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COGNITIVE SKILLS OR DIPLOMAS – WHAT MATTERS MORE FOR WAGES IN POLAND?

Abstract. A vast – and constantly growing – literature provides evidence on the importance of formal education and cognitive skills on individual wages in contemporary, knowledge-based economies and societies. The OECD Programme for the International Assessment of Adult Competencies (PIAAC) provides measures of literacy and numeracy that have been used in numerous analyses. The Polish follow-up study of PIAAC (postPIAAC) includes a measure of another factor of cognitive skills, namely, processing speed. In this paper, we apply the Mincerian wage regression to assess the returns to formal education, numeracy, processing speed, and several control variables using the Polish PIAAC and postPIAAC data. The results confirm the findings from other analyses that formal education matters more than cognitive skills for wages in Poland.

Keywords: returns to skills, formal education, earnings, cognitive skills, Poland, PIAAC, postPIAAC.

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ZDOLNOŚCI POZNAWCZE CZY DYPLOM – CO SIĘ W POLSCE BARDZIEJ OPŁACA?

Abstrakt. Istnieje obszerna – i stale rosnąca – literatura dostarczająca dowodów o znaczeniu formalnego wykształcenia i umiejętności poznawczych dla indywidualnych wynagrodzeń we współczesnych gospodarkach i społeczeństwach opartych na wiedzy. Międzynarodowe Badanie Kompetencji Osób Dorosłych OECD (PIAAC) dostarcza miar umiejętności rozumienia tekstu i rozumowania matematycznego, które są wykorzystywane w wielu analizach. Polskie badanie uzupełniające PIAAC (postPIAAC) obejmuje pomiar innego czynnika umiejętności poznawczych, a mianowicie szybkości kodowania. W niniejszym artykule stosujemy regresję płacową Mincera do oceny zwrotów z edukacji formalnej, umiejętności rozumowania matematycznego, szybkości kodowania i szeregu zmiennych kontrolnych wykorzystując polskie dane PIAAC i postPIAAC. Wyniki potwierdzają ustalenia z innych analiz, że to formalne wykształcenie ma większe znaczenie dla wynagrodzeń w Polsce niż umiejętności kognitywne.

Słowa kluczowe: zwrot z umiejętności, edukacja formalna, zarobki, umiejętności kognitywne, Polska, PIAAC, postPIAAC.

1. Introduction

The topic of what shapes the wages is important for both individuals and researchers, including sociologists, economists, psychologists, and statisticians. The vast corpus of existing research points to a long list of individuals' as well as job characteristics that correlate with higher earnings. Education is usually listed as one of the most important factors shaping the earnings. However, the level of education or the number of years of schooling are themselves just information stated on diplomas and what should actually matter are the cognitive skills that the schooling aims to develop. Most of the social or labour market datasets lack information on skills and this is why only the education variable is included in the wage models, usually. There have been attempts to capture the level of cognitive skills in the large-scale surveys with an example of the Organisation for Economic Co-operation and Development's (OECD) Programme for the International Assessment of Adult Competencies (PIAAC) and there have been attempts to use these estimates to explain the heterogeneity in wages.

The aim of this paper is to use the PIAAC and the Polish follow-up study to PIAAC (postPIAAC) measures on cognitive skills as well as the information on education in order to explain the variability of wages in Poland. The cognitive skills considered here are literacy, numeracy and processing speed. The first two are the measures already exploited in numerous analyses, but processing speed is a new measure which, to the best of our knowledge, has not been so far analyzed in the context of its relation to labour market. Our research question we ask in this paper reads as follows: is it the formal education (diplomas) or directly measured cognitive skills that matter more on the labour market in contemporary Poland.

2. Literature review

Most of the existing research in economics and sociology on an individual's labor-market success traces back to the seminal contributions by Becker (1962) and Mincer (1970, 1974) who both have shown that human capital has positive effects on individual earnings. It is the work of Mincer, however, that was especially important in establishing the course of subsequent empirical investigations in this area. Mincer argued that a primary motivation for schooling was developing the general skills of individuals and, therefore, that it made sense to measure human capital by the amount of schooling completed by individuals. From this, he has shown how wage differentials could be significantly explained by school attainment and, in a more nuanced form, by on-the-job training investments. The standard Mincer formulation assumes that schooling is the sole systematic source of skill differences (Hanushek et al. 2015: 105).

