Development Accounting using PIAAC Data

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Motivation

Availability of comparable cognitive skill measures for adults

- PIAAC: *Program for the International Assessment of Adult Competences*
  - **Cognitive tests for representative adult population, age 16-65**
  - Information about individual characteristics mostly related to working life: work experience, on the job training, wages, health status, etc.
  - Survey carried out by the OECD in **33 mostly high-income countries** (2011: 24 and 2014: 9).
- Potentially highly valuable for measuring human capital
- Human capital measure: Crucial for development accounting

Introduction

Development accounting: Why are some countries so much richer than others?

- Determinants:
  - Inputs: Physical and **human capital**
  - Efficiency- total factor productivity (TFP)
- Key for measuring $Income = F(inputs, efficiency)$
  - i) choose functional form F
  - **ii) accurately measure inputs**
  - iii) accurately measure income
  - efficiency is backed out as a residual
- Current consensus
  - Physical capital accounts only for a small fraction of income differences
  - Unsettled: relative importance of TFP vs human capital in accounting for income differences:
    - Human capital accounts for 1/5 (Hall & Jones 1999) to 4/5 (Manuelli & Sheshadri 2014, Jones 2014) of cross-country income differences.

Introduction

Policy implication

- If differences in capital are sufficient to explain income differences: policy makers need to **focus on factors explaining the low investment**

- If they are insufficient to account for variation in income: policy makers need to **focus on technology, misallocation of resources, competition and other determinants of the efficient use of resources**

Motivation

Development Accouting and Human Capital Measures

Measures of human capital typically used in developing accounting:

- Quantity: Years of schooling of adult population
- Quality?

Motivation

Quality-adjusted human capital measures

- Most measures for the quality of human capital refer to a country's student population:
  - Direct measures: Student test scores (PISA, TIMS, etc.)
  - Indirect measures: Estimated education production function with inputs such as teacher-student ratios, expenditure for education, etc.
- Concerns:
  - Underlying assumption is that educational improvements are very slow, but quality of schooling changes over time and potentially differently across countries
  - Migration: Workers have not necessarily acquired schooling in country of residence.
  - Ignores human capital accumulation after schooling
  - Skills acquired in school can be lost or even enhanced over time

Motivation

Quality-adjusted human capital measures

- Few measures refer to the human capital of the adult population.
- Inferred from looking at migrants' and natives wages in the US:
  - Average wage differences natives and immigrants in US (Hendricks, 2002)
  - Returns to schooling of migrants in US (Schoellman, 2012)
- Direct measures?

Summary: What do we do?

- **Question:** How useful are direct measures of adults human capital developed by PIAAC for explaining cross-country differences in output per worker?
  - Test usefulness in simple development accounting framework.
  - Run Mincer wage regressions for US to estimate parameters for a variety of potential dimensions of of human capital in PIAAC (years of schooling, test scores, experience, health status, on-the-job training).
  - Extent development accounting framework to incorporate imperfect substitutability of workers with different levels of education.
- Caveat: Our sample is limited to 30 countries and data is measured in two instances (2011 and 2014).

Usefullness of PIAAC data

- Representative sample of the working age population at the national level
- Issues of data quality across diverse countries and database is eliminated
- Measures very different components of human capital:
  - years of schooling,
  - cognitive skills,
  - actual work experience,
  - health status,
  - on-the-job training,
- Includes wages
- It is more plausible that these 30 countries operate under a common aggregate production function compared to samples with highly diverse economies but still significant variation on GDP per worker.

Summary: Findings

- Combined with differences in physical capital, our broad measure of human capital (schooling, cognitive skill, experience, health, on-the-job-training) can account for 42% of the variance in output per worker
- A model with difference in physical capital and years of schooling accounts for 27% of the variance in output per worker.
- Differences in cognitive skills play largest role, health and experience less so.
- Taking into account imperfect substitutability of human capital of workers with and without college education can improve explanatory power further.

