The Rising Return to Non-Cognitive Skill

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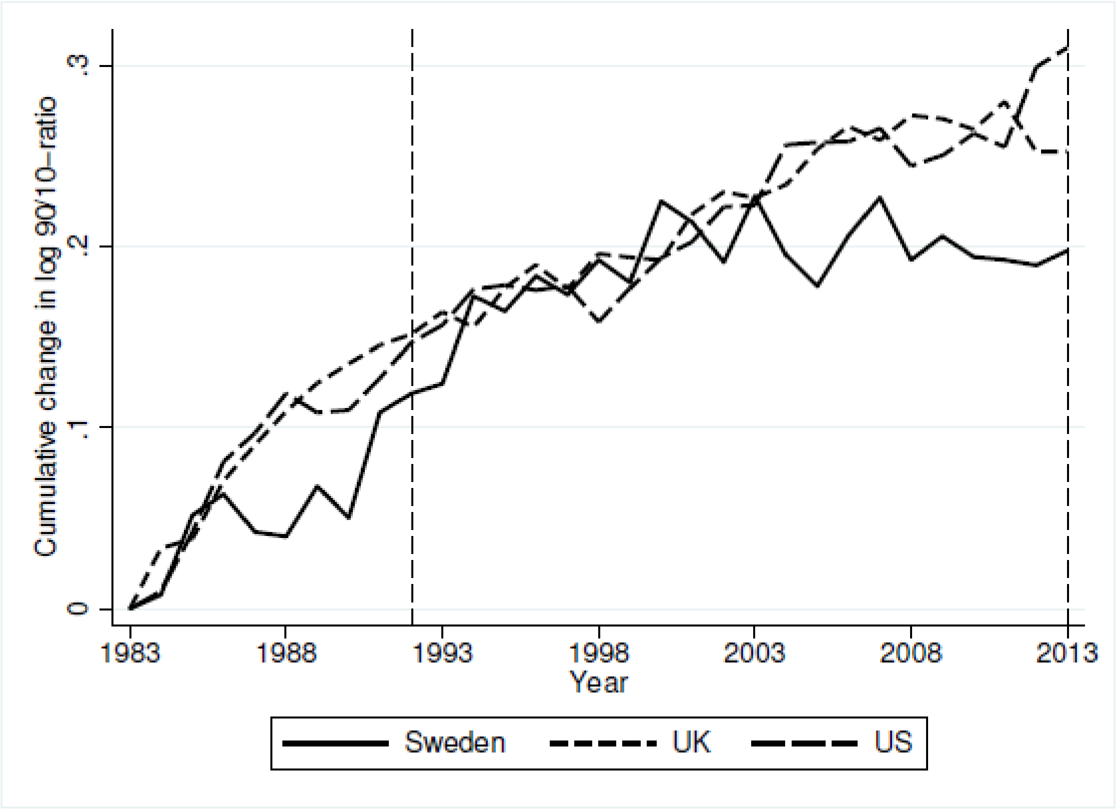
I Introduction