Most analyses of the returns to skills in the labor market rely on the Mincerian wage regression, derived from a theoretical framework of optimal human capital investment, which allows estimating the rate of return to schooling (Hampf, Wiederhold, Woessmann 2017: 5). This Mincerian wage regression is a very simple underlying model of human capital which one can write simply as:

$$y = \gamma H + \varepsilon \tag{1}$$

where individual earnings (y) are a function of the labor-market skills, or human capital, of the individual (H). The stochastic term (ε) represents idiosyncratic earnings differences, generally presumed in empirical investigations to be orthogonal (unrelated) to H. This basic model of earnings determination is central to most empirical investigations of wages and individual productivity. Skills in this model are affected by a range of factors including family inputs, the quantity and quality of inputs provided by schools, individual ability, and other relevant factors which include labor market experience, health, and so forth (Hanushek, Woessmann 2008: 609–610).[1]

Because information on school attainment is frequently measured and reported in surveys and censuses that also contain earnings information, in much of the subsequent research following Mincer's initial contributions human capital was operationalized in Eq. (1) simply as years of schooling. Research accumulated since the publication of Mincer's first works delivers ample evidence on the existence of returns to schooling (Harmon, Oosterbeek, Walker 2003). In the overwhelming majority of the extant studies one finds a positive relationship

[1] Such studies that take into consideration how other factors, in addition to school attainment and on-the-job training, determine skills are referred to in the literature as research into "educational production functions." For a general discussion about it, see Hanushek (2002).

between schooling and individual earnings: on average, an additional year of schooling is associated with roughly a 10% increase in earnings. These estimated returns to schooling, however, vary significantly between studies and countries analyzed (Psacharopoulos, Patrinos 2004).

Since 1990s, with the expansion of direct measurement (testing) of skills in the OECD and OECD-affiliated countries carried out on nationally representative samples of pupils (such studies as: the Trends in International Mathematics and Science Study, or TIMSS; the Progress in International Reading Literacy Study, or PIRLS; and the Programme for International Student Assessment, or PISA) and adults (such studies as: PIAAC and earlier the International Adult Literacy Survey, or IALS), it became possible for researchers to go beyond the standard Mincer approach of using years of schooling as the sole measure of human capital (Hanushek, Woessmann 2015: 16–21). Thus, e.g., in their comparative studies based on the PIAAC survey (Hanushek et al. 2015, 2017) used as their baseline empirical model a simple analog to a Mincer equation except that it is built on measured cognitive skills (literacy and/or numeracy) controlled for years of actual labor-market experience and gender (Hanushek et al. 2015: 107) or controlled for gender and age (Hampf et al. 2017: 9; Hanushek et al. 2017: 16).

The topic of returns to education and cognitive skills in Poland lacks a deeper insight. Although Hanushek et al. (2015, 2017) and Hampf et al. (2017) consider a set of countries, including Poland, their results are discussed on an international level. On the other hand, there are at least several research papers that attempt to estimate the returns to education in Poland, but not to skills. These articles base their empirical analyses on official statistics data, including social survey data, i.e. Household Budget Survey (e.g. Strawiński 2006, 2008; Myck, Nicińska, Morawski 2009), Labour Force Survey (e.g. Gajderowicz, Grotkowska, Wincenciak 2012), as well as the establishment survey: Structure of Wages and Salaries by Occupations (e.g. Rogut, Roszkowska 2007; Adamczyk, Jarecki 2008; Roszkowska, Majchrowska 2014). The official statistics data does not cover any measures of cognitive skills. For the adult working-age population in Poland the only large-scale survey including the cognitive skills direct assessment is PIAAC which can be supplemented with the data from the postPIAAC follow-up study.[2]

In our own work we build upon the conceptualization of the relationship between individual earnings and human capital suggested by Hanushek et al. (2015, 2017) but on the one hand we limit our investigation to one country only (Poland) and on the other hand we expand our understanding of human capital by

[2] Although studies based on the analysis of the POLPAN data (Słomczyński et al. 2023; Tomescu-Dubrow et al. 2021) include – since its 2003 wave – direct measures of cognitive skills that correspond to the measurement of fluid reasoning (Firkowska-Mankiewicz, Zaborowski 2002), they do not measure directly such skills as literacy or numeracy.

including in it the third measure of cognitive skills beyond literacy and numeracy: namely, processing speed.

