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Cognitive Skills and Employment Status: Is There a Gender Difference?*

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Abstract

This paper examines the gender differences in the association between cognitive skills and employment status. Using data from the Socio-Economic Panel (SOEP) spanning 2003–2019, we measure cognitive skills through the Symbol Digit Test (SDT), administered in three waves and assumed to be time-invariant. Our findings reveal a prominent and statistically significant positive relationship between cognitive skills and employment probability, with considerable gender disparities. In particular, the returns to cognitive skills are consistently higher for men. These results remain robust across different estimation methods and hold when considering both time-invariant and time-variant cognitive skills. We explore potential mechanisms driving these patterns, including social norms and individual heterogeneity.

JEL Codes: C23, I26, J24

Keywords: Cognitive Skills, Employment Status, Panel Data Models, Gender Differences

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Bilişsel Beceriler ve İstihdam: Cinsiyete Dayalı Bir Fark Var Mı?

Öz

Bu çalışma, bilişsel beceriler ile istihdam durumu arasındaki ilişkide cinsiyet farklılıklarının rolünü incelemektedir. 2003–2019 yıllarını kapsayan Sosyo-Ekonomik Panel (SOEP) verileri kullanılarak, bilişsel beceriler üç dalga halinde uygulanan ve zaman içinde sabit kaldığı varsayılan Sembol-Rakam Testi (SDT) sonuçlarıyla ölçülmektedir. Bulgularımız, bilişsel beceriler ile istihdam olasılığı arasında anlamlı ve pozitif bir ilişki olduğunu ve bu ilişkinin cinsiyetler arasında belirgin farklılıklar gösterdiğini ortaya koymaktadır. Özellikle erkekler için bilişsel becerilerin getirisi sistematik olarak daha yüksektir. Bu sonuçlar, farklı tahmin yöntemleri kullanıldığında ve bilişsel becerilerin zamanla sabit ya da değişken biçimleri dikkate alındığında da tutarlılığını korumaktadır. Ayrıca, sosyal normlar ve bireysel farklılıklar gibi bu farklılıkları açıklayabilecek muhtemel mekanizmalar da tartışılmaktadır.

JEL Kodları: C23, I26, J24

Anahtar Kelimeler: Bilişsel Beceriler, İstihdam Durumu, Panel Veri Modelleri, Cinsiyet Farklılıkları

1. Introduction

Cognitive skills play an important role for different economic outcomes of individuals (e.g., Anger and Heineck, 2010; Bishop, 1989; Blau and Kahn, 1996; Carbonaro, 2007; Murnane et al., 1995; Hanushek and Woessmann, 2008; Heineck and Anger, 2010; Zax and Rees, 2002). The pertinent literature investigates the relationship between cognitive skills and labour market outcomes of individuals measured via labour force participation, as well as several other dimensions of labour supply and work-related outcomes (Lee and Newhouse, 2013; Lin et al., 2018). Cognitive skills capture different aspects of skills, including adapting to new environments, solving novel problems, and using complex reasoning, which operate in individuals' labour market activities (e.g. Protsch and Solga, 2015). People who score high on these skills may be more successful in the labour market, in holding their existing jobs or switching to more meaningful and satisfying ones (Bechichi et al., 2018; Glewwe et al., 2022). Yet, an under-investigated issue in this literature is how gender relates to labour market returns of cognitive skills.

Analysing gender differences in the returns to cognitive skills in labour supply helps understand labour market inefficiencies. Those inefficiencies can stem from gender division of labour (Chafetz, 1988; Iversen and Rosenbluth, 2006), feminisation of labour (Murphy and Oesch, 2016), and occupational segregation (Brooks et al., 2003; Busch, 2020; Fritach et al., 2022; Gedikli, 2020; Martin, 2005). These structural obstacles can contribute to discrimination in the hiring process (Baert et al., 2016), labour force participation gap (Castellano and Rocca, 2014), gender pay gap (Auspurg et al., 2017; Rotman and Mandel, 2023), motherhood penalty (Correll et al., 2007; Zamberlan and Barbieri, 2023), and glass ceiling (Collischon, 2019; Cukrowska-Torzewska and Mtysiak, 2020). There are several reasons to expect gender differences in the returns to cognitive skills in labour supply, particularly in terms of the employment premium. First of all, women might face discrimination in the labour market. Second, social norms or stereotypes related to the performance of women in occupations that require computational and analytical skills might lead to a lower return on cognitive skills. Finally, the types of education, occupational choice, and family roles of men and women might be related to varying returns on cognitive skills in the labour market.

This study utilises the Socio-Economic Panel (SOEP), a longitudinal dataset covering the past two decades. The dataset includes three waves of cognitive skill measurements, assessed through ultra-short surveys on intellectual performance (Lang et al., 2007). The primary measure of cognitive ability is based on the Symbol Digit Test (SDT), which evaluates fluid intelligence. This test is widely recognised as a valid and reliable proxy for cognitive skills (Lang et al., 2005, 2007). The measure is computed using within-person means and transformed into a time-invariant variable based on the assumption that intelligence remains relatively stable over time (Deary et al., 2000; Rönnlund et al., 2015). To estimate the relationship between cognitive skills and employment status, we employ a correlated random effects (CRE) model. The specification includes a rich set of time-variant controls to account for potential correlations between unobserved factors, cognitive skills, and other observed characteristics. Additionally, to mitigate endogeneity concerns, we incorporate alternative proxies to capture omitted variables. Drawing on the literature on non-cognitive skills and labour market outcomes, we control for locus of control (Hennecke, 2024). Further robustness checks include controls for self-esteem and life satisfaction, ensuring that unobserved personality traits do not drive the results.

The primary objective of this paper is to examine how gender interacts with cognitive skills in determining the employment premium and to explore the potential mechanisms driving gender differences in this premium. To achieve this, we first analyse how the returns to cognitive skills vary in relation to employment probability. Next, we investigate potential channels by incorporating various proxies that capture the roles of social norms (e.g., urban vs. rural residence, age groups) and family responsibilities (e.g., marital status, parenthood). Additionally, we assess the influence of past labour market experience to better understand its impact on the gendered employment premium. Estimation results show that cognitive skills, as measured by the SDT, are positively associated with employment probability and are highly statistically significant. This finding suggests that higher fluid intelligence is associated with a higher likelihood of employment. Second, a distributional analysis across cognitive skill levels indicates that the observed effects are primarily driven by individuals scoring around the mean. Among those in the first and fourth quartiles of the cognitive skills distribution, the gender difference in the employment premium is statistically imprecise, whereas for individuals in the second and third quartiles, gender differences become statistically significant. Third, the results indicate that the association between cognitive skills and employment premium is stronger for men than women, and this difference is highly statistically significant. Fourth, we find heterogeneous effects based on various demographic and socioeconomic characteristics, including age (young vs. old), household size, region of residence (East vs. West Germany, urban vs. rural), migration status (native vs. migrant), prior work experience, education level, and family characteristics (marital status, parental status). Notably, proxies related to social norms, such as region of residence and having children, are significantly associated with the magnitude of gender differences in employment premiums. Finally, the results remain robust across alternative estimators and model specifications, different definitions of the dependent variable, and model specifications incorporating an alternative set of control variables.

