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The Interplay Between Intelligence and Health in Shaping Income: Evidence from Poland

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Abstract

Existing studies on the economic returns to human capital always overlook the independent and joint roles of cognitive skills and health, and most evidence is limited to either high-income Western countries or low-income developing economies. Using microdata from the second cycle of the PIAAC survey in Poland, as a representative post-socialist economy in Central and Eastern Europe (CEE), this study extends the Mincer earnings function by incorporating an interaction term between self-reported health and three PIAAC-based cognitive proxies: literacy, numeracy, and problem-solving, with findings validated through robustness and heterogeneity checks. The results confirm that both intelligence and health independently exhibit significantly positive effects on income. More importantly, the interaction terms reveal a substitution mechanism: when health worsens by one-unit standard deviation based on its standardized continuous specification, the income returns to intelligence proxies range from 1.5% to 1.7%. The overall pattern suggests that cognitive skills become more economically valuable when physical health is poor. To reinforce these key findings, a general intelligence index (g factor) derived from principal component analysis, the baseline models without education control, along with the binary health specification are implemented. Furthermore, heterogeneity analyses indicate that the substitution effect is only effective among males and high-income groups but absent among females and lower income individuals, highlighting that this substitution mechanism varies systematically with labor market structures and institutional conditions. Filling a gap in the CEE literature, this study provides novel evidence of a substitution pattern between health and intelligence, emphasizing the need for policy frameworks that recognize the joint functioning of health and cognitive skills.

Keywords: Intelligence, Health, Income, Interaction Mechanism, PIAAC, Poland

CERCS: S180 (Economics); S196 (Social economics)

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1. Introduction

The determinants of individual income have long been a central topic in exploring the labor market and economic performance. Education and work experience have been recognized by earlier studies as the primary drivers of earnings (Becker, 1964; Mincer, 1974), serving as the foundation for most empirical models of income determination. In recent decades, however, the growing complexity of labor markets, rising income inequality, and institutional changes have intensified scholarly attention to the various forms of human capital that influence earnings beyond traditional factors such as education levels and work experience, and increasing emphasis has been placed on intelligence and health status. Technological advancement, the polarization of labor market, and the expansion of knowledge-intensive sectors have magnified the economic returns to cognitive ability, while persistent disparities in health continue to shape labor force participation, productivity, and career lifespan (Autor, 2014; Case & Deaton, 2017). Specifically, cognitive ability affects income by enhancing learning efficiency and enabling individuals to acquire and apply complex skills in the workplace (Heckman et al., 2006; Hanushek & Woessmann, 2008). It also affects occupational matching, as individuals with higher cognitive skills are more likely to enter better-paid and cognitively demanding jobs (Strenze, 2007; Schmidt & Hunter, 2004). Similarly, health affects income by determining individuals' physical capacity for productivity and labor market participation (Contoyannis & Rice, 2001). Moreover, poor health is associated with more frequent career interruptions and limited experience accumulation, leading to lower long-term earnings (Smith, 1999; Jäckle & Himmler, 2010).

Although intelligence and health have typically been examined as separate influences on income, a growing body of literature has begun to explore whether these two human capital dimensions interact in shaping economic outcomes (e.g., Vogl, 2014; Bhalotra et al., 2022). One emerging perspective suggests a complementary relationship, whereby cognitive skills are more effectively applied when supported by good health (Bhalotra et al., 2022; Hoddinott et al., 2008). In contrast, an alternative view highlights a substitution mechanism, where intelligence and health compensate for each other, particularly in disadvantaged contexts. Individuals with poor health may rely more on cognitive abilities to remain employable, while those with lower cognitive capacity may depend on physical fitness to perform manual jobs (Nilsson, 2015; Van Zon et al., 2017). Such diverse mechanisms indicate that the interaction between intelligence and health is likely to be context-dependent, shaped by job structure, institutional factors, and broader socioeconomic conditions. However, in terms of national contexts examined, most existing research on the relationship between intelligence, health, and income has primarily focused on either high-income developed countries or low-income developing nations. In advanced economies such as the United States and the United Kingdom, the availability of rich longitudinal datasets has facilitated extensive studies examining the independent effects of intelligence and health on socioeconomic outcomes (e.g., Batty et al., 2006). Meanwhile, research in developing countries such as Guatemala (Behrman et al., 2009) and Indonesia (LaFave & Thomas, 2017) have focused on early-life health interventions and their long-term impacts on cognitive development and adult earnings. Additional cross-country evidence from China, Pakistan, Ethiopia, and Vietnam, summarized by Nilsson (2015), reinforced these findings by demonstrating that improvements in early-life health and nutrition consistently enhance cognitive outcomes, which are strongly linked to later educational and income gains.

However, the CEE region has received little attention in studies examining the interaction between intelligence and health. Particularly, CEE countries present a unique post-socialist context characterized by rapid institutional transition, partially marketized welfare systems, and uneven human capital development. These features may lead to different patterns of how intelligence and health interact in shaping income, compared to both high-income Western countries and low-income developing regions. As one of the largest and most representative CEE countries, Poland offers a unique context for examining the interaction between intelligence and health on income. Firstly, it has undergone one of the earliest and most comprehensive transitions from a centrally planned to a market economy with the most enormous population. Secondly, Poland experienced rapid educational expansion after the 1990s, yet continues to face challenges such as skill mismatches and regional disparities in education quality. Thirdly, despite improvements in average health indicators, substantial inequalities in access to healthcare and health outcomes remain, particularly among low-income and rural populations. Fourthly, Poland provides high-quality, internationally comparable microdata from the Programme for the International Assessment of Adult Competencies (PIAAC), which enables rigorous analysis of individual-level cognitive skills, self-reported health, and income in a post-socialist labor market context.

Unlike most existing studies based on Western or developing economies, this study investigates how intelligence and health interact in determining income within a post-socialist labor market of Poland. Building on Mincer's (1974) log-wage equation, this study systematically extends the theoretical model by incorporating interaction terms between intelligence and health. Specifically, Intelligence in this study is proxied by three cognitive domains provided in PIAAC: literacy, numeracy, and problem-solving. Although PIAAC defines these as "skills," several studies have shown that they strongly reflect general cognitive ability and are commonly used as proxies for intelligence in empirical research (Pesta, 2022; Rammstedt et al., 2016; Maehler et al., 2024). For instance, Pesta (2022) derived U.S. state-level IQ estimates partly from PIAAC literacy and numeracy scores, highlighting their validity as intelligence indicators due to their real-world task design and population representativeness. Similarly, Rammstedt et al., (2016) concluded that the PIAAC cognitive assessments "capture core aspects of general cognitive ability" and are appropriate for use in psychological and economic research. Besides, as emphasized by Ganzach & Patel, (2018, p.2), while large-scale surveys tend to adopt a skills-based interpretation of test scores, *"the difference between skills and abilities is rarely discussed in the literature, perhaps because it is practically impossible to construct tests that differentiate between the two concepts."* It supported the view that cognitive skills measured by PIAAC are functionally indistinct from general intelligence in practice.

Moreover, health status is measured by the self-reported health indicator based on a five-point Likert scale, being reverse-coded into the regression models for better interpretation. Furthermore, the primary aim of this study is to evaluate the independent effects of intelligence and health on income and to explore whether their interaction functions as a complementary or substitution mechanism in shaping labor market outcomes in Poland. This study adopts a multi-step empirical strategy: firstly, baseline regressions are conducted using three cognitive proxies, including literacy, numeracy, and problem-solving skills, each interacted with self-reported health to test for possible complementarity or substitution effects. Secondly, to capture general cognitive ability, a general intelligence (g) factor is constructed via principal component analysis (PCA), combining all three cognitive indicators to re-estimate the interaction mechanism. This approach is supported by several studies showing that literacy, numeracy, and problem-solving scores from PIAAC load strongly on a common cognitive factor and can be meaningfully aggregated to reflect general intelligence (Maehler et al., 2025; Engelhardt et al., 2021). For instance, Maehler et al., (2025) provided psychometric evidence that these skill domains are highly correlated with general intelligence and load strongly on a common cognitive factor. Moreover, further robustness checks: the health variable is re-specified as a binary indicator and the baseline models without education controlling are implemented. Additionally, heterogeneity is examined through gender-categorized regressions and income quantile regressions to assess whether the substitution or complementarity pattern varies across the labor market segments. The empirical results provide consistent support for the substitution mechanism between intelligence and health: (1) The results show that literacy, numeracy, problem-solving skills, and the PCA-derived g factor all display significant negative interactions with health, providing consistent support for the substitution mechanism, which indicates that cognitive ability provides greater income returns when health is poor. (2) Further robustness checks demonstrate that the substitution mechanism holds under alternative model assumptions and variable specifications. (3) Heterogeneity analysis reveals that the interaction is only statistically significant among males and high-income individuals rather than females and low-income groups, suggesting that substitution effects are concentrated in labor market segments with higher exposure and returns to cognitive skills. This may also be explained by structural and occupational segregation in labor market, where many low-income or female individuals are involved in limited cognitive demands. Overall, the findings support a substitution mechanism between intelligence and health in influencing earnings and demonstrate that this mechanism is shaped by gender and income-related heterogeneity.

This study makes significant contributions to the relationship between intelligence and health affecting income jointly from three perspectives: Firstly, it offers empirical evidence of the substitutive interaction between health and intelligence in determining income, based on the context of Poland as a representative CEE case. This pattern contrasts with findings in advanced or developing countries that typically support complementary mechanisms (e.g., Sörberg et al., 2013; Lundborg et al., 2014; Bhalotra et al., 2022). More importantly, the empirical results highlight the importance of considering institutional contexts and provide support for future research on CEE countries. Secondly, the study highlights substantial heterogeneity in the interaction effect across diverse groups, indicating that the relationship between health and intelligence is not uniform but shaped by occupational structure and socioeconomic vulnerability. Additionally, the results carry important policy implications. Promoting income growth and economic efficiency requires not only addressing cognitive or health disparities separately, but more importantly recognizing their interactive effects. Policies should integrate the substitution mechanism and observed heterogeneity by offering targeted support: enhancing cognitive training for individuals in poor health and improving healthcare access for those with limited cognitive resources, thereby enhancing earnings resilience and labor productivity in the labor markets of Poland.

This paper is structured as follows: Section 2 reviews existing literature related to the income effects of cognitive ability, health, and their interaction patterns, highlighting theoretical debates and empirical gaps. Section 3 outlines the conceptual framework and details the data, variable construction, and empirical strategy used to examine the interaction between intelligence and health. Furthermore, section 4 presents the key regression findings, including baseline regressions, robustness checks, and heterogeneity analyses, showing that the substitutive effect is particularly efficient among men and individuals in higher income quantiles. Section 5 concludes by highlighting the implications for labor policy, especially in terms of targeting cognitive and health interventions to enhance earnings resilience in CEE.

2. Literature Review

Exploring the determinants of income growth has long been a central concern in labor economics and human capital theory. While traditional studies have primarily focused on education and work experience as key drivers of earnings-most notably in the works of Mincer (1974) and Becker (1964), more recent research highlights the critical roles of intelligence and health as fundamental components of human capital (e.g., Hoddinott et al., 2008; Bhalotra et al., 2022). Moreover, an emerging body of literature suggests that the effects of intelligence and health may be interdependent, with several studies (e.g., Hanushek et al., 2015; Vogl, 2014; LaFave & Thomas, 2017) demonstrating their interaction in shaping income trajectories, though the underlying mechanisms remain contested.

A key starting point in examining the role of intelligence and health in income determination lies in how these constructs are defined and measured. For intelligence, most studies use IQ test scores as proxies for cognitive ability, including the Armed Forces Qualification Test (AFQT) from the National Longitudinal Survey of Youth (NLSY) dataset (Herrnstein & Murray, 1994; Zagorsky, 2007; Lundborg et al., 2014), as well as literacy and numeracy proficiency scores from the PIAAC, which are officially defined as cognitive skills by the OECD, but increasingly used in empirical studies as proxies for intelligence (e.g., Rammstedt et al., 2016; Maehler et al., 2024), as well as non-verbal assessments such as Raven's Progressive Matrices (Vogl, 2014). Besides, books such as Rindermann (2018) and Lynn, R., & Becker, D. (2019) compiled and synthesized IQ test scores from various assessments to provide cross-country comparisons of average IQ levels, presenting a consolidated view of global cognitive ability.

In the case of health, proxies used in the literature are even more diverse. Early studies often rely on physical indicators such as height, which is interpreted as a long-term marker of early-life health and nutrition (Case et al., 2005; Lundborg et al., 2014; Vogl, 2014). Furthermore, many studies adopt binary or categorical indicators of health status, such as the presence of chronic illness, disability, or heart conditions (Haveman et al., 1994; Smith, 1999). In addition, self-reported health-typically measured through individuals' subjective assessments on a Likert scale, is widely used as a proxy, despite its inherent subjectivity (Sundberg, 1996; Jäckle & Himmler, 2010; Contoyannis & Rice, 2001). The variation in measurement approaches reflects both theoretical perspectives and data availability and is a major source of inconsistent findings across studies, highlighting the critical importance of proxy selection.

This literature review is structured into two main sections to examine how intelligence and health influence income both independently and interactively: the first section integrates theoretical and empirical research on the individual effects of intelligence and health on income. Besides, the second section investigates the extent to which these two dimensions interact in shaping income patterns.

2.1 Intelligence and Health as Determinants of Income

(1) Intelligence as a Determinant of Income

The concept of intelligence in economic and psychological literature fundamentally started with the idea of a general cognitive factor, known as Spearman's g. As stated "*All branches of intellectual activity have in common one fundamental function*", Spearman (1904, p.284) was the first to quantify intelligence by identifying a latent factor—g factor, which represents a general mental ability that underlies performance across diverse cognitive tasks, such as reasoning, memory, and verbal ability. Although the g factor is difficult to measure directly, Spearman's contribution laid the foundation for modern intelligence research, providing a theoretical basis for understanding cognitive ability as a measurable and economically relevant variable. As various intelligence standardized tests, such as IQ tests, literacy and numeracy assessments, or problem-solving scales, are commonly used as proxies for general intelligence in economic research, a substantial body of research has examined their effect on income from both theoretical and empirical perspectives. The key literature summarized in Table 1 helps contextualize the diverse perspectives of comparing the importance of intelligence relative to other factors, as well as highlighting the various results across studies and the heterogeneity observed between different countries.

Intelligence vs education or experience:

Firstly, whether intelligence is more critical than education level or socioeconomic background (SES) has been one of the central debates in research on the determinants of income. Using AFQT scores from the NLSY79 of young US, a widely accepted proxy for intelligence that assesses word knowledge, paragraph comprehension, math knowledge, and arithmetic reasoning, both Herrnstein & Murray (1994) and Hanushek & Woessmann (2008) identified cognitive ability as a key variable with greater explanatory power than years of schooling or SES, exerting a significant positive effect on income. Herrnstein & Murray (1994) was the first to systematically explore the relationship between intelligence and socioeconomic status, highlighting intelligence's key role in socioeconomic status and economic performance. Despite its controversial discussion of race and intelligence, it remains an important reference in the study of intelligence and social inequality, still widely cited and discussed today. Specifically, Herrnstein & Murray (1994) mainly employed the simple OLS regression model, focusing on the correlation between IQ and income, employment, and poverty. After controlling for variables such as education and SES, it was found that IQ remained one of the most essential factors in influencing socioeconomic status and occupation placement. Building on broader data, by combining micro-level data from the NLSY79 with international literacy data from the International Adult Literacy Survey (IALS), Hanushek & Woessmann (2008) introduced intelligence assessment indicators into the Mincer's Log-Wage Model and found that standardized test scores, such as mathematics and literacy scores, outperformed traditional indicators like years of schooling in predicting individual income levels. In contrast, Cawley et al., (1996) directly responded to the limitations of *The Bell Curve* by Herrnstein & Murray (1994), criticizing its oversimplified model specification, which did not adequately control for covariates, such as years of education and work experience, possibly overstating the direct impact of IQ on earnings. By adopting the same NLSY data, Cawley et al., (1996) constructed a more complex model, introducing six different measurement approaches for the *g* factor and incorporating R^2 decomposition and grouped regressions. They found that once these key variables were included in the model, the marginal contribution of IQ to wages decreased significantly, and the contribution of R^2 was much lower than that of education and experience, thereby calling into question the "intelligence dominance" theory. While some studies (e.g., Cawley et al., 1996) argue that including education and experience substantially reduces the income returns to IQ, this does not necessarily undermine the central role of intelligence. As Murray and other cognitive theorists discussed, intelligence is inherently embedded in many of these variables: individuals with higher cognitive ability are more likely to perform well across educational and occupational domains. Therefore, in studying the income returns to intelligence, careful consideration must be given to model specification and the selection of control variables.