The Cattell–Horn–Carroll (CHC) theory of cognitive abilities provides the theoretical basis for our investigation of the relationship between selected aspects of cognitive abilities and wages. CHC theory is the integration (McGrew 2009) of Cattell and Horn's Gf-Gc (fluid reasoning-comprehension knowledge) theory (Horn 1968, 1988, 1991; Horn, Noll 1987) and Carroll's three-stratum (3S) cognitive ability theory (Carroll 1993, 1998; McGrew 2023). According to CHC theory, one can distinguish nine broad cognitive abilities that are listed and described in detail in Table 1.

Table 1. Nine CHC broad abilities

Broad ability	Acronym	Description
Stores of acquired knowledge		
Comprehension Knowledge	Gc	Breadth and depth of knowledge including verbal communication, information, and reasoning when using previously learned procedures.
Quantitative Ability	Gq	Ability to comprehend quantitative concepts and relationships, the facility to manipulate numerical Symbols.
Reading-Writing	Grw	An ability associated with both reading and writing, probably including basic reading and writing skills and the skills required for comprehension/expression.
Thinking abilities		
Long-Term Retrieval	Glr	Ability to efficiently store information and retrieve it later, often through association.
Visual-Spatial Thinking	Gv	Spatial orientation and the ability to analyze and synthesize visual stimuli. The ability to hold and manipulate mental images.
Auditory Processing	Ga	Ability to discriminate, analyze, and synthesize auditory stimuli. Includes phonological awareness.
Fluid Reasoning	Gf	Ability to reason, form concepts, and solve problems that often involve unfamiliar information or procedures. Manifested in the reorganization, transformation, and extrapolation of information.
Cognitive efficiency		
Processing Speed	Gs	Ability to rapidly perform automatic or simple cognitive tasks.
Short-Term Memory	Gsm	Ability to hold information in immediate awareness and use it within a few seconds. Includes working memory.

Source: (Camarata, Woodcock 2006: 232)

"The identification of these broad abilities, or factors, has been primarily through the application of exploratory and confirmatory factor analysis procedures to large samples of subjects that have been administered a variety of intellectual and achievement tests" (Camarata, Woodcock 2006: 232).

In the PIAAC survey, literacy is defined as "the ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential" while numeracy refers to "the ability to access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life" (OECD 2013a: 59). Thus, these two measures represent acquired knowledge, sometimes called crystallized intelligence (Desjardin, Warnke 2012: 6–32), or more precisely: literacy represents Comprehension Knowledge (Gc) and numeracy represents Quantitative Ability (Gq).

With respect to processing speed (Gs), within the context of Cattell–Horn–Carroll (CHC) Theory it is defined as "the ability to automatically perform cognitive tasks when under pressure to maintain attention and concentration" (Camarata, Woodcock 2006: 249; see also Flanagan, McGrew, Ortiz 2000). Carroll (1993: 613–619) identifies processing speed (Gs) as the factor that measures speed of cognitive performance. Horn, in turn, calls processing speed (Gs) Attentive Speediness and describes it as: "a quickness in identifying elements, or distinguishing between elements, of a (visual) stimulus pattern, particularly when measured under press to maintain focused attention" (Horn 1988: 666). He states that processing speed "is measured most purely by tests that require rapid scanning and responding to intellectually simple tasks that almost all people would get right if the task were not highly speeded" and notes that this "Speediness in scanning, inspecting and becoming aware of the salient features of problems is a pervasive source of individual differences in cognitive tasks" (Horn 1991: 215, 222). Processing speed is a very complex mental capacity which throughout the human lifespan is characterized by pronounced age differences (Kail, Salthouse 1994) and which is reciprocally linked to a plethora of neurobiological, e.g. brain structure and its development (Imms et al. 2021; Li et al. 2024), neurovascular health (Flinkenflügel et al. 2024; Sivakolundu et al. 2020)] as well as lifestyle and psychological factors such as: smoking cigarettes, drinking alcohol, engaging in physical activity or exercising, having an increased Body Mass Index (BMI), or displaying depressive symptoms (Jaarsma et al. 2024).

3. Data and methods

3.1. PIAAC and postPIAAC data

We use the data for Poland coming from the Programme for the International Assessment of Adult Competencies (PIAAC) conducted in 2011–2012 and coordinated by the OECD at the international level (OECD 2013a). The institution responsible for PIAAC in Poland was Educational Research Institute. The PIAAC sample in Poland amounted to 9366 respondents aged 16-65 (Burski et al. 2013). The PIAAC data provides the information on socio-demographic characteristics of the respondents, their situation on the labour market as well as the estimates on their literacy and numeracy level of skills.

