

Article

How Far Are NEET Youth Falling Behind in Their Non-Cognitive Skills? An Econometric Analysis of Disparities

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Abstract: Youth not in education, employment, or training (NEET) refers to the most vulnerable group in the transition from school to work. While much research focuses on institutional factors behind the NEET incidence, the current study approaches the problem of the NEET youth from the perspective of non-cognitive skills. For measuring non-cognitive skills, the Big Five personality characteristics (openness, conscientiousness, extraversion, agreeableness, neuroticism) as well as grit were analyzed. The analysis was carried out using propensity score matching based on the data of the Russian Longitudinal Monitoring Survey (RLMS HSE) for 2016. This study shows that the majority of young people in the NEET group come from the poorest families. Nearly half of the NEET youth are not only not working, but they are also not looking for a job either. The analysis revealed that NEET youth fall behind in different non-cognitive abilities, with statistically significant differences in conscientiousness, extraversion, and grit, as well as a greater severity of neuroticism.

Keywords: NEET youth; non-cognitive skills; big five; labor market; education system

JEL Classification: J24; I24; I25



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1. Introduction

The ability to find a decent job that matches one's education is a problem everyone faces when transitioning from adolescence to adulthood. While some young people fully maximize the human capital accumulated in the formal education system, others start with jobs below their career expectations. Of course, there are also those who do not study, do not develop professional skills, and are unsuccessful in the labor market. These people are referred to as NEET youth (not in education, employment, or training), a cohort of individuals aged 15–24 years, who do not receive formal education, do not undergo professional training, and do not work. It is widely recognized that the level of NEET youth indicates the effectiveness of the transition from study to work, youth inclusion, and their participation in socio-economic life (Elder 2015).

Today, NEET youth are one of the most common at-risk groups and priorities of social policy in low-, middle-, and high-income countries, which is supported by the global agenda for sustainable development. Thus, the Sustainable Development Goals (SDGs) include the prevalence of NEET youth aged 15–24 years as one of the key indicators of SDG 8, related to decent work and economic growth. Indeed, the latest data from the International Labour Organization, which is responsible for this indicator, show that even in high-income countries, 1 in 10 young people aged 15–24 years have difficulty transitioning from the education system to the labor market. In Russia, according to the data from the national statistical office, the level of NEET youth accounts for 16%, which is comparable to numbers in economically developed countries. Moreover, SDG monitoring data indirectly suggest that this level is primarily due to insufficient inclusiveness of the labor market for youth; according to the UNESCO Institute of Statistics, the out-of-school rate for youth in the upper secondary general

school age (16–18 years) in Russia was only 2.5%, one of the lowest in the world. Nevertheless, young people face difficulties entering the labor market, and governments need to develop support measures for this cohort within the framework of labor policy.

The reasons for the prevalence of NEET youth in society may relate either to institutional factors characterizing the effectiveness of the education system or the labor market demand for skilled labor (Amendola 2022; Bal-Domańska 2022; Maynou et al. 2022; Bingöl 2020), or to those representing the labor supply side and describing the individual characteristics of economic agents. In addition to the basic socio-demographic parameters such as gender and age, these characteristics mainly include the highest level of education received and professional experience; existing data emphasize that early employment is an important factor in reducing the likelihood of falling into NEET (Ballo et al. 2022; Berlin et al. 2021). It goes without saying that such factors as work experience and education level are well known to economists as key predictors of the Mincer wage equation, also used to assess the return on education. On the other hand, to explain earnings, labor, and other socio-economic outcomes of individuals, over the last decades economists have become increasingly interested in individual heterogeneity, which has psychological roots and was interpreted in the Mincer equation as unobserved abilities (i.e., model error). In other words, it was recognized that a number of other factors, besides education and professional experience, explain income differences, but historically they received limited attention. In this regard, the interest of economists in personality factors behind economic success represents a reasonable attempt to pay more attention to individual characteristics traditionally considered as unobservable in economics. Thus, it led to the emergence of a new trend in economic research that investigates the impact of personality traits on individual outcomes in the labor market and beyond (Almlund et al. 2011; Lindqvist and Vestman 2011; Glewwe et al. 2017; Bowles et al. 2001; Mueller and Plug 2006; Carneiro et al. 2007; Kniesner and Ter Weel 2008).

The economic literature interprets these personality traits as non-cognitive or socio-emotional skills (Wichert and Pohlmeier 2010; Schmit et al. 1993; Heckman et al. 2006; Mueller and Plug 2006; Zetterberg 2005; Nyhus and Pons 2005). An increasing amount of work in economics pays special attention to these skills, especially in the context of continuing education (Laible et al. 2020), employment status (Heckman et al. 2011), and wages (Almlund et al. 2011; Lindqvist and Vestman 2011). However, so far, there has been limited research on non-cognitive skills in the context of NEET youth. In this regard, the current study focused on the following research question: is there a gap observed in the possession of non-cognitive skills depending on the NEET status of youth. In other words, the purpose of this research was to examine the magnitude to which NEET youth lag behind their peers in the non-cognitive skills so essential for the inclusive socio-economic participation of youth in modern economies.

