descriptive evidence

Hungary is a relatively small transition country and a member of the soviet-bloc before 1989, which might suggest that the data we use or our results might be particular. If one takes a look at Hungary's recent social and economic development, it becomes clear that this is not the case. Not only was Hungary the first to go forward with thorough privatization, but its society has adapted rapidly to the new circumstances: it is safe to say that the transition was by and large over by 2000 (see Brown, 1999).

Despite the overall settling down of the transition process, higher education enrolment and the graduate labor market still showed some signs of a peculiar transition around 2000. As the number of individuals obtaining higher education degree was artificially restricted before the transition, we have observed a great increase in the number of higher education students (see Lannert, 2005, for example). Because of the resulting excess demand, higher education diploma earned a substantial premium on the labor market at the same time, as shown by Kertesi and Köllő (2007), for example. Nevertheless, comparisons with international evidence makes us confident that these changes do not influence our results.

At age 22, the individuals in the survey could be enrolled in higher education, working, unemployed or inactive. The focus of this paper is on enrollment into higher education, but we'll also look at whether those not enrolled work. Table 3 shows the distribution of the 312 individuals in the sample according to their status at age 22.

Table 3 here

The three states are defined as mutually exclusive. Full-time enrolment in higher education is defined as a single category regardless of other activity (25 out of the 180 students have reported some work for pay). A dozen students already completed college and they are counted in this category as well. According to this definition, 58 per cent of the 22 year-old continued their studies in higher education. Gender differences are small: 60 per cent of women versus 55 per cent of men continued in higher education.

Of the non full-time students, two thirds were employed and one third were not employed. There are no gender differences in terms of unconditional employment probabilities (somewhat below 30 per cent). The gender non-employment differential mirrors the higher education differential, with men being slightly more likely to be not employed than women. Table 4. shows the test scores for men and women by their status at age 22.

Table 4 here

Cognitive capacity is measured by a Raven IQ score, standardized to the entire sample. Since those with very low education are excluded from the estimation sample, the overall mean in Table is positive, at 0.07. There is a small gender difference in the scores, with men scoring 0.17 standard deviation higher than women.

More importantly, enrollment in higher education is strongly positively related to cognitive capacity: the difference is above 0.6 standard deviations. This is in line with results previously found in the literature, see e.g. Figure 3 in Borghans et al. (2008). The difference is somewhat larger for women (0.66) than for men (0.58). The gender differential is larger among employed and non-employed non-students. Non-employed women have significantly lower cognitive scores, but the same is not true for men.

Extraversion seems to be weakly negatively related to higher education overall. The difference between students and non-students is -0.14, which is also within the range of what was previously found in the literature, again see Borghans et al. (2008). Contrary to cognitive capacity, however, the overall relationship between higher education and extraversion is a result of two large but opposing relationships for women and men. According to Table 4, females in higher education score 0.25 points higher in terms of extraversion than their non-student peers. At the same time, male students score 0.53 points lower than non-student males.

The gender difference in the relationship of employment and extraversion is smaller. Employed women are 0.2 points more extraverted than non-employed women, while employed men are similar in terms of extraversion than non-employed men (and all more extraverted than non-student women). Overall gender differences in terms of extraversion are negligible.

In order to see whether the relationships documented in Table 4 are preserved when the two test scores are conditioned on each other, we estimated simple probit models for the probability of being in higher education. Cognitive test scores at age 22 are probably endogenous for at least two reasons: measurement error and reverse causality. Measurement error if classical is likely to understate the effect of intelligence, while reverse causality is likely to overstate it, because higher education in itself may have a positive effect on test scores (students are more "in shape" for such tests, and they are likely to take them more seriously). In order to treat that endogeneity, we re-estimated the probit models instrumenting age 22 cognitive test scores by age 5 cognitive test scores.

Table 5 shows the results, in the forms of average partial effects (also called as marginal effects). Analogously to Table 4, first we looked at females and males separately and then pooled together. The coefficient estimates and other details are to be found in Table A2 of the Appendix.

