Personality traits as an engine of knowledge: A quantile regression approach

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Abstract

We use a unique micro-level data set to investigate the impact of personality traits on education. To the best of our knowledge this is the first study shedding light on the contribution of each of the Big Five personality traits on the education decision made by the individuals. Our findings, uncover a significant effect of non-cognitive skills on the level of education. Specifically, we argue that the estimated signs of the non-cognitive skills remain stable across the quantiles. It is shown that people with high emotional stability invest in human capital. Lastly, our model survived robustness checks under the inclusion of two aggregated higher-order factors.

JEL classifications: I21; J24; C31
Keywords: Non-cognitive skills; Big Five personality traits; Education, Quantiles

1. Introduction

During the last decades, economists have tried to disentangle personality traits as a type of non-cognitive skills that may have significant impact on human behaviour and adulthood (Raymundo et al, 2018; Cobb-Clark and Schurer, 2012).

Although there is an emergent literature examining the way personality traits affect various individual economic and social outcomes (e.g wages, job search, criminal behavior, health, etc), surprisingly little evidence exists on the extent to which the non-cognitive skills affect the level of education between the individuals.

Most of the existing studies try to link personality traits with academic performance and adolescence (Hoeschler et al, 2018; Heckman et al, 2013). However, they fail to provide answers to the following research questions: (a) Do personality traits affect education? (b) How do personality traits contribute to knowledge spillovers? (c) Does the equality of the slope coefficients hold across the quantiles?

In this study, we use a unique data set to investigate the impact of personality traits on education. The empirical findings, provide sufficient evidence that non-cognitive skills play a significant role in the education level, with the estimated signs remaining stable across the quantiles. It is shown that individuals with high emotional stability invest in human capital.

The rest of this paper is structured as follows. Section 2 presents the data and discusses the methodology employed. The results of our analysis are presented in Section 3, while Section 4 performs the necessary robustness checks to test for the validity of our findings. Finally, Section 5 concludes the paper.

2. Data and methodology

2.1 Data and descriptive statistics

We rely on a specially designed survey of 1,660,638 individuals in the U.S during the period 2009-2015 (Wei et al, 2017). To measure personality traits, we employ the widely-used Big Five Inventory ("*Five Factor Model*") including Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional Stability. We supplement our analysis with the use of three socio-demographic variables representing Education (number of years), Age and Gender (Male = 0, Female = 1). The following table portrays the summary statistics.

Table 1: Summary statistics

Variables	Obs	Mean	Standard Deviation	Min	Max
Education	1,660,638	15.41	177.4	13	19
Age	1,660,638	27.05	11.00	16	60
Gender	1,660,638	0.653	0.476	0	1
Openness to experience	1,660,638	3.647	0.659	1	5
Conscientiousness	1,660,638	3.626	0.699	1	5
Extraversion	1,660,638	3.305	0.838	1	5
Agreeableness	1,660,638	3.813	0.662	1	5
Emotional Stability	1,660,638	3.126	0.819	1	5
Alpha	1,660,638	3.537	0.539	1	5
Beta	1,660,638	3.495	0.564	1	5

2.2 Econometric methodology

Quantile regressions (QR) allow the estimation of various functions of a conditional distribution where each quantile characterizes a particular (i.e center or tail) point of the conditional distribution. Putting together a number of different quantile regressions gives us a more complete description of the underlying conditional distribution. Moreover, quantile regressions also provide a richer characterization of the data, allowing us to consider the impact of a covariate on the entire distribution of the dependent variable, not merely its conditional mean. It is worth mentioning that QR is invariant to monotonic transformations such as natural logarithms.

In simple words, while in the OLS application the estimated parameters represent the change in the dependent variable caused from a unit change in the independents, the parameters of the QR estimate the change in a specific quantile of the dependent variable due to a unitary change in the independent variable. This allows comparisons among the quantiles in terms of how much they are influenced from specific characteristics in relation to the other quantiles (Halkos and Polemis, 2018). This can be seen in the change in the magnitude of the coefficients. QR are extremely useful when we face heteroskedasticity and/or no normality in the disturbance term (Buchinsky 1998). Moreover, QR are especially useful when dealing with non-identically distributed data (Distante et, al, 2018). In these situations one should expect to observe significant discrepancies in the estimated 'slopes' at different quantiles with respect a given set of covariates (Machado and Mata, 2000). Such discrepancies may reflect not just into location shifts, but also into scale shifts (i.e., changes in the degree of dispersion) and/or asymmetry reversals (i.e., changes in the sign of the skewness).