The paper is organised as follows. Section 2 outlines the conceptual framework. Section 3 reviews the related literature. Section 4 describes the data and econometric specification. Section 5 presents the baseline results, explores observed heterogeneity, and discusses the underlying mechanisms and robustness checks. Finally, Section 6 concludes.

2. Conceptual Framework

The literature builds on the standard labour supply model, in which individuals decide how much to work to maximise their utility. In this framework, individuals allocate their time between work and leisure, balancing their consumption needs with their preferences for leisure. According to the neoclassical model, an individual's consumption depends on their hourly wage, total hours worked, and any non-labour income they receive. We extend this model by introducing cognitive skills as a key source of heterogeneity in labour supply decisions. Specifically, we argue that individual characteristics influencing the work-leisure trade-off are systematically linked to cognitive abilities. Individuals with higher cognitive skills are expected to have greater consumption demands, as they may prioritise future financial stability and long-term investment in their well-being. This expectation is grounded in the neoclassical macroeconomic model of labour supply, which identifies wages as a primary determinant of labour market participation. Since empirical research consistently finds that cognitive skills are associated with higher earnings (e.g., Anger and Heineck, 2010; Heineck and Anger, 2010; Holzer and Lerman, 2015), individuals with more potent cognitive abilities may face higher opportunity costs for leisure. The prospect of foregoing high wages may incentivise people with higher cognitive skills to work more instead of choosing leisure.

Beyond economic considerations, cognitive skills may also shape intrinsic motivations related to labour supply. Individuals with higher cognitive skills may derive intellectual stimulation and personal satisfaction from work, reinforcing their preference for employment over leisure. Additionally, cognitive skills are closely linked to behavioural traits, such as patience and risk-taking tendencies (Bortolotti et al., 2021; Burks et al., 2009). More cognitively skilled individuals tend to be more patient and less prone to present bias, meaning they may place greater emphasis on future utility rather than immediate gratification. In contrast, individuals with lower cognitive skills, who are found to exhibit lower patience, may prioritise instant gratification, preferring leisure today over the delayed benefits of working and consuming later.

This paper utilises cognitive performance test scores from the two ultra-short cognitive performance tasks included in the SOEP. Drawing on life-span psychology, these tasks are designed to measure both the mechanics and pragmatics of cognition (Lang et al., 2007). The ultra-short surveys provide cognitive measures suitable for large-scale longitudinal studies and are implemented to capture core cognitive competencies. Their results are comparable to those obtained from more comprehensive cognitive tests (Lang et al., 2007). The internal validity and reliability of these measures have been well-documented (Lang et al., 2007). SDT assesses the mechanics of cognition, such as perceptual speed, while the Animal Naming Task (ANT) measures crystallised intelligence, particularly word fluency (Lindenberger and Baltes, 1994).[1] Fluid intelligence captures an individual's capacity to learn and adapt, whereas crystallised intelligence involves the application of accumulated knowledge. Educational attainment enhances crystallised intelligence, with measures often derived from achievement tests (Almlund et al., 2011).

In contrast, intelligence tests typically assess fluid intelligence (Almlund et al., 2011). For instance, a medical doctor relies on both forms of intelligence: crystallised intelligence for utilising medical knowledge in diagnosis and treatment, and fluid intelligence for developing adaptive responses during emergencies or unforeseen surgical complications. On the other hand, fluid intelligence is particularly valuable for entrepreneurs, as it underpins the ability to generate innovative ideas and navigate uncertain economic environments.

Gender differences in cognitive skills have been a long-standing area of research for decades (Hyde and Linn, 1988; Maccoby and Jacklin, 1972; Shields, 1975). The literature mainly focused on the differences in components of cognitive skills. Early studies posited that women outperform in verbal ability, whereas men excel in mathematical and spatial reasoning (Linn and Petersen, 1985; Maccoby and Jacklin, 1972). However, more recent research challenges these claims, arguing that men and women exhibit more similarities than differences in cognitive domains (Downing et al., 2008; Hyde, 2005; 2016; Lindberg et al., 2010; Spencer et al., 1999). The *Gender Similarities Hypothesis* (Hyde, 2005) posits that gender-based cognitive differences are minimal and inconsistent. In her meta-analysis of 46 studies, Hyde (2005) finds no substantial gender gap in reading comprehension and mathematical performance, a finding later supported by Lindberg et al. (2010), who analyse 242 studies and report no significant gender disparities in mathematical ability. Despite these findings, some recent studies also continue to document differences in specific cognitive components, particularly in spatial reasoning and quantitative skills, where men tend to perform better (Kaufman et al., 2009; Steinmayr et al., 2010; Wechsler et al., 2014).

The mechanism of how cognition is shaped has long been discussed in the literature, primarily within the nature versus nurture framework (Bouchard Jr., 2004;

[1] The literature uses various cognitive measures to analyse the effects of cognitive skills on labour market outcomes, including the Wechsler Adult Intelligence Scale, SAT scores, and the Armed Services Vocational Aptitude Battery (Almlund, 2011).

Kan et al., 2013; Plomin, 1997). Following the approach of Lin et al. (2018), we treat cognitive skills as fundamental abilities, abstracting from discussions about heritability and environmental influences, such as education or socioeconomic factors. This approach allows us to focus on the correlations between cognitive skills and labour market outcomes without attempting to disentangle the complex causal pathways that may underlie these relationships. Cognitive skills, primarily associated with abstract reasoning and problem-solving, are linked to higher adaptability, which in turn may be positively correlated with the likelihood of employment. Building on the existing literature on the effects of cognitive skills on the labour market, this study contributes by examining how cognitive skills are associated with employment probability while accounting for non-cognitive traits such as locus of control and self-esteem. Additionally, we investigate gender differences in employment premiums in Germany. We hypothesise that cognitive skills are positively associated with employment probability. Furthermore, we expect higher employment premiums for men compared to women. To explain this heterogeneity, we explore the role of socio-demographic factors and social-gender norms, assessing how these elements shape the relationship between cognitive skills and employment outcomes.

