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Abstract

Using matched PISA and PIAAC data from Denmark, we investigate the return to cognitive and non-cognitive skills with respect to labor market outcomes. We measure cognitive and non-cognitive skills at childhood and when the respondents have entered the labor market. Hence, we are able to split up the analysis contingent on cognitive and non-cognitive skills measured before entering the labor market. In this way we can measure both whether cognitive and/or non-cognitive skills relate to earnings and employment rate as well as how important the timing of acquiring skills are for outcomes on the labor market. Overall we find that cognitive skills are important for both earnings and employment rate but that the timing of the acquisition of the skills is of less importance. On the contrary, non-cognitive skills are important for earnings independent on whether the worker had high or low cognitive skills at childhood, but only important for employment rate for workers with high cognitive and low non-cognitive childhood skills. Overall our findings suggest that both cognitive and non-cognitive skills are important but that the dynamics differ.

Keywords: Cognitive skills, non-cognitive skills, earnings, employment, PIAAC, PISA

JEL codes: J21, J24

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1 Introduction

A natural point of departure when describing a worker's labor market career is to assess the rate of employment and earnings. However, to comprehend the underlying structures of labor market outcomes, we need to understand the determinants of these structures. This paper investigates how, contingent on childhood skills, post labor market entry cognitive and non-cognitive skills relate to labor market outcomes.

Ever since the seminal works of Mincer (1958), Becker (1962), Ben-Porath (1967) and others it has been known that earnings and employment rate correlate well with human capital measured by educational attainment, experience accumulation, and tenure. A later literature argues that cognitive skills contribute most to the explanation of the formation of earnings (e.g. Herrnstein and Murray (1994)) while others find non-cognitive skills to play at least as big a role as cognitive skills in the formation of labor market outcomes (Heckman, Stixrud, and Urzua (2006)). In the recent years, another expanding literature has emerged which analyzes the formation of cognitive and non-cognitive skills and their subsequent influence on labor market outcomes (Cunha and Heckman (2007), Cunha and Heckman (2008), and Heckman et al. (2006)). However, it still remains an open question whether cognitive skills dominate non-cognitive skills in the formation of labor market outcomes or it is the other way around. Lately, there has been studies trying to close this gap (see e.g. Mueller and Plug (2006) and Lindqvist and Vestman (2011)). This paper expands the literature by investigating the relation between cognitive/non-cognitive skills and labor market outcomes. We measure cognitive/non-cognitive skills both at childhood and post labor market entry. This strategy enables us to split up the relationship between labor market outcomes and contemporary skills contingent on cognitive and non-cognitive skills at childhood - i.e. before entering the labor market. In this way we can measure both whether cognitive and/or non-cognitive skills relate to earnings and employment rate as well as how important the timing of skill acquisition is.

We derive post labor market entry cognitive and non-cognitive skills from the

Programme for the International Assessment of Adult Competencies (PIAAC). Labor market outcomes are recorded from administrative registers, measured by earnings and a dummy for whether the worker has been employed for at least five weeks during the year. Our sample consists of workers who have participated in both PIAAC in 2011/2012 and OECD's *Programme for International Student Assessment* (PISA) in 2000. Thus, we can measure not only cognitive and non-cognitive skills of our sample in 2011/2012, but also condition on childhood cognitive and non-cognitive skills in 2000. This particular feature delivers a unique opportunity to estimate return to cognitive and non-cognitive skills when at the labor market conditional on childhood cognitive and non-cognitive skills.

Two challenges arise when evaluating the return to cognitive and non-cognitive skills. First, a definition of and distinction between cognitive and non-cognitive skills is desirable. As discussed by Borghans, Duckworth, Heckman, and Weel (2008), the economic literature tends to equate non-cognitive skills with personality traits and juxtapose cognitive and non-cognitive skills. Borghans et al. (2008) point out that, despite of the intuitive appeal, the definition and the distinction can potentially be confusing as *"... few aspects of human behavior are devoid of cognition"*. We recognize this overlap and provide detailed descriptions of our measures of both cognitive and non-cognitive skills and relate them to measures used in the existing literature. Second, cognitive and non-cognitive skills are latent variables and hence not observed by the econometrician. The literature has handled this by using directly observable proxy variables or by eliciting measures of the latent variables.[1] We follow the latter measuring cognitive skills by using estimates of workers' reading ability (measured both at childhood and adulthood). Our measures of non-cognitive skills are formed using exploratory factor analysis. The non-cognitive skills measured at childhood relate to the workers' perseverance while the latter measure is capturing how much the worker enjoys learning.

To the best of our knowledge, this paper is the first to combine PISA scores from childhood with PIAAC scores from the early stages of a worker's working life

[1] E.g. DellaVigna and Paserman (2005) use information on having a bank account as a measure of the non-cognitive skill patience.

and adding register based labor market outcomes. Doing so we are able to extract important relations between cognitive and non-cognitive skills at childhood, investigate how they affect cognitive and non-cognitive skills, and study their implications for labor market outcomes. We find that the combination of cognitive and non-cognitive skills is important for the formation of labor market outcomes. Specifically, we show that while cognitive skills are important for earnings the timing of the acquisition of those cognitive skills might be less so.

The rest of the paper is organised as follows: Section 2 presents the data and our measures of cognitive and non-cognitive skills while Section 3 provides descriptive statistics. Our estimation strategy is presented in Section 4 while estimation results are presented in Section 5. Finally, Section 6 concludes.

2 Data

This paper uses combined survey data and register data from Denmark. The survey data consists of data from the Organisation for Economic Co-operation and Development's (OECD) *Programme for International Student Assessment* (PISA) from 2000 (OECD (2001), Andersen, Egelund, Jensen, Krone, Lindenskov, and Mejding (2001)) combined with data from the OECD *Programme for the International Assessment of Adult Competencies* (PIAAC) from 2011/2012 (OECD (2013a), Rosdahl, Fridberg, Jakobsen, and Jørgensen (2013)). The PIAAC sample is a subsample of the PISA sample and the interviews took place from November 2011 to April 2012. The contents of the two surveys differed and hence, we are only able to construct comparable but not identical measures across the waves. Using unique person identifiers, we are able to match the survey data with register data from Statistics Denmark using the Integrated Database for Labor market research (IDA).[2]

[2]Integrerede Database for Arbejdsmarkedsforskning in Danish. A description of the database can be found at www.dst.dk/da/Statistik/dokumentation/Times/ida-databasen.aspx.