Related Literature

- Development accounting
  - *Classical:* Casselli (2005), Hsieh and Klenow(2010,) Hall and Jones(1999)
  - *Imperfect substitution*: Jones(2014), Caselli and Coleman(2006) and Malmberg (2017).
- Distinct/Innovative measures of human capital
  - *Quality of education*: Hendricks (2002), Schoellman (2012).
  - *Work experience*: Klenow and Rodriguez-Clare (1997), Lagakos et al (2012).
  - *Health*: Weil (2007), Shastry and Weil (2003).
  - *On-the-job-training*: Manuelli and Seshadri (2014).
- Estimation of Mincer wage equations
  - *Using PIAAC data*: Hanushek et al. (2015)

Theoretical considerations for development accounting

Average GDP per worker:

$$y_j = A_j k_j^{\alpha} h_j^{1-\alpha},$$

with h_j average human capital.
Assuming that TFP is equal across countries (and constant across three years):

$$y_{KHj} = k_j^{\alpha} h_j^{1-\alpha}.$$

Success or explanatory power:

$$success = \frac{var(log(y_{KH})}{var(log(y))}.$$

Theoretical considerations: measuring human capital

A country's average human capital

$$h_j = g(s_j, c_j, x_j, hl_j, ojt_j),$$

being a positive function of formal schooling s_j, cognitive skills c_j, work experience x_j, health status hl_j and on-the-job-training ojt_j.
One can show that under perfect competition (free entry, zero profits):

$$\frac{\partial h(.)}{\partial x} = \frac{\partial logw(.)}{\partial w} \frac{\partial w(.)}{\partial x}$$

with $x = s_j, c_j, x_j, hl_j, ojt_j$.

$\rightarrow$ Coefficients from a Mincer wage regressions can be used to estimate parameters for the production function of human capital.

Aggregate PIAAC Data for Development Accounting

- **30 countries:** Austria, Belgium, Canada, Chile, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, Lithuania, Netherlands, New Zealand, Norway, Poland, Singapore, Slovakia, Slovenia, Spain, Sweden, Turkey, UK, US.
- **Weighted country averages for individuals age 25-65:** years of schooling, PIAAC test scores (numeracy and literacy), work experience, health status, on-the-job-trained.
  - Missing data: For Canada and Turkey self-reported health measures are missing, substituted with US and Italian means respectively.
- Complemented with data from **Penn World Table**
  - GDP (PPP)
  - Employed population
  - Physical capital stock

Descriptive Statistics Development Accounting

Table: Country averages per worker (PIAAC and Penn Word Tables)

Variable	Mean	Std. Dev.	Min.	Max.
GDP per worker	78,192	22,516	48,325	151,909
Capital per worker	329,433	106,890	120,136	502,747
Years of schooling	12.547	1.320	8.100	14.595
Numeracy	262.015	18.803	202.828	289.411
Literacy	265.384	16.716	216.161	295.997
Job experience	20.307	2.503	14.102	24.224
Potential experience	23.812	2.092	20.323	28.044
Health status*	3.332	0.301	2.525	3.764
On-the-job-training	0.290	0.096	0.075	0.447
College educated	0.349	0.109	0.137	0.553
Observations	30			

Individual level PIAAC data for Mincer regression

- PIAAC data for 2011 for US (reference country)
- **Main individual level variables:** hourly wage, years of schooling, PIAAC test scores (numeracy and literacy), work experience, health status, ojt.
- Sample: 25-65 years, men and women, workers.

Descriptive Statistics: Individual PIAAC Data, US

Variable	Mean	Std. Dev.	Min.	Max.
Log hourly wage	2.972	0.591	1.992	4.012
Years of schooling	14.021	3.019	6	21
Numeracy standardized	0.116	1.053	-3.159	3.2
Literacy standardized	0.076	1.055	-3.534	3.026
Experience	22.289	11.683	0	47
Potential experience*	20.096	11.851	0	50
Health status	3.75	0.962	1	5
On-the-job-training	0.541	0.498	0	1
College educated	0.518	0.5	0	1
Observations	2,141			

*Number of observations for potential experience: 2,129.