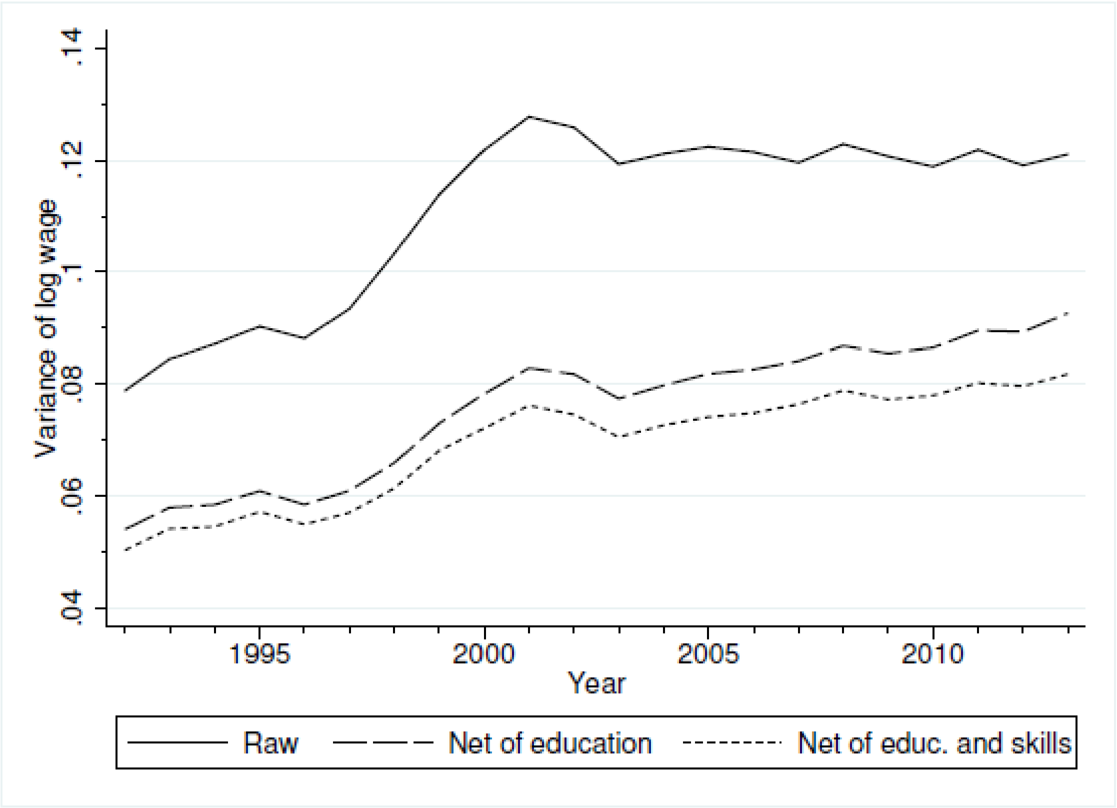
2 Wage inequality in Sweden

Figure 1: Changes in earnings inequality, men, 1983-2013



Notes: The data pertain to men and come from the OECD Earnings Distribution Database. For all countries we normalize each series with the log of the 90/10 ratio in 1983. Vertical dashed lines mark the start and end-year of our main analysis.

Figure 2: Wage inequality among men aged 38-42, 1992-2013



Notes: The sample pertains to men with valid draft scores. The dashed line nets out fixed effects for educational attainment and age, although doing the latter makes little difference; the dotted line, in addition, nets out second order polynomials in cognitive and non-cognitive skills.

3 Data

3.1 Cognitive and non-cognitive skills

Table 1: Correlations between skills and schooling

	Men age 38-42		
	1994-96	2009-11	Change
Cognitive skill and yrs of schooling	0.506	0.524	0.019
Non-cognitive skill and yrs of schooling	0.295	0.316	0.021
Cognitive and non-cognitive skill	0.338	0.366	0.028

4 The increase in the return to non-cognitive skills

Figure 3: Employment and earnings returns

(a) Probability of employment (all males aged 38-42)