Disparities in the returns to Intelligence:

While the explanatory power of intelligence vs other factors is still debated, empirical results from multiple studies suggest a moderate causal relationship between intelligence and income, although estimates of the income return to IQ vary across studies. Firstly, Strenze (2007) conducted a meta-analysis based on the U.S. 135 samples from the General Social Survey and the NLSY, indicating that the average correlation between Intelligence and income was about 0.20, significantly lower than its correlation with education ($r = 0.56$) and occupation ($r = 0.43$). One possible explanation for these discrepancies was that while cognitive ability plays a key role in shaping one's educational and occupational trajectories, intelligence may exhibit diminishing marginal returns in earnings: Once an individual reaches a certain level of intelligence, such as being in the 90th percentile, additional increases in intelligence are unlikely to significantly affect income, except in fields like research or complex engineering, where higher cognitive ability is typically required. Furthermore, based on PIAAC data from 22 countries, Hanushek et al.(2015) employed the Mincer earnings model and found that a one standard deviation increase in cognitive skills is associated with wage increase returns ranging from 12% to 28%. In separate regressions for different intelligence dimensions, numeracy showed the highest return (17.8%), followed by literacy (17.1%) and problem-solving skills (14.3%). The robustness of this article is enhanced by the study's use of larger sample sizes, comprehensive skill assessments, and rigorous controls for key covariates, including education and experience (modelled nonlinearly). Overall, these studies uniformly demonstrate a robust positive link between intelligence and income, and variations in effect size can largely be attributed to differences in age structure, cognitive skill measurement tools and sample countries.

Heterogeneity:

In addition to studying the return of intelligence on income, more studies have further pointed out that the impact of intelligence on income presents significant heterogeneity with different group characteristics and institutional environments. For institution and context heterogeneity, Hanushek & Woessmann (2008) used cross-country data to construct an interaction term between cognitive skills and institutional quality, revealing that the income returns to intelligence are notably higher in countries with high-quality institutional environments. Building on this, Hanushek et al., (2015) further demonstrate that cognitive skills yield higher returns in countries with greater economic openness, more flexible labor markets, and smaller public sectors such as the US and Germany; Conversely, Sweden, the Czech Republic, Norway, and other countries are significantly lower. Similarly, Nikolov et al. (2020) provided evidence of domain-specific and geographic heterogeneity in the income effects of intelligence. By analyzing two South African datasets- urban youth (CAPS) and rural older adults (HAALSI)-they found that numeracy skills significantly predicted earnings in urban samples, while memory and orientation skills played a larger role in rural contexts. Additionally, Rindermann's (2018) book emphasized that intelligence cannot fully realize its potential without strong institutions or a high concentration of intelligent individuals. In societies lacking these conditions, cognitive abilities have less impact on income growth, highlighting the important role of institutional and social factors in translating intelligence into economic rewards.

Table 1 summarizes the significant positive impact of intelligence on income, drawing on literature that compares the importance of intelligence relative to other factors, highlights the varying results across studies, and examines the heterogeneity observed between different countries.

Table 1

Intelligence-Related Literature Summary

Research Theme	Main Findings	Key Literature	Methodology
Intelligence vs Education/SES	Intelligence > Education (disputed)	Herrnstein & Murray (1994); Hanushek & Woessmann (2008) Cawley et al., (1996);	OLS regressions; interaction models
Returns to Intelligence	Positive (varies by studies)	Strenze (2007); Hanushek et al., (2015); Ozawa et al., (2022);	Meta-analysis; standard wage equations
Heterogeneity in Intelligence Effects	Varies by institutions	Hanushek & Woessmann (2008); Hanushek et al., (2015); Nikolov et al. (2020); Rindermann (2018)	Subgroup regression; R^2 decomposition

Source: compiled by the author

(2) health as a Determinant of Income

Grossman's (1972) "health capital theory" model viewed health as a durable form of human capital stock. It indicated that health investments, such as nutrition and medical care, can enhance productivity and reduce work loss, ultimately thereby increasing earnings, which has laid a robust foundation for studies on the effect of health on income.

Direction of Causality:

Many empirical studies support a positive one-way causal link between health and income. For instance, obtaining economic data from 1424 rural Guatemalan individuals between 2002 and 2004, Hoddinott et al., (2008) exploited a natural nutrition intervention experiment to follow the sample of children for 35 years to analyze their adult wages. Its OLS regression results found that early-life health improvements led to a 46% increase in adult wages, offering one of the strongest causal identifications of the “health → income” pathway. Besides, the randomized natural design and long follow-up period enhance the robustness and credibility of the outcomes, although some limitations remain, such as high attrition and unobserved village-level confounders that may affect external validity. Similarly, adopting group data from the German Socio-economic Research Group (GSOEP), Jäckle and Himmler (2010) found that healthy males earn between 1.3% and 7.8% more than those in poor health, after controlling for endogeneity, sample selection bias, and unobserved heterogeneity; Berkowitz et al., (1983) examined a model where health capital influences productivity as well as labor supply. Using U.S. data on white males from a survey of disabled and non-disabled adults, they estimated the wage effects of different disability dichotomies using GLS to account for heteroskedasticity and found that six out of eight indicators had significant negative effects on wages.

However, several articles have emphasized the bidirectional causal relationship between health and income. Notably, using the Health and Retirement Survey (HRS) and the NLSY data in the U.S., on the one hand, Smith (1999) found that serious health problems would lead to a decrease of about 4 working hours per week, a decrease of 15 percentage points in the labor participation rate, and an average annual income loss of $2600, emphasizing that the negative income impact of health deterioration to labor supply and economic output, that is, income. On the other hand, it used the Ordered Probit model to analyze and show that both total household income and wealth have statistically significant positive effects on self-reported health status, especially in low-income groups. More recently, Zheng et al. (2023) used Mendelian randomization (MR) methods to provide strong genetic evidence for a two-way causal relationship between income and health. Their findings showed that higher household income significantly reduces genetic susceptibility to major cardiovascular diseases such as myocardial infarction and high blood pressure, supporting the idea that economic advantages contribute to better health. Conversely, reverse MR Analysis suggests that heart failure may lead to lower household income by reducing work capacity and labor force participation. These results suggest that there may be a persistent feedback effect between health and income, in which improved economic status promotes health, while good health enhances an individual's economic capacity. While these studies emphasize the importance of identifying causal directions, this paper does not attempt to address bidirectional causality directly, but rather focuses on estimating partial correlations and interaction patterns between health and intelligence in shaping income.

Empirical methodologies：

How to control potential endogeneity, sample selection bias, and measurement error is a critical issue that needs to be addressed in empirical studies when evaluating the causal relationship of health effects on income. Firstly, Madden (2004) used cross-sectional data on 8747 couples from the U.K.1995 Family Resources Survey and argued that failing to account for the endogeneity of health leads to a systematic underestimation of its true effect on income when using traditional OLS estimates. The model also controls for a range of individual and family background characteristics, addressing potential omitted variable bias. Secondly, based on British Household Panel Survey (BHPS) data, Contoyannis & Rice (2001) used the lagged health variables and family background characteristics (such as parental education and occupation) as instrumental variables to effectively address potential endogeneity issues and unobserved heterogeneity that may simultaneously affect both health and wages. Furthermore, Jäckle and Himmler (2010) complemented previous studies on the effects of health by addressing these problems in one comprehensive framework. For the endogeneity problem, the number of medical visits of individuals in the last three months was adopted as an instrumental variable and combined with the fixed-effect two-stage least square method (FE-2SLS) to estimate the sources of exogenous variation in the health variables. Then, to control selection bias, following the approach proposed by Semykina & Wooldridge (2010), it estimated individuals' probability of labor market participation using a Probit model in the wage equation to account for non-random sample selection. Besides, the fixed effect (FE) model and the Mundlak adjustment were introduced to effectively control for time-invariant individual traits, such as genetic endowments or health preferences, thereby reducing the impact of omitted variables. As a result, the empirical results indicated that the wages of healthy men are significantly higher than those of unhealthy men, which was still valid under various robustness tests above. Finally, Lee (1982), Haveman et al., (1994) and Sundberg (1996) used Simultaneous Equations to identify endogeneity and verify that health has a significant positive impact on wages.

Heterogeneity:

Although a large body of empirical research supports the positive effects of health on income, a large body of literature has found significant heterogeneity in health returns, and the magnitude and direction of the effects may vary with national background, gender differences, and age phrases. For cross-country heterogeneity, Erdil & Yetkiner (2004) applied Granger causality tests to address this topic based on balanced panel data from 75 countries between 1990 and 2000. The countries were classified into low-income (LIC), middle-income (MIC), and high-income (HIC) groups according to the World Bank’s income classification, and the results highlighted substantial heterogeneity in the causal direction between health and income: LIC and MIC are more likely to show that "income affects health," while reverse causality - that is, "health spending drives economic growth" is more pronounced in high-income countries. This causal heterogeneity is thought to be closely related to countries' health systems, public spending structures, and the degree of dependence on human capital. Moreover, for the gender difference, Contoyannis & Rice (2001) differentiated health proxies into GHQ-12 (psychological health) and SAH (self-assessed health) and suggested that reduced psychological health lowers hourly wages for males, while excellent self-assessed health increases hourly wages for females. Lee (1982), Haveman et al., (1994) and Sundberg (1996) also conclude that the mechanisms through which health affects income show notable gender differences. Finally, Smith (1999) also highlights age-related heterogeneity by comparing middle-aged and elderly samples based on HRS and the Asset and Health Dynamics of the Oldest Old survey (AHEAD) data, and the results found that older individuals experience more apparent income losses in response to health shocks.

Table 2 summarizes the relationship between health and income, focusing on the positive causal effect of health on income, possible bidirectional causality, and the heterogeneity of health effects across countries, genders, and age groups.

Table 2

Health-Related Literature Summary

Research Theme	Main Findings	Key Literature	Methodology
Health → Income (causal)	Positive (robust evidence)	Grossman (1972); Hoddinott et al., (2008); Jäckle and Himmler (2010)	Human capital models; longitudinal data
Bidirectional Causality	Bidirectional	Smith (1999); Zheng et al. (2023)	Bidirectional Mendelian Randomization
Heterogeneity in Health Effects	Varies by country, gender, age	Erdil & Yetkiner (2004); Contoyannis & Rice (2001); Smith (1999)	Panel data; fixed effects; IV

Source: compiled by the author

2.2 Interaction Mechanisms between Intelligence and Health

Although numerous studies have separately confirmed the independent effects of intelligence and health on income, several pieces of literature have taken a further step by exploring their interaction mechanism—emphasizing that health and intelligence are not only interrelated dimensions of human capital but may also exert complementary effects that jointly influence individuals' labor market participation and income levels.

(1) Literature supports independent mechanism：

Becker (1964) suggested that people with higher abilities or better physical health were more likely to receive additional education and on-the-job training, resulting in higher income. Although the interaction between health and cognitive ability was not explicitly studied, his framework showed that both factors were interrelated and together affected income, which also stimulated subsequent research into the potential interaction of health and intelligence in affecting income.

Some studies support the "independence" hypothesis, suggesting that health and intelligence affect income through relatively separate mechanisms. Firstly, based on a randomized intervention in Guatemala, Behrman et al., (2009) examined the long-term impacts of early-life health and cognitive development on adult earnings. After addressing endogeneity using several instrumental variables, including early nutrition exposure, community-level characteristics, and parental characteristics, the results found that only cognitive ability retained a significant effect on earnings, while health's effect became statistically insignificant, implying that health and intelligence may operate through relatively independent channels, with cognitive ability playing a more dominant role in the earnings equation. Similarly, using the data from the Mexican national longitudinal household survey, Vogl (2014) assessed how height and cognitive ability, measured by Raven's test scores, affect income. The study also found that while height is positively correlated with wages, after controlling for education and occupation instrumental variables, its effect almost completely disappears, suggesting that it mainly affects income indirectly through education and occupation channels. Additionally, the results found that when Raven's test scores were added to the regression, the height premium decreased by about 13%, indicating that cognition may play a partial mediating role in the health-income path.

(2) Interaction Mechanisms between Intelligence and Health:

Although the main related studies have focused on the separate effects of health and intelligence on income, an emerging body of research has started to explore their interactive dynamics. Most of the existing literature (e.g., Herrnstein & Murray, 1994; Sörberg et al., 2013; Bhalotra et al., 2022) supports a complementary relationship between intelligence and health, suggesting that the two factors tend to reinforce each other in shaping income outcomes. However, a few studies have also highlighted the possibility of a substitution effect, where one factor may partially compensate for the other under specific conditions (e.g., Marius Vaag Iversen & Strøm, 2020; Nilsson, 2015; Van Zon et al., 2017). For example, individuals with high intelligence may mitigate the adverse income effects of poor health, and physically healthy individuals may sustain stable earnings despite lower cognitive ability.

Complementary Effects between Intelligence and Health:

A growing body of literature (e.g., Herrnstein & Murray, 1994; Bhalotra et al., 2022; Hoddinott et al., 2008; Lundborg et al., 2014) supports the idea that intelligence and health do not affect income independently, but rather reinforce each other through complementary mechanisms. This section explores two main interaction pathways: the first channel highlights how intelligence reinforces the positive effects of health on labor market outcomes by enhancing individuals' ability to address health shocks and optimizing occupation choices, demonstrating a complementary mechanism between intelligence and health. Meanwhile, the second study considered how early life health indirectly affects income through positive effects on cognitive development, thereby reinforcing the role of intelligence as a mediating channel.

The Moderating Role of Intelligence in Health–Labor Returns:

Psychologists analyzed nuns' diaries and found that those who wrote with greater clarity and complexity tended to live longer. Interestingly, this effect was observed even in the absence of specialized intelligence tests (Snowdon et al., 1999). The study used early-life linguistic ability, measured by idea density and grammatical complexity in autobiographical essays, as a proxy for cognitive functioning and found that higher idea density was significantly associated with reduced mortality risk. Although income return was not assessed, the findings suggest that cognitive ability may promote better health and longer life expectancy, thereby potentially extending individuals' participation in the labor market and enhancing lifetime earnings. Multiple empirical studies have shown that intelligence plays a key moderating role in the health-income relationship (Herrnstein & Murray, 1994; Sörberg et al., 2013; Batty et al., 2006). Firstly, Herrnstein & Murray (1994) suggested that men with low intelligence are more likely to enter physically demanding and high-risk occupations, such as blue-collar, manual jobs, which increases the likelihood that they will experience workplace injuries or chronic health problems, which can lead to early labor market exit. In contrast, men with higher cognitive abilities were more likely to work in white-collar jobs with lower physical strain and greater employment stability. This occupational classification implied that health risk exposure is structurally affected by cognitive ability, positioning intelligence as a key regulatory pathway between health and income. Besides, this moderating mechanism is further supported by Sörberg et al., (2013), who conducted a large-scale longitudinal study in Sweden from 1991 to 2008. Their findings indicated that a one-step decrease on the nine-point stanine scale of cognitive ability was associated with a 26% higher risk of receiving a disability pension in middle age. Importantly, the graded relationship remained significant even after controlling for childhood health and socioeconomic background, suggesting that cognitive ability moderates the impact of health on labor market participation, with higher cognitive ability supporting continued labor force participation after health shocks, thereby helping to preserve long-term earnings potential. Overall, these studies highlight the key moderating role of intelligence in shaping the impact of health on labor market outcomes and income, emphasizing intelligence as a structural factor that can amplify or mitigate the economic consequences of health conditions.