2. Literature Review

Unlike cognitive skills, which are developed during formal education and consolidated with certified qualifications, non-cognitive skills, mostly not included in compulsory education play a crucial role in overall human capital formation (Kuzminov et al. 2019). These factors, characterizing individual heterogeneity and referring to personality traits, are considered skills because they meet three key criteria and represent qualities that are (i) productive, i.e., can be used to create value, (ii) expandable, meaning they can be enhanced through training and targeted policy interventions, and (iii) social, articulating the key role of the socio-economic environment in their formation. These three criteria are known within the so-called PES approach to the general definition of skills, which seeks to produce a multidisciplinary synthesis of economics, psychology, and sociology in addressing this issue (Green 2011). Therefore, non-cognitive skills are defined as patterns of thoughts, feelings, and behaviors (Borghans et al. 2008) that are formed in the socio-economic environment, can be developed with training programs or targeted interventions, and produce economic or social value (Zhou 2016).

Despite its popularity in economic literature, the term “non-cognitive skills” has been criticized in other disciplines, including psychology—the field of knowledge from which it historically originated. As noted, with a general understanding of what cognitive skills are, attempts to define what makes up other important skills seem much more complicated (Cabus et al. 2021). The definition using the exclusion approach, i.e., explaining non-cognitive skills through what they are not (Messick 1978, p. 2), has been widely criticized for creating a so-called false opposition (Farrington et al. 2012; Duckworth and Yeager 2015), which excludes the cognitive component from the considered personality traits. The second difficulty in using this concept is related to the taxonomy of non-cognitive skills, a question that still remains open and even debatable in the academic community. Since scholars in their research on non-cognitive skills use quite different characteristics to measure their impact on a person’s social or economic outcomes, the confusion about the nature of these skills may seriously hinder the universality of statistical conclusions and analysis in this field.

Despite all the open questions and unresolved contradictions in the conceptualization of non-cognitive skills, the most common approach to their taxonomy refers to the 5-factor model of personality, also known as the “Big Five” (BFI) personality traits. This model includes traits such as extraversion, neuroticism, conscientiousness, openness to new experience, and agreeableness (Goldberg 1992). The model emerged in response to the need for scientific classification of personality and its fundamental components. Despite the wide representation in science of multifactorial personality models—predecessors of the Big Five, such as H. Eysenck’s 3-factor model of personality and R. Cattell’s 16-factor model, as well as a number of other classifications (Almagor et al. 1995; De Raad and Szirmak 1994; Benet-Martínez and Waller 1997; Di Blas and Forzi 1999; Lee and Ashton 2006)—the Big Five is currently the most popular and is spreading in other disciplines studying human behavior. Early psychometric measurements demonstrated the orthogonal nature of the traits proposed by this model, i.e., the absence of mutual correlation between the factors that explain the five key sources of variation in a series of descriptive characteristics of personality in different languages (Saucier and Goldberg 2002). Although subsequent research (Hussey and Hughes 2020; Viswesvaran and Ones 2000) questioned the complete independence of the five factors, the psychometric characteristics of this model still surpass the others, explaining its popularity in psychology and other behavioral sciences. Although initially the specified characteristics were interpreted as personality traits, recent literature rather interprets them as skills, since these characteristics, on the one hand, are instrumental (i.e., produce value and have a return on the labor market), and on the other hand, can be developed through targeted interventions, especially at an early age (Heckman et al. 2011).

For these reasons, non-cognitive skills are of particular importance in the context of NEET youth—a vulnerable group facing risks of poverty, socio-economic exclusion, and health problems. The economic literature emphasizes the influence of non-cognitive skills on wages in different countries and socio-economic contexts. It was proven that the return on non-cognitive skills in developed countries increased over time from 1993 to 2013, whereas the effect of cognitive abilities began to decline from 2000. Moreover, it was highlighted that the return on non-cognitive skills exceeds the return on cognitive ones (Edin et al. 2022). Measurements in developing countries also confirmed that non-cognitive skills largely explain earnings (Perez 2020). For example, special attention in this context was paid to traits such as conscientiousness and extraversion (Nyhus and Pons 2005); on the other hand, neuroticism and agreeableness usually have a negative impact on earnings (Fletcher 2013).

Studies on the relationship between the development of non-cognitive skills, on one hand, and education and employment, on the other, prove the existence of this connection and indicate that social activity of the younger generation is directly related to personality traits (Caliendo et al. 2015; Mohanty 2010; Uysal and Pohlmeier 2011; Cuesta and Budría 2017; Varshavskaja 2016). Numerous studies point at the role of non-cognitive skills in further learning. Thus, based on a sample of more than 10,000 people from the adult population who participated in the German National Educational Panel Study (NEPS), the

authors found that openness to experience is positively associated with participation in further education.