Table 5 here.

The first three columns show the simple probit results. They confirm what we have seen in Table 4. Cognitive scores are positively related to higher education: one extra standard deviation of IQ increases the probability of higher education by 25 percentage points for women and 17 percentage points for men (22 percentage points combined). Extraversion is not related to higher education for women and overall, but it is significantly negatively related to higher education for men. One extra standard deviation of extraversion decreases the probability of higher education by 13 percentage points.

The IV results for the effect of cognitive scores are more than double of the simple probit estimates. This indicates substantial measurement error in cognitive scores. The results on extraversion are virtually unchanged. At the same time, the large measurement error in cognitive scores indicate that similar errors may be present in the extraversion tests as well. If that is indeed the case, the true negative effects of extraversion on higher education for men may be even stronger than the estimates shown here.

The differential role of extraversion in higher education for women versus men is the focus of this paper. There are several possible explanations for the phenomenon. One of these might be that there is a exogeneous barrier (a "glass ceiling") above women building their career that men do not have to fight. If this barrier is easier to fight for a higher education graduate, the returns to college can be higher for women, ceteris paribus. Alternatively, the differentials in returns can be a bit more endogeneous. In the spirit of the Weiss and Gronau (1981) model, one might say that the difference between men and women is that the latter, on average, can expect an interruption of her career after childbirth. Given the break itself and the lessened capacity to earn on the job credentials, one might expect that women will try to obtain more formalized resources under such circumstances. In particular, a college diploma is a certificate that has value even with little labour market experience and after a gap, whereas a career based on on the job learning and presence would be severely hindered by such an interruption. Although both idea can motivate the differences we see here, we do not pursue them in detail, but move on to a more structural model.

4 A more structural model

In order to disentangle the possible mechanisms, we jointly analyze the probability of higher education and the probability of employment if not in higher education. The analysis takes the form of a multinomial probit model, with an explicit structure for the returns to personality traits.

Let *S* denote the vector of personality traits, including intelligence and extraversion. Assume that earnings (*W*) are determined on a competitive labor market by a fixed wage rate for units of human capital *H*. Human capital is a function of personality traits *S* and education *ed*. For simplicity and without loss of generality, set this fixed wage rate to unity. Then

$W=H(S,ed)$

Let *ed=high* denote education of college or more, and let *ed=low* denote less than college education (but at least 11 grades according to our sample restriction). Rewrite the returns to personality traits if education is low and if high by $a(S)$ and $b(S)$, respectively:

$a(S)=H(S,ed=\text{low})$
$b(S)=H(S,ed=\text{high})$

Achieving higher education also entails costs, denoted by *c*, also possibly a function of personality traits *S*: $c(S)$ Moreover, assume that by not working at age 22, one can achieve a utility level that is equivalent to receiving earnings *d*.

The value of the three states, not working, working, and studying towards a higher education degree, are then the following:

$$\begin{aligned} V(notworking) &= V_0=d \qquad (1)\\ V(working) &= V_1 = a(S) \\ V(studying) &= V_2 = b(S) - a(S) \end{aligned}$$

To be more precise, the last equation denotes an expected value, and thus $b(S)$ should be interpreted as expected returns, while $c(S)$ as expected costs.
The probability of each state is then

$$p_0 = \Pr(notworking) = \Pr[V_0 > V_2 \,\&\, V_1 \le V_0]$$

$$p_1 \quad = \Pr\ (\textit{working}) = \Pr\left[V_1 > V_0\ \&\ V_2 \le V_1\right]$$

$$p_2 \quad = \Pr\ (\textit{studying}) = \Pr\left[V_2 > V_1\ \&\ V_0 \le V_2\right]$$