2.1 Cognitive Skills

As Humlum, Kleinjans, and Nielsen (2012) we measure cognitive skills using PISA and PIAAC test scores in reading. Both surveys measure *literacy* and as discussed in Rosdahl (2014), the definitions of literacy are similar in PISA and PIAAC. In both surveys literacy relates to being able to read and understand texts with the purpose of being able to participate in everyday life, develop knowledge and understanding and achieve personal goals (Rosdahl (2014)). OECD (2013b) also finds that the definitions are highly comparable and that the measurements rely on the same concepts and methods. The main difference between the two measures relates to the age differences in the two populations. Another apparent difference between the two measures is the scales. PISA measures literacy on a scale form 0 to 1,000 while PIAAC uses a scale from 0 to 500. However, the difference has no practical importance as we standardize the measures.

The PISA and PIAAC reading scores are provided in the data as plausible values. In addition, the PISA reading score is also provided as a mean weighted likelihood estimate (WLE). As we only use the PISA reading score to divide the sample above and below the median, we rely on the WLE. The reason for providing plausible values and not a single variable is that reading proficiency is measured with uncertainty at the individual level. The plausible values take this individual level uncertainty into account and are draws from a latent skill distribution for each observation (Wu (2005)). Estimation using variables provided as plausible values in the control set requires non-standard software. We use the `REPEST` package provided by the OECD for Stata (Avvisati and Keslair (2015)).

2.2 Non-cognitive Skills

The measures of non-cognitive skills are derived using data collected along with the PISA and PIAAC literacy tests. In PISA the respondents answered a Student Questionnaire and a Cross-Curricular Competencies Questionnaire (CCCQ) while the respondents answered a Background Questionnaire (BQ) in PIAAC. We conduct explorative factor analyzes on the data from the CCCQ and the BQ.

Table A1 presents the 28 items from the CCCQ question battery one. All items are questions on the form *How often do these things apply to you?* with the response categories *totally disagree, partly disagree, both/and, partly agree and totally agree.* Table A2 presents the number of observations and Cronbach's α overall and whether each item is left out one at a time. In addition, the table presents the results of an initial explorative factor analysis. The factor analysis is carried out following the method described by Truxillo (2005). In short, the method utilizes information from all observations despite potential missing data. Notice, we conduct the factor analyzes using the full PISA-PIAAC sample.

Three factors satisfy the Kaiser criterion of an eigenvalue larger than one and are thus retained. To avoid cross loading across items, the factor analysis is carried out again including only items with rotated factor loadings higher than 0.5 and cross loadings below 0.3. The results of these subsequent factor analyzes are presented in Table A3. The wording of the items comprised by each factor give inspiration to naming the factors. Hence, the factors are named *self-confidence*, *perseverance* and *future orientation*, respectively.

The goal of forming measures of non-cognitive skills using the associated survey data is to obtain measures predicting labor market outcomes. Psychology has a long tradition of using personality traits models to capture information on non-cognitive skills. An example of such a personality trait model is the five-factor model also denoted the *Big Five* model (Digman (1990)).[3] A widely used version of the five-factor model is the Revised NEO Personality Inventory (NEO-PI-R) describing personality using the traits/factors openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (Costa and McCrae (1992)). The personality traits are broken down into facets and the facets of e.g. conscientiousness (using the NEO-PI-R) are competence, order, dutifulness, achievement striving, self-discipline and deliberation. As pointed out by MacCann, Duckworth, and Roberts (2009), "*conscientiousness has been linked to a myriad of positive outcomes*" but also that different versions of the five-factor model define conscientiousness differently. Using

[3]The Big Five model has found its way into the economics literature. An example is Cobb-Clark and Tan (2011) using the Big Five to measure non-cognitive skills and predict occupational attainment.

conscientiousness items from different models MacCann et al. (2009) uncovers eight facets of conscientiousness including a facet denoted perseverance.

Our PISA-based measures of non-cognitive skills do not have a direct correspondence with traits or facets from the five-factor model. Nevertheless, we think of our measure of perseverance as in relation with, or family to, conscientiousness. Since we only use PISA measures to divide out sample, for simplicity, we disregard the factors denoted self-confidence and future orientation and focus solely on perseverance.

The PIAAC survey includes a Background Questionnaire in which the respondents are, among other things, asked about their attitudes towards new ideas and learning new things. The items are presented in Table B1 and as before an exploratory factor analysis is conducted to condense the data into fewer variables. The results are presented in Table B2. Cronbach's α suggests keeping all items and the factor analysis results in one factor satisfying the Kaizer criterion. Given the wording of the items, the retained factor is named *enjoy learning*.

We think of our PIAAC-based measure of non-cognitive skills as related to the personality trait named Typical Intellectual Engagement (TIE). Cognitive skills are typically based on a measure of maximum intellectual engagement. An example is IQ tests but also our measures of cognitive skills based on the PISA and PIACC reading scores are measures of maximum intellectual engagement. Goff and Ackerman (1992) suggest a distinction between maximum intellectual engagement and typical intellectual engagement. The distinction is motivated by a long-lasting effort in psychology to understand the link between personality and intelligence. An example is Johnson, Nagoshi, and Ahern (1983) trying to link 27 personality scales to different WAIS-measures (Wechsler Adult Intelligence Scale). Goff and Ackerman (1992) argue that typical intellectual engagement gives a clearer understanding of the personalty-intelligence link. In relation to the five-factor model, TIE is linked to openness to experience.