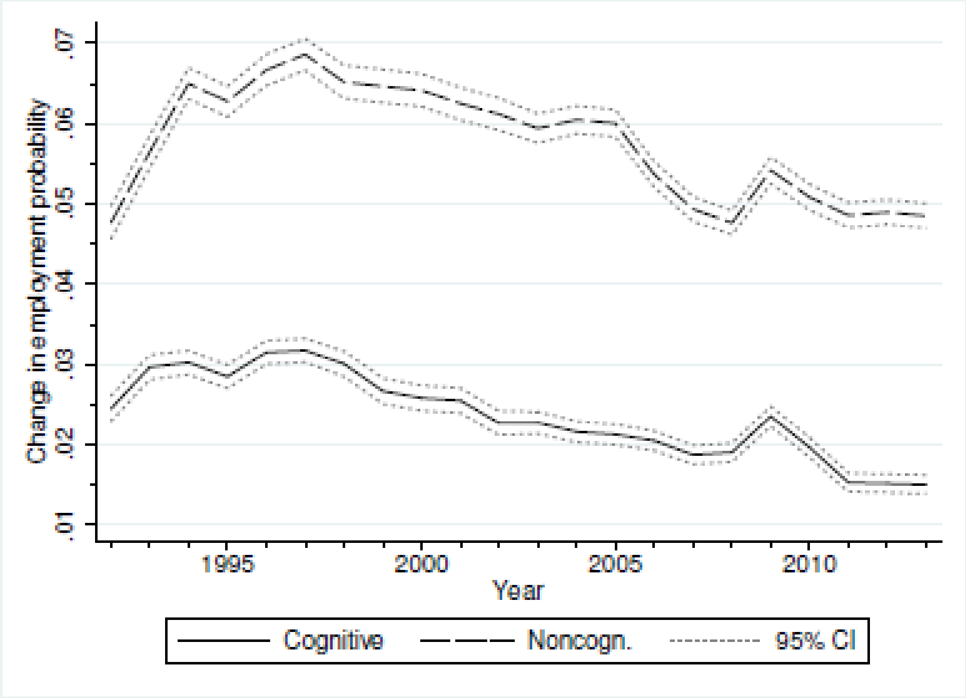
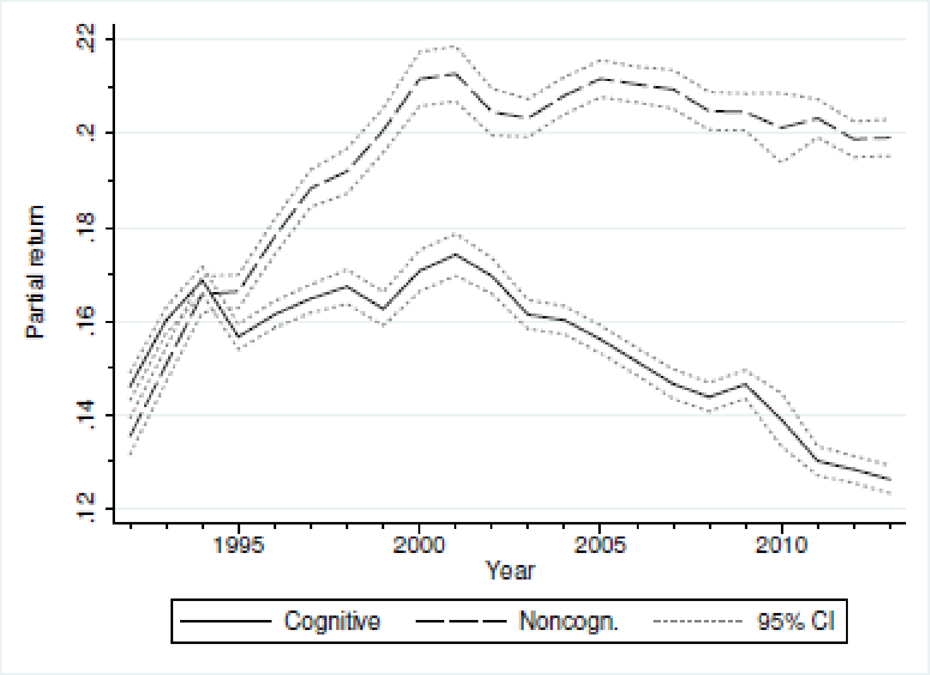


Figure 3: Employment and earnings returns

(b) Earnings return to skills (all males aged 38-42)



Notes: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist et al. (2017). Appendix A5 outlines the procedure.

Estimate wage regressions of the following kind:

$$\ln(wage)_{iat} = \alpha_{at} + \beta_t^C C_i + \beta_t^{NC} NC_i + \epsilon_{iat} \qquad (1)$$