Minceriian wage regression: Main estimation

$$logw_i = \beta_0 + \phi s_i + \tau c_i + \psi_1 x_i + \psi_2 x_i^2 + \theta hl_i + \varsigma ojt_i + \epsilon_i$$

Years of schooling	0.095***	0.067***	0.069***	0.064***	0.061***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Numeracy standardized		0.135***	0.127***	0.121***	0.118***
		(0.018)	(0.018)	(0.018)	(0.018)
Experience			0.033***	0.033***	0.032***
			(0.004)	(0.004)	(0.004)
Experience^2/100			-0.047***	-0.045***	-0.045***
			(0.008)	(0.008)	(0.008)
Health				0.066***	0.065***
				(0.012)	(0.012)
On-the-job training					0.085***
					(0.023)
Constant	1.639***	2.019***	1.555***	1.372***	1.372***
	(0.058)	(0.070)	(0.083)	(0.091)	(0.091)
Observations	2,144	2,144	2,142	2,141	2,141
R^2	0.235	0.273	0.330	0.342	0.347

Parameters: Estimated Returns

Parameter	Value
Schooling (ϕ)	0.06
Numeracy (τ)	0.12
Experience (ψ_1)	0.03
Experience squared/100 (ψ_1)	-0.05
Health (θ)	0.07
On-the-job-training (ς)	0.09
Capital share	0.33

$$h_j = exp(\phi s_j + \tau c_j + \psi_1 x_j + \psi_2 x_j^2 + \theta hl_j + \varsigma ojt_j),$$

$$y_j = A_j k_j^{\alpha} h_j^{1-\alpha}$$

Results Development Accounting

Model	(1) Success	(2) Difference
$y = k^{\alpha}$	0.222	
$y = k^{\alpha}(h(s))^{1-\alpha}$	0.268	
$y = k^{\alpha}(h(s, c^{num}))^{1-\alpha}$	0.330	0.062
$y = k^{\alpha}(h(s, c^{num}, x))^{1-\alpha}$	0.377	0.109
$y = k^{\alpha}(h(s, c^{num}, x, hl))^{1-\alpha}$	0.408	0.140
$y = k^{\alpha}(h(s, c^{num}, x, hl, ojt))^{1-\alpha}$	0.416	0.148

Imperfect substitutability of workers

$$y_{KHj} = k_j^{\alpha} \left(\gamma_c \left(h_{c,j} L_{c,j} \right)^{\rho} + (1 - \gamma_c) \left(h_{nc,j} L_{nc,j} \right)^{\rho} \right)^{\frac{1-\alpha}{\rho}} ,$$

where

$$h_{c,j} = exp(\beta_c + \phi_c s_{c,j} + \tau_c c_{c,j} + \psi_{c,1} x_{c,j} + \psi_{c,2} x_{c,j}^2 + \theta_c hl_{c,j} + \varsigma_c ojt_{c,j}),$$

and

$$h_{nc,j} = exp(\beta_{nc} + \phi_{nc} s_{nc,j} + \tau_{nc} c_{nc,j} + \psi_{nc,1} x_{nc,j} + \psi_{c,2} x_{nc,j}^2 + \theta_c hl_{nc,j} + \varsigma_c ojt_{nc,j}),$$

- Mincer wage equation for the US for college and non-college educated separately
- Country averages by workers with and without college education.
- ρ determines elasticity of substitution - $ES = \frac{1}{1-\rho}$
- γ_c is the labor share of college educated workers.