In order to get to an estimable model, we consider linear specifications of the a, b, and c functions and allow for random variation in each as well as in d. For easier notation, let lowercase s denote the vector of personality traits contained in uppercase S, augmented by a first element of one in order to allow for a constant. Thus we get

$$p_0 \quad = \Pr\left[-(\beta-\gamma)'s+\delta > \varepsilon_b-\varepsilon_c-\varepsilon_d\ \&\ \alpha' s-\delta \le -\varepsilon_a+\varepsilon_d\right]$$

$$p_1 \quad = \Pr\left[\alpha' s-\delta > -\varepsilon_a+\varepsilon_d\ \&\ (\beta-\gamma-\alpha)'s \le -\varepsilon_b+\varepsilon_c+\varepsilon_a\right]$$

$$p_2 \quad = \Pr\left[(\beta-\gamma-\alpha)'s > -\varepsilon_b+\varepsilon_c+\varepsilon_a\ \&\ -(\beta-\gamma)'s+\delta \le \varepsilon_b-\varepsilon_c-\varepsilon_d\right]$$

Let e_1 be the identity vector with one in the first element and zeros elsewhere. Then we can simplify notation by introducing the following π vectors:

$$\pi_{02} \quad = -\beta+\gamma+\delta e_1 \qquad (2)$$

$$\pi_{10} \quad = \alpha-\delta e_1 \qquad (3)$$

$$\pi_{21} \quad = \beta-\gamma-\alpha$$

Similarly, we can collect the random variation into single variables:

$$u_{02} \quad = \varepsilon_b-\varepsilon_c-\varepsilon_d \qquad (4)$$

$$u_{10} \quad = -\varepsilon_a+\varepsilon_d \qquad (5)$$

$$u_{21} \quad = -\varepsilon_b+\varepsilon_c+\varepsilon_a$$

Then we can rewrite the probabilities the following way:

$$p_0 \quad = \Pr\left[\pi_{02}' s > u_{02}\ \&\ \pi_{10}' s \le u_{10}\right] \qquad (6)$$

$$p_1 \quad = \Pr\left[\pi_{10}' s > u_{10}\ \&\ \pi_{21}' s \le u_{21}\right]$$

$$p_2 \quad = \Pr\left[\pi_{21}' s > u_{21}\ \&\ \pi_{02}' s \le u_{02}\right]$$

If we specify random variation to be i.i.d. normal, (6) defines a multinomial (also known as a conditional) probit model developed by Hausman and Wise (1978). The coefficients of the model are the coefficients π_{10}, π_{20} and π_{21}, and the covariance matrix of the unobservables u_{10}, u_{20} and u_{21}. The multinomial probit allows for arbitrary correlation across the structural unobservables ε - in contrast to, for example to the multinomial logit. Allowing for such a correlation is important here. Unobserved heterogeneity in productivity in low-education jobs (e_α) are likely to be correlated with unobserved heterogeneity in productivity in high-education jobs (e_β). Potential examples include health, motivation, self-esteem, and the ability to cope with difficult situations. Multinomial probability models can also yield consistent estimates for average effects if the effects themselves are heterogeneous (as in the original Hausman and Wise application).

All probability models impose natural restrictions on the coefficients. Since the probabilities need to add up to one, anything that increases one probability should lead to an equally large decrease in the other probabilities combined. As a consequence, the π coefficients sum up to zero. It is satisfied in our case as well: $\pi_{10}+\pi_{20}+\pi_{21}=0$.

The multinomial probit model estimates normalized versions of the all parameters. Normalization is required because the variance of the unobservable components are not all identified. The standard restriction is to set one of the variances to unity and identify all parameters (including the π coefficients of interest) relative to the "true" value of the restricted variance. Since the normalization is done by a single positive number, it affect neither the sign nor the relative magnitude of the coefficients.

From estimated parameters π, one needs to identify the structural parameters α, β, γ and δ by (2). Evidently, not all parameters are identified. Less importantly, the constants in the linear approximations to the *a*, *b* and *c* functions are not identified separately from *d*. This means that returns to and costs of education at fixed personality traits are not identified from simple cross-sectional comparisons (a standard problem in identifying labor demand).