3. Related Literature

The literature on cognitive skills in economics primarily focuses on how the environment influences these skills (Plomin, 1997; Bouchard Jr., 2004; Kan et al., 2013) and their impact on economic outcomes (Heckman et al., 2006; Heineck and Anger, 2010; Glewwe et al., 2022). It also focuses on how cognitive skills relate to earnings (Anger and Heineck, 2010; Cawley et al., 2001; Leuven et al., 2004; Murnane et al., 1995), how the returns to cognitive skills differ internationally (Hanushek et al., 2017), and how those skills determine labour force participation (Lee and Newhouse, 2013). Cognitive skills, such as IQ, verbal ability, and numerical proficiency, have long been recognised as key determinants of labour market outcomes and are associated with positive returns in employment and earnings (Anger and Heineck, 2010; Autor, 2014; Chetty et al., 2011; Hanushek et al., 2017; Holzer and Lerman, 2015; Murnane et al., 1995; Glewwe et al., 2022). According to Mohanty (2010), females benefit more from an increase in the Armed Forces Qualification Test (AFQT) scores for employers' hiring decisions and workers' labour force participation decisions. Murnane et al. (1995) highlight the increasing labour market returns to cognitive skills in the United States. They report that the effect of a one-point increase in high school math scores on future wages is higher for females, even though skill improvements are greater for males. Using SOEP data, Anger and Heineck (2010) find a positive relationship between fluid and crystallised intelligence and earnings. However, they note that this association is weaker for crystallised intelligence. Men benefit more from an increase in fluid intelligence in terms of wage returns than women. Similarly, Bonikowska et al. (2008) examine the impact of cognitive skills on labour market returns in Canada and provide evidence on the sources of skill differences between natives and immigrants. Their findings suggest that the quality of education, mainly where skill formation occurs, plays a crucial role, with those who completed their education in Canada experiencing better labour market outcomes than those educated abroad. They further indicate that immigrant men are in a more disadvantaged position than immigrant women when both are compared with their Canadian-born counterparts.

Cognitive and non-cognitive skills shape labour market outcomes, including the hiring process and labour force participation. Protsch and Solga (2015) examine whether cognitive skill signalling affects the first hiring stage for male labour market entrants. Using school reports, they find that cognitive skills are a significant signal for employers, although non-cognitive skills play a more substantial role in hiring decisions. Beyond the hiring stage, numerous studies highlight the broader significance of non-cognitive skills in labour market participation (Lin et al., 2018; Segal, 2012). Hennecke (2024) finds that women with an internal locus of control are likelier to participate in the labour force than those with an external locus of control. Similarly, Mohanty (2010) concludes that a positive attitude toward life increases the probability of labour force participation. Mohanty (2010) suggests that positive attitudes affect both employers' hiring decisions and workers' participation decisions, while they significantly affect only participation decisions for females. Optimism affects only female hiring decisions.

An emerging body of research concentrates on how cognitive skills are associated with labour supply. Lee and Newhouse (2013) show that higher cognitive skills are associated with a lower probability of unemployment and a higher likelihood of higher-status occupations. The gender differences in enrolment, unemployment, wages, and working probability differ depending on the dataset used. Overall, women benefit more in terms of enrolment, whereas men enjoy lower unemployment probability in response to an increase in cognitive skills. Glewwe et al. (2022) report positive effects of cognitive skills on working as a salaried worker. They report insignificant gender differences in wage returns. Using data from the National Longitudinal Survey of Youth (1980–2014), Lin et al. (2018) hypothesise that individuals with higher cognitive skills work longer hours, and they examine how AFQT scores, measured at the end of secondary school, influence future labour market outcomes across different age groups and ethnicities in the U.S. Their findings indicate that returns to cognitive skills increase with age. They also report that higher cognitive skills are positively associated with annual work hours, though the effect varies significantly between men and women. Among men aged 30 to 50 years old, the effect of cognitive skills is positive and increasing, with the highest impact observed at 50. However, while the effect remains positive for women, the magnitude is the greatest at 30 and decreases through 50.

The labour market returns to education and cognitive skills are intertwined concepts, and the strand of literature dates to the 1970s. The literature often discusses the causal effect between schooling and cognitive skills (Carlsson et al., 2015; Heckman and Vytlacil, 2001). Crystallised intelligence is found to increase years of schooling (Schneeweis et al., 2014). Meanwhile, schooling also positively affects intelligence (Carlsson et al., 2015; Falch and Massih, 2010). Thus, cognitive skills should be taken into account when analysing the effect of education on economic outcomes, as omitted variables, such as school quality and different learning sources, are determinants of cognitive skills, and omitting cognitive skills causes distorted analysis and policy suggestions (Hanushek and Woessmann, 2008; Hanushek and Woesmann, 2012). Similarly, Heckman and Vytlacil (2001) note that not controlling for cognitive skills in analysing, i.e. labour market returns to education, can suffer from ability bias.

4. Data and Econometric Specifications

This study employs the SOEP, a rich longitudinal dataset covering 1984–2020. The dataset provides detailed information on various individual characteristics, including age, gender, health satisfaction, marital status, region of residence, and various non-cognitive skills measures. In the beginning, the SOEP operated for West Germany; right after the German reunification in 1990, it expanded its scope with East Germany. The dataset now includes almost 15,000 households covering both natives and migrants.

The estimation sample comprises migrants and German natives, with a focus on individuals aged 25 to 65. This selection is based on several considerations. First, we aim to mitigate confounding effects related to education. By restricting the sample to individuals aged 25 and older, we reduce the potential bias arising from the interaction between educational attainment and cognitive skills. Second, the age range aligns with the stability assumption of cognitive skills (Deary et al., 2000; Heineck and Anger, 2010; Rönnlund et al., 2015). The literature on the stability of cognitive skills suggests that cognitive skills exhibit temporal stability. While crystallised intelligence constantly increases until the 60s, it starts deteriorating afterwards (Lindenberger and Baltes, 1995). On the contrary, fluid intelligence is demonstrated to undergo distinct phases throughout a person's lifetime. It peaks in the mid-20s and begins to drop after the 40s (McArdle et al., 2000; Salthouse, 2004; Lindenberger and Baltes, 1995). Throughout time, different arguments on the stability of intellectual abilities have dominated the literature on the stability of cognitive skills. Initially, the prevailing notion was that general intelligence declined after early adulthood (e.g., Jones and Conrad, 1933). Following the seminal work of Bayley and Oden (1955), which focused on the maintenance of intellectual abilities in gifted adults, the prevailing idea was that intellectual abilities indeed continue to develop. Owens (1953), who conducted one of the first longitudinal studies in the 1950s, concluded that cognitive skills demonstrated temporal stability throughout adulthood. Later longitudinal studies reported a stable correlation between childhood and adult intelligence levels, especially between the ages of 18 and 65 (Deary et al., 2000; Rönnlund et al., 2015). Thus, our sample selection ensures that we capture individuals during the most stable phase of their cognitive abilities. On average, the dataset contains 122,325 observations, though the final sample size varies depending on the specific analysis. The exact number of observations is reported in the empirical analysis tables. To minimise confounding factors, we limit the analysis to 2003–2019. This restriction helps avoid distortions caused by the Hartz II labour market reforms, which introduced mini-jobs, and the COVID-19 pandemic, significantly affecting labour market conditions.