Table 1 displays the measures of cognitive and non-cognitive skills derived from the two OECD surveys. Whereas the measures of cognitive skills are comparable, the measures of non-cognitive skills are more diverse. The PISA and PIAAC surveys

Table 1: Measures of cognitive and non-cognitive skills

Survey	**Type of factor**	**Name**
PISA	Non-cognitive	Perseverance
	Cognitive	Reading score (PISA)
PIAAC	Non-cognitive	Enjoy learning
	Cognitive	Reading score (PIAAC)

do not include the same batteries of questions and hence, the present measures are, on one hand, the art of the possible. As discussed above, we obtain a measure from PISA comparable to conscientiousness from the five-factor model while we obtain a measure from PIAAC comparable to openness (again from the five-factor model) and TIE. On the other hand findings in psychology suggest that all three measures are good predictors of academic performance (Premuzic, Furnham, and Ackerman (2006); von Stumm, Hell, and Chamorro-Premuzic (2011). von Stumm et al. (2011) go as far as denoting *intellectual curiosity* the third pillar of academic performance with intelligence and conscientiousness/effort as the first two. Hence, we find our measures highly relevant with respect to predicting labor market outcomes for young adults.

2.3 Register Data

We might suspect that if we regressed labor market outcomes solely on cognitive and non-cognitive skills we would end up allocating more explanatory power to them than what could actually be observed. If e.g. workers with high non-cognitive skills are also more prone to have a qualifying education, then the estimated return to non-cognitive skills might be upward biased if we did not control for having a qualifying education. We therefore merge the survey data with administrative labor market register data (IDA).

IDA is a matched employer-employee longitudinal administrative database containing socio-economic information on the entire Danish population, the population's attachment to the labor market, and at which firms the worker is employed. Both workers and firms are registered from 1980 onwards. The reference period in IDA is given as follows; The linkage of workers and firms refers to the end of

November, ensuring that seasonal changes (e.g. shutdown of establishments around Christmas) do not affect the registration, meaning that the creation of jobs in the individual firms refers to the end of November. Since the PIAAC data are collected primo 2012 and the register data are recorded ultimo 2012, the timing between explanatory variables and outcomes is not a concern. The data are confidential but our access is not exclusive. Following the literature on earnings and employment rate we include information of a personal character - the gender of the worker, and whether he or she is cohabiting with a partner or not - educational attainment (measured by having completed a qualifying education or not - defined as having completed a vocational degree, a bachelor degree or above) and lastly labor market experience, defined by the years of actual employment.

2.4 Trimming the Sample

Since we will be measuring labor market outcomes we cannot use the entire sample that participated in both PISA and PIAAC as some of these will still be in the educational system in 2012 and thus have not yet entered the labor market. However, to avoid biasing our factors, we estimate our measures of cognitive and non-cognitive skills on the full population. I.e. they are estimated before we exclude the workers who are still in the education system at the time of our labor market measure. In this way we ensure that if e.g. all the highly skilled readers are excluded from the sample, we will not be manually assigning the low skilled readers as highly skilled readers. After estimating the latent factors, we exclude all that have not yet entered the labor market in 2012 (591 individuals). Due to lack of PISA cognitive and non-cognitive skills for 2 and 76 individuals respectively, these have also been excluded. Moreover we have trimmed the sample by excluding 2 workers for whom we do not observe a non-cognitive measure from the PIAAC survey. Table 2 shows the process of trimming the sample, leading to a final sample size of 1,210 workers of which 92 workers have zero earnings. I.e. when estimating the employment rate, the sample consists of 1,210 workers and when estimating earnings, due to the log transformation, we are restricted to a sample of 1,118 workers.

Table 2: Overview of the sample selection

Corrections	Observations excluded/not used	Sample size
Joint PISA/PIAAC sample		1,881
Have not yet entered the labor market	591	1,290
No measure of cognitive skills in PISA	2	1,288
No measure of non-cognitive skills in PISA	76	1,212
No measure of non-cognitive skills in PIAAC	2	1,210
Outcomes		
Employment status not observed	0	1,210
Earnings equal to zero	92	1,118
Final analysis sample		**1,210**

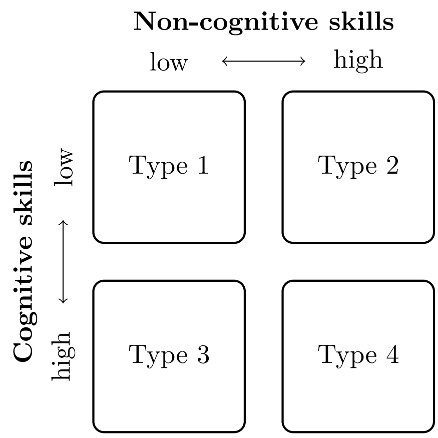
2.5 Worker Types

Figure 1 depicts four types of workers that we split our sample into. Type 1 workers are those who scored below the median in both the cognitive and non-cognitive dimensions. I.e. they are characterized by having relatively low reading skills and low non-cognitive skills. Economic theory would predict type 1 workers to fare worse than other types in terms of earnings and maybe also employment rate. Type 4 workers, on the other hand - those with above median skills in both dimensions - are expected to excel at the labor market compared to the other types. Economic theory would, however, have difficulties at specifying an unambiguous expectation towards worker of type 2 and 3. It is therefore interesting to investigate whether workers with low cognitive but high non-cognitive skills do better than workers with high cognitive and low non-cognitive skills on the labor market.

By applying the classification of worker types to skills acquired at childhood and also after labor market entry we gain important knowledge. Not only can we characterise the importance of cognitive versus non-cognitive skills but we can also analyze the importance of the timing of acquisition of skills.