More importantly, the slope coefficients on *s* are identified for *a* (returns to personality traits in low-education jobs) but not for *b* and *c* separately. The latter two would separate the returns to personality traits in high-education jobs from the effect of such traits on the costs of getting higher education. Given the data at hand, only the net returns are identified: returns to traits minus their effects on the costs.

The identification problem is partly due to the fact that we do not observe higher education graduates on the labor market. But even in such a case one would need enough college graduates to be unemployed for reasons that are exogenous to personality traits. It is an analogous argument for lower education workers that allows us to identify returns to personality traits for them (α): there we assumed that the value of outside options $(d = \delta + \varepsilon_d)$ does not depend on personality traits *S*. An analogous assumption is unlikely to hold for the costs of education (therefore $c = c(S)$). As a result, in reduced-form cross-sectional settings, labor market returns to personality traits for higher educated employees can in general be estimated only relative to their effects on the costs of higher education.

5 Results

We estimated the multinomial probit model specified in (6) in four ways. All four models contain the standardized IQ and extraversion scores, both measured at age 22, both fully interacted with gender.

Model (1), the baseline specification, enters no other covariates. Model (2) includes the measures on other four dimensions of the Big Five personality battery, again interacted with gender. The four other personality traits are the following: agreeableness, conscientiousness, neuroticism and openness. With the number of observations at hand, it is impossible to estimate the effect of each personality trait in a precise fashion. Our aim is simply to see whether the estimated effect of extraversion is modified by entering the other traits, and whether estimates on those other traits are broadly in line with those found in the literature.
Model (3) and (4) try to proxy for the cost component (γ) in the net expected returns to higher education $(\beta - \gamma)$. If the net effect of personality traits operates through the costs of education, we should see the net effect to decrease in magnitude. Model (3) contains grade point average (GPA) in grades 1 through 8 and grades 9 through 12, as well as mother's education. Past GPA can capture the results of the effect of personality traits on costs of schooling in the past. Those results can therefore proxy for personality-related costs of higher

education under the assumption that such costs are related across different levels of education. Parental education is a more direct proxy for such costs (fathers' education is very insignificant on top of mothers' education therefore its omission). Model (4) enters some direct measures of psychic costs of past education: the occurrence of behavioral problems at age 12. Wave 5 of the survey contains a 33-item questionnaire on the prevalence of behavioral problems that parents and schoolteachers answered independently. The questions include items such as lying, aggression, provocative behavior or being the clown of the class. Note that the proxies in Models (3) and (4) may both "underdo" and "overdo" their job. On the one hand, they are unlikely to capture the entire effect of personality on the costs of education (γ). On the other hand, they may capture some of the expected labor market returns of personality traits (β). As well as long as the main measures of personality (IQ and extraversion scores) are measured with error, these proxies can serve as alternative measures of the same traits and thus their coefficient may in part reflect the true effects. Although the net effect is impossible to tell, we can expect the two sets of proxies to have some effects on the coefficients on IQ and extraversion. Lack of finding such effects is indicative of the net returns operating mainly through expected labor market returns as opposed to costs of education.

Parameter estimates on all right-hand side variables as well as other statistics are in the Appendix in Table A2. The main results are to be discussed below. The auxiliary parameter estimates are intuitive. Openness to new experience (Model 2) seems to increase the propensity to higher education almost as much as IQ, exactly what is found in the previous literature on its effects on education (e.g. Borghans et al., 2008). Agreeableness, conscientiousness and neuroticism have no significant effects, again broadly in line with the literature that shows at most modest effects on education. GPA and parental education is strongly associated with higher education (Model 3), and behavior problems at age 12 are negatively associated with higher education, especially if marked by the schoolteacher.

Tables 6 and 7 summarize the most important results. Table 6 shows the average partial effects of IQ and extraversion on the three probabilities, while Table 7 shows the implied structural parameters α and $\beta - \gamma$.