In years 2014–2015 the Educational Research Institute conducted the postPIAAC survey whose aim was to gather the longitudinal information on PIAAC respondents and to supplement them with some extra information on, among others, general intelligence, noncognitive skills and ICT skills-assessment measures (Palczyńska, Świst 2018; Palczyńska, Rynko 2021; Palczyńska 2021). The postPIAAC sample size amounted to 5224 respondents. We are mainly interested in the processing speed – a measure of cognitive ability (cognitive efficiency) that was included in postPIAAC. We append the data on the performance in the processing speed test to the PIAAC data and analyze its relation to earnings. Although the timespan between the PIAAC and post-PIAAC surveys was around 3 years, we assume that the measures of cognitive abilities are stable over such a short period of time, as discussed in Camarata and Woodcock (2006) and Desjardin and Warnke (2012).

In all the analyses presented here we use PIAAC population weights, which is especially important because of the overrepresentation of younger cohorts in PIAAC in Poland. In the regression analyses, the standard errors are estimated using the replication weights to account for the complex sampling scheme in PIAAC. As for the literacy and numeracy estimates, we use the first plausible value only, being consistent with many analyses on PIAAC data (e.g. Hanushek et al. 2015). The multiple imputation methodology (i.e. the plausible values estimation), sampling scheme and variance estimation procedures, as well as the methodology of the direct assessment of literacy and numeracy, are described in the PIAAC international and national reports (OECD 2013a, 2013b; Burski et al. 2013).

The initial sample of 9366 PIAAC respondents was restricted to 5224 after merging both PIAAC and postPIAAC data. Out of 5224 individuals, 53.5% (2794) were employed at the time of PIAAC survey, which further restricts our sample. Also, we exclude the group of self-employed (374) from the analyzed dataset as this type of employment in Poland captures a very diversified group of people[3] and makes the interpretation of the results difficult. Further restrictions on the sample refer to missing or extreme values on the variables included in the analysis. We drop observations with earnings below the 1st and above the 99th percentiles. We also exclude respondents with coding speed test result above 70 (with the maximum of the test score being 90) as being rather unachievable. The final sample consists of 1142 individuals. Using this data set, we estimate the Mincerian wage regression model taking into account both education and skills and controlling for available and theoretically and/or practically relevant individual characteristics.

3.2. Dependent variable

Our dependent variable is the logarithm of gross hourly earnings for wage and salary earners. In the PIAAC interview, the respondents could answer the question on earnings reporting either hourly, daily, weekly, bi-weekly, monthly or yearly earnings, as well as rates per piece. Based on this information and the declared working time, the new variable was derived recalculating the reported income to the comparable amount of hourly earnings, including also the potential bonuses reported. Since the logarithmic transformation is applied here, the change in earnings corresponding to a unit change in an independent variable should be interpreted as a percentage change.

3.3. Independent variables

We included both the education and skills measures in the model. Education is measured as number of years of schooling. This variable was derived from the information on the highest level of education obtained reported by respondents.

The measures of cognitive skills include numeracy and processing speed. We decided not to include literacy, as numeracy and literacy are strongly correlated and convey similar information (Table 2). Numeracy is a slightly better predictor of earnings than literacy as models with numeracy are characterized by a higher value of R^2 than models with literacy. Hanushek et al. (2015) also includes numeracy only, while the basic wage equations presented in the OECD analyses include literacy (OECD 2013a: 227–234).

[3] Typically, the self-employed include both farmers as well as skilled IT or business specialists who – in order to avoid bearing part of the employment costs – decide to formally work as self-employed.

Table 2. Correlation matrix of dependent and independent variables

	Log(wage)	Years schooling	Literacy	Numeracy	Processing speed
Log(wage)	1.0000				
Years schooling	0.4914	1.0000			
Literacy	0.3805	0.5215	1.0000		
Numeracy	0.4022	0.4808	0.8386	1.0000	
Processing speed	0.1666	0.4089	0.3499	0.3141	1.0000

Note: all presented Pearson correlation coefficients are significant at 0.01 significance level
Source: Own elaboration based on PIAAC and postPIAAC data

The measure of processing speed, i.e. the efficiency factor of cognitive ability, is proxied by the result of a coding speed test included in the postPIAAC survey. The test required individuals to match digits with letters as quickly as possible. The maximum amount of correctly assigned digits provides an estimate of the respondent's perceptual information-processing speed. Following the example of another large-scale survey, German Socio-Economic Panel (GSOEP) (Lang et al. 2007: 185, see also Entringer et al. 2022 and Schupp et al. 2008), the coding speed test was constructed after the Symbol-Digit-Modality-Test (Smith 1973). The postPIAAC coding speed test was performed on a paper form and was timed (it lasted 60 seconds). The correlation between processing speed and wages (logarithm of wage) is not big, it is smaller than the correlation between processing speed and education or literacy/numeracy.