A body of work indicates a presence of the relationship between a person's employment and their non-cognitive skills. In a series of studies carried out on large samples in different countries based on socio-economic monitoring, the likelihood of employment and successful education in school and university was confirmed for people with certain personality traits. In particular, in the Russian sample, a strong influence on this probability was shown by personal conscientiousness, which, combined with openness and emotional stability, contributes to the highest results both at work and in study (Rozhkova and Roshchin 2021). Also, based on individual unemployment data from the German SOEP panel survey, a strong negative impact of neuroticism on the immediate likelihood of finding a job was shown. Openness as a personality trait only facilitates employment for women and migrants. The authors did not find any influence of extraversion and conscientiousness on the speed of employment (Uysal and Pohlmeier 2011).

Research on Russian data confirms that introversion as a personality trait, combined with low social activity and underdeveloped communication skills, creates the prerequisites for youth to fall into the NEET group (Skvortsova and Shestakova 2020). At the same time, a person who has been experiencing unemployment for a long time constantly feels inferior and reacts sharply to peer pressure from other people, which leads to decreased self-assessment and labor motivation (Selezneva 2007; Rozhkova 2019). These findings from the Russian data on the impact of NEET status on personality are aligned and expanded by the evidence from Turkey indicating that being NEET can not only increase the likelihood of mental health problems, but it also leads to a higher probability of obesity, smoking, and alcohol consumption (Karaođlan et al. 2022).

Furthermore, it was highlighted that non-cognitive skills of NEET youth in Russia affect their productivity, wage level, occupational choice, and job search duration (Zudina 2022). It was also shown that introversion influences the likelihood of falling into the NEET group for teenagers and young people from families with high socio-economic status. This creates risks of social isolation for these cohorts, as well as a number of economic risks associated with the ineffective utilization of the human capital that their families possess (Seregina 2006; Gimpelson et al. 2020). It was also pointed out that NEET youth have lower levels of trust in the future, in other people, and in social institutions, which leads to lower rates of social participation and creates risks for social exclusion (Alfieri et al. 2015).

The results presented in the literature suggest that the personality traits of people not involved in labor and education may vary depending on the reasons for this non-involvement, from the attitude of the individuals themselves to this fact (for example, that it is their conscious choice or a forced situation), to the duration of their stay in such a status (Skvortsova and Shestakova 2020). Those at risk are usually young people who have experienced personal failures, or had traumatic experiences in relationships with their immediate social environment, and also ones who have gone through difficult life events (Glewwe et al. 2017). The studies indicate that as young people usually lack technical and practical skills, employers are mainly concerned with the low level (or absence) of development of such skills as sociability, teamwork, client work skills (communication), leadership, reliability, and other skills that are not hard in nature (Westwood 2004; Lerman 2013; Shivpuri and Kim 2004).

While mounting evidence points out that personality traits serve as an important predictor of the economic activity of young people, manifested in employment and training, the development of both cognitive and non-cognitive characteristics is closely related to the socio-economic status of the family and the opportunities to invest in the human capital of children, enhanced by the social and cultural capital of parents (Coleman 1988; Bourdieu and Passeron 1977). In total, these characteristics are the starting point for the transition of young people from study to work (Kautz et al. 2014). Moreover, the group of young people who do not have such starting conditions (economic, social, and cultural capital) that allow them to develop the skills for a sustainable return in the education system and the labor market,

as a rule, are predisposed to falling into the NEET category, namely, building a so-called “NEET core” (Quintano et al. 2018). However, a recent study indicates that, though having non-cognitive skills can indeed help young people during a school-to-work transition, it is not always enough to compensate for a low socio-economic status (Ripamonti 2023).

Studies on the non-cognitive components of human capital have shown the influence of these characteristics on the continuation of education and the chances of employment, which allows for considering these skills as a means of educational and labor policy for the socio-economic inclusion of young people and reducing the share of NEET in society. Considering the importance of these skills for various socio-economic outcomes, this work aims to contribute to filling the research gap that exists regarding knowledge about differences observed in possessing non-cognitive skills among young people depending on NEET status.

3. Data and Methods

The materials of the Russian Longitudinal Monitoring Survey (RLMS) (25th wave) for 2016 served as the empirical base of the research. RLMS is a source of information about the socio-economic characteristics of more than 15,000 Russian citizens aged 15 to 24 years. Also, the 25th wave of the RLMS HSE contains information about such non-cognitive skills as the Big Five personality characteristics (agreeableness, conscientiousness, extraversion, neuroticism, openness to new experiences) and grit. The questions used to measure the analyzed non-cognitive skills are presented in Table A1. The aggregation of indices of non-cognitive skills was carried out according to the methodology of the STEP Skills Measurement Survey (2014). The sample parameters, as well as the descriptive statistics of the variables used in the analysis, are presented in Table 1. The descriptive analysis, presented in Table 1, allows us to conclude that the distribution of the studied non-cognitive characteristics in the youth sub-sample aged 15–24 is close to normal.

Table 1. Sample summary.

