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Returns to Skills or Returns to Tasks? A Comment on Hanushek et al. (2015)

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Abstract

We comment on the work of Hanushek et al. (2015) and show that returns to skills are very heterogeneous and depend crucially on the tasks performed in the workplace, in line with the critique by Acemoglu and Autor (2011). Depending on the types of tasks performed at work as well as on occupations, returns to cognitive skills can vary between null and numbers much higher than those reported by Hanushek et al. (2015). We show that both tasks and skills are important factors for determining returns on the labor market.

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1. Introduction

The data set provided by the Programme for the International Assessment of Adult Competencies (PIAAC) survey conducted by the OECD in 2011/12 is a broad multi-country survey of adult skills, which allows researchers to look at previously unresearched aspects of labor markets and human capital. Among others, Hanushek *et al.* (2015), in their widely-cited work (also reported in Hanushek *et al.*, 2017), used the PIAAC data to analyze returns to skills of workers. On the other hand, Acemoglu and Autor (2011) identified a major issue with analyzing the impact of skills on various economic outcomes, as summarized in the following quote:

> *The canonical model is made tractable in part because it does not include a meaningful role for tasks, or equivalently, it imposes a one-to-one mapping between skills and tasks. A task is a unit of work activity that produces an output (goods and services). In contrast, a skill is a worker's endowment of capabilities for performing various tasks. Workers apply their skill endowments to tasks in exchange for wages, and skills applied to tasks produce output. The distinction between skills and tasks becomes particularly relevant when workers of a given skill level can perform a variety of tasks and change the set of tasks that they perform in response to changes in labor market conditions.*

This critique has also been mentioned by Firpo *et al.* (2010), who propose a variant of the model, incorporating task-specific returns to skills. In this short note, we show that this critique is indeed justified: firstly, it is important for the calculation of returns whether the skills or the tasks of workers are analyzed and secondly, what ultimately determines wages is the above-mentioned 'application of skill endowments to tasks', or in other words how skills and tasks are matched.

2. Data and the Empirical Model

We use the subset of the PIAAC data set for Austria, which encompasses a total of 4,810 individual observations. We have access to the Scientific User File (SUF), which differs slightly from the Public User File (PUF) used by Hanushek *et al.* (2015). The main difference between the two variants of the data set, relevant for this study, is that we were able to access the actual hourly wages without having to refer to country deciles[1]. As we show later, some coefficients have a marginally different size. Moreover, we were able to identify the actual number of weekly working hours.

The baseline model used by Hanushek *et al.* (2015) is a variant of the Mincer equation, of the form

$$lny_i = \beta_0 + \gamma C_i + \beta_1 E + \beta_2 E^2 + \beta_3 G_i + \varepsilon_i, \tag{1}$$

where lny_i is the natural logarithm of the gross hourly wages, C_i is the measure of cognitive skills, E is the labor-market experience measured in years and G_i equals one for females. Applying the critique by Acemoglu and Autor (2011), the interaction between skills and actual tasks should be considered, and thus an equation of the form

$$lny_i = \beta_0 + \gamma C_i + \delta T_i + \eta C_i \times T_i + \beta_1 E + \beta_2 E^2 + \beta_3 G_i + \varepsilon_i, \tag{2}$$

[1] Hanushek *et al.* (2015) use information on the median wage of each decile and assign this decile median to each survey participant in the corresponding decile of the country-specific wage distribution.

should be used, where T_i measures the actual tasks performed in the workplace. The most important coefficient of interest is, therefore, η.

The PIAAC data set provides information on the actual tasks performed in the workplace, in particular:[2]

- Numeracy tasks: calculating costs or budgets, preparing charts or tables, using advanced math or statistics, etc.
- Literacy tasks: reading letters and mails, reading professional journals, reading financial statements, etc.
- ICT tasks: using the Internet, using Microsoft Word or spreadsheets, programming, etc.

Additionally, the PIAAC datasets provides us with assessed skill indicators for numeracy, literacy and ICT. Expert groups developed the PIAAC frameworks for each of the skill domains. Three main dimensions of skills are identified: content (tools, knowledge,...), cognitive strategies (the processes to respond to a given content) and the context (different situations in which to read, display numerate behavior, and solve problems). Individual test scores are between 0 and 500, where 500 would be the highest possible score.

Those skills are defined according to the OECD (2012) as follows:

- Literacy skills: Ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential;
- Numeracy skills: Ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life;
- Problem solving skills: Ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks.

For a more detailed information on skill assessment, see OECD (2012). Figure 3 in the Appendix provides the distribution of skills and tasks in Austria.