Our model includes a comprehensive set of individual determinants of labour supply, incorporating key factors such as health satisfaction (five dummy variables for very bad to very good health), age, years of schooling, marital status (five dummies for married, single, legally married but separated, divorced, and widowed), household size, number of children (aged between 0-1, 2-4, 5-7, 8-10, 11-12, 13-15, and 16-18 years old), partner's wage income, migration status (native vs. migrant), non-labour income (rent plus dividends), and region of residence (East vs. West Germany). The final dataset comprises 16,535 individuals, consisting of 7,726 males and 8,809 females.

The primary outcome variable in this study is employment status, defined as a binary variable indicating whether an individual is employed or not. It assigns a value of one to employed individuals and zero otherwise. Employment status encompasses both salaried and self-employed workers, applying to those who worked at least 52 hours in the previous year and reported positive wages. Since our focus is on individuals reporting positive weekly working hours, we classify those who reported zero weekly working hours as unemployed. This restriction ensures that our analysis focuses on regular employment rather than temporary or intermittent work. The goal is to examine how cognitive skills relate to the probability of sustained employment rather than short-term labour force participation.

In our sample, 51.8% of the employed are women. Females constitute 66.1% of the unemployed. Moreover, while 67.5% of females are employed, this rate is 79.1% for males. The average employment rate in the sample is 72,6%.

In this study, we utilise two ultra-short cognitive performance tasks from the SOEP. Specifically, we use the number of correct answers on the Symbol Digit Test (SDT), which measures perceptual speed and is based on the Symbol Digits Test

(Smith, 1973). This performance metric is the number of correct responses within 90 seconds (Lang et al., 2007). The second cognitive test in the survey, the Animal Naming Task (ANT), assesses word fluency, which is linked to crystallised intelligence. However, tests measuring crystallised intelligence, particularly word fluency, have been criticised for cultural dependency, making them less culture-fair (Cattell, 1963). The internal validity of the ANT is lower than that of the SDT, with a higher susceptibility to measurement errors due to the greater training required for interviewers (Lang et al., 2007). We focus only on SDT and exclude ANT from our analysis for two major reasons. First, since our sample includes both natives and migrants, the SDT is our primary measure of cognitive skills. Second, the number of observations, including those from ANT, is considerably insufficient, rendering the comparability of results impossible.

Respondents begin by reading short instructions before taking the SDT test. During the assessment, graphical symbols and corresponding numbers appear on the screen. Participants must quickly match the displayed symbol with the correct number (ranging from 1 to 9) using a computer keyboard. The total number of correct answers is recorded as the performance measure. The test automatically ends after 90 seconds, and the software calculates the number of correct responses. A screenshot of the test screen is provided in Appendix Figure 1. The SDT is available in three SOEP waves: 2006, 2012, and 2016. The total number of observations for the SDT is 18,708. To ensure consistency over time, we assume that cognitive skills remain stable, following the approach of Heineck and Anger (2010). To operationalise this assumption, we calculate individual means of the test scores for each respondent and take the natural logarithm of the values to account for potential nonlinear relationships between cognitive skills and employment probability.

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics by employment status and gender. The mean age in the sample is 45.09 years (s.d., 10.611). Women comprise 55.7% of the sample (s.d., 0.497). Marital status is also a key characteristic, with 66.4% of individuals being married (s.d., 0.472), and this proportion rises to 71.4% among employed men (s.d., 0.452). The average years of education in the sample is 12.34 years (s.d., 2.783), with employed women reporting the highest educational attainment. The mean weekly working hours is 26.21 (s.d., 20.037), with men working more hours per week than women. Working men report the highest monthly non-labour income on average (mean, 3,015.414, s.d., 25,606.655). Partner incomes are, on average, higher for women, particularly for employed women (mean, 2,540.968 and s.d., 3,680.282). This pattern may be attributed to assortative mating tendencies. Conversely, unemployed men have the lowest partner income (mean, 551.784 and s.d., 1,244.030). Regarding demographic composition, 77.7% of the sample are natives (s.d., 0.417), and 79.8% reside in Western Germany (s.d., 0.402). The mean SDT score is 30.83 (s.d., 9.074), with employed men scoring the highest, followed by employed women. The SDT scores exhibit a normal distribution across the sample. Furthermore, we conduct a t-test to determine the gender differences in each variable listed in the table. Most of the characteristics between genders exhibit statistically significant differences. Therefore, we control for those variables in our analyses.

Table 1. Descriptive Statistics

	Whole Sample	**Whole Sample**		**Employed (Employment Status=1)**		**Unemployed (Employment Status=0)**	
		Female	**Male**	**Female**	**Male**	**Female**	**Male**
Age in years	45.092	44.788	45.475	44.594	44.646	45.191	48.603
	(10.611	(10.530	(10.699	(9.547)	(9.888)	(12.316	(12.851
Gender (female = 1)	0.557	1.000					
	(0.497)	(0.000)					
Marital status	0.664	0.637	0.698	0.617	0.714	0.678	0.634
(married=1)1)	(0.472)	(0.481)	(0.459)	(0.486)	(0.452)	(0.467)	(0.482)
Household size	3.130	3.114	3.149	3.019	3.215	3.312	2.902
	(1.439)	(1.395)	(1.493)	(1.289)	(1.431)	(1.575)	(1.683)
Number of kids	1.033	1.050	1.011	0.951	1.059	1.256	0.832
	(1.208)	(1.190)	(1.229)	(1.071)	(1.191)	(1.382)	(1.348)
Years of education	12.335	12.325	12.348	12.739	12.677	11.465	11.105
	(2.783)	(2.716)	(2.865)	(2.695)	(2.853)	(2.555)	(2.549)
Working hours	26.211	20.145	33.834	29.841	42.795		
	(20.037	(17.767	(20.125	(13.351	(11.349		
Non-Labour Income	2,504.7	2,319.7	2,737.1	2,348.7	3,015.4	2,259.4	1,686.5
(annual)	(20782.	(18397.	(23436.	(18364.	(25606.	(18467.	(12089.
Partner Income	1,757.8	2,348.9	1,014.8	2,541.0	1,137.5	1,949.7	551.8
(monthly)	(2979.6	(3667.8	(1462.1	(3680.3	(1490.7	(3609.1	(1244.0
Migration Status	0.777	0.787	0.763	0.821	0.798	0.717	0.630
(native=1)	(0.417)	(0.409)	(0.425)	(0.383)	(0.401)	(0.450)	(0.483)
Living in West	0.798	0.797	0.799	0.806	0.819	0.779	0.722
Germany(=1)	(0.402)	(0.402)	(0.401)	(0.396)	(0.385)	(0.415)	(0.448)
Symbol Digit Test	30.828	30.715	30.969	31.446	32.011	29.195	27.036
(SDT)	(9.074)	(8.840)	(9.357)	(8.550)	(9.007)	(9.231)	(9.608)
#Observations	122,325	68,122	54,203	45,988	42,853	22,134	11,350

Note: Standard deviations are in parentheses. We conduct a t-test between the mean differences of the groups and find that our variables (at the mean) are statistically different from each other at the 1% significance level, except for education (for the whole sample), living in West Germany (for the whole sample) and age (among the employed).