The Role of Health in Shaping Income through Cognitive Pathways：

Several empirical studies have revealed how health indirectly affects the labor market's income level by promoting cognitive ability development (Bhalotra et al., 2022; Hoddinott et al., 2008; Lundborg et al., 2014). Firstly, drawing on a 1930s infant health intervention in Sweden, Bhalotra et al., (2022) suggested that improvements in early-life health enhanced children's cognitive ability, as measured by primary school GPA, which in turn increased educational attainment and access to skilled occupations—ultimately leading to significant increases in adult earnings and pension income. Specifically, one year of exposure to the intervention led to a statistically significant increase of about 0.08 standard deviations in average GPA and raised secondary school enrollment among girls by 12.4 percentage points. Moreover, these educational gains translated into a 19.5% increase in earnings and a 7% increase in pension income, with no significant effects observed among men. Similarly, Hoddinott et al., (2008) exploited a nutritional intervention in rural Guatemala and found that men who received protein-rich supplements before the age of two scored higher on cognitive tests, as measured by Raven’s Progressive Matrices, and earned 46% more in wages compared to those who did not receive the supplements, underscoring an indirect pathway from early-life health to adult income through improved cognitive ability. Furthermore, using data from Sweden's large-scale military service registration, Lundborg et al., (2014) employed height as a proxy variable for early health status and found t a strong positive correlation between height and cognitive test scores (r = 0.33). Then, after controlling cognitive ability, the regression coefficient of height's influence on income decreased by more than 1/3, indicating that the "height premium" operates largely through cognitive channels. However, the study used height as a substitute proxy for health, which may not fully reflect early health conditions, and the sample is limited to males, raising concerns about the external validity of the findings. Additional support for this mechanism is provided by Ozawa et al. (2022), who found that early-life health and nutrition interventions consistently improve cognitive outcomes in the LMICs, including China, Pakistan, Ethiopia, and Vietnam, reinforcing the idea that the health component promotes income by increasing intelligence. Taken together, these studies suggested that a significant portion of the impact of early health on income may be mediated by improved intelligence, providing strong empirical support for the health-intelligence-income pathway.

Substitution Effects between Intelligence and Health：

While many studies highlight the complementary roles of health and intelligence in human capital, there are a few studies specifically analyzing the substitution effects between them (e.g., Contoyannis & Rice, 2001; Nilsson, 2015; Marius Vaag Iversen and Strøm, 2020).

This section examines two substitution pathways, the first mechanism is that, in the presence of poor health, higher cognitive ability may serve as a buffer, enabling individuals to maintain their labor market attachment and avoid exclusion. Conversely, the second pathway considers that for individuals with limited cognitive or educational capital, good physical health may serve as a compensatory resource, playing a decisive role in income generation and partially offsetting cognitive disadvantages.

Intelligence compensates for poor health：

Some studies suggest that cognitive ability may compensate for vulnerabilities in the job market among individuals with poor health, allowing individuals to maintain labor market attachment and preserve earnings capacity despite health limitations. Firstly, Marius Vaag Iversen and Strøm (2020), using microdata from the PIAAC survey, indicated that cognitive skills have a significantly stronger effect on employment outcomes among individuals with poor health and lower educational attainment. Specifically, among individuals with poor health, one standard deviation increases in numeracy skills increased the probability of employment by 5.7 percentage points, while for the whole sample, the corresponding effect was only 2.8 percentage points. This suggests that cognitive ability has a stronger marginal value for individuals facing health disadvantages, highlighting its compensatory role in the labor market. Furthermore, according to Nilsson's (2015) research, for individuals in poor health, a one percentage point increase in the unemployment rate leads to an average decrease of approximately 0.4 percentage points in their employment probability. However, among those with higher cognitive ability, the decline is significantly smaller, indicating a buffering effect of cognitive skills against health-related disadvantages. This effect is particularly evident among younger and middle-aged groups, implying that cognitive ability not only helps individuals with poor health maintain employment but also provides protection across different stages of the working life course. Overall, cognitive ability can partially compensate for limited health capital and serves as an important resource for mitigating unemployment risks.

Health compensates for low cognitive ability:

Conversely, some studies argue that good health may compensate for limited cognitive or educational capacity, enabling individuals to sustain labor market participation and achieve stable income even in the absence of strong cognitive skills. Empirical evidence provided by Contoyannis & Rice (2001), and Van Zon et al. (2017) suggested that health plays a more important role in income determination among individuals with lower levels of education. Firstly, based on wage regressions estimated separately by educational attainment, Contoyannis and Rice (2001) argued that the effect of self-assessed health is larger and statistically significant for the low-education group, while it is weaker and often not significant for the high-education group. The results implied that when cognitive or educational capital is limited, good health becomes a more decisive factor in securing earnings, thereby supporting the notion of a substitution effect between health and intelligence. From another perspective, Van Zon et al. (2017) found that the combination of low education and poor health substantially increases the risk of unemployment, especially during early and mid-career stages. They further argued that individuals with low education are more vulnerable in the labor market and therefore rely more on good health to sustain employment. Although these studies applied educational level indicators, educational attainment is often closely related to cognitive ability and can therefore be considered an indirect measure of it. The results show that in the context of limited cognitive or educational capital, health plays a more critical role in human capital structure and becomes an important resource affecting employment, supporting the substitution effect of health on cognitive ability.

Heterogeneity of Interaction Mechanisms：

Although previous studies have revealed the interaction between intelligence and health on income, the strength and significance of this interaction mechanism also show significant heterogeneity across different groups and institutional contexts. For studies conducted in different national contexts, Behrman et al., (2009), using data from Guatemala, concluded that the effects of health on income are largely mediated by cognitive ability. In contrast, LaFave & Thomas (2017), drawing on data from Indonesia, found that health and cognition independently predict wages, with no strong evidence of interaction between the two. These contrasting findings underscore the role of institutional and socioeconomic environments in shaping the extent to which intelligence and health jointly affect income. For gender differences, Behrman et al., (2009) found that the "health-cognition-income" pathway was significantly stronger among women, especially in skills-intensive public sector occupations such as teachers and nurses. The explanation was that this gender difference was partly due to the expansion of the Swedish welfare state at the time, which led to a significant increase in the demand for highly skilled labor in female-dominated occupations. Moreover, Sörberg et al., (2013) and Lundborg et al., (2014) were both conducted using Swedish male samples, without including female participants, which may limit the generalizability of their findings and overlook gender-specific mechanisms in the intelligence and health interaction pathway.

Overall, the interaction between health and intelligence in shaping income, along with its underlying mechanisms and group-specific heterogeneity, has been widely discussed and remains a promising area for further study. Table 3 summarizes the three key interaction mechanisms between intelligence and health in shaping income: the independent mechanism, the complementary interaction, and the substitution mechanism.

Table 3

Intelligence-Health Interaction Mechanism Literature Summary

Research Theme	**Main Findings**	**Key Literature**
Independent Mechanism	Intelligence and health affect income through separate channels	Behrman et al., (2009); Vogl (2014)
Complementary Interaction	Intelligence—Health—Income	Snowdon et al., (1999); Herrnstein & Murray (1994); Sörberg et al., (2013);
	Health—Intelligence—Income	Bhalotra et al., (2022); Hoddinott et al., (2008); Lundborg et al., (2014)
Substitution Mechanism	High intelligence may offset poor health in income effects	Marius Vaag Iversen and Strøm (2020); Nilsson (2015)
	good health may compensate for low cognitive ability in earning capacity	Contoyannis & Rice (2001); Van Zon et al. (2017)

Source: compiled by the author

3. Conceptual Framework and Methodology

3.1 Conceptual Framework

Theoretically, intelligence and health have independent effects on income through different channels. Cognitive ability improves individual productivity and earnings by improving learning ability, problem-solving ability, and adaptability to work complexity. People with higher intelligence are more likely to achieve occupational attainment and remain competitive in environments of technological change (Strenze, 2007; Hanushek et al., 2015). Meanwhile, health quality directly affects an individual's ability to provide work, including the duration of work hours, labor force participation, and the affordability of engaging in intensive labor. Good health can not only extend career span but also help improve productivity and employment stability (Ozawa et al., 2022; Smith, 1999).

More importantly, more scholars have begun to pay attention to the potential interaction mechanism between intelligence and health on income, and there is still academic debate on whether interaction operates as complementary or substitutive effects. For complementary effects, intelligence and health may jointly enhance individual labor market performance. On the one hand, people with higher intelligence are more likely to enter cognitively intensive and less physically demanding occupations, thereby reducing their exposure to long-term health risks and supporting consistent work participation over time (Batty et al., 2006). On the other hand, early health investments, such as childhood nutrition and access to basic healthcare, have been empirically shown to significantly enhance cognitive ability, thereby leading to substantial gains in adult earnings (Bhalotra et al., 2022; Hoddinott et al., 2008). For substitutive effects, on the one hand, when health status is poor, individuals with higher levels of intelligence can still maintain labor participation by engaging in non-physical, technology-intensive, or remote flexible work, thereby reducing the negative impact of health on income, which can find alternative employment opportunities more quickly and avoid dropping out of the labor market altogether (Marius Vaag Iversen and Strøm, 2020; Nilsson, 2015). On the other hand, when cognitive abilities are limited, individuals in good health can maintain a fundamental source of income by relying on physical labor, high attendance, or working in repetitive positions. Especially for the low-education group, health becomes an essential guarantee for maintaining labor supply and economic achievement (Contoyannis & Rice, 2001; Van Zon et al., 2017).

Many studies have shown that the relationship between health and other forms of human capital (such as education and cognitive ability) is complex in the labor market, and the introduction of interaction terms helps to reveal this complexity. For instance, Bhalotra et al., (2022) employed an interaction term between health and education to explore how health status moderates the return to education in terms of income. Based on these insights, this study conducted empirical models by introducing the interaction term of "intelligence x health" to explore whether the joint effect of the two is significant and the direction of interaction based on Poland's dataset. Furthermore, to capture the potential heterogeneity of the interaction effect, the analysis also performs subgroup regressions across gender and income levels, aiming to reveal for whom and under what conditions the interplay between intelligence and health becomes most prominent.

Based on the insights and findings from the literature review, the diagram (Figure 1)illustrates the conceptual framework of this study：

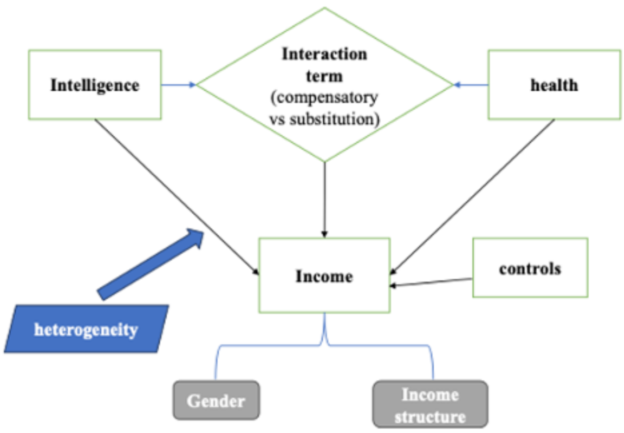

Figure 1. The conceptual framework diagram
Source: created by the author

3.2 Data and Variable Description

We use data from the 2nd cycle of the Programme for the International Assessment of Adult Competencies (PIAAC), conducted by the OECD’s Survey of Adult Skills and collected between September 2022 and August 2023. The second cycle provides internationally comparable microdata on adults' cognitive abilities, labor market outcomes, and background characteristics for individuals aged 16 and above across 31 countries. PIAAC is one of the most comprehensive and methodologically rigorous assessments of adult skills. It directly measures cognitive abilities such as literacy, numeracy, and problem-solving, while also collecting rich background information on education, employment, income, and health. Compared to traditional self-reported surveys, PIAAC provides more objective and standardized measures of human capital, making it a highly reliable and precise data source for analyzing the relationship between cognitive ability, health, and income.

Based on the PIAAC dataset, we define the key variables used in the empirical analysis as follows, including income (response variable), intelligence, health, and their interaction terms (main explanatory variables), and a set of individual-level controlling variables, as summarized in We also include a categorical control for occupational skill level, using the ISCOSKIL4 classification. This variable categorizes current or most recent jobs into four skill-based groups: (1) skilled occupations, (2) semi-skilled white-collar, (3) semi-skilled blue-collar, and (4) elementary occupations. We construct three dummy variables “occ_1, occ_2, occ_3” accordingly, with (4) elementary occupations as the reference category.

Table 4.

Variable Construction:

Response variable:

The dependent variable is the respondents' monthly income in US dollars adjusted for purchasing power parity (PPP), reported as EARNMTHALLPPPC2 in the PIAAC dataset. This derived variable is constructed by the OECD based on self-reported gross monthly income, including salary, bonus, and self-employment income. This measure captures the total labor income of various types of employment and provides a reliable and standardized outcome variable for analyzing the determinants of income in a nationally representative sample of Poland.

Explanatory variables:

(1) Intelligence is measured using three cognitive dimensions from PIAAC: literacy (PVLIT), numeracy (PVNUM), and problem-solving in technology-rich environments (PVAPS), with each dimension represented by ten plausible values (PV1–PV10).

Each domain captures a distinct aspect of intelligence, as defined by OECD (2013):

- *Literacy (PVLIT):* "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."
- *Numeracy (PVNUM):* "The ability to access, use, interpret, and communicate mathematical information and ideas to engage in and manage the mathematical demands of a range of situations in adult life."
- *Problem-solving skill (PVAPS):* "The ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks."

Importantly, PIAAC adopts Item Response Theory (IRT) instead of Classical Test Theory (CTT) to estimate cognitive ability scores. This methodological approach allows for more accurate measurement by accounting for item difficulty and test design variation across individuals, particularly under adaptive testing conditions. Unlike CTT, which assumes each item contributes equally to the final score, IRT allows for more precise estimations of latent ability even when respondents complete only a subset of test items. Based on IRT, PIAAC generates ten plausible values (PVs) for each cognitive domain, which reflect measurement uncertainty. Following OECD's (2013) guidelines, these PVs are recommended to be jointly used in empirical analysis to obtain unbiased and robust estimates of the relationship between cognitive ability and socioeconomic outcomes.

(2) General Health (self-reported health: I2_Q03_T)

Self-assessed general health (I2_Q03_T) is measured on a 5-point Likert scale and treated as a continuous variable, a common approach in economic studies examining the income-health relationship (e.g., Smith, 1999; Contoyannis & Rice, 2001). For empirical analysis, the scale is usually reverse coded so that higher values reflect better health, facilitating a more intuitive interpretation of regression coefficients. Therefore, the answers are recorded on a five-point Likert scale: 5 = "Excellent", 4 = "Very good", 3 = "Good", 2 = "Fair", and 1 = "Poor". Although self-reported health is a subjective measure, it has been consistently validated in the literature as a strong predictor of mortality, disability, and stress, with robust associations observed regardless of socio-economic background (Hanushek & Woessmann, 2008; Hanushek et al., 2015; Ozawa et al., 2022). Additionally, due to its extremely small sample size (only 3 observations), the "Poor" category (value = 1) is merged with the "Fair" category (value = 2), to preserve observations without introducing estimation bias. The health classification is later reported in the health distribution statistics (see Table 6)."

Individual-level controls:

To account for other key determinants of income beyond intelligence and health, our models control for a range of demographic and labor market variables, including gender (GENDER_R), education (B2_Q01), work experience (C2_Q10) and sector categories (ISCOSKIL4).

(1) Gender is coded as a binary variable (1 = male; 2 = female).

(2) Education level is measured using a detailed version of the International Standard Classification of Education (ISCED), coded from 0 to 30. This classification not only reflects the highest level of education completed (ranging from ISCED 0 to ISCED 8), but also distinguishes between general and vocational tracks, short-cycle programs, and whether the qualification provides access to higher education levels. Given its strong correlation with cognitive ability, education is included as a key control to isolate the independent income return to intelligence beyond formal schooling. Since the ISCED-based coding reflects an ordered and approximately linear progression of educational attainment, it can be reasonably treated as a continuous variable in regression models.

(3) Work experience is proxied by the total number of years of paid work throughout the respondent's lifetime. It is controlled for it reflects accumulated human capital through on-the-job learning, directly influencing productivity and wages.

(4) We also include a categorical control for occupational skill level, using the ISCOSKIL4 classification. This variable categorizes current or most recent jobs into four skill-based groups: (1) skilled occupations, (2) semi-skilled white-collar, (3) semi-skilled blue-collar, and (4) elementary occupations. We construct three dummy variables "occ_1, occ_2, occ_3" accordingly, with (4) elementary occupations as the reference category.