The years of schooling, numeracy and processing speed variables were standardized (on the full sample of 5224 observations), so that we analyze the effect of a change in each of these variables by one standard deviation (ceteris paribus) on the dependent variable. Thanks to the standardization, we can directly compare the magnitude of the association between earnings and schooling and earnings and cognitive skills.

3.4. Control variables

We also control for years of labour market experience, whether the respondent is a manager and whether the respondent works in public sector. Following previous papers that study gender gaps in skills and labor market outcomes using PIAAC data (Gilboa 2024; Graves, Kuehn 2021; Rebollo-Sanz, De La Rica 2022) we also control for gender (men being the reference category). To account for the occupation-based class structure (Erikson, Goldthorpe 1993: 35–47), we control for the respondent's membership in one of the four occupational categories derived from ISCO-08 code (ILO, 2012): elementary occupations, semi-skilled blue-collar occupations, semi-skilled white-collar occupations (reference category), and skilled occupation. However, because of the low numbers of respondents assigned to elementary occupations and non-significant coefficient estimates next to this category in the regression models, we decided to merge the elementary and semi-skilled blue-collar occupations into one category "blue-collar" occupations in the regression model.

Finally, to account for the continuing persistence of wage gap between villages and cities in Poland (Chmielewska, Zegar 2022)[4] and because various poverty indicators are still higher in the countryside than in cities (Kalinowski 2022), we included in our baseline model a variable for the size of respondents' place of residence. Because such terms as "village" or "rural areas" are ambiguous and lack uncontested definitions (Stanny 2014), we decided to operationalize this variable according to definition used by Statistics Poland (GUS 2018: 17), with villages and small towns (below 20 000 inhabitants) serving together as one category, and subsequently with medium-sized town (between 20 000 and 200 000 inhabitants) serving as the reference category, and large towns or cities (200 000 or more inhabitants).

We do not control for age in the regression models. Firstly, because there is the potential problem of multicollinearity between age, experience and years of schooling. Secondly, besides the general model for the whole sample analyzed, we estimate separate models for three distinct age groups: entry age (25–34 years, n = 573), prime-age (35–54 years, n = 453) and exit-age (55–65 years, n = 116), similarly as in Hanushek et al. (2015). The big sample size for the entry age reflects the overrepresentation of respondents aged 25–26 years. On the other hand, the small sample size of the exit age individuals reflects the early labour market exits due to the lower retirement age of women and other possibilities of e.g. early retirement pensions or disability pensions that are built in the Polish retirement system. When we weight the data, the proportions of entry, primary and exit age are 34.8%, 52.6% and 12.6% respectively in the dataset under analysis.

3.5. Descriptive statistics

The descriptive statistics for the whole sample analyzed, as well as for the subsamples of individuals defined by their age are presented in Table 3 and Table 4.

Table 3. Descriptive statistics for continuous variables

	mean	**sd**	**min**	**Q1**	**median**	**Q3**	**max**
	1	2	3	4	5	6	7
Full sample, 25–65 years (n = 1142)							
wage	16.22	8.92	4.24	9.81	13.96	20.23	75.15
years schooling	13.50	2.96	6.00	11.00	13.00	17.00	21.00

[4] It has to be noted, however, that the Polish countryside catches up with Polish cities in terms of earnings (Wilkin 2022: 22–23).

	1	2	3	4	5	6	7
numeracy	266.00	48.34	80.59	234.62	266.86	299.66	409.06
processing speed	32.10	9.34	2.00	26.00	32.00	38.00	69.00
experience	17.54	11.09	0.00	8.00	15.00	26.00	47.00
Entry age, 25–34 years (n = 573)							
wage	16.08	8.58	4.58	10.41	13.78	20.11	58.11
years schooling	14.55	2.66	6.00	13.00	15.00	17.00	21.00
numeracy	274.65	46.61	123.69	242.47	276.39	308.04	409.06
processing speed	36.21	8.67	8.00	31.00	36.00	42.00	69.00
experience	7.10	3.63	0.00	4.00	6.00	10.00	18.00
Prime age, 35–54 years (n = 453)							
wage	15.90	8.52	5.16	9.36	13.87	19.55	55.54
years schooling	13.03	2.87	6.00	11.00	13.00	15.00	21.00
numeracy	260.87	48.28	80.59	232.80	262.14	295.53	374.12
processing speed	30.58	9.20	2.00	25.00	31.00	36.00	61.00
experience	20.32	8.06	1.00	15.00	20.00	26.00	39.00
Exit age, 55–65 years (n = 116)							
wage	17.93	11.10	4.24	9.57	15.72	23.12	75.15
years schooling	12.56	3.30	6.00	11.00	12.00	15.00	21.00
numeracy	263.53	50.31	111.61	232.97	269.38	295.67	393.97
processing speed	27.08	7.07	12.00	22.00	27.00	31.00	45.00
experience	34.82	6.00	1.00	32.00	36.00	39.00	47.00