The Total Number of Observations: 12,554										
Gender										
Male: 5775					Female: 6779					
Residence										
Urban: 8411					Rural: 4143					
NEET										
NEET youth: 203					Non-NEET youth: 1099					
Socio-Economic Status										
Quintile groups by per capita income of the household	Poorest		Poor		Middle		Rich		Richest	
	24%		21%		18%		18%		20%	
Subjective well-being	1 (least)		2		3		4		5	
	4%		11%		23%		18%		27%	
Education	Without Education		Secondary Education		Secondary Professional Education		Higher Education			
	9%		26%		48%		18%			
Non-Cognitive Skills										
Variable	Min		Mean		Median		SD		Max	
Openness	−3.13		−0.03		0.21		1		1.88	
Conscientiousness	−3.63		0		0.14		1		2.03	
Extraversion	−2.69		−0.01		0.05		1		2.24	
Agreeableness	−3.19		0.02		−0.18		1		2.23	
Neuroticism	−2.38		−0.01		0.21		1		2.28	
Grit	−2.51		0		0.17		1		2.32	

4. Econometric Verification Model

Since the key research question of the study was to identify the differences in non-cognitive skills between NEET and non-NEET youth, traditional methods of comparing means across groups, such as the *t*-test, ANOVA, or linear regression with a categorical predictor, would inevitably yield biased estimates due to several limitations of the sample. Firstly, the data used represent a sub-sample of observations of youth aged 15–24. Regardless of the sample model, from the originally random probability sample of the monitoring, we selected observations describing the group of persons in accordance with the questions and problems of the study (youth in the case of this work), thus inevitably losing representativeness (Heckman and MaCurdy 1986, p. 1937). Secondly, out of all 12,554 observations, the share belonging to the treatment group accounted for less than 10% of the sample, and such insufficient representation of observations (i.e., the small size of the NEET group in the overall structure of youth in the general population) created risks of bias in the estimation of the studied effects. Thirdly, as a result of the first and second, respondents in the treatment group may have significantly differed from the other respondents in the sample, and belonging to this group was not controlled by the researchers in terms of randomization principles (Toomet and Henningsen 2008).

All this made the econometric analysis of the data subject to strong sample selection bias, which can significantly shift the calculated indicators towards their distribution in the sample. Although the RLMS data used in our analysis provide a rich choice of covariates to control parameters, which would be unobservable in most other data, several authors note that linear regression, supplemented with various covariates, may actually increase the error in calculating the assumed effect of the impact when the true relationship between the covariate and the outcome is even moderately nonlinear; these risks are especially high when there are large differences in the means and variances of predictors in the treatment and control groups (Heckman et al. 1998; Rubin and Thomas 2000; Rubin 2001). One of the methods to overcome sample selection biases is propensity score matching (Rosenbaum and Rubin 1983).

Taking into account that having a large number of observables in the regression model cannot be a stable solution for reducing selection bias when using the least squares method, many authors have suggested using matching methods, which allow for ignoring linearity conditions and may reduce the role of selection biases in the estimation of the effects (Dehejia and Wahba 2002; Dehejia 2005). As noted in the research literature, the PSM method is more accurate compared to regression analysis when the researcher has a relatively small number of observations against a large number of confounders that need to be included in the analysis (Grjibovski et al. 2016). When using matching, an important point is to achieve a balance between the model variables by the propensity score, which shows the probability for each study observation to fall under the influence of the studied factor. In this regard, several matching approaches were tested, and the best results were shown by the full matching method on the propensity scale, achieving maximum balance across all variables, which allowed matching all observations of the treatment and control groups. As NEET status was a treatment variable, at the first step, logistic regression predicted belonging to the treatment group by using propensity scores. In order to do so, we used socio-economic status as a major confounder. Gender, age, and place of residence (urban/rural) were control variables. The final stage of the study was represented by a series of linear regression models, in which the dependent variable *Y* comprised the non-cognitive skills of the Big Five taxonomy. As independent predictors, the following were used: level of education, binary indicator of respondents' affiliation to NEET, predictor of socio-economic status, as well as the effect of their interaction, subjective well-being, place of residence, gender, and age of respondents. The matching procedure was performed using the "MatchIt" package version 4.5.5 (Stuart et al. 2013) in the R (version 4.3.2) statistical programming language.

5. Results

5.1. Non-Cognitive Skills of Russian Youth

Since the focus of this study was on the NEET youth group, it was necessary to consider the differences in the distribution of non-cognitive skills between youth groups, both those included and not included in the NEET group. The distribution of measured variables broken down by groups is shown in Figure 1.