4.2. Econometric Specifications

We employ a binary choice model within a random utility framework, which can be estimated with a logit model. However, we use a linear probability model (LPM) within a CRE framework to allow flexible functions of unobserved heterogeneity, which can correlate with cognitive skills. This specification is justified for several reasons beyond its simplicity. First, the random effects model assumes that there is no correlation between the explanatory variables and individual-specific effects, a restriction that is often considered unrealistic. Second, a fixed effects approach is infeasible, as our stability assumption for cognitive skills prevents identification. As an alternative, we adopt a CRE model, which accounts for potential correlation between individual characteristics and explanatory variables. This is achieved by including the individual means of time-varying independent variables (e.g., partner's wage or number of children) in the model, following Mundlak's (1978) formulation.

$$Emp_{it} = 1\left(\theta_1 ln(CS_i) + \theta_2 D_i^{Gender} + \theta_3 ln(CS_i) D_i^{Gender} + X'\gamma + \epsilon_{it} > 0\right) \quad (1)$$

$$\epsilon_{it} = State_s + T_t + \eta_i + \varepsilon_{it} \quad (2)$$

In Equations (1) and (2), i and t represent the individual and year, respectively. Cognitive skills are denoted by CS_i and assumed to be time-invariant. We apply a log transformation to the cognitive skills variable to capture potential diminishing returns of cognitive skills on employment probability. The term D_i^{Gender} is a gender dummy, which takes the value 1 for females and 0 for males. The coefficient θ_1 represents the main effect of cognitive skills, while θ_2 captures the main effect of gender. To capture gender differences, we introduce an interaction term rather than splitting the sample by gender. This approach ensures comparability by allowing gender differences to be examined within a single estimation framework. We then estimate the interaction effect using post-estimation techniques and report the results. The interaction term, represented by θ_3, accounts for gender differences in the effect of cognitive skills on employment probability. The matrix X contains the control variables, and the corresponding vector of coefficients is denoted by γ. Additionally, we control for state-fixed effects (State_s) and time-fixed effects (T_t). η_i represents individual-specific effects, while the final term corresponds to the error term. η_i is assumed to be normally distributed, and to allow correlation between η_i and observed characteristics X, we allow for the within-person means of time-variant variables, including age, health satisfaction, household size, number of kids, non-labour income and partner income.

In Equations (1) and (2), cognitive skills might be endogenous. To deal with the potential omitted variables problem, we control for the locus of control (LOC), which refers to an individual's perception of the extent to which they control their own life. Conceptualised by Rotter (1996) and adapted for SOEP using the Rotter Scale (Kara and Zimmermann, 2023), the LOC scale was created by Nolte et al. (1997) and has been included in SOEP surveys since 1999. This study uses four waves of locus of control information—2005, 2010, 2015, and 2020—to capture short- and medium-run changes. The scale consists of two subcategories: internal and external locus of control. Following Cobb-Clark and Schurer (2013), we assume that locus of control is relatively stable in the short- and medium-run and compute individual means for each respondent. Individuals with a high internal locus of control believe they are responsible for their own actions. In contrast, those with a high external locus of control attribute life events to external forces beyond their control. We also take the natural logarithm of these variables and include them in our set of control variables. To check this point further, we also control for a time-invariant self-esteem measure in our robustness analysis, which reflects an individual's self-perception and confidence, which can correlate with cognitive abilities. The measure is obtained with the responses to the statement: "I have a positive attitude toward myself," measured on a seven-point ordinal scale (ranging from "does not apply to me" to "applies to me perfectly"). Finally, we add the life satisfaction measure obtained using the following question: "How satisfied are you with your life in general?" The answers are obtained on an eleven-point scale (ranging from "completely unsatisfied" to "completely satisfied").

5. Empirical Results

5.1. Main Results

Cognitive Skills and Employment Probability: Table 2 presents the main results. We first start with the model specification without interaction.[2] These results are given in the upper part of the table. In all specifications, the number of observations is 122,325. The results are obtained from the correlated random effects linear probability model, which includes all within-means of time-variant variables. All specifications (Columns I- IV) include the whole list of socio-demographic and -economic characteristics. These include gender, age, and age squared, years of schooling, health satisfaction (five dummies representing very bad health to very good health), a native dummy, non-labour income (rents and dividends), and living in West Germany. In the following columns, we add characteristics related to household structure (Column II, marital status, household size, number of kids, and

[2] To be brave, we only show the key results. The full estimation results are provided in Appendix Table 1.

partner's income), region of residence and time dummies (Column III), and non-cognitive skills (Column IV, internal and external LOC) to get initial sensitivity checks. As expected, a positive and highly statistically significant association exists between cognitive skills and employment status. The results suggest that, across the specifications (Column I-IV), a ten per cent increase in SDT scores is associated with a 0.95 to 1.27 percentage point increase in employment probability, on average. Adding these key variables or any combination of within means in the correlated random effects specification does not significantly affect the estimation results.

Gender Differences: Having presented the average association between cognitive skills and employment probability, we estimate our interaction model specification in the lower part of Table 2. The baseline model includes an interaction term that aims to investigate gender differences. Our baseline results suggest that there is a significant gender premium on the employment probability by cognitive skills. The basic model in Column I indicates that the average association (0.127) is heterogeneous, with an estimate of 0.097 for females and 0.157 for males. The difference between the estimated coefficients (the interaction term in Equation 1, θ_3) is highly statistically significant (p-value<0.001).

Table 2. Cognitive Skills, Gender, and Employment Probability

Dependent Variable: Employment Status	(I)		(II)		(III)		(IV)	
Without Interaction								
SDT	0.127	***	0.119	***	0.109	***	0.095	***
	(0.008)		(0.008)		(0.008)		(0.008)	
R-Squared	0.172		0.214		0.220		0.227	
With Interaction: Baseline								
Female × SDT	0.097	***	0.092	***	0.081	***	0.069	***
	(0.011)		(0.011)		(0.011)		(0.010)	
Male × SDT	0.157	***	0.147	***	0.136	***	0.122	***
	(0.011)		(0.011)		(0.011)		(0.011)	
p-value	**0.000**		**0.000**		**0.000**		**0.000**	
R-Squared	0.172		0.215		0.221		0.227	

Note: Column (I) includes only socio-demographic characteristics (without household characteristics), while Column (II) incorporates household characteristics including marital status (five dummies of married, single, married but separated, widowed, and divorced), household size, number of kids (aged 0-1, 2-4, 5-7, 8-10, 11-12, 13-15, and 16-18), and log of partner's income. Column (III) further adds time and year dummies, and Column (IV) additionally controls for non-cognitive skills (internal and external LOC). Robust standard errors in parentheses. *** significant at 1%; ** significant at 5%; * significant at 10%.