4.1 Non-linearities in the return to skills?

Figure 4: The returns to cognitive and non-cognitive skills, 1992-2013

(a) All workers

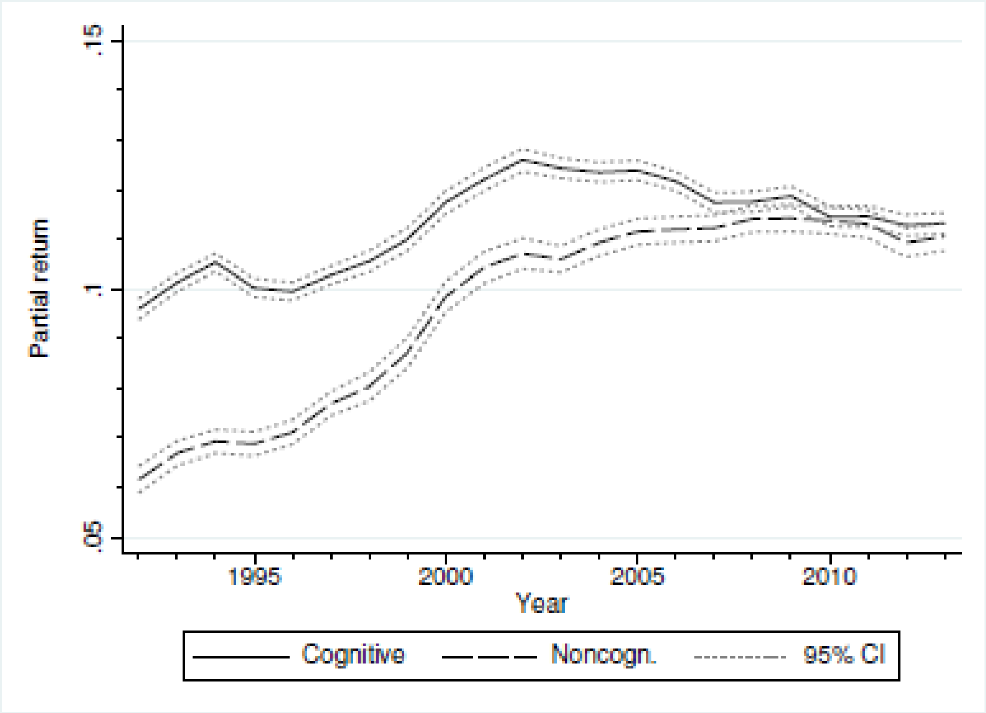
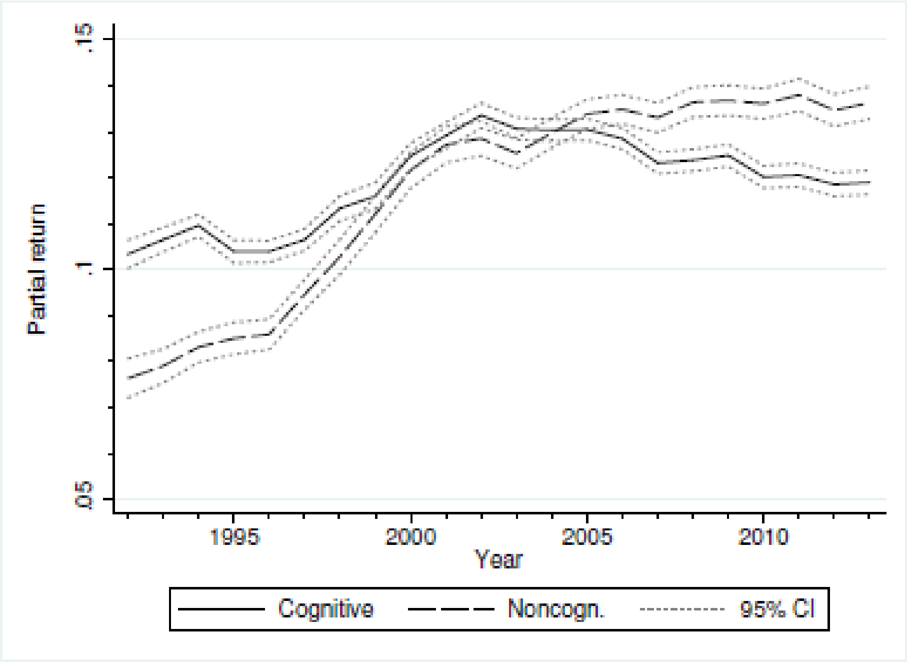


Figure 4: The returns to cognitive and non-cognitive skills, 1992-2013

(b) Private sector workers



Notes: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist et al. (2017). Appendix A5 outlines the procedure.