Source: Own elaboration based on PIAAC and postPIAAC data.

The descriptive statistics allow for a preliminary characterization of the labour market and the cognitive skills distribution features in Poland. The central tendency measures show that wage is slightly higher for the younger cohorts than for the primary age groups and is the highest for the oldest age group. These differences may reflect the structure of earnings in Poland, the fact that wages often depend on experience and/or tenure to a big extent. Also, the selection processes have to be taken into account – the presented data concerns only working individuals for whom we obtained all the information of interest. Especially the exit age group is subject to selection process of who stays in the labour market – those who stay in the labour market are often younger individuals, better educated, characterized by better health condition, working full time and living in urban areas (see e.g. Instytut Badań Edukacyjnych 2014: 22–23). Also, selected cognitive abilities measures show positive correlation with economic activity for the older age groups (Palczyńska, Rynko 2016).

Experience naturally increases with age. As for years of schooling, we see the opposite – the younger cohorts are on average better educated, which is consistent with other data sources (e.g. Instytut Badań Edukacyjnych 2011: 19–26). Cognitive abilities are generally shown to decrease with age and this is consistent with the presented statistics for processing speed. For numeracy, we see a higher mean for the exit group as compared to the prime age group, but this is most likely because of the selection process of the exit group. The general age profile for numeracy (independently on the labour market status) shows clear decrease of these skills starting from around 35 years of age (Burski et al. 2013: 54).

As for the control variables included in our analysis, we observe differences in the proportion of women in the subsamples analysed, but also in the proportions of managers, occupations held, being employed in the public sector and living in the rural or urban areas. Again, many of these differences are related to the selection processes of the exit age groups – those who stay in the labour market are more often men (mainly because of their higher retirement age), managers and live in cities. As for the differences in the jobs held, better educated younger cohorts have easier access to white-collar jobs than older cohorts.

Table 4. Descriptive statistics (%) for the categorical variables

	Full sample (n = 1142)	**Entry age (n = 573)**	**Prime age (n = 453)**	**Exit age (n = 116)**
Female	47.5	46.6	49.5	41.3
Manager	24.1	21.8	25.2	26.1
Public sector	34.8	26.1	41.0	33.2
Occupation				
skilled	37.4	45.0	33.1	34.7
semi-skilled white-collar	23.8	27.3	22.2	20.9
blue-collar	38.7	27.6	44.7	44.5
Size od locality of residence				
village & town < 20 thous.	49.2	49.4	50.6	42.4
town >= 20 thous. & < 200 thous.	30.7	31.6	29.9	31.6
city >= 200 thous.	20.2	19.0	19.5	26.1

Source: Own elaboration based on PIAAC and postPIAAC data

4. Results

We estimated four linear regression models – one for the whole sample of individuals aged 25–65 years of age and separate models for entry age, prime age and exit age subsamples. The regression models refer to Mincerian wage regression specification with the logarithm of wage as the dependent variable, years of schooling and measures of cognitive abilities as independent variables and a set of control variables: gender, experience, occupation, size of locality of residence, manager and public sector dummies. We included also the interaction between gender and processing speed as it has been shown that processing speed is higher among women (Camarata, Woodcock 2006: 249). The interactions between gender and numeracy, as well as gender and years of schooling were statistically insignificant and are not included in the final specification of the models. We tried several different specification of the models, taking into account different categorization of occupational classes, size of locality of residence, inclusion of quadratic specification of experience variable, replacing experience with tenure.[5] The specifications presented in Table 5 provide the best estimates in terms of the proportion of the variance explained by the models as well as the significance and interpretability of the explanatory variables.