Labor share of college educated - γ_c

- Under perfect competition the wage of college educated workers w_c (non-college educated workers w_{nc}) equals their marginal product of $\frac{\partial Y}{\partial L_c}(\frac{\partial Y}{\partial L_{nc}})$.
- Using average hourly wages of collge and non-college educated workers in the US from PIAAC we obtain γ_c from:

$$\frac{w_c}{w_{nc}} = \frac{\gamma_c}{1-\gamma_c}\left(\frac{h_c}{h_{nc}}\right)^{\rho}\left(\frac{L_c}{L_{nc}}\right)^{\rho-1}.$$

Table: Calibrated values for γ_c

	$ES = 2.5$	$ES = 2.2$	$ES = 1.9$	$ES = 1.6$	$ES = 1.3$
γ_c	0.508	0.510	0.512	0.515	0.519

Development Accounting - Imperfect Substitutability

Model	$ES = 2.5$	$ES = 2.2$	$ES = 1.9$	$ES = 1.6$	$ES = 1.3$
$y = k^{\alpha}(\sum_{e=c,nc}(h_h(s)L_h)^{\rho})^{\frac{1}{\rho}})^{1-\alpha}$	0.270	0.275	0.281	0.291	0.306
$y = k^{\alpha}(\sum_{e=c,nc}(h_e(s,c)L_h)^{\rho})^{\frac{1}{\rho}})^{1-\alpha}$	0.324	0.328	0.334	0.344	0.359
$y = k^{\alpha}(\sum_{e=c,nc}(h_e(s,c,x)L_h)^{\rho})^{\frac{1}{\rho}})^{1-\alpha}$	0.376	0.381	0.389	0.400	0.418
$y = k^{\alpha}(\sum_{e=c,nc}(h_e(s,c,x,hl)L_h)^{\rho})^{\frac{1}{\rho}})^{1-\alpha}$	0.404	0.409	0.416	0.426	0.443
$y = k^{\alpha}(\sum_{e=c,nc}(h_e(s,c,x,hl,ojt)L_h)^{\rho})^{\frac{1}{\rho}})^{1-\alpha}$	0.412	0.417	0.424	0.434	0.450

Depending on human capital composite considered 8-12% more explanatory power when taking into account imperfect substitutability of college and non-college educated workers.

Robustness Checks

- Experience: To be comparable to literature - potential instead of actual work experience.
- Cognitive skills:
  - Literacy instead of numeracy
  - Distribution of cognitive skills
- Alternative Samples:
  - Individuals age 30-65
  - Including self-employed individuals
- Excluding Norway from the exercise
- Additional dimensions of human capital
  - Non-cognitive skills
  - Interaction between components of human capital

Conclusions

- Using PIAAC data we build multidimensional measures for the stock of human capital in 30 countries - including schooling, cognitive skills, experience, health and on-the-job-training.
- Running Mincerian wage regression we estimate weights of each dimension using US individual level data from PIAAC.
- Within classical development accounting exercise we can explain 42% of the variance in output per worker when combining our measure with stock of physical capital (27% when schooling is used).
- Imperfect substitutability of workers of different levels of education increases explanatory power of the model.
- Better measures for non-cognitive skills (“Big-Five”) in PIAAC would allow to also include this important dimension of human capital in development accounting.

Thank you !

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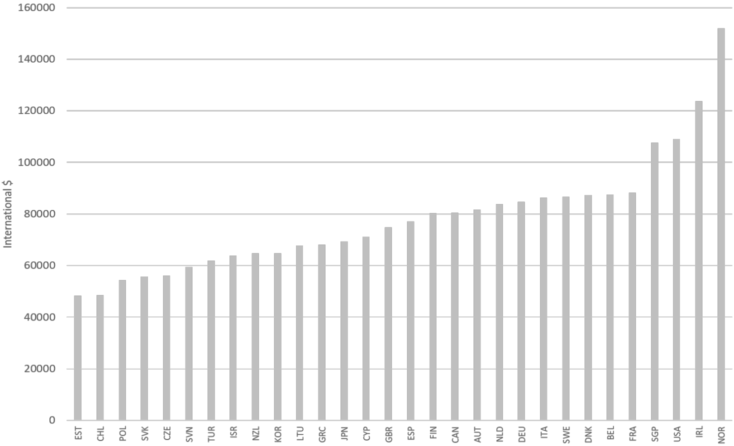
GDP per worker



Data: Penn World Table 2011 (Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia and Turkey: 2014)