Consider the following conditional quantile function:

$$Q(\lambda \mid \mathrm{X}_i \beta(\lambda)) = \mathrm{X}'_j \beta(\lambda) \tag{1}$$

where $$\beta(\lambda) = \arg mm_{\beta(\lambda)} \{ \sum_j \rho_\lambda (\mathrm{Y}_j - \mathrm{X}'_j \beta(\lambda)) \tag{2}$$

Similarly to Koenker and Bassett (1978), we show that:

$$\sqrt{i}(\hat{\beta}(\lambda)) - \beta(\lambda)) \sim \mathrm{N}(0, \lambda(1-\lambda) S(\lambda)^2 J^{-1}) \tag{3}$$

where

$$J = \lim_{i \to \infty} (\sum_j X_j X_j{}' / i) = \lim_{n \to \infty} (X'X / i) \tag{4}$$

and $S(\lambda) = F^{-1\prime}(\lambda) = \dfrac{1}{f(F^{-1}(\lambda))}$ (5)

S(λ) is the quantile density function. We can calculate $S(\lambda)$ with the use of the Kernel density estimator. The latter is given as follows:

$$\hat{S}(\lambda) = \frac{1}{\left[(1/i)\sum_{j=1}^{i} c_i^{-1} L\left(\hat{\varepsilon}_j(\lambda) \big/ c_i\right)\right]} \tag{6}$$

where $\hat{\varepsilon}_j$ denotes the residuals of the quantile regression. By defining the coefficient vector of this procedure as:

$$\beta = (\beta(\lambda_1)', \beta(\lambda_2)', \ldots, \beta(\lambda_\kappa)')' \tag{7}$$

we have
$$\sqrt{i}(\hat{\beta} - \beta) \sim \mathrm{N}(0, \Omega) \tag{8}$$

where
$$\Omega_{ij} = \left[\min imum\left(\lambda_i, \lambda_j\right) - \lambda_i \lambda_j\right] H^{-1}(\lambda_i) J H^{-1}(\lambda_i) \tag{9}$$

In the case of i.i.d. Ω becomes $\Omega = \Omega_0 \otimes J$ where Ω_0 as representative element has

$$\omega_{ij} = \frac{\min(\lambda_i, \lambda_j) - \lambda_i \lambda_j}{f(F^{-1}(\lambda_i)) \cdot (f(F^{-1}(\lambda_j))} \tag{10}$$

Estimation of Ω may be done using the bootstrap method.

The test of slope equality was suggested by Koenker (2005) and it is a robust heteroskedasticity test

$$H_o : \beta_1(\lambda_1) = \beta_2(\lambda_2) = \ldots = \beta_\kappa(\lambda_\kappa)$$

Where we have $(p-1)(k-1)$ restrictions in the coefficients. The corresponding Wald test is distributed as $\chi^2_{(p-1),(k-1)}$. Similarly, the symmetry test was proposed by Jones (1992) and relies on the idea that if

$$\frac{\beta(\lambda) + \beta(1-\lambda)}{2} = \beta(1/2) \tag{11}$$

then we may estimate this restriction using the Wald test with H_0 having $p(k-1)/2$ restrictions and the Wald test is distributed as $\chi^2_{p(k-1)/2}$.[1] This test compares the estimates of the first and third quantile with the median specification. Based on the above, we estimate the following linear model:

$$Education_i = \alpha + b_1 Openess_i + b_2 Conscientiousness_i + b_3 Extraversion_i + b_4 Agreeableness_i + b_5 Emotional\ Stability_i + b_6 Age_i + b_7 Gender_i + e_i$$