The results suggest that the association between cognitive skills and employment probability is stronger for males than for females. As we discussed above, gender roles might be important in this difference, which can initially reflect through marital status, having kids, and partner's income. Yet, Column II suggests that the gender difference is about the same. Adding region and time dummies does not significantly affect the results. Finally, to capture potential omitted variables, we add the internal and external LOC (Column IV). The magnitude of the estimates is significantly lower for both females (0.081 vs. 0.069) and males (0.136 vs. 0.122). We note that the difference between the estimated coefficients is about the same across all specifications, and they are statistically significant with a p-value<0.001.

5.2. How Can We Explain the Differences?

We now estimate models to capture the observed heterogeneity in the gender differences across various dimensions, including the distribution of cognitive skills, age, marital status, parenthood, geographic location (urban vs. rural areas), migration status, past work experience, and education level. To capture the heterogeneity of the gender differences across these observed characteristics, we employ a double interaction model incorporating a heterogeneity measure, a gender dummy, and cognitive skills (in log). Our full sample consists of 122,325 observations. The model specifications include the same variables in Column IV of Table 2. The results are obtained from the correlated random effects linear probability model as in the main results. The results of the heterogeneity analysis are given in Table 3. We present the baseline results (Column IV, Table 2) in the first row to compare the results.

We start with a distributional analysis of the cognitive skills distribution quartiles. We first generate three dummy variables indicating those individuals in the first quartile of the cognitive skills distribution (Q1, $n = 31, 940$), second and third quartiles combined (Q2+Q3, $n = 62, 325$), and the fourth quartile (Q4, $n = 28, 060$). Our findings reveal a concave relationship, suggesting that cognitive skills have a concave association with employment probability at the highest cognitive levels. The gender difference is absent among people who score low (Q1) on the SDT scale. The significant gender difference occurs among people around the centre of the distribution (Q2+Q3). While cognitive skills positively affect employment probability, they are statistically imprecise for females (for Q2+Q3 and Q4). Yet, the estimated coefficient is very large for males, and the difference between the coefficients for females and males is highly statistically significant (p-value=0.002). Notably, we find that cognitive skills negatively relate to employment probability among individuals who score very high (Q4) on the SDT scale. The negative coefficient is statistically significant only for men. We do not observe a gender difference among these people.

Overall, we find no significant disparities at the tails of the distribution. In low-skilled jobs, factors other than gender, such as physical job requirements or careoriented occupations, may play a more significant role in hiring decisions. For blue-collar jobs, physical demands may outweigh cognitive skills, while horizontal occupational segregation may prevent men and women from competing for the same positions. However, significant gender differences emerge for individuals scoring around the mean. Social norms and cultural factors may be more influential for this group, which constitutes 50% of the population in a normally distributed cognitive skill variable. Vertical occupational segregation likely plays a crucial role, with women in this category more vulnerable to discrimination.

At the upper end of the distribution, cognitive skills may mitigate the effects of vertical occupational segregation. Women with high cognitive ability may pursue different career paths, while employers hiring for cognitively demanding roles may prioritise merit over gender. Credentials might be correlated with decreased gender discrepancies in these fields. For individuals with the highest cognitive skills, employment patterns may differ significantly from the general labour market. Many may opt for academia or self-employment, delaying labour market entry to pursue further education. Individuals in standard jobs may experience job dissatisfaction due to a skill mismatch, which can lead to unemployment or job transitions. Consequently, for this end of the distribution, gender differences in employment premiums become statistically insignificant, as men and women compete under similar conditions. At this level, men may derive fewer advantages from occupational segregation.

We now employ a double interaction model specification, incorporating dummy variables for several dimensions of heterogeneity rather than splitting the sample by different levels of these variables. First, we create a dummy for past working experience, which takes a value of one if an individual's work experience is greater than or equal to the sample median (12.4 years) and zero otherwise. Among individuals with high past work experience, gender differences in employment premiums from cognitive skills become statistically insignificant (Row 2). In contrast, for those with lower past work experience, the results remain similar to the baseline. This suggests that individuals may be leveraging their cognitive skills more efficiently, which in turn helps mitigate gender differences in employment probability. To explore heterogeneity in educational attainment, we generate a dummy variable that equals one for individuals with years of schooling at or above the sample median (11.5 years) and zero otherwise. In both high- and low-education groups, gender differences remain significant, with men benefiting more from cognitive skills than women in both cases (Row 3). However, the gender gap is smaller among individuals with higher education.

Table 3. Observed Heterogeneity in the Gender Differences

	Female ⨉ SDT (a)		Male ⨉ SDT (b)		Ho : a=b p-	R-Squared	
Baseline	0.069	***	0.122	***	**0.000**	0.227	122,325
	(0.010)		(0.011)				
Distribution of Cognitive Skills							
Q1	0.052	**	0.061	***	0.751	0.253	31,940
	(0.020)		(0.021)				
Q2 + Q3	0.074		0.280	***	**0.002**	0.205	62,325
	(0.047)		(0.048)				
Q4	-0.070		-0.136	*	0.505	0.191	28,060
-	(0.069)		(0.073)				
High (Past) Working Experience	0.088	***	0.111	***	0.105	0.232	122,020
	(0.011)		(0.011)				
Low (Past) Working Experience	0.068	***	0.116	***	**0.001**		
	(0.010)		(0.011)				
High Education ⨉ …	0.068	***	0.128	***	**0.000**	0.229	122,325
	(0.011)		(0.011)				
Low Education ⨉ …	0.052	***	0.128	***	**0.000**		
	(0.011)		(0.011)				
Older ⨉ …	0.099	***	0.127	***	**0.061**	0.176	122,325
	(0.013)		(0.013)				
Younger ⨉ …	0.086	***	0.142	***	**0.000**		
	(0.012)		(0.013)				
Native ⨉ …	0.046	***	0.094	***	**0.001**	0.227	122,325
	(0.012)		(0.012)				
Migrant ⨉ …	0.106	***	0.150	***	**0.003**		
	(0.014)		(0.015)				
West ⨉ …	0.052	***	0.110	***	**0.000**	0.228	122,325
	(0.011)		(0.011)				
East ⨉ …	0.128	***	0.172	***	**0.002**		
	(0.017)		(0.018)				
Rural Areas ⨉ …	0.090	***	0.139	***	**0.001**	0.227	122,325
	(0.015)		(0.015)				
Urban Areas ⨉ …	0.060	***	0.112	***	**0.000**		
	(0.012)		(0.012)				
Married ⨉ …	0.048	***	0.127	***	**0.000**	0.234	122,325
	(0.012)		(0.012)				
Others ⨉ …	0.084	***	0.122	***	**0.007**		
	(0.014)		(0.014)				
Having Kids (Yes) ⨉ …	0.056	***	0.110	***	**0.000**	0.225	122,325
	(0.012)		(0.012)				
Having Kids (No) ⨉ …	0.098	***	0.104	***	0.669		
	(0.013)		(0.013)				

Note: Q1, Q2, Q3, and Q4 stand for the quartiles of cognitive skills distribution. The models are separately estimated for distributional analyses. All other results are estimated with the double interaction of the respective dummy, gender dummy, and cognitive skill measure. All specifications are correlated random effects linear probability model. Standard deviations are in parentheses. *** significant at 1%;** significant at 5%; * significant at 10%. See notes under Table 2.