The worker type framework deployed with respect to the skills measured in PISA can also be used with respect to skills measured in PIAAC. Again type 1 refers to an observation with low cognitive and non-cognitive skills while type 2 refers to a person with low cognitive skill and high non-cognitive skills etc. If childhood skills perfectly identify adulthood skills - i.e. if we observe complete persistence

Figure 1: Worker types depending on cognitive and non-cognitive skills



in PISA/PIAAC types - then grouping worker types in the way we do would be redundant. On the contrary, if there is no association between childhood types and adulthood types, then we would be concerned that allocation to a worker type would be random. To test for this concern, Table 3 presents a cross-tabulation of the PISA and PIAAC types with Pearson's χ^2 test for independence. Illustrated by the adjusted residuals in brackets, the table shows evidence of clustering on the diagonal indicating persistence in types across the years rejecting randomness of allocation to childhood type.[4] We also see that although there are too few off-diagonal entries in order for the type allocation to be random, there are still considerable mass in order to reject perfect dependence between childhood types and adulthood types.

3 Descriptives

We present summary statistics on our samples in Table 4 for the entire sample and for each of the four worker types. On average each worker earns 276,000 DKK during 2012 - conditional on having positive earnings the average earnings become 299,000 DKK.[5] Splitting this into each worker type, we see that type 1 and 2 are comparable and type 3 and 4 are comparable and earn more than type 1 and 2.

[4]Adjusted residuals are given by $\frac{\text{observed}-\text{expected}}{\sqrt{\text{expected}\cdot(1-\text{row proportion})\cdot(1-\text{col. proportion})}}$.

[5]This corresponds roughly to 49,000-54,000 USD.

Table 3: PISA and PIAAC worker types

		PISA			
		Type 1	Type 2	Type 3	Type 4
PIAAC	Type 1	170	135	48	48
		[6.87]	[4.31]	[-5.38]	[-6.69]
	Type 2	89	112	36	54
		[0.43]	[5.60]	[-4.11]	[-2.31]
	Type 3	50	29	91	88
		[-4.05]	[-6.08]	[6.40]	[4.50]
	Type 4	49	38	78	95
		[-4.28]	[-4.71]	[4.07]	[5.57]

Notes The PIAAC types are based on the average of the 10 plausible values. P-value: 0.000 (Pearson's χ^2-test). Adjusted residuals in brackets.

Table 4: Average outcomes and explanatory variables

	All	Type 1	Type 2	Type 3	Type 4
Outcomes					
Earnings	276,213	256,714	258,219	300,651	298,836
	(144,949)	(149,865)	(142,602)	(143,086)	(136,919)
Earnings (earnings > 0)	298,942	285,415	282,511	319,599	314,274
	(126,253)	(129,465)	(123,968)	(125,252)	(121,857)
Employment rate	0.849	0.830	0.822	0.870	0.884
	(-)	(-)	(-)	(-)	(-)
Explanatory variables					
PIAAC based					
Cognitive skills	-0.151	-0.487	-0.547	0.323	0.317
	(0.969)	(0.927)	(0.900)	(0.802)	(0.837)
Non-cognitive skills	-0.106	-0.260	-0.104	-0.121	0.100
	(1.001)	(1.067)	(1.063)	(0.899)	(0.894)
PISA based					
Cognitive skills	-0.103	-0.731	-0.789	0.744	0.690
	(0.955)	(0.693)	(0.667)	(0.548)	(0.488)
Non-cognitive skills	0.005	-0.782	0.805	-0.806	0.835
	(0.987)	(0.514)	(0.608)	(0.518)	(0.633)
Register based					
Woman	0.502	0.408	0.475	0.553	0.604
	(-)	(-)	(-)	(-)	(-)
Cohabiting	0.616	0.595	0.624	0.625	0.625
	(-)	(-)	(-)	(-)	(-)
Experience	5.119	6.040	5.657	4.110	4.264
	(2.856)	(2.852)	(2.843)	(2.657)	(2.510)
Qualifying education	0.828	0.796	0.803	0.854	0.874
	(-)	(-)	(-)	(-)	(-)
N	1,210	358	314	253	285

Notes Earnings are in units of 1,000 DKK. Employment rate is a dummy for being employed for at least five weeks during 2012. Numbers in parentheses denote standard deviations (left out for dummy variables).

This suggests that childhood cognitive skills might be more important for labor market earnings than childhood non-cognitive skills. Table 4 also shows that this observation is reflected in only somewhat higher employment probabilities among type 3 and 4 compared to type 1 and 2, indicating that wages might be higher for those with higher childhood cognitive skills.[6] Furthermore, it is seen that workers of type 3 and 4 are more likely to be female with less work experience but higher probability of having a qualifying education compared to workers of type 1 and 2.

Figure 2 shows average earnings and employment rate during 2012 for combined quintiles of PIAAC cognitive and non-cognitive skills. There is a positive relationship between the combination of high levels of cognitive and non-cognitive skills and earnings during 2012. Overall, the surface shape is slightly steeper in cognitive skills than it is in non-cognitive skills, although workers in the fifth quintile of the non-cognitive skills distribution seem to have the highest average earnings in total. Splitting the sample into the four worker types reveals that the average earnings differences from Table 4 go through the entire distribution of cognitive and non-cognitive skills for all worker types. We see a similar pattern, only slightly steeper, for the employment rate where it is the combination of high cognitive and non-cognitive skills that follows higher average employment rates.