Table 4

All variables used in the analysis, corresponding labels and coding details

Variable Type	Variable name	Explanation
Response variable	EARNMTHALLPPPC2	Monthly earnings including bonuses for wage and salary earners and self-employed, PPP corrected $US (derived)
Explanatory variables	I2_Q03_T(reversed)	General health (Trend-IALS/ALL)：1: Poor; 2: Fair; 3: good; 4: Very Good; 5: Excellent
	PVLIT1-10	Literacy scale score-Plausible value 1-10
	PVNUM1-10	Numeracy scale score-Plausible value 1-10
	PVAPS1-10	Adaptive Problem-Solving scale score - Plausible value 1-10
Controlling variables	GENDER_R	Gender dummy (1 = Male, 2 = Female)
	B2_Q01	Education - Highest qualification based on ISCED, coded from 0 to 30
	C2_Q10	Current Status/work history - Years of paid work during lifetime
	ISCOSKIL4	Occupational classification of respondent's job (4 skill-based categories): 1: Skilled occupations; 2: Semi-skilled white-collar occupations; 3: Semi-skilled blue-collar occupations; 4: Elementary occupations

3.3 Empirical Model Specification

Motivated by the empirical framework of the Mincer earnings function, this study adopts a log-linear income regression model that extends the traditional specification by incorporating cognitive ability and self-reported health. In addition to estimating their independent contributions to income, the model further includes an interaction term to explore whether intelligence and health exert complementary or substitutive effects when combined. The baseline specification is expressed as follows:

$$Ln(Incomei) = \alpha + \beta 1 \cdot IQi + \beta 2 \cdot Healthi + \beta 3 \cdot (IQi \times Healthi) + \gamma Xi + \varepsilon i \quad (1)$$

where ln (Incomei) is the natural logarithm of monthly earnings (PPP-adjusted) for the individual$i$ with the top and bottom 5% winsorized to address outliers; IQ captures cognitive ability, proxied by plausible values of literacy, numeracy, and problem-solving skills from PIAAC, which are increasingly adopted in empirical research as valid proxies for general intelligence; Health refers to the reverse-coded individual's self-reported general health status; *(IQi×Healthi)* represents the interaction term between intelligence and health; *Xi* is a vector of control variables including gender, education, work experience, and sector categories; εi is the error term.

In this specification, the marginal effect of cognitive ability on income is conditional on health and equals $\beta 1$+$\beta 3$*Health, while the marginal effect of health on income is conditional on cognitive ability and equals $\beta 2$+$\beta 3$*IQ. The interaction term β3 captures whether the income returns to intelligence vary with health status, indicating the substitution mechanism ($\beta 3 < 0$) or complementary mechanism ($\beta 3 > 0$), given that health is reverse coded as higher values indicate better self-reported health.

The key hypothesis of this model concerns the interaction term between intelligence and health：

H_0: $\beta_3 = 0$, indicating that there is no interaction effect between intelligence and health on income.

H_1: $\beta_3 \neq 0$, Intelligence and health jointly influence income. The specific interpretation depends on the sign of $\beta 3$:

- β3 > 0: implying a complementary mechanism, where better health amplifies the income benefits of cognitive ability, or vice versa.
- β3 < 0: implying a substitution mechanism, where cognitive skills yield higher income returns when health is poor, or vice versa.

To address key methodological considerations, the following steps were taken in the estimation process:

(1) Log-transformation of the dependent variable: Monthly income is expressed in the natural logarithmic form to account for the right-skewed distribution of earnings and to facilitate the interpretation of regression coefficients in percentage terms.

(2) Multiple proxies for cognitive ability: As PIAAC provides three domains of cognitive skills-literacy, numeracy, and problem-solving skills, each regression is first estimated separately using ten plausible values from each domain. A general intelligence score (g factor) is also constructed from their first principal component and employed in an additional specification to test robustness. All regressions are weighted using the PIAAC-provided sampling weights (SPFWT0–SPFWT80) under OECD IRT-based procedures to obtain unbiased and representative estimates.[1]

(3) Standardization and coding procedures: Standardizing both health and cognitive variables facilitates coefficient comparability and interpretation in standard deviation terms. The interaction term is constructed as the product of these standardized scores. Since the scales of the two explanatory variables are different (one is the health score of 2-5, and the other is the cognitive score of 0-500), the multiplicative interaction term is difficult to interpret and is easily affected by the scale of the variable. The interaction term after standardization can eliminate this influence and make the results of the interaction term more stable and interpretable.

4. Empirical analysis

4.1 Descriptive Statistics

(1) The monthly income variable (EARNMTHALLPPPC2) exhibits substantial dispersion, ranging from zero to nearly $485,000 (PPP-adjusted). While the mean

[1] All estimations are conducted using the *repest* package in Stata, which applies replicate weights (SPFWT0–SPFWT80) following OECD's IRT-based procedure.

income is \$3,015.48, the standard deviation is as high as \$10,357.42, and the maximum value far exceeds the much lower median of \$2,405.84. These figures highlight a heavily right-skewed distribution of earnings, primarily driven by extreme outliers in the upper tail. At lower bound, such extremely low-income values (like under \$50 per month) appear implausibly low for full-time employment. These observations are likely attributed to part-time or informal jobs, periods of temporary unemployment, or reliance on non-wage sources such as social assistance or family transfers. Conversely, the maximum monthly income of \$485,000 appears as an isolated outlier in the distribution, suggesting a potential data reliability problem or recording error. Meanwhile, although some individuals earning over \$100,000 per month may represent genuine high earners, such as top executives, self-employed professionals, or individuals with multiple income streams, these cases account for only a rare fraction of the income distribution. Due to the presence of such extreme income values, their statistical leverage can distort regression estimates, leading to unstable coefficients and inflated standard errors.

The kernel density plot of monthly income exhibits a highly right-skewed distribution (Figure 2. Density of Monthly Income (Full Sample). To better visualize the main body of the income distribution, a winsorized 5% version (Figure 3) clearly shows that most observations lie between \$1,000 and \$5,000.

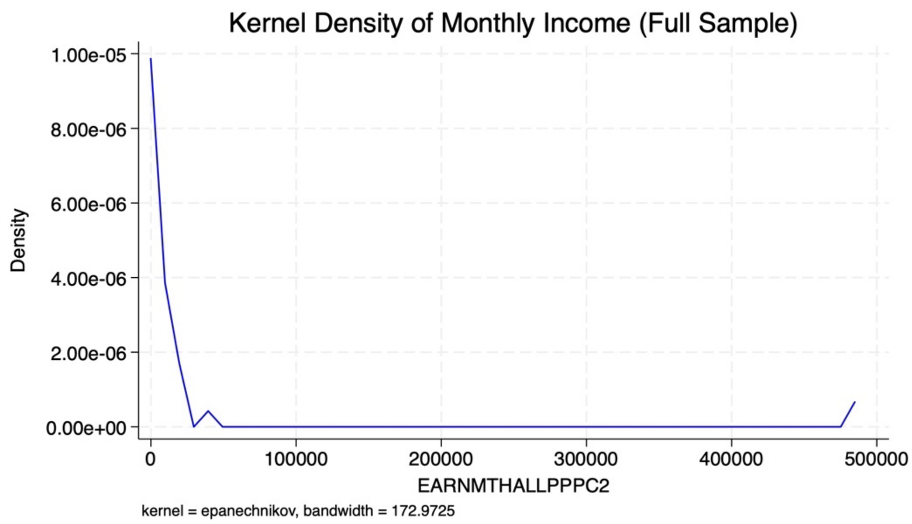

Figure 2. Density of Monthly Income (Full Sample)
Source: author’s calculations

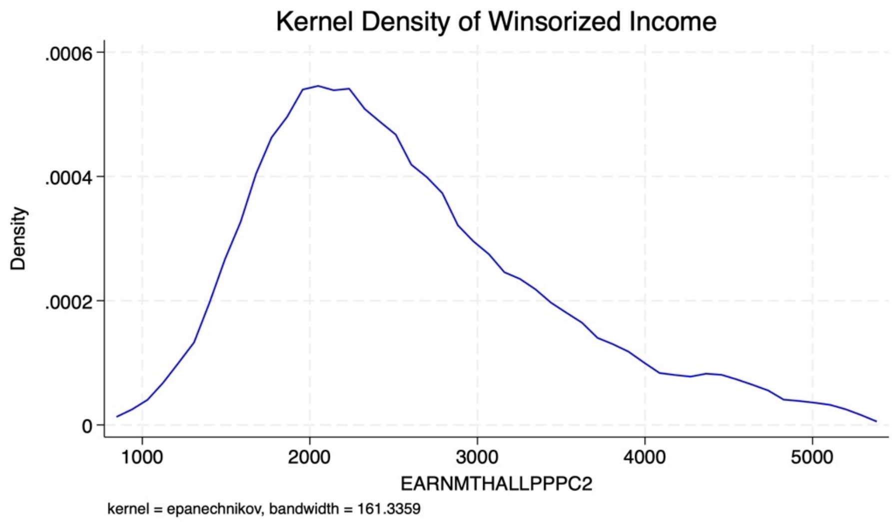

Figure 3. Density of Winsorized Monthly Income (5% Winsorization)
Source: author's calculations

When studying income data, dealing with outliers is essential to ensure the accuracy of the regression analysis and common methods include Winsorization and Trimming. For instance, when adopting the income dataset from the PIAAC, Hanushek et al., (2015) limited the sample to full-time employees aged 35 to 54 and trimmed the bottom and top 1% of the wage distribution to reduce the impact of outliers. Jäckle and Himmler (2010) estimated the effects of wages on health by excluding very low-income observations to avoid interference from non-primary earners or marginal labor market participants. Mogstad et al. (2025) applied a 5% winsorization to the wage variable before conducting country-level analyses to mitigate the influence of extreme values on cross-country comparisons. Therefore, this study applies a 5% winsorization to the income variable to address the influence of outliers, reduce heteroskedasticity, and improve the interpretability and robustness of regression estimates. Furthermore, the income variable is transformed into a logarithmic form. Log-transforming income helps correct right-skewed skewness, reduces the influence of extreme values on linear models, and enables the interpretation of coefficients in percentage terms.

(2) The health variable is measured on a 1-5 Likert scale based on self-assessed general health. As shown in Table 5, the average self-rated health score is 3.60 with a standard deviation of 0.74, suggesting that the overall health condition of the Polish sample is relatively good.

(3) Cognitive ability is captured using three proxies from the PIAAC assessment: literacy, numeracy, and problem-solving skills. We present PVLIT1, PVNUM1, and PVAPS1 as representative plausible values (PVs) for each domain for descriptive purposes. As shown in Table 5, the average PVLIT1 is 241.86, with a standard deviation of 47.96, while the average PVNUM1 has a slightly higher mean of 246.86 and a standard deviation of 52.03, and PVAPS1 scores are comparably lower, averaging 232.52 with a standard deviation of 40.59. The distributions of all three indicators span wide ranges (e.g., literacy scores range from 10.43 to 439.44), reflecting substantial variability across respondents and enabling the model to capture meaningful cognitive differences relevant to income analysis.

Table 5 reports the summary statistics of the key variables prior to variable transformation and cleaning; Full descriptive statistics across all PVs and controlling variables are reported in Appendix A1.

Table 5

Summary Statistics of Key Variables (before data cleaning)

Variables	N	Mean	SD	Min	P50	Max
EARNMTHALLPPPC2	2278	3015.48	103577.42	0	2405.84	484897.60
Health	2278	3.60	0.74	1	4	5
PVLIT1	2278	241.86	47.96	10.43	246.04	439.44
PVNUM1	2278	246.86	52.03	29.61	251.10	473.25
PVAPS1	2278	232.52	40.59	0	233.83	375.08

Note. The summary table is based on the raw sample before data cleaning. In the main analysis, income is winsorized (5% tails) and the "poor" health category is merged into “Fair” due to very few observations (n=3).

Source: author’s calculations

Table 6

Frequency Distribution of Health Categories

Health Category	Health labels	Frequency	Percent	Cumulative Percent
1	Poor	3	0.13	0.13
2	Fair	100	4.39	4.52
3	Good	942	41.35	45.87

4	Very good	986	43.28	89.16
5	Excellent	247	10.84	100.00

Source: author's calculations

Correlation analysis：

Table 7 presents the pairwise correlations among key variables. Log monthly income (Wage) is positively correlated with all three cognitive proxies- PVLIT1 (r = 0.108***), PVNUM1 (r = 0.147***), and PVAPS1 (r = 0.103***). These modest yet statistically significant correlations suggest that higher cognitive skills are associated with better income outcomes. Health also shows a significant positive correlation with wage (r = 0.146***), reinforcing the idea that better self-perceived health contributes to improved labor market performance. Additionally, strong intercorrelations are observed among the three cognitive domains (ranging from 0.742*** to 0.800***), reflecting overlapping dimensions of measured abilities. All reported correlations are statistically significant at the 0.1% level. All correlations are statistically significant at the 0.1% level. These findings provide preliminary support for including both intelligence and health in the income regression model.

Table 7

Correlation Matrix of Key Variables

Variables	(1)	(2)	(3)	(4)	(5)
(1) Wage	1.000				
(2) Health	0.146***	1.000			
(3) PVLIT1	0.108***	0.076***	1.000		
(4) PVNUM1	0.147***	0.058***	0.800***	1.000	
(5) PVAPS1	0.103***	0.133***	0.763***	0.742***	1.000

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses; Self-rated health is treated as a continuous variable.
Source: author's calculations

A full correlation matrix including all control variables is presented in Appendix Table A2.

4.2 Baseline Regression Results

This section presents the results from a series of baseline regressions to analyze the independent and joint effects of intelligence and health on income. Specifically, three cognitive skill measures from the PIAAC dataset: literacy, numeracy, and problem-solving, are used as alternative proxies for intelligence. Each is included in a separate regression model alongside standardized health status and their interaction term.

Table 8 presents three baseline regression results using three separate cognitive proxies together with health and their interaction terms, focusing on the coefficients and significance of the main explanatory variables, while the full regression models with stepwise-added controls are reported in Appendix Tables B1-B3.

Table 8

Baseline Regression Results Using Separate Cognitive Proxies

	(1) Literacy	(2) Numeracy	(3) Problem-solving
IQ	0.016^{*}	0.023^{***}	0.017^{**}
	(0.008)	(0.008)	(0.008)
Health_z	0.056^{***}	0.056^{***}	0.056^{***}
	(0.008)	(0.008)	(0.008)
Interaction_z	-0.017^{**}	-0.016^{**}	-0.015^{*}
	(0.008)	(0.008)	(0.009)
Controls	Yes	Yes	Yes
N	2033	2033	2033
R-squared	0.250^{***}	0.252^{***}	0.250^{***}

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. All models include gender, education, work experience, and three occupational dummies (referenced to the "Elementary occupations" category) as control variables.

Source: author's calculations

(1) *Independent Effects of Intelligence and Health*

Table 8 shows that intelligence and self-reported health have statistically significant and positive effects on log monthly income. Across all three regression models adopting different cognitive proxies (literacy, numeracy, and problem-solving skills), the coefficients on intelligence show positive and statistically significant at the 1% level, indicating strong evidence of its positive income returns. Firstly, numeracy skill demonstrates the most substantial main effects ($\beta1 = 0.023$, $p < 0.01$) in predicting earnings, highlighting the critical role of quantitative reasoning and numerical capacity required by high-skilled and better-paid sectors, such as interpreting statistical data or performing technical tasks. This is consistent with previous PIAAC research showing that numeracy skills are more directly related to practical tasks and decisions in the labor market and income determination compared to literacy and problem-solving skills (Hanushek et al., 2015). Furthermore, literacy and problem-solving skills also report statistically significant and positive relationships with income with $\beta1 = 0.016$ and $\beta1 = 0.017$, respectively. Higher literacy skills facilitate information comprehension and evaluation, effective communication and coordinating tasks, and adapting to new knowledge, thereby enhancing productivity and income potential (Hanushek et al., 2015; OECD, 2013). Besides, problem-solving skills in technology-rich environments enhance income by enhancing individuals' ability to adapt to digital tools, tackle complicated tasks and implement innovative progress (Strenze, 2007).