Next, a dummy is generated to capture age differences. The variable takes a value of zero for individuals aged 45 (median age) or older (Row 4). Our findings indicate that gender differences are statistically significant across both age groups, though the gap is narrower among older individuals. There might be several explanations for this finding. First, this may reflect that older individuals use their cognitive skills more efficiently. Second, the demand-side factors can be at play as cognitive skill signals could be more influential among younger new entrants to the labour market.

We then examine heterogeneity between natives and migrants using a native dummy, which equals one for natives and zero for migrants. The results indicate statistically significant gender differences (Row 5). Overall, migrants receive a greater employment premium from cognitive skills than natives, though the gender gap remains similar in magnitude. However, among natives, men benefit from cognitive skills more than twice as much as women.

Social norms may vary by geographic location. Given that Eastern Germany was part of the German Democratic Republic (GDR) before reunification in 1990, historical differences in labour market participation may persist. Our results indicate statistically significant gender differences in both regions (Row 6). Women in the West receive lower employment premiums than in the baseline specification, while men in the West benefit almost twice as much as women. Interestingly, both men and women in the East obtain higher employment premiums than men in the baseline. However, interpretation requires caution, as 80% of our sample resides in the West. While the gender gap in employment probability remains, it is smaller in the East, as women in the West receive higher employment premiums than men in the baseline.

To further examine the role of social norms, we analyse heterogeneity based on urban versus rural residence. We generate a dummy variable for rural areas, which equals one if an individual resides in a rural area and zero otherwise (Row 7). The results indicate a higher employment premium for cognitive skills in rural areas, with a larger gender gap in urban areas. This pattern may be attributed to occupational composition. Rural labour markets may offer fewer job options, with occupations that are more gender-neutral compared to urban settings. Additionally, cognitive skills may mitigate gender disparities in areas where traditional gender norms are more deeply embedded.

Social norms might also relate to marital status and parental responsibilities. We define a marital status dummy, which equals one if an individual is married and zero if they are single, divorced, widowed, or separated. Similarly, the parent dummy equals one for individuals with children aged 0–18 and zero for those without children or with children older than 18. The results indicate significant gender differences across both marital status and parental status (Row 8 and Row 9). Married men experience the highest employment premium from cognitive skills, while gender differences are less pronounced among unmarried individuals. Fathers benefit from an increase in cognitive skills nearly twice as much as mothers, with a statistically significant gender gap. However, for individuals without children, gender differences in returns to cognitive skills become insignificant, suggesting that childcare responsibilities are related to the variation of how cognitive skills are linked to employment probability for mothers. These findings provide strong evidence for the role of gender norms in shaping the relationship between cognitive skills and employment outcomes.

5.3. Robustness

Table 4 presents several dimensions of robustness checks, including estimators, dependent variables, sample selections, and additional control variables. We first examine the sensitivity of our results to different estimation methods. We estimate the pooled OLS and logit models. The pooled OLS results, presented in the first panel of Table 4, align with our baseline with some minor differences in magnitudes. Men receive nearly twice the employment premium from cognitive skills as women, with statistically significant coefficient estimates and gender differences. Given that our dependent variable is binary, we also report estimates from a pooled logit regression. The interaction parameter estimates (average marginal effects) from the pooled logit model yield similar results to those of the baseline.

Next, we test the robustness of our findings by analysing alternative dependent variables using different labour supply measures in Rows 3-5 of Table 4. First, we examine the probability of being a salaried employee, redefining employment status by assigning self-employed individuals a value of zero in the employment status dummy. The results stay the same as in the baseline dependent variable. We then use an alternative employment status variable, replacing the weekly working hours threshold with annual working hours while correcting inconsistencies in self-reported employment status. The results remain similar, with coefficients of larger magnitude.

To investigate the stability assumption of cognitive skills, we restrict the sample to those waves (2006, 2012, and 2016) in which the cognitive skills are observed (Row 6). We then estimate the correlated random effects linear probability model with these three years. In this model specification, we assume that the cognitive skills are time-variant with six-year intervals. As the within variation is very low and there are significant time gaps between waves, the fixed effect linear probability model is not possible to estimate. The correlated random effects model suggests that the baseline results are robust. There is a significant gender premium in employment based on cognitive skills. To investigate the impact of sample selection on the results, we restrict the sample to observations between 2006 and 2016, as shown in Row 7 of Table 4. The results remain robust. Additionally, we narrow the sample to align with the International Labour Organization (ILO, 2011) definition of the labour force, excluding individuals in education, early retirement, or the military. The results remain unchanged regarding significance and gender differences, though coefficient magnitudes increase.

Table 4. Robustness

	Employment Status (Baseline)				p-value	R-Squar	#Obs
	Fem		Male				
Estimators							
OLS	0.04	***	0.091	***	**0.00**	0.240	122,32
	(0.00		(0.00				
Logit	0.02	***	0.111	***	**0.00**	0.211	122,32
	(0.00		(0.00				
CRE with Three Waves (2006, 2012,	0.06	***	0.108	***	**0.00**	0.292	18,708
	(0.01		(0.01				
Dependent Variable							
Salaried Employee=1	0.06	***	0.121	***	**0.00**	0.231	113,80
	(0.01		(0.01				
Full-Time=1	0.03	***	0.143	***	**0.00**	0.283	116,68
	(0.01		(0.01				
Employment Status (with annual	0.08	***	0.110	***	**0.06**	0.209	122,32
	(0.01		(0.01				
Different Sample Selection							
Year Selection: 2006-2016	0.06	***	0.136	***	**0.00**	0.227	82,304
	(0.01		(0.01				
In Labour Force	0.07	***	0.118	***	**0.00**	0.198	113,83
	(0.01		(0.01				
Different Controls and Proxies for Omitted							
Full-Time Work Experience	0.05	***	0.132	***	**0.00**	0.249	122,02
	(0.01		(0.01				
Life Satisfaction	0.06	***	0.119	***	**0.00**	0.232	122,25
	(0.01		(0.01				
Positive Attitudes	0.06	***	0.114	***	**0.00**	0.211	110,86
	(0.01		(0.01				

Note: Pooled logit estimates are the average marginal effects. The salaried employee variable excludes the self-employed. A full-time dummy takes the value of one when the weekly working hours are 35 hours or more and zero otherwise. Employment status in Row 5 is defined in terms of annual working hours instead of weekly working hours. Row 8 includes people who are currently in the labour force (excluding those in education, early retirement, or the military). Standard deviations are in parentheses. *** significant at 1%; ** significant at 5%; * significant at 10%.