4 Model and Estimation

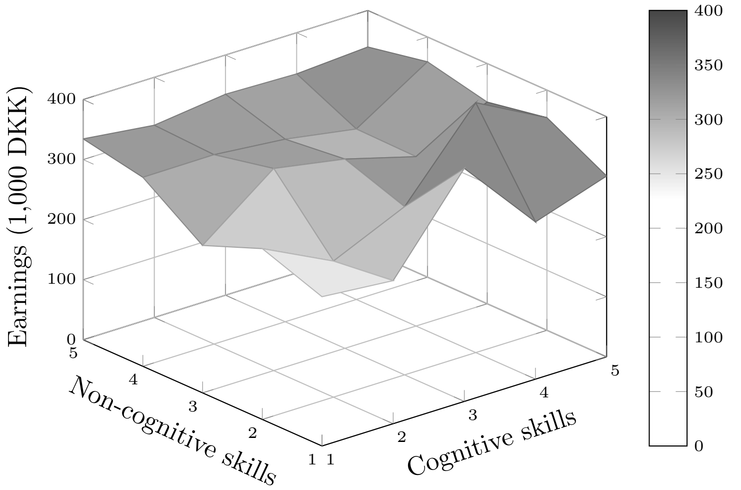
Consistent with the literature on the return to cognitive and non-cognitive skills on labor market outcomes, we model labor market outcomes as a function of cognitive skills, non-cognitive skills, and human capital. I.e.

$$Q_j = f_j(\theta_{ct}, \theta_{nt}, \theta_{ht}), \quad j \in \{\text{earnings, employment rate}\}.$$

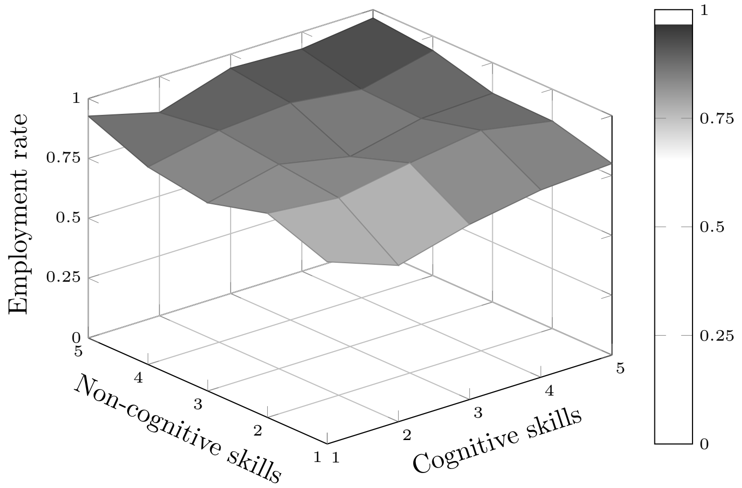
with Q_j being labor market outcomes, and θ_{ht} contains human capital characteristics. θ_{ct} is cognitive skills and θ_{nt} is non-cognitive skills both measured in the PIAAC. Following the literature we model $f_{\text{earnings}}(\cdot)$ and $f_{\text{employment rate}}(\cdot)$ as a lin-

[6]Earnings conditional on being employed are (in thousands) 315, 299, 304, 335, and 329 for all and type 1-4 respectively.

Figure 2: Level of earnings and employment rate for quintiles of PIAAC cognitive and non-cognitive skills



(a) Earnings



(b) Employment rate

ear and logistic function of cognitive skills, non-cognitive skills, and human capital, respectively. To ensure flexibility we later also add squared versions of cognitive and non-cognitive skills as well as an interaction term.

5 Results

In this section we present our results on how cognitive and non-cognitive skills at childhood affect labor market outcomes as a young worker. Log earnings are used as outcome in Section 5.1 while employment rate is used as outcome in Section 5.2.

5.1 Earnings

The first labor market outcome we consider is log earnings and our estimation results are provided in Table 5. Column 1 and 2 present the estimates of the return to cognitive and non-cognitive skills without and with controls, respectively. We see that the return to both cognitive and non-cognitive skills are significantly positive and even increases when adding the controls. The formation of cognitive and non-cognitive skills are likely to take place through a process where the two affect each other through dynamic complementarities. If cognitive skills are affected by non-cognitive skills, then the estimate of return to cognitive skills in an estimation including non-cognitive skills might be misleading. To assess the bounds of the estimates to cognitive and non-cognitive skills, column 3 and 4 present the results with only one skill measure at the time. Comparing column 1 with 3 and 4 thus reveals upper bounds on the return to cognitive and non-cognitive skills, respectively. The differences between the point estimates in column 1 are not statistically significantly different from the upper bounds found in columns 3 and 4. In column 5 we present results where squared skills have been added allowing for a more flexible relationship between cognitive and non-cognitive skills and log earnings. The overall return to both cognitive and non-cognitive skills is concave on their supports reaching the maximum values at the upper end and at the value 1 for cognitive and non-cognitive skills, respectively.

Since we believe that cognitive and non-cognitive skills at childhood affect the return to cognitive and non-cognitive skills on labor market outcomes, we show estimates for each of the four worker types in Table 6. We saw in Table 4 that earnings were on average higher for workers of type 3 and 4 (high childhood cognitive skills) than for workers of type 1 and 2 (low childhood cognitive skills). Table 6 shows comparable estimates of the impact of adulthood non-cognitive skills on log earnings across worker types, but that adulthood cognitive skills are only significant for workers with low childhood cognitive skills. This result indicates that cognitive skills are important for earnings but the timing of the acquisition of those cognitive skills might be less important.

Table 5: Estimated effect of cognitive and non-cognitive skills on log earnings

	(1)	(2)	(3)	(4)	(5)
Cognitive skills	0.108***	0.135***	0.124***		0.118***
	(0.025)	(0.024)	(0.024)		(0.026)
Non-cognitive skills	0.105***	0.115***		0.121***	0.082***
	(0.026)	(0.025)		(0.026)	(0.020)
Cognitive skills sq.					-0.012
					(0.023)
Non-cognitive skills sq.					-0.033
					(0.032)
Cognitive×Non-cognitive					-0.053*
					(0.031)
Constant	5.557***	4.875***	5.549***	5.547***	4.946***
	(0.020)	(0.131)	(0.020)	(0.020)	(0.149)
Controls	No	Yes	No	No	Yes
R^2	0.046	0.141	0.026	0.026	0.153
Observations	1,118	1,118	1,118	1,118	1,118

Notes All regressions are estimated using ordinary least squares and dependent variable log earnings. The conditioning set used as controls consist of dummy for being a woman, dummy for cohabitation, years of experience, years of experience squared and a dummy for having a qualifying education or not.
***, **, * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