3. Results and discussion

In the case of Model 1 (OLS) it is evident that nearly all the estimated coefficients are statistically significant. Specifically, the coefficient of conscientiousness is positive as one would have expected, while extraversion has a negative and statistically significant estimate of -0.289 (Table 2). Similarly the coefficient of emotional stability is negatively correlated with the education level (-1.526), which is quite surprising since individuals with higher levels of neuroticism tend to have worse psychological well-being (Dwan and Ownsworth, 2017). The remaining trait (Agreeableness) does seem to have a positive impact on education, at least from a statistical point of view (1.090). Moreover, the other two control variables (Age and Gender) have positive impact on education level as indicated by their estimated coefficients. The quantile regression analysis unveils a more differentiated picture (see Model 2). For instance, Openness to experience is now significant in all of the estimated quantiles. The sign of this variable is in line with our expectations since individuals that are characterized by a high level of openness "*tend to lean, in occupation and hobby, towards the arts, being, typically, creative and appreciative of the significance of intellectual and artistic pursuits*" (Friedman et al, 2016).

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[1] As there is no clear positive relationship between the values of the quantiles and the estimated coefficients we may say that the conditional quantiles are i.i.d.

Table 2: Estimation results

Variable	Model 1 OLS (1)	Model 2 Quantiles τ								
		(2) Q(0.15)	(3) Q(0.20)	(4) Q(0.25)	(5) Q(0.30)	(6) Q(0.40)	(7) Q(0.50)	(8) Q(0.60)	(9) Q(0.70)	(10) Q(0.80)
Openness to experience	0.347	-0.293***	-0.335***	-0.578***	-0.345***	-0.0954***	-0.0744***	-0.0809***	-0.147***	-0.03896***
	(0.214)	(0.00757)	(0.00584)	(0.0132)	(0.00613)	(0.00232)	(-42.44)	(0.00183)	(0.00279)	(0.00168)
Conscientiousness	0.532***	-0.312***	-0.289***	-0.370***	-0.237***	-0.0594***	-0.0437***	-0.0616***	-0.147***	-0.04165***
	(0.220)	(0.00781)	(0.00602)	(0.0137)	(0.00632)	(0.00239)	(-24.20)	(0.00189)	(0.00287)	(0.00173)
Extraversion	-0.289*	0.0930***	0.109***	0.198***	0.127***	0.0362***	0.0336***	0.0403***	0.0814***	0.01705***
	(0.176)	(0.00623)	(0.00480)	(0.0109)	(0.00505)	(0.00191)	(23.29)	(0.00151)	(0.00229)	(0.0013)
Agreeableness	1.090***	0.182***	0.226***	0.464***	0.345***	0.0860***	0.0530***	0.0382***	0.0314***	0.00961***
	(0.233)	(0.00826)	(0.00636)	(0.0144)	(0.00669)	(0.00253)	(27.71)	(0.00200)	(0.00304)	(0.00183)
Emotional Stability	-1.526***	-0.0423***	-0.0401***	-0.0512***	-0.0146**	-0.00612***	-0.0078***	-0.00679***	0.00650**	0.00385**
	(0.201)	(0.00712)	(0.00549)	(0.0125)	(0.00577)	(0.00218)	(-4.75)	(0.00172)	(0.00262)	(0.0015)
Age	0.256***	-0.0694***	-0.0921***	-0.127***	-0.162***	-0.152***	-0.1306***	-0.110***	-0.0881***	-0.06874***
	(0.0129)	(0.000458)	(0.000353)	(0.000800)	(0.000371)	(0.000140)	(-1231.77)	(0.000111)	(0.000168)	(0.0001)
Gender	2.529***	-0.121***	-0.0963***	-0.0575***	0.0146*	-0.000743	-0.0081***	-0.000815	0.0311***	0.0108***
	(0.308)	(0.0109)	(0.00841)	(0.0191)	(0.00884)	(0.00335)	(-3.22)	(0.00264)	(0.00402)	(0.00242)
Constant	-36.48***	17.10***	18.12***	19.87***	20.86***	20.92***	20.6915***	20.56***	20.77***	20.271***
	(1.228)	(0.0435)	(0.0335)	(0.0761)	(0.0352)	(0.0133)	(2052.15)	(0.0105)	(0.0160)	(0.0096)
Observations	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638
F-statistic /Pseudo R^2	153.26***	0.0003	0.0023	0.0023	0.0073	0.0111	0.0108	0.0073	0.0105	0.0072

Notes: Model 1 was estimated using OLS allowing for robust standard errors. Model 2 was estimated using the quantile regressions methodology at different quantiles τ allowing for 100 repetitions. The numbers in parentheses denote the standard errors. Significant at ***1%, **5% and *10% respectively.