We consider the returns to skills as conditional on the tasks performed in the workplace. Although the standard Roy model (see, e.g., Roy, 1951; Heckman and Honore, 1990) predicts that workers systematically sort themselves into diverse occupations, the correlation between the measure of tasks and the measures of cognitive skills suggests that there is considerable variation, as shown in Table 1.

Various skills correlate strongly with each other in our data set. Literacy and numeracy skills have a correlation coefficient of 0.860, the coefficient for literacy skills and

[2]The PIAAC questionnaire asks participants how often they use particular skills at work. From participants' answers, several indices are calculated. The mean score and standard errors are normalized with a mean equal to two and a standard error equal to one, across the OECD countries participating in PIAAC. We further normalized the tasks variables to have a mean value equal to zero.

Table 1: Correlations between tasks and skills

Variables	Numeracy (skill)	Numeracy (task)	Literacy (skill)	Literacy (task)	Problem-solving (ICT skill)
Numeracy (task)	0.262				
Literacy (skill)	0.860	0.240			
Literacy (task)	0.313	0.438	0.290		
Problem-solving (ICT skill)	0.707	0.195	0.787	0.157	
ICT (task)	0.260	0.487	0.271	0.500	0.273

problem-solving skills is 0.787 and for numeracy skills and problem-solving skills it is 0.707.

While skills show strong correlations between one another, tasks and skills do not correlate strongly (correlation coefficients vary between 0.262 and 0.290). This observation allows us to look at the differential effects of tasks on the returns to skills.

Autor and Handel (2013) show that even while tasks correlate with education, demographics and occupations, they also have additional predictive power for wages. We are interested in whether skills also have additional predictive power when we control for tasks, since skills correlate only weakly with tasks.

3. Results

The main results are presented in Table 2. We firstly replicate the basic regressions of Hanushek *et al.* (2015) and subsequently augment them with interaction terms.

Table 2: Main results

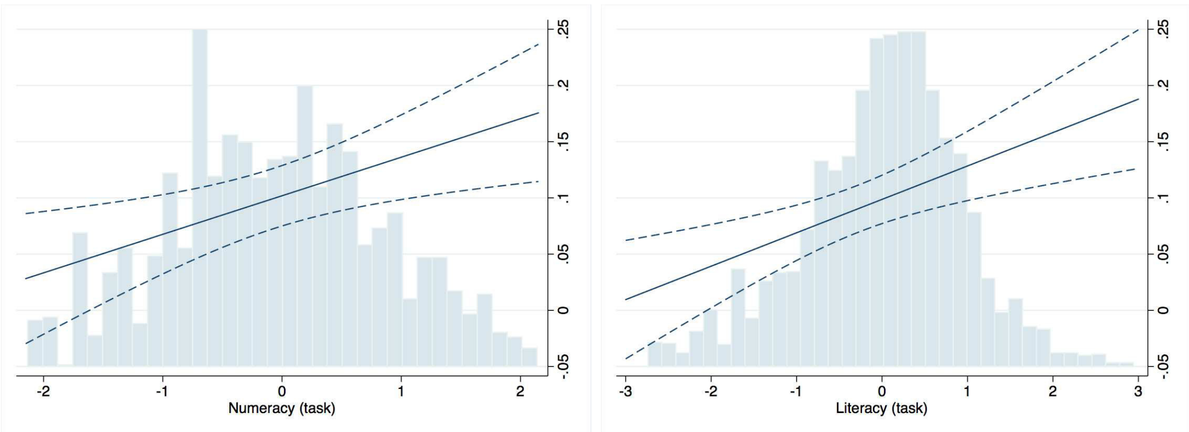
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Numeracy (skill)	0.120***	0.102***	0.102***						
	(0.010)	(0.014)	(0.014)						
Numeracy (task)		0.070***	0.064***						
		(0.013)	(0.012)						
Numeracy (skill) × Numeracy (task)			0.034***						
			(0.013)						
Literacy (skill)				0.121***	0.096***	0.099***			
				(0.010)	(0.011)	(0.011)			
Literacy (task)					0.097***	0.102***			
					(0.012)	(0.012)			
Literacy (skill) × Literacy (task)						0.030***			
						(0.009)			
Problem-solving							0.110***	0.069***	0.069***
							(0.013)	(0.014)	(0.014)
ICT (task)								0.095***	0.095***
								(0.013)	(0.013)
Problem-solving × ICT (task)									0.011
									(0.014)
Years of schooling	0.055***	0.054***	0.054***	0.055***	0.044***	0.042***	0.059***	0.055***	0.055***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Experience	0.021***	0.031***	0.032***	0.022***	0.021***	0.022***	0.018**	0.026***	0.026***
	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.007)	(0.009)	(0.009)
Experience^2	-0.028**	-0.044**	-0.046***	-0.028**	-0.027**	-0.027**	-0.016	-0.032*	-0.032*
	(0.013)	(0.017)	(0.017)	(0.013)	(0.013)	(0.013)	(0.015)	(0.018)	(0.018)
Female	-0.115***	-0.104***	-0.101***	-0.141***	-0.136***	-0.133***	-0.118***	-0.123***	-0.124***
	(0.020)	(0.023)	(0.023)	(0.020)	(0.020)	(0.020)	(0.023)	(0.023)	(0.023)
Constant	1.666***	1.562***	1.534***	1.665***	1.803***	1.809***	1.674***	1.681***	1.673***
	(0.094)	(0.127)	(0.125)	(0.090)	(0.097)	(0.095)	(0.101)	(0.129)	(0.128)
Observations	1169	921	921	1169	1114	1114	938	792	792