Secondly, the self-rated general health also shows positively and significantly relationships with income across all three models, and the estimated coefficients for health remain stable at around $\beta2 = 0.056$ and are statistically significant at the 1% level, suggesting that a one standard deviation increase in health is associated with approximately 5.6% increase in monthly income, excluding the marginal variation introduced by the interaction term. This finding supports the "health premium" in the studies of income returns, which states that healthier individuals are more likely to actively participate in the labor market, maintain stable employment, and achieve higher productivity and earnings (Grossman, 1972; Contoyannis & Rice, 2001).

Theoretically, intelligence and health affect income through distinct mechanisms: cognitive skills improve task abilities and performance, whereas good health sustains labor participation and efficiency. The mechanisms highlight their independent and additive roles in shaping earnings, providing a theoretical foundation for the subsequent analysis of their interaction.

(2) *Interaction Effects between Intelligence and Health*

To examine whether the income returns to intelligence vary by health status or whether the economic benefits of good health are affected by cognitive ability, this study incorporates an interaction term between standardized intelligence and health variables in the baseline regression models. Table 8 indicates that the interaction terms are consistently negative across all three models, indicating a potential substitution pattern between these three cognitive proxies and health in affecting income.

Firstly, when literacy is used as the cognitive proxy, the interaction term between intelligence and health yields a coefficient β3 of -0.017 with the significance of 5%, indicating that as health worsens by one-unit standard deviation, the income return to literacy increases by approximately 1.7%. The result indicates a substitution mechanism, where cognitive ability provides stronger income returns when health is poor, compensating for physical limitations in the labor market. One possible explanation is that in good health status, physically healthy workers, such as those in manufacturing or agriculture sectors, can maintain productivity through physical strength, rather than relying on basic literacy skills as a core driver of output. Conversely, for individuals with poorer health, stronger literacy enables them to pursue careers involving administrative support, scheduling, or paperwork, where effective written communication and task coordination can help compensate for physical limitations. This interpretation aligns with findings from Bhalotra et al., (2022), who argue that cognitive ability becomes especially critical when physical capacity is constrained, reinforcing the compensatory role of intelligence under adverse health conditions.

Secondly, when numeracy is used as the cognitive proxy, the interaction term is -0.016 and statistically significant at the 5% level. The coefficient result also suggests a potential substitution effect: as health worsens by a one-unit standard deviation decrease, the income return to numeracy increases by approximately 1.6%, implying that individuals with poorer health rely more on their cognitive skills to achieve earnings. On the one hand, the substitutive effect of health on numeracy appears similar to that of literacy, as physically healthy individuals may sustain wages through productivity in manual or labor-intensive jobs without relying heavily on numerical skills. On the other hand, individuals with strong numeracy skills may engage in occupations that require budgeting, technical calculations, or financial analysis, such as accounting, engineering, or data-related occupations, where numeracy can compensate for limited physical capacity.

Besides, when problem-solving is used as the cognitive proxy, the interaction coefficient is $\beta_3 = -0.015$ and statistically significant at the 10% level, demonstrating a similar substitutive pattern as literacy and numeracy. This suggests that even higher-order cognitive abilities can compensate for deteriorating health in the labor market. Although problem-solving involves more complex reasoning and integrative thinking, its ability to offset health disadvantages indicates that such advanced skills are also valued when physical capacity declines.

To visually support the regression findings, Figure plots the predicted log-income across standardized literacy scores (using PV1) levels under four categories of self-reported health status. The figure shows that the slopes of the lines differ by health status: the income return to literacy is highest among individuals with poor health (Fair), and the slope of the literacy-wage relationship gradually flattens as health status improves, becoming nearly flat for those in excellent health. This pattern supports the substitution mechanism: cognitive ability becomes more economically valuable when health deteriorates, serving as compensation in labor market returns. Although based on a single plausible value without applying PIAAC replicate weights, the figure provides an intuitive visual illustration of the interaction between cognitive ability and health. Therefore, the figure should be interpreted as illustrative rather than conclusive.

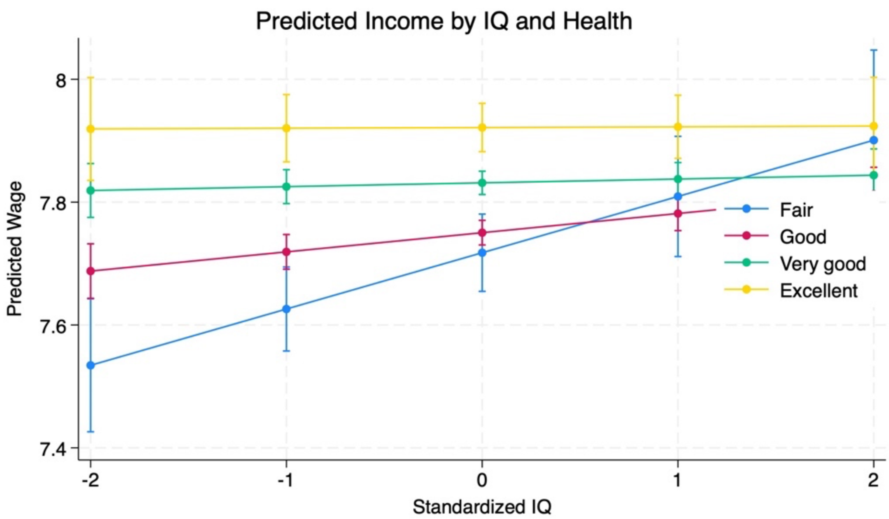

Figure 4. Predicted log-income across levels of literacy and health (PV1)
Source: author's calculations

Overall, the baseline regression results indicate that both intelligence and health have significant and positive relationships with income independently, confirming their central roles as components influencing income. Moreover, while different cognitive dimensions, such as literacy, numeracy, and problem-solving skills show heterogeneity in their interaction with health to some extent, the overall substitutive pattern remains consistent. More importantly, these insights also carry important policy implications: strategies to improve income and productivity should address both health and cognitive development as interrelated components. however, it is important to note that although the interaction effect between intelligence and health appears significant, caution is needed in interpreting this as causal, since the data is cross-sectional and variables may be endogenous.

4.3 Robustness Checks

To examine the robustness of the main findings, three alternative model specifications are conducted: (1) A g factor is constructed through PCA from three cognitive proxies and entered the regression model as a unified intelligence measure; (2) a re-specification of the health variable as a binary indicator to reconstruct the interaction term with cognitive proxies; (3) Re-estimate the model without education controls to assess potential over-controlling bias.

Table 9 reports the regression results based on a g factor derived from PCA across all 10 plausible values, while Table 10 further presents regression results based on binary health measures, allowing for assessing whether the interaction model holds under a simplified health specification. Table 11 re-estimates the main models without education controls. Full regression outputs including all control variables are provided in Appendices C1-C3.

(1) ***Introduction and Analysis of the g factor***

Specifically, the g factor is derived by conducting separate principal component analyses (PCA) on each of the 10 plausible value sets (PV1 to PV10), using literacy, numeracy, and problem-solving scores as inputs. For each set, only the first principal component is retained and standardized to obtain a general cognitive ability score (iq_g_z1 to iq_g_z10). This approach ensures consistency with the PIAAC methodology and incorporates uncertainty from the imputed PVs in later analysis. This study further uses the *g factor* before conducting regression analysis on its interaction with health variables to check whether the direction and significance of interaction terms were consistent with the results of single indicators or not.

Table 9 shows the regression results based on the *g factor*, indicating that the index itself has a significant positive impact on income (coefficient 0.021, significance level of 1%), and the interaction coefficient between it and health is -0.017, with significance level of 5%. This implies that when health worsens by one standard deviation, the income return to the g factor increases by approximately 1.7%, indicating a substitution effect between intelligence and health. Furthermore, the direction is consistent with the regression results of literacy and numeracy, which further verifies the robustness of the "slight substitution effect". The consistency of the models in both directions and statistical sense demonstrates the robustness of the main findings, confirming that the mechanism of interaction between cognitive ability and health is stable even under a uniform intelligence proxy.

Table 9

Baseline Regression Using General Intelligence Factor (g)

	(1) g factor
Standardized g	0.021***
	(0.008)
Health_z	0.056***
	(0.008)
Interaction: g_z × Health_z	-0.017**
	(0.008)
N	2033

	(.)
R-squared	0.252^{***}
	(0.020)

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. R^2 values are averaged across regressions using 10 plausible values (PVs), and standard errors are computed using replicate weights following PIAAC methodology. All models include gender, education, work experience, and three occupational dummies (referenced to the "Elementary occupations" category) as control variables.
Source: author's calculations

(2) *Robustness Check Using a Binary Health Indicator*

In related empirical studies, it is common practice to define health as a binary variable (e.g., Smith, 1999; Contoyannis & Rice, 2001), as it simplifies the interpretation of health status. To test the sensitivity of the results of baseline models to the setting of health variables, the reverse-coded five-point Likert scale of self-rated health variable is further dichotomized into binary dummy variable, where scores of 4-5 are coded as "healthy" with value 1 and 2-3 as "unhealthy" with value 0, and interaction terms are reconstructed accordingly for robustness check.

Table 10 reports the regression results based on a binary specification of the health variable across four cognitive proxies. Regarding the independent effects, the health dummy variable remains positive and statistically significant at the 1% level across all models, with coefficients ranging from 0.0941 to 0.0977, indicating that moving from the unhealthy group to the healthy group is associated with an approximately 9.5% increase in income, excluding any additional effect from the interaction term. Similarly, the regression coefficients of literacy (0.0349), numeracy (0.0400), problem-solving (0.0316), and the *g factor* (0.0385) are all positively significant, confirming the robustness of intelligence's positive income effects even under a simplified health specification.

More importantly, the interaction terms remain negative across all models, supporting the previously observed substitution mechanism. The coefficients of the interaction terms for literacy (-0.0340) and numeracy (-0.0293) are statistically significant at the 5% and 10% levels, respectively, suggesting that the income returns to cognitive ability are higher among individuals with poorer health. For problem-solving skills, the interaction coefficient (-0.0236) is also negative but statistically insignificant, which may be due to the reduction in variation and information compared to the original five-point scale, which limits the model's ability to detect moderate interaction effects. Finally, the interaction term between the *g factor* and health is -0.0310, significant at the 5% level, further confirming that the marginal income return to intelligence tends to decline slightly among healthier individuals. Overall, the findings remain consistent with those based on the original five-point Likert scale of health, emphasizing that intelligence and health may play a partially substitutive role in shaping labor market outcomes.

Table 10

Re-estimation Based on Binary Health Specification

	(1)	(2)	(3)	(4)
	Literacy	Numeracy	Problem-solving	*g factor*
IQ_z	0.0349^{***}	0.0400^{***}	0.0316^{***}	0.0385^{***}
	(0.0129)	(0.0122)	(0.0119)	(0.0120)
Healthy	0.0977^{***}	0.0962^{***}	0.0941^{***}	0.0955^{***}
	(0.0162)	(0.0161)	(0.0162)	(0.0161)
Interaction_z	-0.0340^{**}	-0.0293^{*}	-0.0236	-0.0310^{**}
	(0.0157)	(0.0150)	(0.0157)	(0.0152)
Controls	Yes	Yes	Yes	Yes
N	2033	2033	2033	2033
R-squared	0.242^{***}	0.245^{***}	0.242^{***}	0.244^{***}

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. All models include gender, education, work experience, and three occupational dummies (referenced to the "Elementary occupations" category) as control variables.

Source: author's calculations

(3) *Robustness Check by Excluding Education Controls*

While education is commonly controlled for in earnings regressions, some scholars (e.g., Cawley et al., 1996) argue that doing so may partially obscure the full effect of intelligence, since cognitive ability is a strong determinant of educational attainment. This raises concerns about potential over-controlling bias in models that include both variables. To address this concern, this section re-estimates the model without education controls to test whether the observed effects of intelligence and its interaction with health remain robust.

Table 11 reports the results from this specification, where gender, work experience, and occupation are included as controls, but education is excluded. For the independent effects of intelligence and health, excluding the education variable leads to a noticeable increase in the coefficients of all three cognitive indicators (literacy, numeracy, and problem-solving). For instance, the coefficient for literacy rose from 0.016 to 0.0329, for numeracy from 0.023 to 0.0388, and for problem-solving from 0.017 to 0.0279. This pattern suggests that education may capture part of the explanatory power of intelligence, supporting the hypothesis that including it may attenuate the observed effect of cognitive ability. Meanwhile, the coefficients for health remain stable and statistically significant across specifications. For example, in the numeracy model, the coefficient only slightly changes from 0.056 to 0.0633, and in the literacy model, from 0.056 to 0.0646. This stability confirms the robustness of the health-income association, regardless of whether education is controlled for.

In terms of the interaction effects between intelligence and health, the coefficients remain stable after excluding education, with both the direction and statistical significance largely preserved. For example, the interaction term in the literacy model slightly declines from -0.017 to -0.0168, and the g factor model slightly increases from -0.017 to -0.0172, which continues to support the presence of a substitution mechanism. Overall, this suggests that the interaction effect is not sensitive to model specification with respect to education controls, and thus demonstrates structural stability.

Table 11

Re-estimation without education controls

	(1)	(2)	(3)	(4)
	Literacy	Numeracy	Problem-solving	*g factor*
IQ	0.0329^{***}	0.0388^{***}	0.0279^{***}	0.0363^{***}
	(0.00852)	(0.00863)	(0.00866)	(0.00808)
Health_z	0.0646^{***}	0.0633^{***}	0.0638^{***}	0.0632^{***}
	(0.00845)	(0.00838)	(0.00869)	(0.00846)
Interaction_z	-0.0168^{**}	-0.0163^{*}	-0.0160^{*}	-0.0172^{**}

	(0.00796)	(0.00866)	(0.00928)	(0.00864)
Controls without education	Yes	Yes	Yes	Yes
N	2033	2033	2033	2033
R-squared	0.188***	0.192***	0.186***	0.191***

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.
Source: author's calculations

In conclusion, this study employs three robustness check approaches, including the g factor re-estimation, the binary specification of the health variable and models without education controls to systematically validate the stability of the key findings under different model specifications. The results consistently support that, regardless of changes in model forms or variable constructions, both the independent effects of intelligence and health and their substitutive interaction mechanism remain stable in direction and statistical significance, reinforcing the robustness of the key findings.

4.4 Heterogeneity Analysis

Previous studies have shown significant heterogeneity in both the independent and interactive effects of health and intelligence on income returns (Contoyannis & Rice, 2001; Hanushek et al., 2015). For instance, Contoyannis & Rice (2001) highlighted gender-based differences in health returns, while Hanushek et al. (2015) demonstrated that cognitive skills provide differential returns across wage levels. These findings imply that the marginal effects of intelligence and health may be shaped by individual and socioeconomic structures. Therefore, this section conducts heterogeneity analysis using gender-grouped regressions and income-quantile regressions to examine the robustness of their independent effects and the applicability of the substitution mechanism across different population groups.

(1) Gender-based Heterogeneity

To examine gender-based heterogeneity in the effects of health and intelligence on income, the Poland sample is divided into male (GENDER = 1) and female (GENDER = 2) subsamples based on the GENDER_R variable, and separate regressions are conducted for each group across four cognitive domains. Table 12 and Table 13 present the regression results for male and female subsamples based on four cognitive measures: literacy, numeracy, problem-solving, and the *g factor.*

The Independent Effects of intelligence and health:

Across both male and female subsamples, health demonstrates a consistently strong and statistically significant effect on income, confirming the robust role of health in shaping wage outcomes. In Table *12* (male group), the coefficients of self-reported health range from 0.0582 to 0.0594, all significant at the 1% level. Similarly, in Table *13* (female group), the estimates fall between 0.0507 and 0.0530, also significant at the 1% level. This consistency suggests that the impact of health on income is stable and not structurally different across genders. Meanwhile, among males, numeracy and the g factor are statistically significant at the 5% level, with coefficients of 0.0307 and 0.0229, respectively, while literacy and problem-solving are not significant. In contrast, none of the four cognitive proxies are significantly associated with income in the female group, suggesting a potential gender gap in the economic returns to basic cognitive skills. One possible explanation may be driven by the structural and occupational differences in how such skills are utilized and rewarded. Firstly, women are more concentrated in occupations such as education, administration, and nursing, which require language skills but have a relatively low wage premium (Blau & Kahn, 2017). Secondly, in occupations where language skills such as literacy are generally high, there is limited variation in cognitive ability among individuals, resulting in small marginal returns (OECD, 2016). In contrast, numeracy and problem-solving still have a certain revenue return advantage due to their scarcity and cross-industry adaptability. Moreover, even when women have the same cognitive level as men, their wage returns may still be limited by structural factors such as promotion difficulties and gender stereotypes (Bertrand & Hallock, 2001).