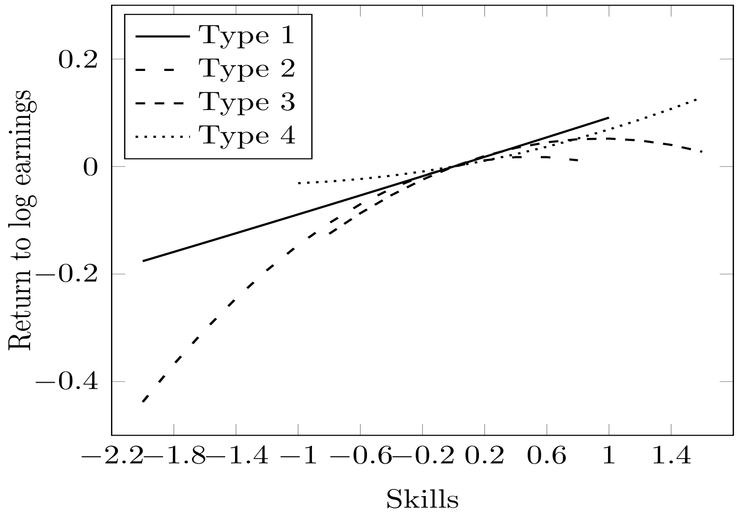
Table 6: Estimated effect of cognitive and non-cognitive skills on log earnings

	Type 1	Type 2	Type 3	Type 4
Cognitive skills	0.088*	0.160**	0.069	0.068
	(0.048)	(0.069)	(0.068)	(0.066)
Non-cognitive skills	0.098**	0.157**	0.073**	0.098*
	(0.039)	(0.073)	(0.037)	(0.058)
Constant	4.957***	4.947***	4.996***	4.406***
	(0.263)	(0.304)	(0.179)	(0.291)
Controls	Yes	Yes	Yes	Yes
R^2	0.157	0.133	0.144	0.229
Observations	322	287	238	271

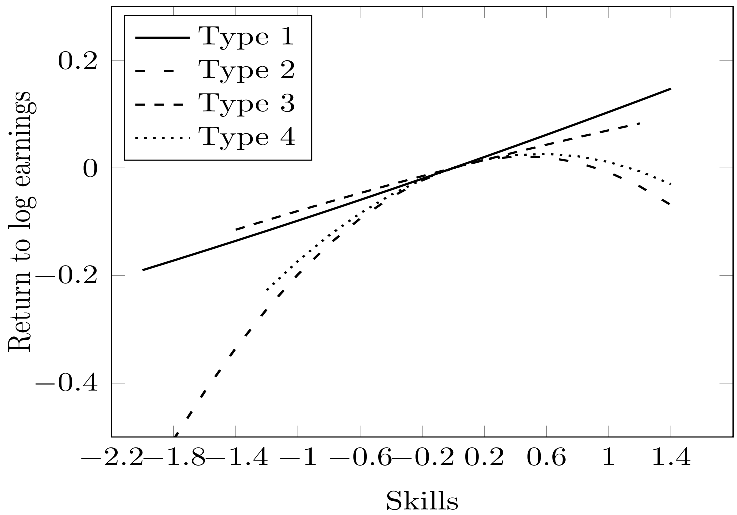
Notes All regressions are estimated using ordinary least squares and dependent variable log earnings during 2012. The conditioning set used as controls consist of dummy for being a woman, dummy for cohabitation, years of experience, years of experience squared and a dummy for having a qualifying education or not.
***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively.

Taking the estimates of the return to cognitive and non-cognitive skills at face value, we can plot them conditional on the skill levels. Figure 3 shows the returns to cognitive and non-cognitive skills on earnings for each worker type. The support of skills for each worker type is cut below and above at 5% and all returns are normalized to pass through origo. Workers of type 1 (those with low levels of childhood cognitive and non-cognitive skills) follow a linear path with higher returns for higher skills (both cognitive and non-cognitive). I.e. for workers with low levels of childhood cognitive and non-cognitive skills, the acquisition of adulthood cognitive and/or non-cognitive skills comes with positive returns to earnings. Type 2 workers gain higher returns to earnings for low levels of both cognitive and non-cognitive skills, but have a diminishing path for high levels of cognitive and especially non-

Figure 3: Return to cognitive and non-cognitive skills on earnings



(a) Cognitive skills



(b) Non-cognitive skills

Notes The returns to cognitive and non-cognitive skills are estimated using OLS on earnings with cognitive and non-cognitive skills included both in levels and squared together with controls and a constant.

cognitive skills. This indicates that workers with low levels of cognitive and high levels of non-cognitive skills measured at childhood gain by acquiring cognitive and non-cognitive skills up to some threshold. Thus, there is an upper level of the return to skills. This level is more pronounced for adulthood non-cognitive skills than for adulthood cognitive skills, which comes natural, as this worker type is characterized by having low levels of childhood cognitive skills but high levels of non-cognitive skills. The opposite worker type, those of type 3 (i.e. high levels of cognitive skills and low levels of non-cognitive skills at childhood), has different return to earnings. Their return to adulthood cognitive skills is very limited while they follow a linear increasing path in the return to non-cognitive skills. As for worker type 2, this group exhibits that both cognitive and non-cognitive skills are important for adulthood earnings, but the timing of the acquisition seems to be of less importance. Finally, workers of type 4 have increasing returns to cognitive skills but a concave return to non-cognitive skills.

5.2 Employment Rate

Table 7 presents results from logit estimations with employment rate as the dependent variable. The parameter estimates are presented as exponentiated parameters and can hence be interpreted as odds ratios. As pointed out by Ai and Norton (2003), presenting marginal effects might be misleading for logit models if interaction terms are included, as the marginal effects of the interaction terms are not necessarily equal to the marginal interaction effects. Hence, we present the estimation results as exponentiated coefficients. Note that the exponentiated parameter estimates for the interactions must be interpreted as multiplicative effects in relation to some baseline odds (Buis (2010)).