Least-squares regressions weighted by sampling weights. Dependent variable: log gross hourly wage. Sample: full-time employees (working over 30 hours per week) aged 35-54. Tasks and skills scores normalized to std. dev. = 1. Experience squared divided by 100. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1

From Table 2 we may form the following conclusions. Firstly, our estimates are broadly consistent with the original results of Hanushek *et al.* (2015), despite using a different dependent variable. The only exception here is the relationship between hourly wages and experience, the coefficient of which is almost twice as high as in the cited study, as well as being statistically highly significant. It remains unclear how the difference can be explained.

Secondly, from columns (2), (5) and (8) it is clear that the returns to skills are in fact lower than those predicted by Hanushek *et al.* (2015), once we control for the actual tasks performed at work. Coefficients for numeracy and literacy are similar, as a result of the above-mentioned high correlation between the two variables. Thirdly and most importantly, returns to skills depend on the actual tasks performed at work, as indicated in columns (3) and (6), although not in (9). This is indicated in the interactions model. For easier interpretation of the results, Figure 1 presents the marginal effects of skills on log hourly wages, conditional on tasks, corresponding to the interactions model. ICT skills are omitted since the interaction is not significant[3].

Figure 1: Marginal effects of skills conditional on tasks



(a) Numeracy

(b) Literacy

Marginal effects of skills conditional on tasks, from Columns (3) and (6) reported in Table 2. Dashed lines correspond to 95% confidence intervals.

The interaction term between skills and tasks indicates the relevance of the matching between cognitive skills and tasks at work. The higher the interaction term of the skill and task variable, the better the match. The coefficients are in all cases positive and statistically significant for literacy and numeracy, indicating that a skill match increases (conditional on task and skills) the wage, while a skill mismatch (over- or under-qualification) reduces the wage (conditional on task and skills).

For both measures of skills, at lower values of the task variables additional cognitive skills have virtually zero returns, whereas returns can be as high as 0.2 at the upper end of the tasks distribution, as Figure 1 indicates. Within one standard deviation from the mean task score, returns to skills vary between 0.067 and 0.136 (numeracy), and between 0.069 and 0.128 (literacy).

[3] As shown by Falck *et al.* (2016) workers with high ICT skills indeed select into the better-paid jobs with high computer use. This selection might result in little variation in computer use for a given level of ICT skills (or vice versa) resulting in the insignificant interaction effect.

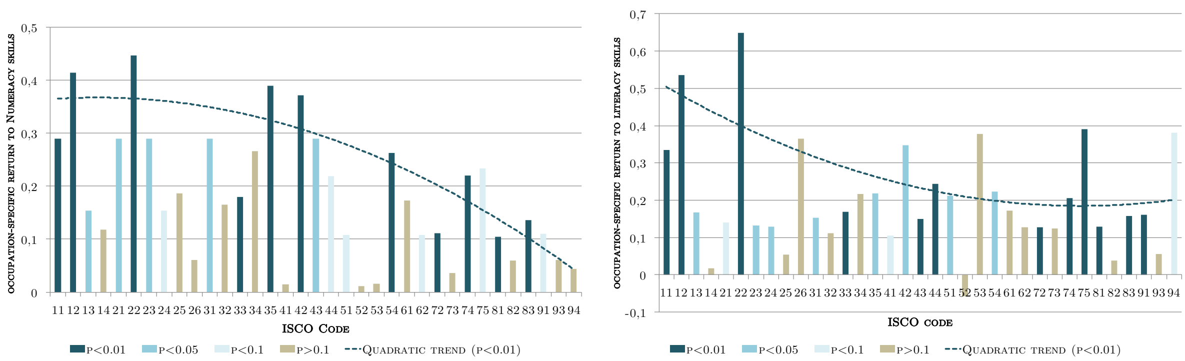
Perry *et al.* (2016) analyze the coefficients on over-skilling for several mismatch measures with the Austrian PIAAC dataset. They find a wage penalty for general over-qualification in Austria between three and 11 percent, depending on the mismatch measure they use. For under-qualification, there is a wage premium of about one to 16 percent.