Finally, to investigate the potential bias due to endogeneity concerns, we introduce additional controls and proxies which function as omitted variables in our model specifications. To this end, we first control for the full-time work experience, which might correlate with both cognitive skills and employment probability. The results in Row 9 suggest that the gender difference increases, and the difference is highly statistically significant. In Row 10, we control for the life satisfaction measure, which can capture the overall stress and anxiety level of workers due to labour market circumstances. The baseline model with life satisfaction produced highly similar results. Finally, we account for self-esteem, which can independently relate to higher employability, correlating with cognitive skills. Yet, Row 11 suggests that differences are only slightly lower. The gender difference in employment probability by cognitive skills remains the same.

6. Conclusion

This study investigates the association between cognitive skills and employment probability across genders. The dataset in use is a long panel (SOEP) spanning two decades, featuring a rich set of cognitive skill measures collected in three waves. Using alternative model specifications and estimators, we show that the cognitive skills measured via the Symbol Digit Test correlate with labour market returns among men and women in a heterogeneous manner. Conditional on individuals' socio-demographic and economic characteristics, we find a robust result that the return is higher on average for men. Yet, the result is found to be related to cognitive skill distribution and social norms, which affect women more than men. A rich heterogeneity analysis suggests that the return differences might be explained by labour market irregularities faced by both genders.

The results in this paper have important implications. First of all, labour market policies should focus more on how to equalise the gender disparities in the correlation between cognitive skills and employment probability. Second, societal norms differentially affecting the labour market activities of men and women should be investigated in future research. A key implication of this paper is that there is a diminishing marginal return on cognitive skills in terms of employment probability. Our results suggest equal returns among individuals who scored at the two extremes of the SDT scores distribution, those without children, and those with higher past work experience. The baseline employment premiums are observed by those who score around the centre of cognitive skill distribution. Finally, the paper also has important limitations. Firstly, as the analysis is based on observational data and standard econometric models (i.e. linear probability correlated random effects and logit estimations), the findings should be interpreted as statistical associations rather than causal effects. Secondly, although the econometric models we use allow for the correlation between the explanatory variable and time-variant individual effects, there can still be concerns about endogeneity that generate bias. As highlighted by Hampf et al. (2017), potential identification problems may arise due to measurement error (attenuation bias) and reverse causality between employment and cognitive skills. Even though we control for non-cognitive skills, such as internal and external locus of control, as baseline control variables, and life satisfaction and self-esteem for our robustness analysis, our measure of cognitive skills might still be endogenous due to unobserved time-invariant factors, such as parental investment. Third, the data includes only partial proxies for cognitive skills. A natural direction for future research should be to combine experimental methods with tailored cognitive skill measures to identify causal relationships.

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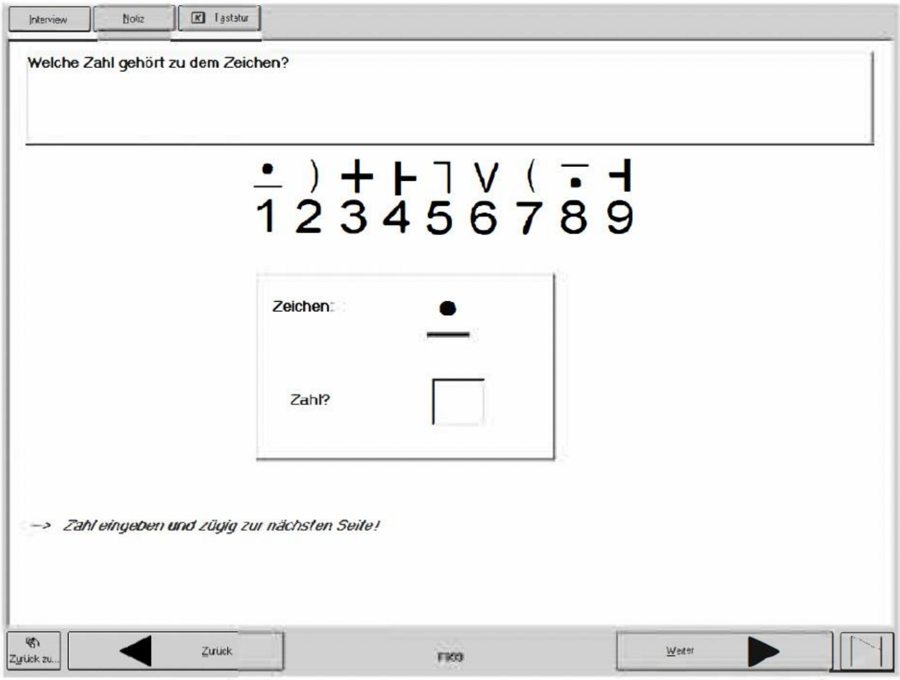
Appendix

Appendix Figure 1. Screenshot of the CAPI version of the SDT (Lang et al.,



2007)

Note: See Lang et al. (2007) for detailed information.

Appendix Table 1. Full Estimation Results

Dependent Variable: Employment Status					
Age	0.079	***	**Health: Very good (c)**	0.067	***
	(0.0020)			(0.0075)	
Age squared	-0.001	***	**Health: Good**	0.083	***
	(0.0000)			(0.0070)	
Native	0.114	***	**Health: Satisfactory**	0.080	***
	(0.0067)			(0.0070)	
Region of Residence (west=1)	0.001		**Health: Poor**	0.060	***
	(0.0182)			(0.0070)	
Marital S. Widowed (a)	0.000		**Non-labour income**	0.006	***
	(0.0168)			(0.0006)	
Marital S. Divorced	0.026	***	**Internal Locus of Control (log)**	0.023	
	(0.0079)			(0.0174)	
Marital S. Single	0.016	**	**External Locus of Control (log)**	0.199	***
	(0.0070)			(0.0134)	
Marital S. Separated	-0.009		**Constant**	-2.584	***
	(0.0091)			(0.0875)	
Partner Wage Income (log)	0.003	***	**Female × SDT**	0.069	***
	(0.0004)			(0.0105)	
#Kids(0–1) (b)	-0.264	***	**Male × SDT**	0.122	***
	(0.0079)			(0.0108)	
#Kids(2–4)	-0.091	***			
	(0.0055)		**R2-overall**	0.227	
#Kids(5–7)	-0.047	***	**#Observations**	122,325	
	(0.0049)				
#Kids(8–10)	-0.043	***			
	(0.0045)				
#Kids(11–12)	-0.035	***			
	(0.0045)				
#Kids(13–15)	-0.031	***			
	(0.0041)				
#Kids(16–18)	-0.019	***			
	(0.0037)				
Household size	-0.005	*			
	(0.0031)				
Years of education	0.050	***			
	(0.0053)				

Note: ***, **, and * indicate significance levels at 1%, 5%, and 10%. The models are estimated by correlated random effects. (a) Omitted category is "married". (b) Omitted category is "not having any child". (c) Omitted category is "very poor health". Year and month dummies are included. Robust standard errors are in parentheses. The model includes the full set of the variables including time and year dummies and individual means of all time-variable variables.