In column 1 we include only the PIAAC-based measures of cognitive and non-cognitive skills in the control set along with a constant. All parameter estimates are significant at the 5% level. As the skill measures have been standardized, the baseline odds of 6.219 are the odds of being employed (versus not being employed) for a person with average cognitive and non-cognitive skills. Moving e.g. one standard deviation in the distribution of cognitive skills changes the baseline odds by (moving down) $1.503^{-1} \cdot 6.219 = 4.138$ and (moving up) $1.503^{1} \cdot 6.411 = 9.347$. Hence, having cognitive skills one standard deviation above the average versus one standard deviation below the average increases the probability of being employed by a factor of $9.347/4.138 = 2.259$.[7]

In column 2 the remaining control set is added among the cognitive and non-

[7] Which is equivalent to the ratio of the parameter estimates to the power of the change in cognitive skills $1.503^{1}/1.503^{-1} = 2.259$.

Table 7: Estimated effect of cognitive and non-cognitive skills on employment rate

	(1)	(2)	(3)	(4)	(5)
Cognitive skills	1.503***	1.647***	1.549***		1.740***
	(0.122)	(0.176)	(0.125)		(0.246)
Noncognitive skills	1.238**	1.278***		1.310***	1.439***
	(0.104)	(0.114)		(0.111)	(0.150)
Cognitive skills sq.					1.008
					(0.092)
Noncognitive skills sq.					1.066
					(0.073)
Cognitive×Non-cognitive					1.131
					(0.104)
Baseline odds	6.219***	0.772	6.003***	5.598***	0.724
	(0.647)	(0.224)	(0.598)	(0.514)	(0.224)
Controls	No	Yes	No	No	Yes
Observations	1,210	1,210	1,210	1,210	1,210

Notes All regressions are estimated using logit regressions with dependent variable being the dummy of having more than five weeks of employment during 2012. Estimates are presented as exponentiated coefficients and can hence be interpreted as odds ratios. The conditioning set used as controls consist of dummy for being a woman, dummy for cohabitation, years of experience, years of experience squared and a dummy for having a qualifying education or not.
***, **, * indicates statistical significance at the 1%, 5%, and 10% level, respectively.

cognitive skill measures (parameter estimates not shown). The baseline odds drop as it is the baseline given all co-variates equal to zero. In the control set years of experience (both in level and squared) is included which is a strong predictor of employment. Having a qualifying education is also usually found to predict employment and hence, the drop is not surprising. More interesting is the stability of the estimates to cognitive and non-cognitive skills. This indicates that the skill measures capture elements not caught by the the more traditional covariates. As both cognitive and non-cognitive skills have been standardized, the estimates show that the return to cognitive skills is higher than the return to non-cognitive skills in terms of employment probability.

As discussed regarding the return on earnings, we also need to assess the bounds of the estimates of the return to cognitive and non-cognitive skills. Column 3 and 4 thus present the results with only one skill measure at the time. In both columns the estimates are higher numerically (but not significantly different) than the estimates presented in column 1. Column 5 presents estimation results with squared skill measures and an interaction between the skill measures in levels. While the estimates to cognitive and non-cognitive skills in levels remain significant, the estimates to the squared skills measures and the interaction are insignificant.

Table 8 presents the employment rate estimations by worker type. As was the

Table 8: Estimated effect of cognitive and non-cognitive skills on employment rate

	Type 1	Type 2	Type 3	Type 4
Cognitive skills	1.706**	1.411*	1.252	1.660
	(0.434)	(0.263)	(0.399)	(0.597)
Non-cognitive skills	1.156	1.232	1.918**	1.069
	(0.205)	(0.225)	(0.482)	(0.197)
Baseline odds	0.398	0.754	0.679	1.451
	(0.227)	(0.361)	(0.522)	(1.127)
Controls	Yes	Yes	Yes	Yes
Observations	358	314	253	285

Notes All regressions are estimated using logit and dependent variable the dummy of having more than 4 weeks of employment during 2012. Estimates are presented as exponentiated coefficients and can hence be interpreted as odds ratios. The conditioning set used as controls consist of dummy for being a woman, dummy for cohabitation, years of experience, years of experience squared and a dummy for having a qualifying education or not.
***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively.

case regarding earnings, we see that workers of type 1 and 2 have statistically significant returns to cognitive skills while only workers of type 3 have statistically significant returns to non-cognitive skills. I.e. workers with low childhood cognitive skills gain in terms of a higher employment rate by acquiring cognitive skills in adulthood. Likewise, workers with high cognitive and low non-cognitive skills in childhood are the only group that gains employment by acquiring non-cognitive skills in adulthood. Comparing worker type 1 and 3 it is remarkable that type 1 does not benefit from non-cognitive skills like type 3. This indicates that cognitive skills are a prerequisite for positive returns to non-cognitive skills with respect to employment. For workers with high childhood cognitive and non-cognitive skills, worker type 4, there is no significant returns of neither adulthood cognitive nor non-cognitive skills. Employment is a dichotomous outcome, and hence it seems reasonable that cognitive and non-cognitive skills do not affect the already well-endowed workers. In comparison, return to cognitive skills with respect to earnings for worker type 4 was not capped as shown in Figure 3(a).

We see the same overall pattern in employment rate as we did for earnings, that cognitive skills are important for labor market outcomes, but the timing of the acquisition of them is of minor importance. With respect to non-cognitive skills we do see a somewhat different pattern: Cognitive skills are a prerequisite for returns to non-cognitive skills and the returns to non-cognitive skills are not significant when the workers are already well-endowed.

6 Conclusion

Using combined PISA, PIAAC and register data from Denmark, we investigate the return to cognitive and non-cognitive skills with respect to labor market outcomes. The respondents were around age 15 and 27 in PISA and PIAAC, respectively, while the labor market outcomes were measured ultimo of the (last) year of the PIAAC survey. We measure cognitive skills by reading scores available in both PISA and PIAAC while we construct measures of non-cognitive skills using exploratory factor analyzes. From PISA we use the associated Cross-Curricular Competencies Questionnaire while we use the Background Questionnaire from PIAAC. Our measures are the best available given the data and we argue they resemble (facets) of conscientiousness and typical intellectual engagement both known from the psychology literature.