Return

Mincer regression: College & non-college individuals

	Non-college	College
Years of schooling	0.030***	0.062***
	(0.011)	(0.009)
Numeracy score	0.085***	0.158***
	(0.027)	(0.020)
Experience	0.034***	0.034***
	(0.006)	(0.005)
Experience^2/100	-0.043***	-0.053***
	(0.012)	(0.011)
Health	0.062***	0.065***
	(0.016)	(0.019)
On-the-job training	0.072**	0.109***
	(0.033)	(0.034)
Constant	1.655***	1.353***
	(0.153)	(0.172)
Observations	941	1,200
R^2	0.220	0.203

Return

Potential instead of actual experience

Years of schooling	0.095 (0.004)***	0.067 (0.005)***	0.079 (0.005)***	0.075 (0.005)***	0.072 (0.005)***
Numeracy score		0.135 (0.018)***	0.147 (0.018)***	0.141 (0.018)***	0.138 (0.018)***
Potential experience			0.021 (0.003)***	0.021 (0.003)***	0.02 (0.003)***
Potential experience^2/100			-.024 (0.007)***	-.023 (0.007)***	-.022 (0.007)***
Health				0.064 (0.012)***	0.064 (0.012)***
On-the-job training					0.097 (0.024)***
Constant	1.639 (0.058)***	2.019 (0.07)***	1.560 (0.082)***	1.378 (0.09)***	1.373 (0.09)***
Observations	2,144	2,144	2,132	2,131	2,131
R^2	0.235	0.273	0.311	0.322	0.328

Potential instead of actual experience

Model	Success	Benchmark
$y = k^{\alpha}(h(s))^{1-\alpha}$	0.284	0.268
$y = k^{\alpha}(h(s, c))^{1-\alpha}$	0.363	0.330
$y = k^{\alpha}(h(s, c, \tilde{x}))^{1-\alpha}$	0.367	0.377
$y = k^{\alpha}(h(s, c, \tilde{x}, hl))^{1-\alpha}$	0.390	0.408
$y = k^{\alpha}(h(s, c, \tilde{x}, hl, ojt))^{1-\alpha}$	0.398	0.416

Return

Literacy instead of numeracy

Years of schooling	0.095***	0.072***	0.073***	0.068***	0.065***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Literacy score		0.112***	0.107***	0.101***	0.098***
		(0.017)	(0.016)	(0.016)	(0.016)
Experience			0.034***	0.034***	0.033***
			(0.004)	(0.004)	(0.004)
Experience^2/100			-0.049***	-0.047***	-0.047***
			(0.008)	(0.008)	(0.008)
Health				0.068***	0.067***
				(0.012)	(0.012)
On-the-job training					0.088***
					(0.024)
Constant	1.639***	1.956***	1.491***	1.302***	1.302***
	(0.058)	(0.071)	(0.082)	(0.089)	(0.089)
Observations	2,144	2,144	2,142	2,141	2,141
R^2	0.235	0.261	0.321	0.333	0.338