Interaction Mechanism Between Health and Intelligence:

Gender-based heterogeneity is most evident in the interaction terms. For the male group, the interaction coefficients for literacy (-0.0196), numeracy (-0.0203), problem-solving (-0.0246), and the g factor (-0.0227) are all statistically significant at the 5% or 10% level. These results align with the baseline findings, indicating that cognitive skills may partially compensate for disadvantages caused by poorer health in determining income for males. However, although all interaction coefficients are negative for the female group, none reach statistical significance, implying that the substitution mechanism between intelligence and health may be more relevant for males, while it appears negligible or absent among females.

This pattern may also be explained by structural and occupational segregation in the labor market: Men are more concentrated in physically demanding or cognitively demanding sectors, such as those in manufacturing and technical sectors, where health compensates for cognitive deficiencies, or better cognitive skills support for productivity regardless of poor health, making substitution mechanisms more apparent (Bertrand & Hallock, 2001). In contrast, women tend to be concentrated in occupations like education, administration, and nursing mentioned above, which require a stable combination of both health and cognitive effort. In these roles, strong performance typically depends on both dimensions simultaneously, thus limiting the substitutive mechanism between them (OECD, 2016).

Overall, gender-based heterogeneity analysis suggests that while the independent effect of health remains stable in both male and female groups, the income returns on cognitive skills, especially numeracy and g factor, are notably weaker and less statistically significant among females. Furthermore, the substitution mechanism between intelligence and health was evident only in the male subgroup, suggesting that gender-specific occupational backgrounds and labor market structures may influence the extent to which health and cognitive skills compensate each other in determining earnings. These findings highlight the importance of considering gender heterogeneity when evaluating the joint effects of health and intelligence on income.

Table 12

Gender-Specific Regression Results (Male Group)

GENDER=1	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
IQ_z	0.0172	0.0307**	0.0158	0.0229**
	(0.0114)	(0.0124)	(0.0111)	(0.0113)
Health_z	0.0585***	0.0594***	0.0593***	0.0582***

	(0.0107)	(0.0106)	(0.0108)	(0.0108)
Interaction_z	-0.0196*	-0.0203*	-0.0246**	-0.0227**
	(0.0101)	(0.0108)	(0.0124)	(0.0111)
Controls	Yes	Yes	Yes	Yes
N	1055	1055	1055	1055
R-squared	0.170***	0.177***	0.172***	0.174***

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. All models include gender, education, work experience, and three occupational dummies (referenced to the "Elementary occupations" category) as control variables.
Source: author’s calculations

Table 13
Gender-Specific Regression Results (Female Group)

GENDER=2	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
IQ_z	0.0147	0.0166	0.0196	0.0188
	(0.0130)	(0.0120)	(0.0125)	(0.0123)
Health_z	0.0530***	0.0511***	0.0507***	0.0513***
	(0.0113)	(0.0112)	(0.0116)	(0.0114)
Interaction_z	-0.0142	-0.0107	-0.00608	-0.0111
	(0.00986)	(0.0118)	(0.0104)	(0.0104)
Controls	Yes	Yes	Yes	Yes
N	978	978	978	978
R-squared	0.246***	0.246***	0.246***	0.247***

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. All models include gender, education, work experience, and three occupational dummies (referenced to the "Elementary occupations" category) as control variables.
Source: author’s calculations

(2) Income-level Heterogeneity

To further examine the heterogeneity in returns between cognitive skills and health across different income levels, quantile regressions are employed at the 25th, 50th, and 75th percentiles of income. The results of Table 14, Table 15 and Table 16 reveal quantile-specific heterogeneity: while the independent effects of health and intelligence remain significant across all income levels, their substitutive interaction becomes statistically significant only at the upper quantile, suggesting that the mechanism varies across the income distribution.

At the 25th income quantile, both cognitive skills and health exhibit independent and significantly positive effects on income. The coefficients for all cognitive proxies are statistically significant at the 5% or 1% levels, ranging from 0.0186 to 0.0223, while the main impact of health is even stronger, with robust coefficients between 0.0631 and 0.0666 ($p < 0.01$). However, the interaction terms are statistically insignificant across all models, suggesting that in low-income groups, intelligence and health contribute independently to income determination. One possible explanation for this pattern is that cognitive skills are less likely to transfer into economic returns under market constraints, limited social sources, and the fact that low-income individuals often do not engage in jobs that heavily rely on cognitive skills. Therefore, poor health cannot be effectively compensated for by intelligence since disadvantaged environments restrict the realization of cognitive potential in the labor market. This may also help explain why health shows a stronger independent influence on income among low-income individuals (Strenze, 2007).

At the 50th income quantile, the income returns to cognitive skills remain positive, with the g factor reaching the highest coefficient of 0.0269 ($p < 0.01$) with the significance of 1% level, and other proxies such as literacy (0.0207), numeracy (0.0257) and problem-solving (0.0261) are significant at the 5% level. Health also remains a robust predictor, with coefficients around 0.0726 to 0.0754 ($p < 0.01$). Among the interaction terms, all four models remain statistically insignificant.

At the 75th income quantile, both cognitive and health variables remain positively and significantly associated with income, but the effect of health slightly declines, while cognitive skill effects become more differentiated. Notably, literacy becomes less significant (0.0218, $p < 0.1$), while numeracy (0.0327, $p < 0.01$) and g factor (0.0282, $p < 0.05$) retain stronger influence. More importantly, the interaction terms become statistically significant and more negative, with coefficients of -0.0231 ($p < 0.05$) for literacy, -0.0217 ($p < 0.1$) for numeracy, and -0.0211 ($p < 0.1$) for the g factor, confirming a stronger substitution mechanism at the upper end of the income distribution. One possible explanation is that for higher-income individuals, particularly in cognitively demanding fields like technology and innovation, individuals can rely more on their cognitive abilities to achieve income returns. And poor health can be compensated by higher cognitive skills, as these sectors often demand less physical labor, thereby creating a stronger substitution effect, where cognitive skills can offset the disadvantages of poor health (Heckman et al., 2006).

Overall, the quantile regression results demonstrate that both health and cognitive ability have consistently positive and significant effects on income across all income levels. Furthermore, their interaction shifts from statistically insignificant among low-income groups to significantly negative at the upper side of the income distribution, indicating a growing substitution mechanism where cognitive ability increasingly compensates for poor health as income increases.

Table 14

Quantile Regression at the 25th Percentile of Wage Distribution

Quantile 25%	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
IQ_z	0.0201**	0.0186**	0.0223***	0.0219***
	(0.00886)	(0.00918)	(0.00817)	(0.00804)
Health_z	0.0657***	0.0631***	0.0666***	0.0655***
	(0.0136)	(0.0138)	(0.0133)	(0.0136)
Interaction_z	-0.0132	-0.00699	-0.0114	-0.0114
	(0.0128)	(0.0135)	(0.0136)	(0.0139)
Controls	Yes	Yes	Yes	Yes
N	2033	2033	2033	2033

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. All models include gender, education, work experience, and three occupational dummies (referenced to the "Elementary occupations" category) as control variables.
Source: author's calculations

Table 15

Quantile Regression at the 50th Percentile of Wage Distribution

Quantile 50%	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
IQ_z	0.0207**	0.0257**	0.0261**	0.0269***
	(0.00933)	(0.0108)	(0.0114)	(0.00948)
Health_z	0.0754***	0.0738***	0.0726***	0.0733***
	(0.00811)	(0.00888)	(0.00845)	(0.00825)
Interaction_z	-0.0121	-0.0132	-0.0105	-0.0135
	(0.00819)	(0.00816)	(0.00868)	(0.00833)
Controls	Yes	Yes	Yes	Yes
N	2033	2033	2033	2033

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. All models include gender, education, work experience, and three occupational dummies (referenced to the "Elementary occupations" category) as control variables.
Source: author's calculations

Table 16
Quantile Regression at the 75th Percentile of Wage Distribution

Quantile 75%	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
IQ_z	0.0218*	0.0327***	0.0262*	0.0282**
	(0.0125)	(0.0120)	(0.0142)	(0.0124)
Health_z	0.0437***	0.0431***	0.0456***	0.0445***
	(0.0110)	(0.0123)	(0.0112)	(0.0113)
Interaction_z	-0.0231**	-0.0217*	-0.0148	-0.0211*
	(0.0103)	(0.0117)	(0.0110)	(0.0111)
Controls	Yes	Yes	Yes	Yes
N	2033	2033	2033	2033

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. All models include gender, education, work experience, and three occupational dummies (referenced to the "Elementary occupations" category) as control variables.
Source: author's calculations

5. Conclusion and Policy Implications

5.1 Principal Findings

This study aims to explore how intelligence and health jointly influence income, particularly in the context of Poland, a representative CEE country. The following key conclusions are obtained through regression analysis based on PIAAC data:

(1) Independent and Interaction Effects of Intelligence and Health:

The empirical regression results of this study show that both intelligence and health have significant independent effects on income. After controlling for variables such as gender, educational background, and work experience, intelligence presents a positive impact on income measured through literacy, numeracy, problem-solving skills, and the g factor. Meanwhile, health is also confirmed as a determinant of income in this analysis: individuals in better health are generally able to maintain their work capacity more effectively, leading to higher wages, and supporting the "health premium" theory. Furthermore, while the effects of intelligence and health in wages have been considered independent in many previous studies, this study found certain substitution effects between these two human capital components in the labor market. For instance, in sectors such as manufacturing, service industries, and agriculture, individuals with lower cognitive abilities can still perform effectively and maintain a higher income due to their better health, highlighting the role of health as a substitute for cognitive skills in affecting income returns.

(2) Robustness Checks:

Three robustness checks are conducted to validate the key findings of the baseline regression, including using the *g factor* to re-estimate, defining health as a binary variable, and the baseline models without education controlling. The results from these checks were largely consistent with the conclusions drawn from the baseline model, although there are slight variations in certain model specifications. These consistent results provide strong evidence that the independent and interactive mechanisms between intelligence and health in income returns are not dependent on specific model choices or transformations of variables but reflect a stable, underlying process.

(3) Heterogeneity Analysis:

The heterogeneity analysis reveals significant differences in how intelligence and health affect income across gender and income quantiles. Firstly, while the independent effect of health on income remains consistent for both male and female subgroups, the income returns on cognitive skills, especially numeracy and the *g factor* are insignificantly influencing income for females. This suggests that females may face marketing barriers in realizing the full income potential of their cognitive skills due to gender-specific constraints in occupational roles and access to higher-paying jobs. Additionally, in terms of the substitution effect, the substitutive mechanism between intelligence and health is significant only in the male subgroups. A possible explanation is that men are more dependent on physical fitness in certain occupations where cognitive skills are less important, making health a stronger substitute for intelligence, whereas this mechanism does not apply to females. Secondly, regarding income quantile models, health has the strongest independent effect on income among lower-income individuals, highlighting its critical role for those with limited social sources.

Meanwhile, although intelligence also exhibits a positive relationship with income in lower-income groups, the substitution effect between intelligence and health does not show statistical significance, suggesting that intelligence may not significantly compensate for the lack of health in determining income. However, for high-income groups, not only does the independent effect of both intelligence and health on income become more evident, but the substitution effect also becomes significant as income increases. Therefore, the heterogeneity analysis suggests that the substitution effect between health and intelligence is of limited applicability, as it is at least insignificant for females and low-income individuals.

5.2 Limitations and Further Directions

Despite this study providing robust regression results of the independent and substitutional interaction effects of health and intelligence on income, it still has several limitations that future research could address, including subjectivity and bias inherent in the self-reported health variable, the endogeneity problem and sample limitations. Firstly, although this study is based on PIAAC data, which is highly representative, the health variable used in this study is self-reported health, rather than more objective measures such as chronic disease incidence rates or clinical health assessments, thereby introducing potential bias and subjectivity, as well as affecting the reliability of the results. Furthermore, the subjectivity of self-reported health data makes it difficult to compare health across countries, as differences in healthcare and education policies may influence how individuals assess and report their health status. Therefore, future research could benefit from incorporating more objective health indicators to improve the accuracy and comparability of health data.

Secondly, this study is based on cross-sectional PIAAC data, which limits the ability to establish causal relationships between intelligence, health, and income. And PIAAC's survey design focused primarily on variables related to skills and lacks appropriate instrumental variables to address potential endogeneity between health and income. Future research could benefit from more comprehensive panel datasets, as well as including indicators such as the frequency of medical visits, which may strongly predict self-reported health while being unlikely to directly affect earnings conditional on health status. Such variables can serve as valid instruments in an instrumental variable (IV) approach, typically implemented via two-stage least squares (2SLS), to improve causal identification between health and income. This would allow future studies not only to address endogeneity but also to explore the causal pathways between health, intelligence, and income. Finally, in terms of sample size, this study mainly uses PIAAC data from Poland. However, the socioeconomic backgrounds of different countries and regions may result in variations in the mechanisms through which intelligence and health affect income. Therefore, future studies could expand the sample to include more CEE countries and examine how national contexts influence the interaction mechanisms between intelligence and health.

5.3 Policy Implications

The key findings of this study, particularly the substitution effect between intelligence and health, offer context-specific implications for Poland's labor market and human capital development. The results suggest that intelligence can partially offset the adverse income effects of poor health, but this substitution is not uniform across all groups.

Firstly, for individuals with poor health conditions that are difficult to improve in the short term, especially in middle-income and high-income groups where the substitution effect is significant, enhancing cognitive skills may be a more effective pathway to income resilience. Policymakers should consider expanding cognitive training and adult learning opportunities tailored to these populations, especially those already facing chronic health issues.

Secondly, for individuals with lower cognitive abilities, improving physical health can compensate for limited intellectual resources. In this case, interventions such as preventive healthcare, nutritional support, and accessible medical services can help maintain stable income through better work attendance, extended labor force participation, and improved physical productivity, particularly in occupations with lower cognitive requirements.

Thirdly, the substitution effect between intelligence and health is not uniformly observed across all groups. Among low-income individuals and female groups, the interaction term becomes statistically insignificant, suggesting that intelligence and health cannot compensate for each other. For low-income groups, dual disadvantages in both health and skills must be addressed through integrated policy programs, such as basic skills training combined with accessible health services. For females, structural constraints like occupational segregation and limited access to cognitive-demanding jobs may weaken the substitutive returns to intelligence. Thus, policies should also aim to eliminate labor market barriers, promote gender equity in cognitive employment, and improve healthcare accessibility to ensure both forms of human capital can be translated into income more effectively.

Overall, these key findings emphasize the need for differentiated policy strategies that go beyond treating intelligence and health as isolated factors. Recognizing their interactive and context-specific nature, especially the unequal substitutive effects across income levels and gender, is essential for designing inclusive labor market interventions.