Table 5. Mincerian regressions estimates for the PIAAC-postPIAAC data

	logwage full sample	**logwage entry age**	**logwage prime age**	**logwage exit age**
Years schooling	0.159*** (7.03)	0.194*** (4.82)	0.163*** (5.94)	0.127* (1.70)
Numeracy	0.0729*** (4.12)	0.102*** (4.34)	0.0650*** (3.06)	0.0179 (0.30)
Processing speed	0.0203 (0.83)	–0.0466 (–1.05)	0.0470 (1.52)	–0.0353 (–0.40)
Female (ref. = male)	–0.179*** (–7.21)	–0.238*** (–4.29)	–0.244*** (–7.67)	–0.0345 (–0.42)
Female # processing speed	0.00498 (0.19)	0.143*** (2.73)	–0.0408 (–1.25)	0.0152 (0.10)
Experience	0.00844*** (6.74)	0.0273*** (3.86)	0.0102*** (4.60)	0.0115 (1.29)
Occupation (ref. = semi-skilled white-collar)				
Skilled	0.247*** (6.04)	0.142** (2.57)	0.246*** (4.42)	0.499** (2.56)
Blue-collar	0.0934** (2.42)	0.123* (1.81)	0.0154 (0.33)	0.390*** (3.16)
Manager (ref. = no)	0.147*** (4.17)	0.121** (2.10)	0.0898** (2.07)	0.332*** (3.24)
Public sector (ref. = no)	0.113*** (4.01)	0.0440 (0.73)	0.124*** (3.74)	0.236** (2.42)

[5] The additional results may be obtained from the Authors upon request.

Table 5. (Continued)

Size of locality of residence (ref. = town >= 20 thous. & < 200 thous.)				
Village & town < 20 thous.	–0.0305 (–1.03)	0.00745 (0.14)	–0.0763** (–2.05)	0.0651 (0.80)
City >= 200 thous.	0.0461 (1.12)	0.199*** (3.60)	0.00282 (0.05)	–0.0381 (–0.35)
Constant	2.298*** (53.38)	2.212*** (25.86)	2.325*** (37.54)	1.853*** (5.62)
Observations	1142	573	453	116
F statistic	48.58	19.43	44.29	13.31
R^2	0.428	0.414	0.514	0.486

Note: *t* statistics in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01. The variables years schooling, numeracy and processing speed are standardized (z-scores)

Source: Own elaboration based on PIAAC and postPIAAC data

The estimated models show some differences with respect to wage modelling across the general population and three different age groups analyzed. The best quality of the model in terms of the proportion of variance of the dependent variable explained (R^2) is noted for the prime age group, which is not surprising as this group has the most stable position on the labour market and the empirical model may be the best appropriate here. The exit age group model is estimated on a small sample, subject to selection processes (i.e. the selection on those who stay in the labour market), which can be the reason why most of the estimated coefficient are not statistically significant. The model for the entry age is characterized by the smallest value of R^2, which can be explained by the fact that this group may still seek its place on the labour market in the sense of job changing. Also, it is young people (compared to people in their prime age), especially women, who are more likely to have their careers broken by periods of parental leave. Therefore, this group may be more heterogeneous in terms of the labour market situation and the selected explanatory variables may be less accurate in capturing the real situation of the individuals. However, the values of R^2 exceed 40% in all four models.

When it comes to the effects of schooling and abilities on wages, the strongest effect is noted for schooling – a change in years of schooling of one standard deviation (nearly 3 years) corresponds to 12.7%–19.4% increase in earnings with the highest effect for the entry age group. An increase in numeracy of one standard deviation (nearly 50 points on a scale 0–500 points) corresponds to an increase in earnings between 1.8% and 10.2%, again, with the highest effect for the youngest group. For the pooled sample, we obtain 15.9% and 7.3% increase in earnings associated with the one standard deviation changes in years of schooling and numeracy, respectively. The effect of formal education is much stronger than the effect of directly measured abilities. This is consistent with the results presented by the

OECD, which places Poland among the countries with the strongest association between education and wages and a much lower importance of skills (OECD 2013a: 232–233). The results presented by Hanushek et al. (2015) also show that the effect of education in Poland is particularly strong compared to other countries. Furthermore, the preliminary analyses conducted on the PIAAC 2023 data[6] show that the effect of education on earnings is still significantly stronger than the effect of skills measured in PIAAC as compared to other selected countries that participated in the recent PIAAC round (Sitek, Penszko 2025).