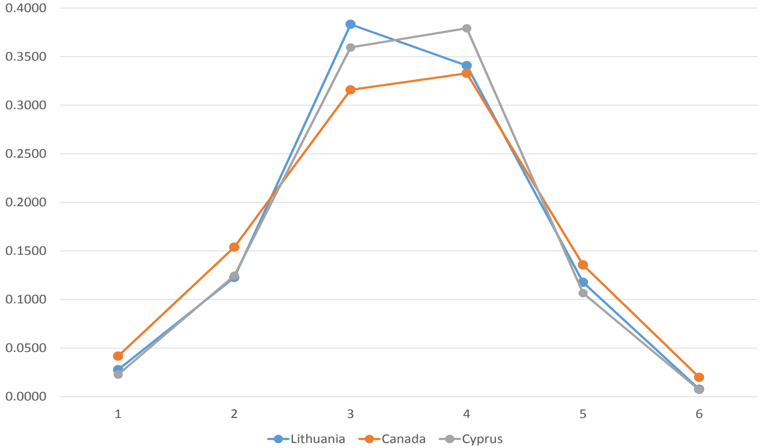
Literacy instead of numeracy

Model	Success	Benchmark
$y = k^{\alpha}(h(s))^{1-\alpha}$	0.284	0.268
$y = k^{\alpha}(h(s,\tilde{c}))^{1-\alpha}$	0.337	0.330
$y = k^{\alpha}(h(s,\tilde{c},x))^{1-\alpha}$	0.384	0.377
$y = k^{\alpha}(h(s,\tilde{c},x,hl))^{1-\alpha}$	0.415	0.408
$y = k^{\alpha}(h(s,\tilde{c},x,hl,ojt))^{1-\alpha}$	0.424	0.416

Return

Distribution of cognitive skills

Individuals with different numeracy “proficiency levels” in countries with similar average scores



Data: PIAAC

Proficiency levels in PIAAC: Examples

- *PIAAC level 1:* Compare dates on super market price tags and indicate which was packed first.
- *PIAAC level 2:* Looking at a a box containing tea light 105 tea light candles. It can be seen that the candles are packed in five rows of seven candles each. Calculate how many layers of tea candles are packed in the box.
- ....
- *PIAAC level 5:* Calculate interest rate on loan that is advertised as “pay only $103 per month in 12 payments for each $1000 borrowed.”

Distribution of cognitive skills

$$\log w_i = \beta_0 + \phi s_i + \sum_{j=1,2,3,4,5} \tau_j dc_{j,i} + \psi_1 x_i + \psi_2 x_i^2 + \theta hl_i + \varsigma ojt_i + \epsilon_i.$$

Years of schooling	0.095 ***	0.068***	0.070***	0.065***	0.062***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Proficiency level 1		-0.009	-0.046	-0.057	-0.064
		(0.063)	(0.060)	(0.060)	(0.060)
Proficiency level 2		0.124**	0.064	0.047	0.037
		(0.062)	(0.060)	(0.059)	(0.059)
Proficiency level 3		0.266***	0.213***	0.189***	0.174***
		(0.067)	(0.064)	(0.064)	(0.063)
Proficiency level 4		0.452***	0.417***	0.399***	0.390***
		(0.075)	(0.072)	(0.072)	(0.072)
Proficiency level 5		0.496***	0.468***	0.438***	0.419***
		(0.124)	(0.111)	(0.114)	(0.113)
Experience			0.034***	0.034***	0.033***
			(0.004)	(0.004)	(0.004)
Experience^2/100			-0.048***	-0.046***	-0.046***
			(0.008)	(0.008)	(0.008)
Health				0.068***	0.067***
				(0.012)	(0.012)
On-the-job training					0.091***
					(0.023)
Constant	1.639***	1.842***	1.407***	1.236***	1.244***
	(0.058)	(0.073)	(0.079)	(0.086)	(0.086)
Observations	2,144	2,144	2,142	2,141	2,141
R^2	0.235	0.279	0.341	0.353	0.359

Proficiency levels instead of average numeracy test scores

Model	Success	Benchmark
$y = k^{\alpha}(h(s))^{1-\alpha}$	0.268	0.268
$y = k^{\alpha}(h(s, dc))^{1-\alpha}$	0.313	0.330
$y = k^{\alpha}(h(s, dc, x))^{1-\alpha}$	0.358	0.377
$y = k^{\alpha}(h(s, dc, x, hl))^{1-\alpha}$	0.388	0.408
$y = k^{\alpha}(h(s, dc, x, hl, ojt))^{1-\alpha}$	0.397	0.416