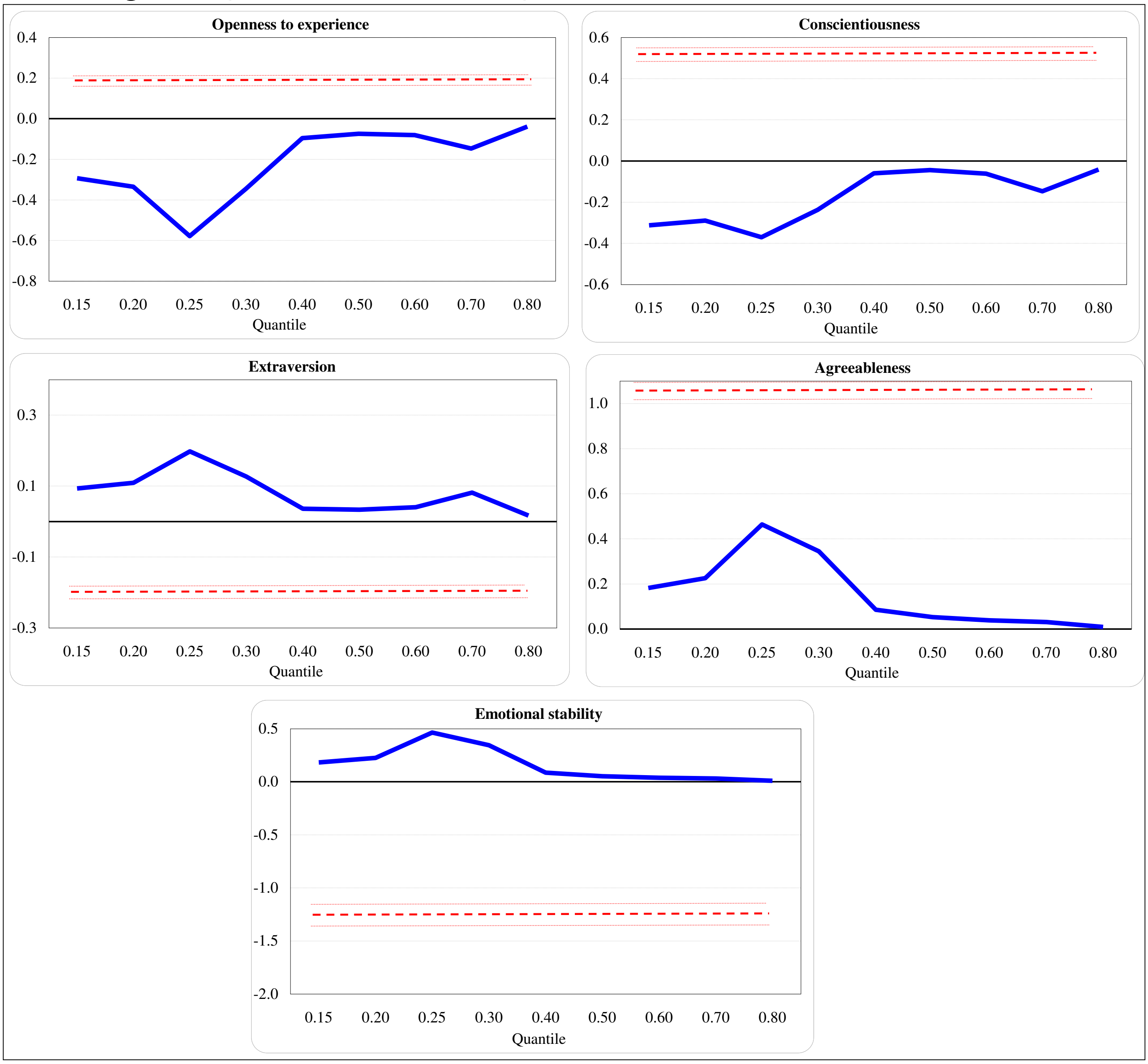
Surprisingly, conscientiousness is negatively correlated with the education level though significant in all of the estimated quantiles. This might indicate that the underlying true relationship "*is non-linear, and that our linear specification captures some kind of average effect*" (Schafer and Schwiebert, 2018).