However, the novelty in our specification concerns the inclusion of processing speed measure, another proxy for cognitive ability. The effect of changes in processing speed on wages is much smaller, generally insignificant and for entry and exit age groups with a surprising negative sign. However, the models contain the interaction of gender and processing speed and the estimated coefficient on the interaction term occurs significant for the entry age group: one standard deviation increase in processing speed result (9.3 points) is associated with nearly 10% increase in earnings, but for females only. This result is comparable to the effect for numeracy for the entry age group. For males and for other age groups the estimates next to the processing speed variables are not statistically significant.

Generally, the results on the association between education, skills and earnings show that these variables have the strongest effects for the entry age group. This should not be surprising as the least experienced employees are difficult to be judged by merits and formal education is an important signal on the labour market on their skills and motivation. Some of the cognitive skills can be noticed relatively quickly by the employer and adequately remunerated. As an employee gains more experience, his or her wage is stronger related to their employment history, tenure and job position.

As for the results obtained on the control variables included in the model, we see a non-surprising negative coefficient next to the gender variable, corresponding to 18% lower earnings for females on average (for the pooled sample of individuals aged 25–65 years old). The wages naturally increase together with the experience: one extra year of experience corresponds to nearly 1% increase in earnings. Employees supervising other employees earn on average nearly 15% more than non-managers. Public sector employment is associated with earnings higher on average by 11%. Those who are in skilled occupations earn on average nearly 25% more than semi-skilled white collar. The difference between earnings for blue-collar and semi-skilled white-collar employees is around 9% in favor of the first group. This probably speaks in favor of some kind of specialization of the blue-collar employees and the potential shortage in the labour supply

[6] The PIAAC 2023 data for Poland should be treated with caution as data control procedures found many unusual answer patterns and several cases of interviewers breaching data collection protocols throughout the survey (see OECD 2024).

of this group on the labour market. Finally, the association between the place of residence and earnings is generally non-significant, only for the entry age group we show that there is a significant effect of living in a large town (city) on earnings (20% increase in earnings as compared to a medium-sized town). The reason why this variable is generally insignificant in the models is probably related to the fact that it conveys the information on where the employee lives, but it should actually proxy the locality of the employer.

5. Conclusions

The present study sought to enrich and expand the existing analyses on returns to skills in Poland based on the evidence from OECD's 2011–2012 PIAAC and 2014–2015 postPIAAC data. More specifically, on the one hand our work is built upon the conceptualization of the relationship between individual earnings and human capital suggested by Hanushek et al. (2015, 2017) in their comparative research (which also included Poland), but on the other hand – in comparison with, e.g. Palczyńska, Świst (2018) – we expand our understanding of human capital by including in it a novel, previously unused measure of cognitive skills beyond numeracy – processing speed.

Our study has confirmed the previous findings that numeracy is positively correlated with individual earnings. Just as in the previous analyses, it also turned out that formal education is more strongly associated with individuals' wages than numeracy. The main effect of processing speed, however, (i.e., the second measure of cognitive skills which we introduced for the first time into a Mincerian wage equation) turned out not to be statistically significant. This particular finding of ours has implications beyond the labor market literature. It suggests that unlike numeracy, processing speed seems not to be a good proxy for cognitive skills in large-scale labor market surveys and should not be used in them, even if it takes less time to take for respondents and is less expensive for the researchers. An obvious limitation of our present study is the fact that our analysis cannot be interpreted causally, but only as correlation. Certainly, there is a need to extend the analysis on the relation between wages, education and skills, by e.g. using the microeconometric causality analysis toolkit.[7]

Our results showing that diplomas are more important than skills may be seen as particularly disquieting as regards the standing of the Polish economy and people working on the Polish labor market in the international division of labor. One can argue that this – to use Bourdieu (1986: 243) terms – domination of the

[7] For a textbook treatment see (Stock, Watson 2007) and for a non-technical discussion of the so-called instrumental-variable estimation and its example applications in the field of education see (Schlotter, Schwerdt, Woessmann 2011).

institutionalized state of cultural capital (i.e., formal educational qualifications) over its embodied state (i.e., long-lasting dispositions of the mind and body, or real abilities and skills) on the Polish labor market can be interpreted a sign that post-socialist systemic transformation in Poland ended up creating what Collins (2019) called "the credential society". Our disquietude about this credentialism *à la polonaise* stems from the realization that in today's knowledge economy, characterized by quick technological progress and profound changes in the labor markets, it is not only formally acquired and ascertained skills, but first and foremost cognitive skills – as it were, sheer brainpower – which become increasingly more and more important for the success of both individuals and the whole economies in the international competition.

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