6. Reference list

1. Autor, D. H. (2014). Skills, education, and the rise of earnings inequality among the “other 99 percent.” *Science*, *344*(6186), 843–851. https://doi.org/10.1126/science.1251868
2. Batty, G. D., Der, G., Macintyre, S., & Deary, I. J. (2006). Does IQ explain socioeconomic inequalities in health? Evidence from a population based cohort study in the west of Scotland. *BMJ*, *332*(7541), 580–584. https://doi.org/10.1136/bmj.38723.660637.AE
3. Becker, Gary S. (n.d.). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*.
4. Behrman, J. R., Hoddinott, J., Maluccio, J. A., & Martorell, R. (2009). Brains versus Brawn: Labor Market Returns to Intellectual and Health Human Capital in a Poor

Developing Country. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1471316

5. Bertrand, M., & Hallock, K. F. (n.d.). *The Gender Gap in Top Corporate Jobs*.
6. Bhalotra, S., Karlsson, M., Nilsson, T., & Schwarz, N. (2022). Infant Health, Cognitive Performance, and Earnings: Evidence from Inception of the Welfare State in Sweden. *The Review of Economics and Statistics*, *104*(6), 1138–1156. https://doi.org/10.1162/rest_a_01031
7. Blau, F. D., & Kahn, L. M. (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, *55*(3), 789–865. https://doi.org/10.1257/jel.20160995
8. Borgonovi, F., & Pokropek, A. (2016). Education and Self-Reported Health: Evidence from 23 Countries on the Role of Years of Schooling, Cognitive Skills and Social Capital. *PLOS ONE*, *11*(2), e0149716. https://doi.org/10.1371/journal.pone.0149716
9. Bowles, S., Gintis, H., & Osborne, M. (2001). The Determinants of Earnings: A Behavioral Approach. *Journal of Economic Literature*, *39*(4), 1137–1176. https://doi.org/10.1257/jel.39.4.1137
10. Case, A., & Deaton, A. (2017). Mortality and Morbidity in the 21st Century. *Brookings Papers on Economic Activity*, *2017*(1), 397–476. https://doi.org/10.1353/eca.2017.0005
11. Cawley, J., Conneely, K., Heckman, J., & Vytlacil, E. (n.d.). *NBER WORKING PAPER SERIES*.
12. Contoyannis, P., & Rice, N. (2001). The impact of health on wages: Evidence from the British Household Panel Survey. *Empirical Economics*, *26*(4), 599–622. https://doi.org/10.1007/s001810000073
13. Engelhardt, L., Goldhammer, F., Lüdtke, O., Köller, O., Baumert, J., & Carstensen, C. H. (2021). Separating PIAAC competencies from general cognitive skills: A dimensionality and explanatory analysis. *Studies in Educational Evaluation*, *71*, 101069. https://doi.org/10.1016/j.stueduc.2021.101069

14. Erdil, E., & Yetkiner, I. H. (n.d.). *A Panel Data Approach for Income-Health Causality*.
15. Ganzach, Y., & Patel, P. C. (2018). Wages, mental abilities and assessments in large scale international surveys: Still not much more than g. *Intelligence*, *69*, 1–7. https://doi.org/10.1016/j.intell.2018.03.014
16. Grossman, M. (n.d.). *On the Concept of Health Capital and the Demand for Health*.
17. Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, *73*, 103–130. https://doi.org/10.1016/j.euroecorev.2014.10.006
18. Hanushek, E. A., & Woessmann, L. (2008). The Role of Cognitive Skills in Economic Development. *Journal of Economic Literature*, *46*(3), 607–668. https://doi.org/10.1257/jel.46.3.607
19. *Health and Wages: Panel Data Estimates Considering Selection and Endogeneity*. (n.d.).
20. Heckman, J. J., Stixrud, J., & Urzua, S. (n.d.). *The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior*.
21. Herrnstein, R. J., & Murray, C. A. (1997). *The bell curve: Intelligence and class structure in American life* (4. Dr.). Free Press.
22. Hoddinott, J., Maluccio, J. A., Behrman, J. R., Flores, R., & Martorell, R. (2008). Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults. *The Lancet*, *371*(9610), 411–416. https://doi.org/10.1016/S0140-6736(08)60205-6
23. *Income Equality in The Nordic Countries- Myths, Facts, and Lessons*. (n.d.).
24. LaFave, D., & Thomas, D. (2017). Height and cognition at work: Labor market productivity in a low income setting. *Economics & Human Biology*, *25*, 52–64. https://doi.org/10.1016/j.ehb.2016.10.008
25. Lee, L.-F. (1982). Health and Wage: A Simultaneous Equation Model with Multiple Discrete Indicators. *International Economic Review*, *23*(1), 199. https://doi.org/10.2307/2526472

26. Lundborg, P., & Nystedt, P. (n.d.). *Height and Earnings: The Role of Cognitive and Noncognitive Skills*.
27. Lynn, R. (2018). The Intelligence of Nations. In R. J. Sternberg (Ed.), *The Nature of Human Intelligence* (1st ed., pp. 256–269). Cambridge University Press. https://doi.org/10.1017/9781316817049.017
28. Madden, D. (2004). Labour market discrimination on the basis of health: An application to UK data. *Applied Economics*, *36*(5), 421–442. https://doi.org/10.1080/0003684041000168213
29. Maehler, D. B., Martin, S., Gorges, J., & Scherer, R. (2025). Determinants of cognitive skills in adulthood: Age cohort patterns. *International Journal of Lifelong Education*, *44*(2), 131–152. https://doi.org/10.1080/02601370.2024.2390070
30. Marius Vaag Iversen, J., & Strøm, B. (2020). Skills, Employment, and Labor Market Institutions: Evidence from PIAAC. *LABOUR*, *34*(3), 277–304. https://doi.org/10.1111/labr.12174
31. *Market work, wages, and men's health*. (n.d.).
32. Mincer, J. (1974). *Schooling, Experience, and Earnings.*
33. Nikolov, P., Jimi, N., & Chang, J. (2020). The Importance of Cognitive Domains and the Returns to Schooling in South Africa: Evidence from Two Labor Surveys. *Labour Economics*, *65*, 101849. https://doi.org/10.1016/j.labeco.2020.101849
34. Nilsson, A. (2015). Who suffers from unemployment? The role of health and skills. *IZA Journal of Labor Policy*, *4*(1), 19. https://doi.org/10.1186/s40173-015-0046-5
35. OECD. (2013). *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*. OECD. https://doi.org/10.1787/9789264204256-en
36. OECD. (2016). *Skills Matter: Further Results from the Survey of Adult Skills*. OECD. https://doi.org/10.1787/9789264258051-en
37. Ozawa, S., Laing, S. K., Higgins, C. R., Yemeke, T. T., Park, C. C., Carlson, R., Ko, Y. E., Guterman, L. B., & Omer, S. B. (2022). Educational and economic returns to cognitive ability in low- and middle-income countries: A systematic review.

World Development, *149*, 105668. https://doi.org/10.1016/j.worlddev.2021.105668

38. Pesta, B. J. (2022). Updated IQ and Well-Being Scores for the 50 U.S. States. *Journal of Intelligence*, *10*(1), 15. https://doi.org/10.3390/jintelligence10010015
39. Rammstedt, B., Danner, D., & Martin, S. (2016). The association between personality and cognitive ability: Going beyond simple effects. *Journal of Research in Personality*, *62*, 39–44. https://doi.org/10.1016/j.jrp.2016.03.005
40. Rindermann, H. (2018). *Cognitive Capitalism: Human Capital and the Wellbeing of Nations* (1st ed.). Cambridge University Press. https://doi.org/10.1017/9781107279339
41. Schmidt, F. L., & Hunter, J. (2004). General Mental Ability in the World of Work: Occupational Attainment and Job Performance. *Journal of Personality and Social Psychology*, *86*(1), 162–173. https://doi.org/10.1037/0022-3514.86.1.162
42. Semykina, A., & Wooldridge, J. M. (2010). Estimating panel data models in the presence of endogeneity and selection. *Journal of Econometrics*, *157*(2), 375–380. https://doi.org/10.1016/j.jeconom.2010.03.039
43. Smith, J. P. (1999). Healthy Bodies and Thick Wallets: The Dual Relation Between Health and Economic Status. *Journal of Economic Perspectives*, *13*(2), 145–166. https://doi.org/10.1257/jep.13.2.145
44. Snowdon, D. A., Greiner, L. H., Kemper, S. J., Nanayakkara, N., & Mortimer, J. A. (1999). Linguistic Ability in Early Life and Longevity: Findings from the Nun Study. In J.-M. Robine, B. Forette, C. Franceschi, & M. Allard (Eds.), *The Paradoxes of Longevity* (pp. 103–113). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-60100-2_9
45. Sörberg, A., Lundin, A., Allebeck, P., Melin, B., Falkstedt, D., & Hemmingsson, T. (2013). Cognitive Ability in Late Adolescence and Disability Pension in Middle Age: Follow-Up of a National Cohort of Swedish Males. *PLoS ONE*, *8*(10), e78268. https://doi.org/10.1371/journal.pone.0078268
46. Spearman, C. (1904). *“General Intelligence,” Objectively Determined and Measured*.

47. Strenze, T. (2007). Intelligence and socioeconomic success: A meta-analytic review of longitudinal research. *Intelligence*, *35*(5), 401–426. https://doi.org/10.1016/j.intell.2006.09.004

48. Sundberg, G. (n.d.). *Self-assessed health and economic status: A Swedish study.*

49. *The optimal stock of health with endogenous wages- Application to partial disability compensation*. (n.d.).

50. Van Zon, S. K. R., Reijneveld, S. A., Mendes De Leon, C. F., & Bültmann, U. (2017). The impact of low education and poor health on unemployment varies by work life stage. *International Journal of Public Health*, *62*(9), 997–1006. https://doi.org/10.1007/s00038-017-0972-7

51. Vogl, T. S. (2014). Height, skills, and labor market outcomes in Mexico. *Journal of Development Economics*, *107*, 84–96. https://doi.org/10.1016/j.jdeveco.2013.11.007

52. Zagorsky, J. L. (2007). Do you have to be smart to be rich? The impact of IQ on wealth, income and financial distress. *Intelligence*, *35*(5), 489–501. https://doi.org/10.1016/j.intell.2007.02.003

53. Zheng, X., Yang, Y., Chen, J., & Lu, B. (2023). Dissecting the causal relationship between household income status and genetic susceptibility to cardiovascular-related diseases: Insights from bidirectional mendelian randomization study. *BMC Public Health*, *23*(1), 749. https://doi.org/10.1186/s12889-023-15561-7

7. Appendix

Appendix A1

Full descriptive statistics across all PVs and controlling variables

Variables	mean	sd	p50	min	max
income	3015.477	10357.42	2405.838	0	484897.6
health	3.603161	.7430714	4	1	5
PVLIT1	241.8643	47.96721	246.0414	10.42601	439.4409
PVLIT2	242.14	47.67248	246.0714	51.04618	397.1958
PVLIT3	242.5785	47.64638	246.3454	28.21952	410.2194
PVLIT4	243.1692	47.07045	247.305	89.69167	395.5732
PVLIT5	242.6451	46.68466	245.2171	78.73983	408.0156
PVLIT6	241.7335	47.66633	245.3179	61.62489	407.1829
PVLIT7	242.4254	47.90106	246.5446	52.22282	413.1744
PVLIT8	243.8496	47.34851	248.552	46.0033	422.3773
PVLIT9	241.7003	48.28636	245.6722	32.10279	406.36
PVLIT10	241.1792	47.52027	245.0556	59.35677	439.528
PVNUM1	246.8635	52.02815	251.0971	29.60568	473.2471
PVNUM2	246.3893	51.73366	249.0342	27.70005	451.5543
PVNUM3	247.0174	51.12262	250.5957	31.30985	475.2148
PVNUM4	245.6747	51.16931	250.4131	30.88238	441.8942
PVNUM5	245.6279	51.2161	247.8904	23.84586	453.5523
PVNUM6	246.8165	51.44657	249.1756	38.53115	433.8938
PVNUM7	246.6903	50.92176	250.4512	28.13184	421.9629
PVNUM8	247.3226	51.32301	250.0455	32.18996	478.9322
PVNUM9	245.7468	52.06774	248.7658	22.801	429.8783
PVNUM10	245.8103	51.3009	248.1446	32.72577	488.5608
PVAPS1	232.5237	40.59167	233.8341	0	375.0834
PVAPS2	231.5289	41.103	232.2068	74.28713	391.2587
PVAPS3	231.3227	41.43104	232.9677	0	384.3304
PVAPS4	231.5374	40.29476	232.585	61.86263	366.2189
PVAPS5	232.0495	40.27557	232.9251	16.44719	372.9109
PVAPS6	232.1186	41.34398	233.5998	14.66118	383.1711
PVAPS7	232.0307	41.49455	232.3395	30.2284	380.0557
PVAPS8	233.1073	40.56526	234.8683	47.61978	391.3363
PVAPS9	232.2016	41.64493	233.3692	0	400.5998
PVAPS10	231.242	40.99242	231.8874	60.2471	376.6927
GENDER_R	1.473222	.4993921	1	1	2
education	14.26131	6.568669	12	1	28
workexperience	17.61723	11.34547	16	0	48
occ_1	.2396839	.4269843	0	0	1
occ_2	.1992976	.39956	0	0	1
occ_3	.2568042	.4369664	0	0	1

Source: author's calculations

Appendix Table A2

Full Correlation Matrix Including Control Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
wage	1										
health	0.146***	1									
PVLIT1	0.108***	0.076***	1								
PVNUM1	0.147***	0.058***	0.800***	1							
PVAPS1	0.103***	0.133***	0.763***	0.742***	1						
GENDER R	-0.254***	0.00800	0.084***	0.051**	0.037*	1					
education	0.253***	0.162***	0.269***	0.270***	0.213***	0.258***	1				
workexperience	0.104***	-0.409***	-0.132***	-0.062***	-0.146***	-0.096***	-0.187***	1			
occ 1	0.192***	0.057***	0.229***	0.233***	0.156***	0.162***	0.553***	-0.069***	1		
occ 2	-0.221***	0.00200	0.088***	0.077***	0.087***	0.271***	-0.064***	-0.094***	-0.281***	1	
occ 3	0.065***	-0.050**	-0.00600	0.0280	-0.0180	-0.393***	-0.322***	0.092***	-0.324***	-0.301***	1

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Although gender and occupational dummies (occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations) are categorical or binary variables, they are included in the Pearson correlation matrix for descriptive purposes.

Source: author's calculations

Appendix Table B1
Baseline Regression: Literacy

	(1) Literacy	(2) Literacy
iq_z_	0.034***	0.016*
	(0.009)	(0.008)
health_z	0.043***	0.056***
	(0.009)	(0.008)
interaction_	-0.019**	-0.017**
	(0.009)	(0.008)
e_N	2056.000	2033.000
	(.)	(.)
e_r2	0.037***	0.250***
	(0.012)	(0.020)
GENDER_R		-0.186***
		(0.017)
education		0.016***
		(0.002)
workexperience		0.006***
		(0.001)
occ_1		0.050**
		(0.025)
occ_2		-0.064***
		(0.019)
occ_3		0.030
		(0.019)
_cons	7.812***	7.749***
	(0.009)	(0.040)

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Reference group for occupation dummies is “Elementary occupations” (ISCO level 4) with occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations.

Source: author’s calculations

Appendix Table B2
Baseline Regression: Numeracy

	(1) Numeracy	(2) Numeracy
iq_zz_	0.046***	0.023***
	(0.008)	(0.008)
health_z	0.042***	0.056***
	(0.009)	(0.008)
interactionn_	-0.018**	-0.016**
	(0.009)	(0.008)
e_N	2056.000	2033.000
	(.)	(.)
e_r2	0.046***	0.252***
	(0.013)	(0.020)
GENDER_R		-0.185***
		(0.017)
education		0.015***
		(0.002)
workexperience		0.006***
		(0.001)
occ_1		0.044*
		(0.025)
occ_2		-0.069***
		(0.020)
occ_3		0.024
		(0.020)
_cons	7.812***	7.756***
	(0.009)	(0.040)

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Reference group for occupation dummies is “Elementary occupations” (ISCO level 4) with occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations.
Source: author’s calculations

Appendix Table B3
Baseline Regression: Problem-Solving Skill

	(1) Problem-Solving	(2) Problem-Solving
iq_zzz_	0.029***	0.017**
	(0.009)	(0.008)
health_z	0.042***	0.056***
	(0.009)	(0.008)
interactionnn_	-0.017*	-0.015*
	(0.010)	(0.009)
e_N	2056.000	2033.000
	(.)	(.)
e_r2	0.033***	0.250***
	(0.012)	(0.019)
GENDER_R		-0.185***
		(0.018)
education		0.016***
		(0.002)
workexperience		0.006***
		(0.001)
occ_1		0.053**
		(0.024)
occ_2		-0.062***
		(0.019)
occ_3		0.033*
		(0.019)
_cons	7.814***	7.745***
	(0.009)	(0.040)

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Reference group for occupation dummies is "Elementary occupations" (ISCO level 4) with occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations.