Return

Summary statistics: Numeracy Proficiency Levels

Variable	Mean	Std. Dev.	Min.	Max.
Individual level data US:				
Numeracy: Proficiency 0	0.083	0.277	0	1
Numeracy: Proficiency 1	0.170	0.376	0	1
Numeracy: Proficiency 2	0.312	0.463	0	1
Numeracy: Proficiency 3	0.309	0.462	0	1
Numeracy: Proficiency 4	0.113	0.316	0	1
Numeracy: Proficiency 5	0.014	0.117	0	1
Country level data:				
Numeracy: Proficiency 0	0.074	0.067	0.01	0.338
Numeracy: Proficiency 1	0.163	0.058	0.07	0.307
Numeracy: Proficiency 2	0.332	0.045	0.237	0.411
Numeracy: Proficiency 3	0.316	0.076	0.101	0.445
Numeracy: Proficiency 4	0.105	0.048	0.015	0.187
Numeracy: Proficiency 5	0.01	0.007	0	0.025

Individuals age 30-65 instead of age 25-65

Years of schooling	0.096***	0.066***	0.067***	0.062***	0.060***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Numeracy score		0.147***	0.137***	0.131***	0.128***
		(0.020)	(0.020)	(0.020)	(0.020)
Experience			0.022***	0.021***	0.021***
			(0.006)	(0.006)	(0.006)
Experience^2/100			-0.029***	-0.027**	-0.027**
			(0.010)	(0.011)	(0.011)
Health				0.070***	0.070***
				(0.013)	(0.013)
On-the-job training					0.070***
					(0.026)
Constant	1.667***	2.087***	1.739***	1.551***	1.549***
	(0.062)	(0.074)	(0.099)	(0.109)	(0.109)
Observations	1821	1821	1819	1818	1818
R^2	0.250	0.293	0.314	0.328	0.331

Individuals age 30-65 instead of age 25-65

Model	Success	Benchmark
$y = k^{\alpha}(h(s))^{1-\alpha}$	0.268	0.268
$y = k^{\alpha}(h(s,c))^{1-\alpha}$	0.371	0.330
$y = k^{\alpha}(h(s,c,x))^{1-\alpha}$	0.418	0.377
$y = k^{\alpha}(h(s,c,x,hl))^{1-\alpha}$	0.455	0.408
$y = k^{\alpha}(h(s,c,x,hl,ojt))^{1-\alpha}$	0.462	0.416

Return

Including self-employed individuals - monthly wages

Years of schooling	0.112***	0.078***	0.081***	0.074***	0.068***
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Numeracy score		0.165***	0.142***	0.132***	0.126***
		(0.024)	(0.023)	(0.023)	(0.023)
Experience			0.061***	0.060***	0.060***
			(0.006)	(0.006)	(0.006)
Experience^2/100			-0.095***	-0.092***	-0.092***
			(0.012)	(0.012)	(0.012)
Health				0.105***	0.104***
				(0.018)	(0.018)
On-the-job training					0.206***
					(0.033)
Constant	6.500***	6.951***	6.158***	5.869***	5.865***
	(0.081)	(0.101)	(0.119)	(0.128)	(0.128)
Observations	2,453	2,453	2,451	2,450	2,450
R^2	0.152	0.178	0.244	0.257	0.270

Individuals self-employed individuals

Model	Success	Benchmark
$y = k^{\alpha}(h(s))^{1-\alpha}$	0.284	0.286
$y = k^{\alpha}(h(s,c))^{1-\alpha}$	0.356	0.330
$y = k^{\alpha}(h(s,c,x))^{1-\alpha}$	0.487	0.377
$y = k^{\alpha}(h(s,c,x,hl))^{1-\alpha}$	0.540	0.408
$y = k^{\alpha}(h(s,c,x,hl,ojt))^{1-\alpha}$	0.568	0.416

Return

Excluding Norway

Model	Success	
$y = k^{\alpha}$	0.288	0.222
$y = k^{\alpha}(h(s))^{1-\alpha}$	0.336	0.268
$y = k^{\alpha}(h(s,c))^{1-\alpha}$	0.412	0.330
$y = k^{\alpha}(h(s,c,x))^{1-\alpha}$	0.471	0.377
$y = k^{\alpha}(h(s,c,x,hl))^{1-\alpha}$	0.511	0.408
$y = k^{\alpha}(h(s,c,x,hl,ojt))^{1-\alpha}$	0.522	0.416

Return