Finally, results including a full set of interactions between cognitive skills and occupations show a substantial variation as indicated in Figure 2[4]. For the occupations typically described as 'high skilled', that is ISCO 1-digit codes 1, 2 and 3, numeracy skills bring a substantial return, whereas for literacy this is only the case for ISCO 1 and 2 occupations.

In general, we see a trend to higher returns for both, numeracy and literacy skills in occupations that are typically assumed to be 'high-task' occupations (ISCO 1,2 or 3), whereas skills are rewarded less in 'low-task' occupations (ISCO 7, 8 or 9). This also indicates, that over-qualification that can be defined as having high skills while working in a 'low-task' occupation leads to a substantial wage loss compared to working in 'high-task' occupation. This finding is in line with the findings of Perry *et al.* (2016), Allen and Van der Velden (2001) and Béduwé and Giret (2011).

Significant returns are also apparent for occupations described as 'low skilled' (codes 7 and 8). Consistently with recent evidence for 'job polarization' (see, e.g., Goos *et al.*, 2009, 2014), returns to cognitive skills are far less significant, in particular for the literacy variable, i.e., text comprehension, which is currently subject to automation.

Figure 2: Occupation-specific returns to skills



(a) Numeracy

(b) Literacy

Calculated on the basis of a regression model with a full set of occupation dummies (ISCO 2-digit) interacting with cognitive skills variables and controlling for years of schooling, experience, experience squared and gender. The sample and weights are as in the baseline model.

4. Conclusions

Our note sheds some light on the discussion about whether wages are typically determined by tasks or by skills. We argue that both tasks and skills are important factors for returns on the labor market. Therefore, controlling only for tasks or only for personal skills is not convincing for a wages regression analysis. We show that the mismatch between

[4]Full results available on request.

tasks at work and personal skills have a significant effect on the labor market return, indicating the need to control for both variables at the same time. Additionally, we show that for 'low-task' occupations, additional skills lead to low or no wage premium, while for 'high-task' occupations, the return to additional skills is substantial.

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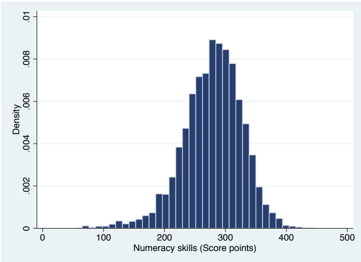
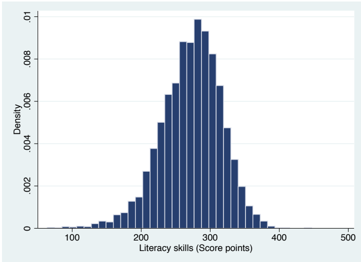
Appendix

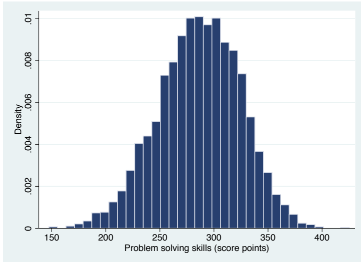
Figure 3: Distribution of skills and tasks in Austria



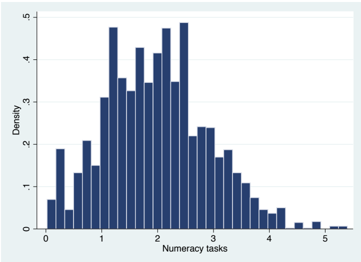
(a) Numeracy skills



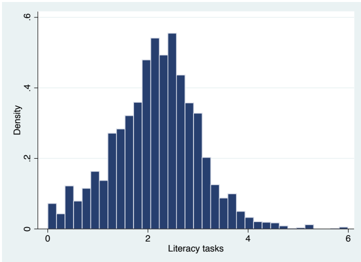
(b) Literacy skills



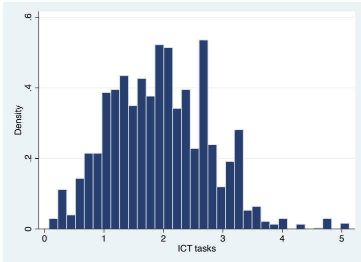
(c) Problem solving skills



(d) Numeracy tasks



(e) Literacy tasks



(f) ICT tasks