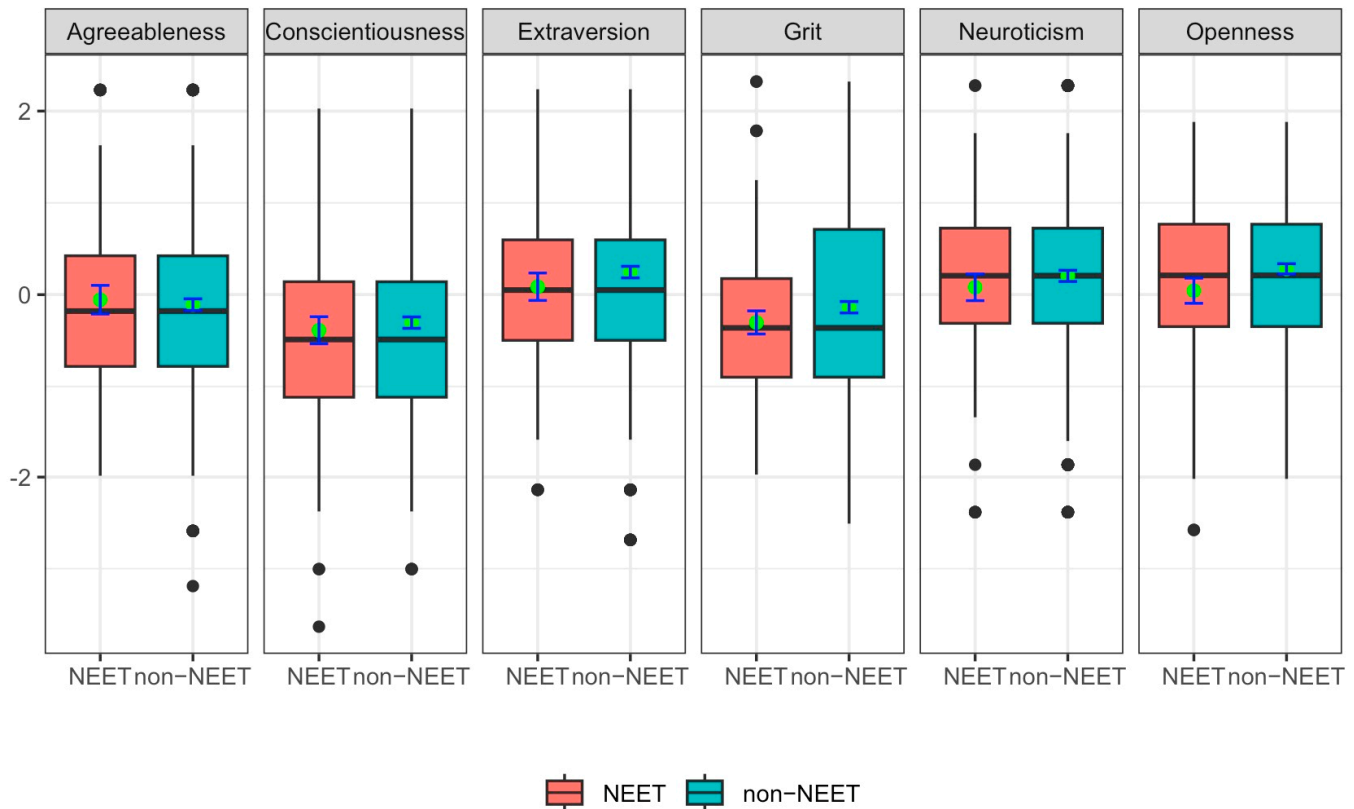


Figure 1. Box plot of the distribution of non-cognitive skills in NEET and non-NEET youth groups. Note: the green points inside the boxes indicate the means for the groups, error bars refer to 0.95% confidence intervals, black dots visualize outliers.

In the present study, a descriptive examination of non-cognitive skill distributions was conducted across two distinct groups, with a focus on discerning the presence of any substantive distributional discrepancies. The analysis employed a box plot approach to elucidate the interquartile range (IQR), median, and outlier presence within the skill sets under investigation, which included agreeableness, conscientiousness, extraversion, grit, neuroticism, and openness. Upon scrutiny, it was observed that, with the exception of grit, there were no marked differences in the IQR between the NEET and non-NEET groups, suggesting homogeneity in the spread of scores amongst the majority of the surveyed skills. Grit, uniquely, exhibited a discernible divergence in its IQR between groups, indicating a variation in this skill's distribution that warrants further investigation.

Outliers were a notable feature in the data, emerging in both cohorts across the majority of the skills, which may suggest the influence of individual-specific factors or experiences not encapsulated by the NEET/non-NEET dichotomy. Central to this exploratory analysis was the comparison of group means, denoted by green dots, around which confidence intervals were constructed. These intervals serve as a statistical instrument to estimate the precision of the group means. It was observed that for most skills, the confidence intervals overlapped when comparing the two groups. This overlap denoted a lack of significant difference in the mean scores between the NEET and non-NEET groups, thereby suggesting

that, on a preliminary basis, NEET status does not appear to be associated with significant differences in the mean levels of most non-cognitive skills examined.

It is, however, important to contextualize these findings within the limitations inherent to exploratory analyses. While the present analysis provides a foundational understanding of the distributional characteristics of non-cognitive skills across NEET status, meaningful analytical inferences cannot be drawn in terms of understanding significance of the observed differences. Furthermore, the non-random nature of the sample might substantially bias the estimates. Inferential statistical methods that account for the sample selection bias help to better untangle the dynamics and potential implications of NEET status on non-cognitive skill development.