On the contrary, extraversion has a positive and statistically significant impact on the dependent variable since it is argued that high extraversion is often perceived as attention-seeking and domineering which may stimulate the education level of the individuals (Dwan and Ownsworth, 2017).

Similarly, agreeableness is positively correlated with education in all of the quantiles, implying that personalities with low agreeableness are often competitive or challenging people, which can surpass the education incentive. While emotional stability seems to negatively affect the level of education, it alternates its sign from the 70^{th} percentile (0.00650) remaining positive across the rest quantiles. The positive sign denotes that people with high emotional stability manifest themselves as stable and calm personalities more eager to invest in human capital (education). Moreover, the two socio-demographic variables (Age and Gender) are statistically significant imposing a negative impact on education at least up to the 70^{th} quantile.

Figure 1 illustrates the quantile treatment effects (QTE) associated with the personality traits, along with the OLS estimates. As it is evident the magnitude of the effects at various quantiles differs considerably from the OLS coefficient estimates. Lastly, we perform the test for the equivalence of the quantile estimates. According to the p-value (0.001), the null hypothesis of equality of the slope coefficients at the three representative quantiles (0.25, 0.50, 0.75) are rejected at the 1% level of significance for each of the estimated coefficients suggesting that personality traits do not appear to have the same impact on education.

Figure 1: Quantile treatment effects (QTE).



Notes: The blue line is the estimated QTE, while the dashed (red) line denotes the OLS estimates. The red dotted lines denote the confidence bands.

4. Robustness checks

To check for the robustness of our findings, we re-estimate our model by aggregating the Big Five personality traits into two higher-order factors namely '*Alpha'* (agreeableness, conscientiousness, and emotional stability), and '*Beta*' (extraversion and openness to experience). The former, represents the socialization and stability factor, while the latter denotes the personal growth and plasticity factor (Wei et al, 2017).

Overall, we find similar results from the inclusion of these factors (Table 3). Specifically, we confirm the stability of the signs of the estimated coefficients for all the personality traits across the quantiles. Moreover, we argue that the socialization factor is negative and significant at the lower and higher quantiles of the conditional education distribution (Model 3). However, it remains positive and significant around the median (Q50). Lastly, the other factor is negatively correlated with the education imposing a larger effect in lower quantiles (Model 4).