Table 6 here

Cognitive scores have strong positive effects of getting a higher education. According the results from Models (1) and (2), one standard deviation increase in cognitive scores is associated with 30 percentage points increase in the probability of enrollment for women, and 20 percentage points for men. The corresponding negative effect on not getting a higher education is similar in magnitude whether working instead or not working for women. For men, the corresponding negative effect is mostly seen in the probability of working.

Models (3) shows somewhat different results. By controlling for past grades and parental education, the effect of IQ is cut by a half for women, and even more for men. As a result, some of previously significant effects become insignificant, but the qualitative pattern remains the same. Model (4) shows the same results as Models (1) and (2).

The effect of extraversion on the probabilities for women are insignificant in all specifications except for Model (3). There, by controlling for past GPA and parental education, extraversion has a moderate positive effect on the probability of higher education and roughly equal negative effects on the probability of being a working or a non-working non-student.

For men, the effect of extraversion is significant and negative on higher education across all specifications. The male extraversion estimates are fairly similar across specifications, being virtually the same for Models (1), (3) and (4). They are somewhat larger for Model (2) when measures for other personality traits are controlled for, but the qualitative patterns remain the same there as well. In the baseline model, one standard deviation increase in extraversion scores is associated with 14 percentage points decrease in the probability of enrollment. The magnitude of the effect is about two-thirds of the estimated effect of IQ for men. The corresponding positive effects for being a non-student are significantly stronger for being employed. One standard deviation increase in extraversion scores is associated with 10 percentage points increase in the probability of employment. Again, the magnitude of the effect is about two-thirds of the estimated (negative) effect of IQ.

Average partial effects on the probabilities are very useful in seeing the magnitudes, but they in themselves cannot answer where the effects come from. In order to answer the more structural questions we need to look at the more structural parameters. The structural parameters implied by the point estimates of Models (1) through (4) are in Table 7.

Table 7 here

According to the point estimates, returns to IQ without higher education (α) are in all specifications. The estimated effects are positive for women and slightly negative for men. In sharp contrast to these results, net returns to IQ are strong and positive for higher education, with no gender difference to speak of. Recall that in Models (1) and (2) only net returns to personal traits are identified for higher education. These are the effects of personality traits on expected earnings minus the effects on costs of getting the higher education degree $(\beta - \gamma)$.

As we argued, Models (3) and (4) may help telling whether net returns to personality traits in higher education are large because they increase expected earnings in high-educated jobs (β) or because they decrease the costs of education (γ). Net returns to IQ stay unchanged in Model (4) where we control for behavioral problems in primary school. In Model (3), however, where past GPA and parental education are controlled for, net returns to IQ decrease by two-thirds both for men and women. As we discussed earlier, this may indicate a larger role played by IQ in reducing costs of higher education. An alternative explanation, also discussed earlier is that past GPA is another measure of cognitive capacity besides the Raven IQ scores measured at age 22. That would change the estimated coefficient of IQ even if it has nothing to do with costs of higher education. Note however that in this latter case, the coefficient on IQ would change roughly the same way in α and in β–γ. The results in Table 7 show that no such change is observable in α. This suggests that IQ increases the probability of higher education enrollment in large part by decreasing the costs of education.

Returns to extraversion in low-educated jobs (α) are very similar to returns to cognitive capacity in such jobs for women, but not for men. Returns are very small but positive for women and practically zero for men (the latter except for Model 2 but small even there).
Net returns to extraversion for higher educated women $(\beta - \gamma)$ are zero, but they are strong and negative for men. The magnitude of the negative net effect of extraversion with higher education is about two thirds of the positive effect of cognitive capacity (in Model 2 it's even larger). The estimated structural effects of male extraversion are virtually the same in Models (1), (3) and (4), indicating that whatever the proxies capture in the last two models, they do not interact with the net effect of extraversion on higher education.