5.2. Socio-Demographic Composition of the NEET

The analysis of the composition of the NEET youth group shows that it had significant differences not only in non-cognitive but also in socio-economic characteristics compared to non-NEET youth. The number of NEET youth decreased with increasing socio-economic status. More than 60% of NEET youth came from poor and the poorest families, indicating their vulnerable position. As a result, there may be a reproduction of poverty patterns, associated with a lack of social elevators capable of lifting this cohort out of a life in poverty. Men made up 55% of the NEET group; rural youth dominated the NEET structure, although their prevalence was insignificant.

An interesting fact was that 16% of NEET youth had higher education but could not find a job. Excluding youth aged 15–19, who cannot complete higher education for objective reasons, the percentage of NEET youth with higher education increased to 20%, i.e., every fifth NEET had higher education but could not find a job. This suggests that young professionals with high qualifications may face insufficient inclusiveness of the labor market. Another important fact was that 45% of NEET youth did not work and were not looking for a job. This indicates a certain inertia of the NEET youth and a lack of desire by almost half of its representatives to leave this group, which may be associated with insufficient motivation. The data are presented in Table 2.

Table 2. Socio-demographic composition of NEET youth.

Gender	
Male: 55%	Female: 45%
Residence	
Urban: 49%	Rural: 51%
Education	
Higher education: 16%	Without higher education: 84%
Employment	
Unemployed: 55%	Inactive: 45%
Quintile groups by per capita income of the household	
Poorest	43%
Poor	23%
Middle	14%
Rich	11%
Richest	9%

5.3. Inequality in Non-Cognitive Skills of Russian Youth Depending on NEET Status

Considering the non-random nature of the sample, the method of assessing differences between NEET and non-NEET youth groups needed to be more robust than traditional regression models. The data showed that due to the small size of the NEET group, the

mean values could be biased, leading to high sensitivity of the analysis results. Therefore, it was necessary to use a method of analysis that controlled for the self-selection bias of the data and, in a counterfactual manner, allowed for comparing NEET and non-NEET youth groups in terms of non-cognitive skills.

The research objective could be accomplished by the matching method, which controls for the bias caused by non-random selection due to observable characteristics and leads to a more reliable estimate of the relationship between the treatment and dependent variables. The summary of regression models is presented in Table 3. Regression models calculated after matching showed that belonging to the NEET group had a statistically significant negative effect on conscientiousness (-0.32 ; $p < 0.01$), extraversion (-0.25 ; $p < 0.01$), and grit (-0.40 ; $p < 0.05$). Moreover, matching allowed us to record a significant increase in the effect of NEET status on neuroticism (0.29 , $p < 0.05$).

Table 3. Results of linear regression models of non-cognitive skills after matching.

Term	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism	Grit
(Intercept)	0.505 ** (0.256)	−1.341 *** (0.245)	0.017 (0.261)	−0.157 (0.273)	0.682 ** (0.276)	−0.578 ** (0.27)
NEET	0.04 (0.11)	−0.319 *** (0.105)	−0.245 ** (0.112)	−0.023 (0.117)	0.279 ** (0.118)	−0.406 *** (0.116)
Area: Urban	−0.019 (0.061)	−0.187 *** (0.058)	0.047 (0.062)	−0.112 * (0.065)	−0.005 (0.065)	−0.066 (0.064)
Gender: Male	−0.135 ** (0.055)	−0.234 *** (0.053)	−0.041 (0.056)	−0.03 (0.059)	0.212 *** (0.06)	−0.073 (0.058)
Age	−0.035 *** (0.013)	0.055 *** (0.013)	0.008 (0.014)	−0.001 (0.014)	−0.05 *** (0.014)	0.025 * (0.014)
Completed Education: Secondary Education	0.103 (0.082)	0.098 (0.079)	0.252 *** (0.084)	−0.002 (0.088)	0.119 (0.089)	0.131 (0.087)
Completed Education: Secondary Professional Education	0.497 *** (0.095)	0.304 *** (0.091)	0.084 (0.097)	0.085 (0.101)	0.176 * (0.102)	0.302 *** (0.1)
Completed Education: Tertiary Education	0.337 *** (0.11)	0.358 *** (0.106)	−0.204 * (0.112)	0.467 *** (0.117)	0.078 (0.119)	0.207 * (0.116)
SES: Q2	0.406 *** (0.079)	0.042 (0.075)	−0.035 (0.08)	−0.113 (0.084)	0.419 *** (0.085)	−0.364 *** (0.083)
SES: Q3	0.53 *** (0.092)	0.151 * (0.088)	−0.077 (0.094)	0.21 ** (0.098)	0.545 *** (0.099)	0.16 (0.097)
SES: Q4	0.555 *** (0.103)	−0.013 (0.098)	−0.023 (0.105)	0.21 * (0.109)	0.646 *** (0.111)	0.124 (0.108)
SES: Q5	0.543 *** (0.107)	0.096 (0.102)	−0.391 *** (0.109)	−0.194 * (0.114)	0.561 *** (0.115)	−0.061 (0.113)
NEET × SES: Q2	−0.274 (0.187)	0.244 (0.178)	−0.065 (0.19)	0.393 ** (0.198)	−0.531 *** (0.201)	0.407 ** (0.197)
NEET × SES: Q3	−0.177 (0.219)	0.289 (0.209)	0.149 (0.223)	0.078 (0.233)	−0.681 *** (0.236)	0.011 (0.231)
NEET × SES: Q4	−0.597 ** (0.243)	0.171 (0.232)	0.153 (0.247)	−0.191 (0.258)	−0.371 (0.261)	0.042 (0.256)
NEET × SES: Q5	−0.045 (0.26)	0.032 (0.248)	0.853 *** (0.264)	0.319 (0.276)	−0.769 *** (0.28)	0.163 (0.274)