Source: author's calculations

Appendix Table C1
PCA model: g factor

	(1)
	g factor
iq_g_z_	0.021***
	(0.008)
health_z	0.056***
	(0.008)
interactiong_	-0.017**
	(0.008)
GENDER_R	-0.185***
	(0.017)
education	0.015***
	(0.002)
workexperience	0.006***
	(0.001)
occ_1	0.047*
	(0.025)
occ_2	-0.067***
	(0.019)
occ_3	0.027
	(0.019)
_cons	7.753***
	(0.040)
e_N	2033.000
	(.)
e_r2	0.252***
	(0.020)

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Reference group for occupation dummies is "Elementary occupations" (ISCO level 4) with occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations.

Source: author's calculations

Appendix C2

Re-estimation Based on Binary Health Specification

	(1)	(2)	(3)	(4)
	Literacy	Numeracy	Problem-solving	*g factor*
iq_z_	0.0349***	0.0400***	0.0316***	0.0385***
	(0.0129)	(0.0122)	(0.0119)	(0.0120)
Healthy	0.0977***	0.0962***	0.0941***	0.0955***
	(0.0162)	(0.0161)	(0.0162)	(0.0161)
interactiondummy_	-0.0340**	-0.0293*	-0.0236	-0.0310**
	(0.0157)	(0.0150)	(0.0157)	(0.0152)
	0.0157***	0.0155***	0.0158***	0.0156***
GENDER_R	(0.00156)	(0.00155)	(0.00157)	(0.00157)
	0.00572***	0.00561***	0.00572***	0.00571***
	(0.000690)	(0.000692)	(0.000695)	(0.000693)
education	0.0465*	0.0409	0.0497**	0.0439*
	(0.0254)	(0.0255)	(0.0245)	(0.0253)
	-0.0683***	-0.0731***	-0.0660***	-0.0711***
workexperience	(0.0195)	(0.0198)	(0.0188)	(0.0195)
	0.0282	0.0226	0.0314*	0.0255
	(0.0192)	(0.0196)	(0.0185)	(0.0192)
occ_1	2033	2033	2033	2033
	(.)	(.)	(.)	(.)
	0.242***	0.245***	0.242***	0.244***
occ_2	(0.0186)	(0.0186)	(0.0185)	(0.0185)
	0.0349***			
	(0.0129)			
occ_3	0.0977***	0.0962***	0.0941***	0.0955***
	(0.0162)	(0.0161)	(0.0162)	(0.0161)
	-0.0340**			
e_N	(0.0157)			
	-0.186***	-0.185***	-0.185***	-0.185***
	(0.0176)	(0.0174)	(0.0176)	(0.0175)
e_r2	0.0157***	0.0155***	0.0158***	0.0156***
	(0.00156)	(0.00155)	(0.00157)	(0.00157)
_cons	7.701***	7.709***	7.699***	7.706***
	(0.0434)	(0.0434)	(0.0431)	(0.0434)

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Reference group for occupation dummies is “Elementary occupations” (ISCO level 4).

Source: author’s calculations

Appendix C3

Robustness Check by Excluding Education Controls

	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
iq_z_	0.0329***	0.0388***	0.0279***	0.0363***
	(0.00852)	(0.00863)	(0.00866)	(0.00808)
health_z	0.0646***	0.0633***	0.0638***	0.0632***
	(0.00845)	(0.00838)	(0.00869)	(0.00846)
interaction_	-0.0168**	-0.0163*	-0.0160*	-0.0172**
	(0.00796)	(0.00866)	(0.00928)	(0.00864)
GENDER_R	-0.162***	-0.160***	-0.160***	-0.160***
	(0.0180)	(0.0179)	(0.0181)	(0.0180)
workexperience	0.00526***	0.00504***	0.00523***	0.00523***
	(0.000742)	(0.000744)	(0.000749)	(0.000744)
occ_1	0.153***	0.146***	0.165***	0.151***
	(0.0228)	(0.0229)	(0.0214)	(0.0226)
occ_2	-0.0732***	-0.0784***	-0.0668***	-0.0759***
	(0.0200)	(0.0203)	(0.0193)	(0.0200)
occ_3	-0.00525	-0.0109	0.00186	-0.00724
	(0.0189)	(0.0194)	(0.0184)	(0.0189)
e_N	2033	2033	2033	2033
	(.)	(.)	(.)	(.)
e_r2	0.188***	0.192***	0.186***	0.191***
	(0.0184)	(0.0187)	(0.0186)	(0.0186)
_cons	7.939***	7.944***	7.932***	7.940***
	(0.0357)	(0.0354)	(0.0356)	(0.0356)

Note. * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Reference group for occupation dummies is “Elementary occupations” (ISCO level 4) with occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations.

Source: author’s calculations

Appendix D1

Full Regression of Gender-Specific Regression Results (Male Group)

	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
iq_z_	0.0172	0.0307**	0.0158	0.0229**
	(0.0114)	(0.0124)	(0.0111)	(0.0113)
health_z	0.0585***	0.0594***	0.0593***	0.0582***
	(0.0107)	(0.0106)	(0.0108)	(0.0108)
interaction_	-0.0196*	-0.0203*	-0.0246**	-0.0227**
	(0.0101)	(0.0108)	(0.0124)	(0.0111)
education	0.0144***	0.0137***	0.0144***	0.0141***
	(0.00210)	(0.00211)	(0.00214)	(0.00214)
workexperience	0.00486***	0.00481***	0.00486***	0.00488***
	(0.000953)	(0.000956)	(0.000955)	(0.000954)
occ_1	0.0388	0.0289	0.0432	0.0358
	(0.0400)	(0.0396)	(0.0388)	(0.0397)
occ_2	-0.108***	-0.119***	-0.109***	-0.114***
	(0.0346)	(0.0356)	(0.0333)	(0.0348)
occ_3	0.0328	0.0236	0.0363*	0.0293
	(0.0230)	(0.0242)	(0.0216)	(0.0232)
e_N	1055	1055	1055	1055
	(.)	(.)	(.)	(.)
e_r2	0.170***	0.177***	0.172***	0.174***
	(0.0249)	(0.0254)	(0.0247)	(0.0251)
_cons	7.607***	7.622***	7.606***	7.614***
	(0.0343)	(0.0356)	(0.0331)	(0.0348)

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Reference group for occupation dummies is "Elementary occupations" (ISCO level 4) with occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations.

Source: author's calculations

Appendix D2

Full Regression of Gender-Specific Regression Results (Female Group)

	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
iq_z_	0.0147	0.0166	0.0196	0.0188
	(0.0130)	(0.0120)	(0.0125)	(0.0123)
health_z	0.0530***	0.0511***	0.0507***	0.0513***
	(0.0113)	(0.0112)	(0.0116)	(0.0114)
interaction_	-0.0142	-0.0107	-0.00608	-0.0111
	(0.00986)	(0.0118)	(0.0104)	(0.0104)
education	0.0168***	0.0168***	0.0170***	0.0168***
	(0.00193)	(0.00188)	(0.00190)	(0.00191)
workexperience	0.00763***	0.00747***	0.00766***	0.00761***
	(0.00102)	(0.00102)	(0.00102)	(0.00102)
occ_1	0.0565*	0.0545*	0.0583**	0.0544*
	(0.0295)	(0.0302)	(0.0287)	(0.0297)
occ_2	-0.0396*	-0.0412*	-0.0381*	-0.0414*
	(0.0214)	(0.0213)	(0.0207)	(0.0212)
occ_3	-0.0272	-0.0328	-0.0270	-0.0310
	(0.0360)	(0.0375)	(0.0364)	(0.0369)
e_N	978	978	978	978
	(.)	(.)	(.)	(.)
e_r2	0.246***	0.246***	0.246***	0.247***
	(0.0264)	(0.0266)	(0.0259)	(0.0261)
_cons	7.325***	7.330***	7.322***	7.329***
	(0.0390)	(0.0384)	(0.0377)	(0.0388)

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Reference group for occupation dummies is “Elementary occupations” (ISCO level 4) with occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations.

Source: author’s calculations

Appendix D3

Full Regression of Quantile Regression at the 25th Percentile

	(1)	(2)	(3)	(4)
	Literacy	Numeracy	Problem-solving	*g factor*
iq_z_	0.0201**	0.0186**	0.0223***	0.0219***
	(0.00886)	(0.00918)	(0.00817)	(0.00804)
health_z	0.0657***	0.0631***	0.0666***	0.0655***
	(0.0136)	(0.0138)	(0.0133)	(0.0136)
interaction_	-0.0132	-0.00699	-0.0114	-0.0114
	(0.0128)	(0.0135)	(0.0136)	(0.0139)
GENDER_R	-0.181***	-0.180***	-0.178***	-0.181***
	(0.0225)	(0.0218)	(0.0221)	(0.0223)
education	0.0146***	0.0147***	0.0148***	0.0145***
	(0.00217)	(0.00188)	(0.00191)	(0.00208)
workexperience	0.00602***	0.00572***	0.00625***	0.00607***
	(0.000873)	(0.000843)	(0.000881)	(0.000850)
occ_1	0.0410	0.0413	0.0449	0.0423
	(0.0319)	(0.0319)	(0.0316)	(0.0313)
occ_2	-0.0296	-0.0321	-0.0336	-0.0324
	(0.0299)	(0.0321)	(0.0279)	(0.0306)
occ_3	0.0373**	0.0330	0.0357*	0.0330*
	(0.0187)	(0.0220)	(0.0212)	(0.0189)
e_N	2033	2033	2033	2033
	(.)	(.)	(.)	(.)
e_r2	0	0	0	0
	(.)	(.)	(.)	(.)
_cons	7.563***	7.567***	7.553***	7.565***
	(0.0451)	(0.0457)	(0.0443)	(0.0449)

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses; R^2 is not reported for quantile regressions, as the model minimizes absolute deviations instead of squared errors, and thus traditional variance-based R^2 is not applicable. Reference group for occupation dummies is “Elementary occupations” (ISCO level 4).

Source: author’s calculations

Appendix D4

Full Regression of Quantile Regression at the 50th Percentile

	(1) Literacy	(2) Numeracy	(3) Problem-solving	(4) *g factor*
iq_z_	0.0207**	0.0257**	0.0261**	0.0269***
	(0.00933)	(0.0108)	(0.0114)	(0.00948)
health_z	0.0754***	0.0738***	0.0726***	0.0733***
	(0.00811)	(0.00888)	(0.00845)	(0.00825)
interaction_	-0.0121	-0.0132	-0.0105	-0.0135
	(0.00819)	(0.00816)	(0.00868)	(0.00833)
GENDER_R	-0.200***	-0.201***	-0.196***	-0.200***
	(0.0187)	(0.0190)	(0.0195)	(0.0193)
education	0.0155***	0.0148***	0.0152***	0.0150***
	(0.00196)	(0.00200)	(0.00194)	(0.00207)
workexperience	0.00708***	0.00690***	0.00717***	0.00695***
	(0.000729)	(0.000782)	(0.000794)	(0.000739)
occ_1	0.0678**	0.0732***	0.0708***	0.0672**
	(0.0275)	(0.0270)	(0.0270)	(0.0273)
occ_2	-0.0611***	-0.0634***	-0.0579***	-0.0626***
	(0.0228)	(0.0221)	(0.0218)	(0.0213)
occ_3	0.0225	0.0146	0.0254	0.0194
	(0.0229)	(0.0236)	(0.0228)	(0.0225)
e_N	2033	2033	2033	2033
	(.)	(.)	(.)	(.)
e_r2	0	0	0	0
	(.)	(.)	(.)	(.)
_cons	7.738***	7.756***	7.734***	7.750***
	(0.0461)	(0.0474)	(0.0452)	(0.0470)

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses; R^2 is not reported for quantile regressions, as the model minimizes absolute deviations instead of squared errors, and thus traditional variance-based R^2 is not applicable. Reference group for occupation dummies is “Elementary occupations” (ISCO level 4) with occ_1: Skilled occupations; occ_2: Semi-skilled white-collar occupations; occ_3: Semi-skilled blue-collar occupations.

Source: author’s calculations

Appendix D5

Full Regression of Quantile Regression at the 75th Percentile

	(1)	(2)	(3)	(4)
	Literacy	Numeracy	Problem-solving	*g factor*
iq_z_	0.0218*	0.0327***	0.0262*	0.0282**
	(0.0125)	(0.0120)	(0.0142)	(0.0124)
health_z	0.0437***	0.0431***	0.0456***	0.0445***
	(0.0110)	(0.0123)	(0.0112)	(0.0113)
interaction_	-0.0231**	-0.0217*	-0.0148	-0.0211*
	(0.0103)	(0.0117)	(0.0110)	(0.0111)
GENDER_R	-0.193***	-0.191***	-0.197***	-0.191***
	(0.0253)	(0.0276)	(0.0264)	(0.0272)
education	0.0186***	0.0181***	0.0181***	0.0182***
	(0.00204)	(0.00215)	(0.00204)	(0.00209)
workexperience	0.00664***	0.00669***	0.00680***	0.00680***
	(0.000905)	(0.00106)	(0.00101)	(0.000966)
occ_1	0.0423	0.0284	0.0455	0.0395
	(0.0279)	(0.0315)	(0.0286)	(0.0285)
occ_2	-0.0979***	-0.108***	-0.0980***	-0.0989***
	(0.0270)	(0.0295)	(0.0290)	(0.0265)
occ_3	0.00534	-0.00101	0.00125	0.00576
	(0.0353)	(0.0336)	(0.0343)	(0.0345)
e_N	2033	2033	2033	2033
	(.)	(.)	(.)	(.)
e_r2	0	0	0	0
	(.)	(.)	(.)	(.)
_cons	7.914***	7.923***	7.925***	7.916***
	(0.0591)	(0.0649)	(0.0609)	(0.0649)

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses; R^2 is not reported for quantile regressions, as the model minimizes absolute deviations instead of squared errors, and thus traditional variance-based R^2 is not applicable. Reference group for occupation dummies is "Elementary occupations" (ISCO level 4).

Source: author's calculations

Resümee

Intelligentsuse ja tervise koosmõju sissetuleku kujundamisel: Poola näitel

Varasemad uuringud inimkapitali majandusliku tasuvuse kohta on sageli jätnud tähelepanuta kognitiivsete oskuste ja tervise iseseisvad ning ühismõjud, keskendudes peamiselt kas kõrge sissetulekuga lääneriikidele või madala sissetulekuga arenguriikidele. Käesolev uurimus kasutab Poola mikrotasandi andmeid PIAACi teise tsükli uuringust, mis pakub ainulaadset võimalust uurida neid mõjusid post-sotsialistlikus Kesk- ja Ida-Euroopa (CEE) kontekstis.

Töö laiendab Minceri palgavõrrandit, kaasates interaktsioonimõiste enesehinnatud tervise ja kolme kognitiivse näitaja (lugemisoskus, arvutamisoskus ja probleemilahendusoskus) vahel. Tulemused kinnitavad, et nii intelligentsusel kui ka tervisel on sõltumatult statistiliselt olulised positiivsed mõjud sissetulekule. Eriti oluline on, et interaktsioonitermid viitavad asendusmehhanismile: kui tervis halveneb ühe standardhälbe võrra, suureneb lugemisoskusest saadav tulu 1.5% ja arvutamisoskusest 1.7%, samas kui probleemilahendusoskus ei näita statistiliselt olulist mõju.

Selleks, et neid olulisi tulemusi kontrollida, rakendatakse üldise intelligentsuse indeksit (g-faktor), mis on saadud peakomponentide analüüs abil, lähtemudeleid ilma haridust arvesse võtmata ning binaarset tervisespetsifikatsiooni. Heterogeensuse analüüs näitab, et asendusmehhanism kehtib ainult meeste ja kesk- kuni kõrge sissetulekuga rühmade puhul, kuid puudub naiste ja madala sissetulekuga isikute hulgas. See viitab sellele, et mehhanismi toimimine sõltub tööturu struktuuridest ja institutsionaalsetest tingimustest.

Uurimus täidab tühimiku CEE regioonis tehtud teadustöös, pakkudes uut empiirilist tõendusmaterjali intelligentsuse ja tervise vahelise asendusmehhanismi kohta ning rõhutades vajadust poliitikaraamistike järele, mis arvestavad nende kahe teguri koosmõju.

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