The results suggests that, for men, the negative effect of extraversion on the probability of higher education operates through lowering the expected returns on the labor market as opposed through costs of education. The results are more mixed for women where models with cost proxies show more positive effects of extraversion. But that is true both for α and $\beta-\gamma$, suggesting that a possibly negative role for extraversion in the costs of education is not the only explanation. In sum, the results do not provide much evidence for extraversion to play a large part in the costs of education. Instead, the measured effects are likely to operate through expected returns on the labor market.

6 Conclusions

Using a unique dataset from Budapest, Hungary, we analyzed the role of extraversion on enrollment into higher education. Doing so, we have joined a growing body of literature looking at the effect of cognitive and non-cognitive skills on labor market outcomes. We have focused on the indirect effect of such skills, operating through the enrolment into higher education.

Our main contribution is twofold. Firstly, instead of a random measure of noncognitive traits, we made use of a standard set of indices, called the Big Five, in particular its dominant measure of extroversion. Secondly, we separated the effects on participation according to gender to uncover substantial differences. Similarly to different approaches, we have found that non-cognitive skills have a significant negative effect on the higher education attainment of young men, while such effect is missing for women. Using proxies for earlier behavioral problems, we obtained results suggesting that non-cognitive traits work mostly through increasing the returns of early entry to the labor market, rather than the cost of higher education.

Our empirical model was agnostic about the sources of the gender differences and the size of our data was enough only to show the existence of the gender-differences. Although our result fits well into the related literature, it will be interesting to see why such differences emerge and what longer term effects do they have. To carry out such an analysis, we have yet to see data that is both long and rich enough not only to follow individuals, but to do so for a long time and such a large number of them that several outcomes are observable over time.

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TABLES

Table 1. Representativeness of the BLSCD sample. Budapest residents in the BLSCD and Budapest residents of the Hungarian Labor Force Survey (HLFS), 2002.

	BLSCD	HLFS
Labor market status		
Not working non-student	0.17	0.21
Working non-student	0.28	0.34
Enrolled in higher education	0.54	0.45
All	1.00	1.00
Former education		
General secondary (or higher)	0.57	0.51
Specialized secondary	0.27	0.25
Vocational	0.07	0.08
Primary or less (0-8grades)	0.09	0.16
All	1.00	1.00
Gender		
Female	0.50	0.50
Male	0.50	0.50
All	1.00	1.00
Observations	294	334

Table 2. Summary statistics

	Female	Male	All
Not employed, non-student	0.12	0.16	0.14
Employed non-student	0.28	0.29	0.28
Enrolled in higher education	0.60	0.55	0.58
IQ	-0.01	0.16	0.07
Extraversion	-0.02	0.01	-0.01
IQ age 5	0.04	0.05	0.04
Agreeableness	0.07	-0.07	0.00
Consciensciousness	0.00	0.00	0.00
Neuroticism	-0.17	0.19	0.00
Openness	-0.07	0.08	0.00
GPA (grades 1 through 8, standardized)	0.11	-0.12	0.00
GPA (grades 9 through 12, standardized)	0.18	-0.19	0.00
Mother’s education (years, standardized)	0.04	-0.04	0.00
Behavior problems (assessed by parent, standardized)	-0.18	0.19	0.00
Behavior problems (assessed by teacher, standardized)	-0.07	0.07	0.00
Number of observations	162	150	312

Note: Estimation sample: educational attainment at least 11 grades (vocational school)

Table 3. Student status and labor market activity at age 22 (per cent).

	Female	Male	All
In higher education	60	55	58
Not in higher education	40	45	42
of which			
employed	28	29	28
not employed	12	16	14
All	100	100	100
Observations	162	150	312

Note: Estimation sample: educational attainment at least 11 grades (vocational school)

Table 4. IQ and extraversion by student status and labor market activity at age 22.