Note: *** p -value < 0.01 ; ** p -value < 0.05 ; * p -value < 0.1 . SES: social economic status. The following categories were chosen as the reference: Non-NEET; Residence: Rural; Completed Education: Without Education; SES: Poorest, Gender: Female.

Given that the calculated coefficients were ATT, within the NEET group, socio-economic status showed significant effects on possessing several non-cognitive skills. Firstly, for NEET youth from higher income quintiles, openness to new experiences was more characteristic. The same applied to neuroticism, as the effect of being in NEET status on it increased for youth from more economically prosperous families. Moreover, NEET youth from wealthier families were also less prone to extraversion and grit. Although at first glance these results may seem counterintuitive, they were consistent with the Russian literature, which indicated that NEET youth from wealthier families may painfully experience their status of being outside the labor market system (Skvortsova and Shestakova 2020; Selezneva 2007; Seregina 2006).

To compare the effect of socio-economic status on non-cognitive characteristics in the treatment group (NEET youth) with that in the control group (other youth), an interaction

effect between NEET and socio-economic status variables was introduced. The most interesting pattern was observed in the case of neuroticism; when using non-NEET youth from the poorest quintile as a reference group, we saw that the higher the socio-economic status of NEET, the lower the level of neuroticism. In other words, the richest NEET youth were more emotionally stable than their non-NEET peers from the poorest group. Conversely, NEET youth from the wealthiest quintile were more likely to be extraverts than non-NEET youth from the poorest quintile. In other words, socio-economic status indeed mediated the relationship between the NEET status and non-cognitive skills, implying that if one was at a certain level on the economic ladder, they would tend to have higher extraversion and be more emotionally stable, and that initial conditions of socialization (e.g., access to better healthcare, education, etc.) affected the way non-cognitive skills developed.

Regression analysis on the dataset after matching also showed a positive influence of education on most non-cognitive skills in the treatment group. For example, amongst NEET youth, completed school education had positive effect on extraversion (0.25, $p < 0.01$). Completed secondary professional (vocational) education increased openness (0.5, $p < 0.01$), conscientiousness (0.30, $p < 0.01$), and grit (0.30, $p < 0.01$). In turn, completed tertiary education resulted in higher levels across almost all studied non-cognitive skills. Although age demonstrated a statistically significant effect on some non-cognitive characteristics, the magnitude of this effect was very low, and this variable acted more as a controller in the model. Interestingly, male NEET youth were more disadvantaged in openness (-0.14 , $p < 0.05$) and conscientiousness (-0.23 , $p < 0.01$), as well as more prone to neuroticism (0.21, $p < 0.01$).

The results showed that the application of matching as a method controlling self-selection bias, allowed for assessing the impact of predictors on non-cognitive skills more accurately, unlike linear regression, which to a lesser extent captured the differences between NEET and non-NEET youth (the results of the OLS model are presented in Appendix A).

The results of the conducted research showed the role of the NEET status of Russian youth in the degree of manifestation of their non-cognitive skills, confirming its negative impact on the development of prosocial personal qualities. On the other hand, it was revealed that the socio-economic status of NEET youth was associated with the development of non-cognitive skills. However, the effect turned out to be significantly more pronounced when interacting with psychological and socio-economic factors, as youth from the poorest and poor segments of the population are more likely than others to fall into the NEET category, which requires adopting separate approaches to support this group and level inequality in terms of education and the development of non-cognitive skills.

A significant part of the youth who fell into the NEET group did not even seek to find a job. According to previous research literature, it is known that the development of non-cognitive skills will stimulate the behavioral motivation of youth, which will open channels of social mobility and ways to exit the NEET status. Therefore, the socio-economic inclusion of NEET youth in public life should be carried out comprehensively at multiple different levels, including personal, educational, and labor. A number of studies have shown that individual training can achieve a fragmentary effect in the form of increased labor motivation (Ushakova 2021; Aysina 2016; Selezneva 2008). However, for a systemic solution to the problem, state regulation measures are necessary.