We use two register based outcomes: Log earnings and the employment rate. With respect to earnings we find that the PIAAC-based cognitive and non-cognitive skills are equally important while cognitive skills are more important than non-cognitive skills with respect to employment. As we are interested in the formation of cognitive and non-cognitive skills and their subsequent influence on labor market outcomes we distinguish between four worker types. The worker types are given by the possible combinations of high/low cognitive and non-cognitive skills measured at childhood (i.e. in PISA). The by-type analyzes suggest that the timing of the acquisition of cognitive skills is of less importance when it comes to earnings. With respect to employment we overall find the same pattern. Cognitive skills are important for employment but the timing of the acquisition is of less importance. One difference seems to be that cognitive skills are a prerequisite for positive returns to non-cognitive skills, though.

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A PISA 2000 CCCQ

Table A1: PISA 2000 – Cross-curricular Competencies Questionnaire (CCCQ)

No.	Variable
Q. 1	**How often do these things apply to you?**
	(Almost never, sometimes, often, almost always)
1	When I study, I try to memorise everything that might be covered
2	I'm certain I can understand the most difficult material presented in texts
3	When I study, I start by figuring out exactly what I need to learn
4	When I sit myself down to learn something really difficult, I can learn it
5	When I study, I memorise as much as possible
6	I study to increase my job opportunities
7	When studying, I work as hard as possible
8	I'm confident I can understand the most complex material presented by the teacher
9	When I study, I try to relate new material to things I have learned in other subjects
10	When I study, I memorise all new material so that I can recite it
11	If I decide not to get any bad grades, I can really do it
12	When studying, I keep working even if the material is difficult
13	When I study, I force myself to check to see if I remember what I have learned
14	I study to ensure my future will be financially secure
15	When I study, I practice by saying the material to myself over and over
16	If I decide not to get any problems wrong, I can really do it
17	When I study, I figure out how the information might be useful in the real world
18	I'm confident I can do an excellent job on assignments and tests
19	When I study, I try to figure out which concepts I still haven't really understood
20	When studying, I try to do my best to acquire the knowledge and skill taught
21	When I study, I try to understand the material better by relating it to things I already know
22	I study to get a good job
23	When I study, I make sure that I remember the most important things
24	If I want to learn something well, I can
25	When I study, I figure out how the material fits in with what I have already learned
26	I'm certain I can master the skills being taught
27	When I study, and I don't understand something I look for additional information to clarify this
28	When studying, I put forth my best effort

Table A2: PISA 2000 – Crombach's α and initial factor loadings

No.	Obs.	Cronbach's	Factor loadings		
		α	1	2	3
1	1,852	0.924	0.289	0.323	0.164
2	1,842	0.922	0.657	0.120	0.105
3	1,843	0.924	0.230	0.305	0.217
4	1,840	0.922	0.584	0.221	0.124
5	1,842	0.923	0.321	0.294	0.252
6	1,838	0.924	0.166	0.163	0.642
7	1,836	0.922	0.402	0.369	0.236
8	1,828	0.921	0.715	0.151	0.172
9	1,820	0.921	0.428	0.438	0.173
10	1,824	0.923	0.261	0.400	0.229
11	1,828	0.923	0.524	0.213	0.135
12	1,830	0.921	0.402	0.514	0.129
13	1,837	0.922	0.139	0.658	0.172
14	1,814	0.923	0.154	0.176	0.703
15	1,816	0.923	0.038	0.601	0.203
16	1,827	0.922	0.514	0.295	0.091
17	1,826	0.923	0.202	0.403	0.235
18	1,825	0.922	0.642	0.131	0.128
19	1,836	0.921	0.377	0.493	0.157
20	1,828	0.921	0.393	0.485	0.215
21	1,827	0.922	0.338	0.473	0.161
22	1,805	0.924	0.120	0.118	0.792
23	1,818	0.922	0.316	0.449	0.271
24	1,818	0.922	0.544	0.248	0.181
25	1,823	0.921	0.359	0.497	0.189
26	1,807	0.921	0.668	0.211	0.159
27	1,819	0.923	0.272	0.485	0.120
28	1,806	0.922	0.268	0.510	0.183
Min. N	1,806	–	–	–	–
Cronbach's α	–	0.925	–	–	–
Eigenvalues	–	–	8.816	1.278	1.020

Table A3: PISA 2000 Factor loadings

Factor	No.	Loading
Self-confidence	2	0.654
	4	0.630
	8	0.734
	11	0.600
	16	0.610
	18	0.676
	24	0.620
	26	0.722
Perseverance	13	0.778
	15	0.686
	28	0.506
Future orientation	6	0.675
	14	0.751
	22	0.802

B PIAAC 2011/2012

Table B1: PIAAC Background Questionnaire

No.	Variable
Q. 4	**To what extent do the following statements apply to you?** *(Not at all, very little, to some extent, to a high extent, to a very high extent)*
1	When I hear or read about new ideas, I try to relate them to real life situations to which they might apply
2	I like learning new things
3	When I come across something new, I try to relate it to what I already know
4	I like to get to the bottom of difficult things
5	I like to figure out how different ideas fit together
6	If I don't understand something, I look for additional information to make it clearer

Table B2: PIAAC Crombach's α and factor loadings

Factor	No.	N	Cronbach's α	Loading
Factor 1	1	1,877	0.725	0.525
	2	1,879	0.714	0.569
	3	1,880	0.715	0.537
	4	1,880	0.706	0.626
	5	1,879	0.685	0.688
	6	1,880	0.724	0.532
Min. N	–	1,877	–	–
Cronbach's α	–	–	0.748	–
Eigenvalue	–	–	–	2.035

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