	IQ			Extraversion		
	Female	Male	All	Female	Male	All
In higher education	0.26	0.42	0.34	0.08	-0.23	-0.07
Not in higher education	-0.43	-0.16	-0.30	-0.17	0.30	0.07
of which						
employed	-0.35	-0.20	-0.28	-0.11	0.32	0.10
not employed	-0.61	-0.10	-0.33	-0.30	0.28	0.02
All	-0.01	0.16	0.07	-0.02	0.01	-0.01

Notes: IQ is measured by standardized Raven IQ, age 22. Extraversion is measured by standardized Big5 scores, age 22. Estimation sample: educational attainment at least 11 grades (vocational school)

Table 5. The probability of higher education as a function of cognitive capacity and extraversion. Average partial effects from probit models.

	Simple probit			IV probit		
	Female	Male	All	Female	Male	All
IQ	0.25	0.17	0.22	0.69	0.46	0.56
[standard error]	[0.04]**	[0.04]**	[0.03]**	[0.20]**	[0.20]*	[0.14]**
Extraversion	0.05	-0.13	-0.04	0.03	-0.12	-0.04
[standard error]	[0.04]	[0.04]**	[0.03]	[0.06]	[0.06]*	[0.04]

Notes: IQ is measured by standardized Raven IQ, age 22. Extraversion is measured by standardized Big5 scores, age 22. Estimation sample: educational attainment at least 11 grades (vocational school).
$^{+}$ significant at 10%; * significant at 5%; ** significant at 1%

Table 6: Estimated average partial effects from the multinomial probit models

	Pr(not employed)			
	(1)	(2)	(3)	(4)
IQ X female	-0.12	-0.12	-0.06	-0.16
	[0.03]**	[0.04]**	[0.03]	[0.05]**
IQ X male	-0.05	-0.05	0.00	-0.05
	[0.03]	[0.03]	[0.03]	[0.04]
Extraversion X female	-0.05	-0.03	-0.06*	-0.02
	[0.03]	[0.03]	[0.03]	[0.04]
Extraversion X male	0.04	0.05	0.04	0.04
	[0.03]	[0.03]	[0.03]	[0.04]

	Pr(employed)			
	(1)	(2)	(3)	(4)
IQ X female	-0.18	-0.18	-0.08	-0.16
	[0.05]**	[0.05]**	[0.05]	[0.05]**
IQ X male	-0.14	-0.14	-0.04	-0.13
	[0.07]**	[0.05]**	[0.05]	[0.04]**
Extraversion X female	-0.02	-0.01	-0.06	-0.02
	[0.04]	[0.05]	[0.04]	[0.04]
Extraversion X male	0.10	0.15	0.09	0.10
	[0.04]*	[0.05]**	[0.04]*	[0.04]*

	Pr(higher education)			
	(1)	(2)	(3)	(4)
IQ X female	0.30	0.30	0.14	0.27
	[0.06]**	[0.06]**	[0.07]*	[0.06]**
IQ X male	0.20	0.19	0.04	0.18
	[0.05]**	[0.05]**	[0.05]	[0.05]**
Extraversion X female	0.07	0.04	0.13	0.06
	[0.04]	[0.04]	[0.05]**	[0.04]
Extraversion X male	-0.14	-0.20	-0.13	-0.14
	[0.05]**	[0.05]**	[0.05]**	[0.05]**

* significant at 5%; ** significant at 1%

Table 7: Point estimates of the structural parameters of interest

	α			
	(1)	(2)	(3)	(4)
IQ X female	0.15	0.18	0.19	0.13
IQ X male	-0.10	-0.12	-0.13	-0.12
Extraversion X female	0.19	0.10	0.24	0.21
Extraversion X male	0.03	0.18	0.01	0.03
	$\beta - \gamma$			
	(1)	(2)	(3)	(4)
IQ X female	0.80	0.77	0.24	0.73
IQ X male	0.80	0.81	0.31	0.76
Extraversion X female	-0.04	0.00	0.14	-0.06
Extraversion X male	-0.53	-0.91	-0.46	-0.50