5.4. Limitations of the Study

The main limitation of the study is that the presented conclusions cannot be interpreted in a cause-and-effect logic, although the method of comparing propensity scores is often used in econometrics as a way of performing causal analysis (Caliendo and Kopeinig 2008; Essama-Nssah 2006; Heinrich et al. 2010; Basu et al. 2017). Moreover, it is necessary to take into account that reverse causality is present in the relationship between non-cognitive skills and NEET status, as certain personality characteristics can affect the fact of falling into the NEET group; however, being in the NEET status, especially in the long term, can affect

personality skills. The proposed analysis, without claiming to identify causal mechanisms between NEET status and non-cognitive skills, aimed to examine whether there is a gap in these skills between NEET and other youth, controlling for those self-selection biases that are inevitably present in the sample.

The second limitation relates to the absence of the duration of stay in NEET status as one of the predictors of the gap in non-cognitive skills. Although the RLMS is a longitudinal study, the monitoring design is such that the inclusion of this variable in the analysis is possible only for a very limited number of respondents in the 2016 sample; given that the matching method is sensitive to missing values, the current analysis could not take this criterion into account.

Finally, it is impossible not to note the limitations imposed by the measurement approach. To measure non-cognitive characteristics, a scale developed for the STEP Skills Measurement Survey was used; however, the limited number of questions for measuring each of the Big Five factors (three questions per factor), as well as the short interval of the ordinal scale (1–4), do not allow it to fully capture the variability in the possession of non-cognitive skills necessary for more accurate predictive analysis.

6. Conclusions

This study touches on the global problem of NEET youth, a group that emerges during the school-to-work transition when some cohorts of youth, after completing a certain level of education, do not find a place in the labor market. This work considers the problem of NEET youth from the point of view of their lag in non-cognitive skills, characteristics that play a key role in life success and inclusive socio-economic participation. The study results showed that a significant proportion of the NEET youth were young people with higher education; that is, higher education graduates with advanced competencies were not demanded in the labor market, which demonstrates the absence of economic returns from investments in education. Moreover, most young people who were in the NEET group came from poor families, which may indicate the lack of social elevators and an inequality in access to the education system, the labor market, and opportunities for developing key skills necessary for successful employment. Almost half of the youth in the NEET group not only did not work but also did not seek to find a job, which speaks of the need to develop personal characteristics, including non-cognitive skills, which can act as motivation drivers.

The analysis revealed that the NEET youth had a statistically significantly lower level in a number of non-cognitive skills compared to their peers. They were less conscientious, less emotionally stable, and did not have grit. These three skills indicated the main areas of lag behind other youth. A less noticeable gap was observed in extraversion.

In turn, policy measures that facilitate the effective transition of young people from the education system to the labor market could serve as mechanisms to support vulnerable youth groups experiencing the highest risks of early drop-out from the education system. It is necessary to improve public policy to support NEET youth, including through the development of non-cognitive skills through targeted social programs.

Future research endeavors in this field should pivot towards a more rigorous exploration of the causal relationships between the development of non-cognitive skills and the incidence of NEET. While recognizing the complex interplay of macroeconomic, social, and demographic determinants that contribute to NEET categorization, it is imperative to incorporate non-cognitive skills into the scholarly agenda surrounding NEET individuals. This inclusion promises to deepen our understanding of the school-to-work transition, not only in the context of systemic and institutional forces but also through a lens that captures the nuanced individual attributes on the labor market's supply side. Such a holistic approach in research, as well as the abovementioned policy implications, would be pivotal for both developing and developed economies, as they underscore the importance of individual agency in conjunction with broader economic and societal structures.

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Appendix A

Table A1. Descriptive statistics of questions on non-cognitive skills (% of responses).

No.	Item	Almost Always	Most of the Time	Some of the Time	Almost Never
Openness					
1	Do you come up with ideas other people haven't thought of before? *	17	44	32	5
2	Are you very interested in learning new things? *	15	13	48	36
3	Do you enjoy beautiful things, like nature, art and music? *	3	15	31	50
Conscientiousness					
1	When doing a task, are you very careful? *	1	17	64	16
2	Do you prefer relaxation more than hard work?	16	36	39	7
3	Do you work very well and quickly? *	3	26	49	19
Extraversion					
1	Are you talkative? *	5	30	37	26
2	Do you like to keep your opinions to yourself? Do you prefer to keep quiet when you have an opinion?	11	45	35	7
3	Are you outgoing and sociable; for example, do you make friends very easily? *	7	26	41	22
Agreeableness					
1	Do you forgive other people easily? *	7	35	42	14
2	Are you very polite to other people? *	0	12	53	32
3	Are you generous to other people with your time or money? *	16	40	27	16
Neuroticism					
1	Are you relaxed during stressful situations? *	11	38	40	10
2	Do you tend to worry?	10	29	48	11
3	Do you get nervous easily?	14	21	51	12
Grit					
1	Do you finish whatever you begin? *	1	23	56	19
2	Do you work very hard? For example, do you keep working when others stop to take a break? *	15	50	27	6
3	Do you enjoy working on things that take a very long time (at least several months) to complete? *	37	39	17	6

Note: reverse questions marked *. Source: authors' calculations based on RLMS HSE data (26th wave).

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