Table 3: Robustness results

Variable	Quantiles τ								
	(2) Q(0.15)	**(3) Q(0.20)**	**(4) Q(0.25)**	**(5) Q(0.30)**	**(6) Q(0.40)**	**(7) Q(0.50)**	**(8) Q(0.60)**	**(9) Q(0.70)**	**(10) Q(0.80)**
Model 3									
Alpha	-0.182*** (0.0112)	-0.111*** (0.00720)	0.0138 (0.0183)	0.0661*** (0.00752)	0.0182*** (0.00285)	0.00140 (0.00223)	-0.0291*** (0.00229)	-0.111*** (0.00363)	-0.0229*** (0.00210)
Openness to experience	-0.279*** (0.00882)	-0.304*** (0.00567)	-0.567*** (0.0144)	-0.331*** (0.00592)	-0.0908*** (0.00225)	-0.0736*** (0.00176)	-0.0750*** (0.00180)	-0.155*** (0.00286)	-0.0316*** (0.00165)
Extraversion	0.0996*** (0.00720)	0.103*** (0.00463)	0.201*** (0.0118)	0.124*** (0.00483)	0.0335*** (0.00183)	0.0322*** (0.00144)	0.0403*** (0.00147)	0.0947*** (0.00233)	0.0159*** (0.00135)
Age	-0.0708*** (0.000529)	-0.0934*** (0.000340)	-0.127*** (0.000864)	-0.169*** (0.000355)	-0.152*** (0.000135)	-0.131*** (0.000105)	-0.110*** (0.000108)	-0.0891*** (0.000171)	-0.0693*** (9.89e-05)
Gender	-0.128*** (0.0120)	-0.0851*** (0.00774)	-0.0127 (0.0197)	0.0610*** (0.00808)	0.00559* (0.00307)	-0.00375 (0.00240)	-0.000494 (0.00246)	0.0140*** (0.00390)	0.00440* (0.00225)
Constant	17.13*** (0.0496)	18.10*** (0.0319)	19.94*** (0.0810)	21.19*** (0.0333)	20.96*** (0.0126)	20.71*** (0.00989)	20.54*** (0.0101)	20.78*** (0.0161)	20.25*** (0.00928)
Observations	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638
Pseudo R^2	0.003	0.0023	0.0038	0.0072	0.0110	0.0108	0.0073	0.0048	0.0072
Model 4									
Beta	-0.171*** (0.00988)	-0.173*** (0.00652)	-0.306*** (0.0188)	-0.191*** (0.00704)	-0.0506*** (0.00281)	-0.0352*** (0.00228)	-0.0403*** (0.00309)	-0.0485*** (0.00353)	-0.0123*** (0.00231)
Conscientiousness	-0.292*** (0.00857)	-0.258*** (0.00566)	-0.341*** (0.0163)	-0.205*** (0.00610)	-0.0504*** (0.00244)	-0.0398*** (0.00198)	-0.0953*** (0.00268)	-0.167*** (0.00306)	-0.0257*** (0.00201)
Agreeableness	0.187*** (0.00909)	0.215*** (0.00600)	0.472*** (0.0173)	0.355*** (0.00647)	0.0897*** (0.00258)	0.0639*** (0.00210)	0.0382*** (0.00285)	0.0301*** (0.00325)	0.00555*** (0.00213)
Emotional Stability	-0.00812 (0.00775)	0.00325 (0.00512)	0.0202 (0.0147)	0.0326*** (0.00552)	0.00786*** (0.00220)	0.00271 (0.00179)	0.0132*** (0.00243)	0.0366*** (0.00277)	0.00760*** (0.00182)
Age	-0.0702*** (0.000501)	-0.0905*** (0.000331)	-0.125*** (0.000953)	-0.168*** (0.000357)	-0.152*** (0.000142)	-0.131*** (0.000116)	-0.102*** (0.000157)	-0.0888*** (0.000179)	-0.0691*** (0.000117)
Gender	-0.0651*** (0.0119)	-0.0400*** (0.00786)	0.0442* (0.0226)	0.102*** (0.00848)	0.0181*** (0.00338)	0.00577** (0.00275)	0.0332*** (0.00373)	0.0745*** (0.00425)	0.0117*** (0.00279)
Constant	16.73*** (0.0465)	17.53*** (0.0307)	18.90*** (0.0885)	20.53*** (0.0331)	20.79*** (0.0132)	20.57*** (0.0107)	20.51*** (0.0146)	20.65*** (0.0166)	20.19*** (0.0109)
Observations	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638	1,660,638
Pseudo R^2	0.0003	0.0023	0.0038	0.0072	0.0110	0.0108	0.0073	0.0048	0.0072

Notes: Model 3 and 4 were estimated using the quantile regressions methodology at different quantiles τ allowing for 100 repetitions. The numbers in parentheses denote the standard errors. Significant at ***1%, **5% and *10% respectively.

5. Conclusions

By utilizing a flexible quantile regression analysis, we investigate the impact of non-cognitive skills on education. To the best of our knowledge this is the first study shedding light on the contribution of each of the Big Five personality traits on the education decision made by the individuals.

Our findings, uncover a significant effect of non-cognitive skills on the level of education, with the signs remaining stable across the different quantiles. Lastly, our model survived robustness checks under the inclusion of two aggregated higher-order factors.

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