Appendix

Table A1: Detailed results of the probit models predicting higher education

	Female	Male	All	Female	Male	All
IQ	0.770	0.508	0.635	1.783	1.179	1.451
	[0.152]**	[0.132]**	[0.097]**	[0.521]**	[0.513]*	[0.358]**
Extraversion	0.159	-0.376	-0.103	0.094	-0.309	-0.091
	[0.117]	[0.120]**	[0.080]	[0.121]	[0.129]*	[0.080]
Male			-0.235			-0.39
			[0.152]			[0.166]*
Constant	0.288	0.070	0.273	0.318	-0.039	0.294
	[0.107]**	[0.111]	[0.105]**	[0.110]**	[0.137]	[0.106]**
					First stage (dep. var.: cognitive capacity at age 22)	
IQ age 5				0.259	0.225	0.242
				[0.072]**	[0.069]**	[0.050]**
Extraversion				0.063	-0.091	-0.013
				[0.065]	[0.071]	[0.048]
Male						0.174
						[0.091]
Constant				-0.024	0.151	-0.025
				[0.060]	[0.068]	[0.063]
Log-likelihood	-92.44	-89.02	-187.70	-277.45	-273.16	-558.87
Pseudo-R2	0.15	0.14	0.12			
Observations	162	150	312	162	150	312

* significant at 5%; ** significant at 1%

Table A2: Detailed results of the multinomial probit models

	π_{10}				π_{21}			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
IQ X female	0.15	0.18	0.19	0.13	0.95	0.95	0.43	0.86
	[0.22]	[0.23]	[0.25]	[0.23]	[0.21]**	[0.22]**	[0.26]	[0.22]**
IQ X male	-0.10	-0.12	-0.13	-0.12	0.70	0.69	0.18	0.64
	[0.20]	[0.20]**	[0.22]	[0.21]	[0.19]**	[0.22]	[0.21]	[0.20]**
Extraversion X female	0.19	0.1	0.24	0.21	0.15	0.1	0.38	0.15
	[0.22]	[0.25]	[0.23]	[0.23]	[0.17]	[0.20]	[0.20]	[0.17]
Extraversion X male	0.03	0.18	0.01	0.03	-0.50	-0.73	-0.45	-0.47
	[0.21]	[0.21]**	[0.21]	[0.21]	[0.18]**	[0.25]	[0.19]*	[0.18]*
Agreeableness X female		0.00				0.28		
		[0.23]				[0.18]		
Agreeableness X male		0.06				0.28		
		[0.20]				[0.18]		
Conscienciousness X female		0.18				0.05		
		[0.25]				[0.19]		
Conscienciousness X male		0.39				-0.19		
		[0.23]				[0.19]		
Neuroticism X female		0.06				-0.05		
		[0.19]				[0.16]		
Neuroticism X male		-0.03				-0.08		
		[0.21]				[0.20]		
Openness X female		0.13				0.13		
		[0.21]				[0.18]		
Openness X male		-0.58				0.69		
		[0.25]*				[0.23]**		
GPA 1 through 8			0.08				0.88	
			[0.18]				[0.17]**	
GPA 9 through 12			0.20				0.57	
			[0.18]				[0.17]**	
Mother's education			0.22				0.41	
			[0.16]				[0.14]**	
Behavior problems (parent)				-0.03				-0.18
				[0.14]				[0.12]
Behavior problems (teacher)				-0.07				-0.24
				[0.14]				[0.12]*
Male	-0.27	-0.36	-0.19	-0.27	-0.20	-0.11	0.45	-0.09
	[0.28]	[0.24]	[0.31]	[0.29]	[0.23]	[0.32]	[0.26]	[0.23]
Constant	0.69	-0.64	0.80	0.71	0.67	-0.78	0.60	0.62
	[0.21]**	[0.16]**	[0.24]	[0.22]	[0.15]**	[0.23]**	[0.19]**	[0.16]**
Log-likelihood	-264.4	-251.5	-208.8	-258.8				
Observations	312	312	312	312				

* significant at 5%; ** significant at 1%