Figure 5: Quantile regression estimates, 1992-2013

(a) Non-cognitive skills

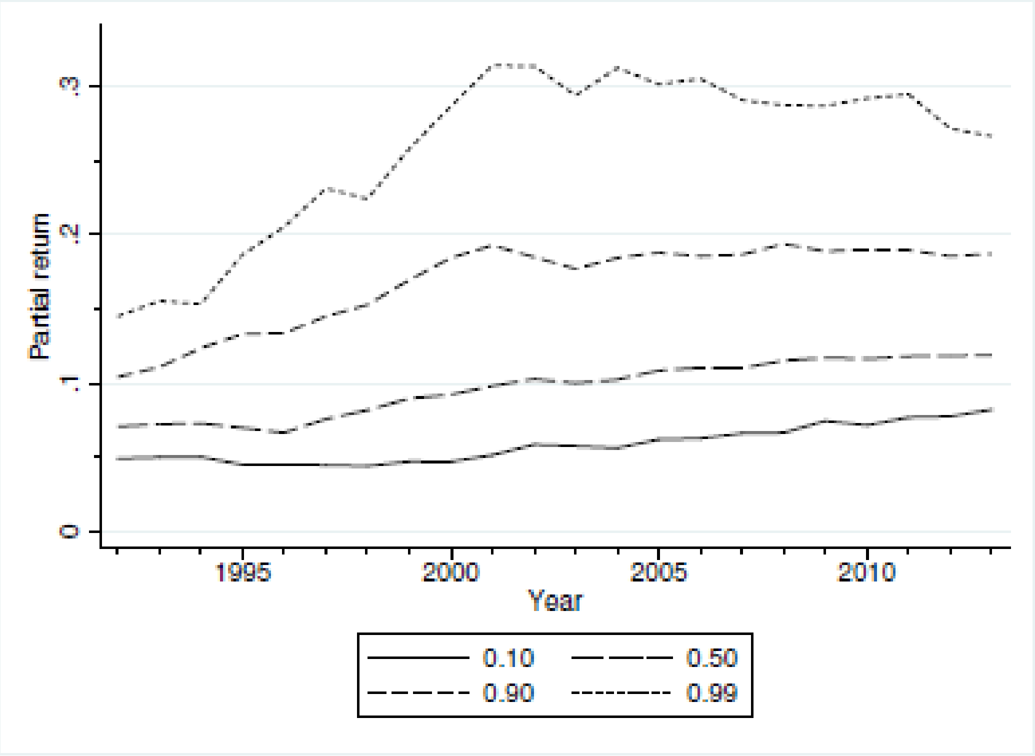
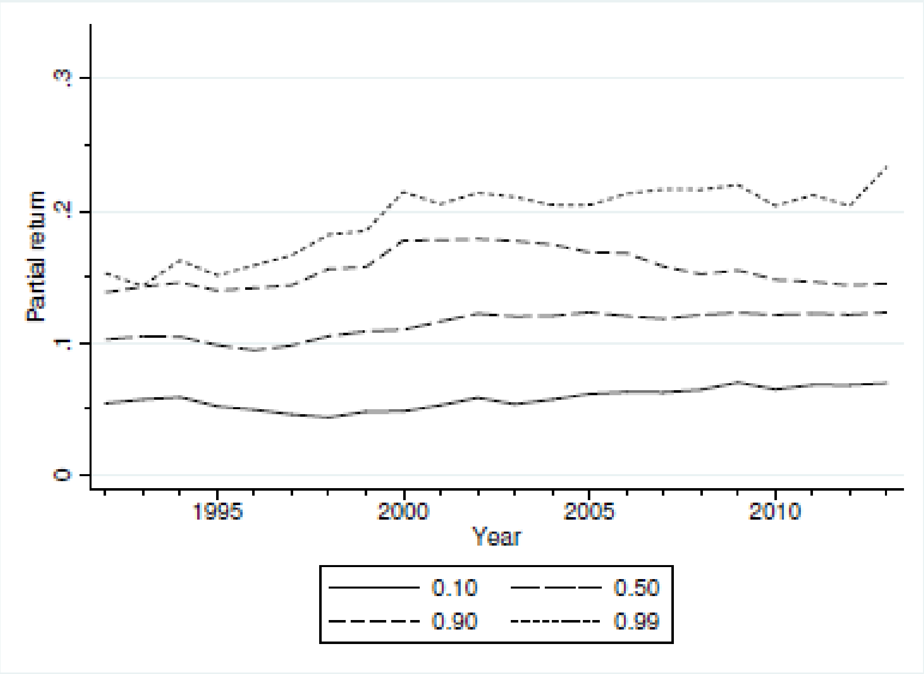


Figure 5: Quantile regression estimates, 1992-2013



(b) Cognitive skills

Notes: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist et al. (2017). Appendix A5 outlines the procedure.

Figure 6: Predicted log wages across the skill distributions

(a) Predicted log wage by bins of non-cognitive skill

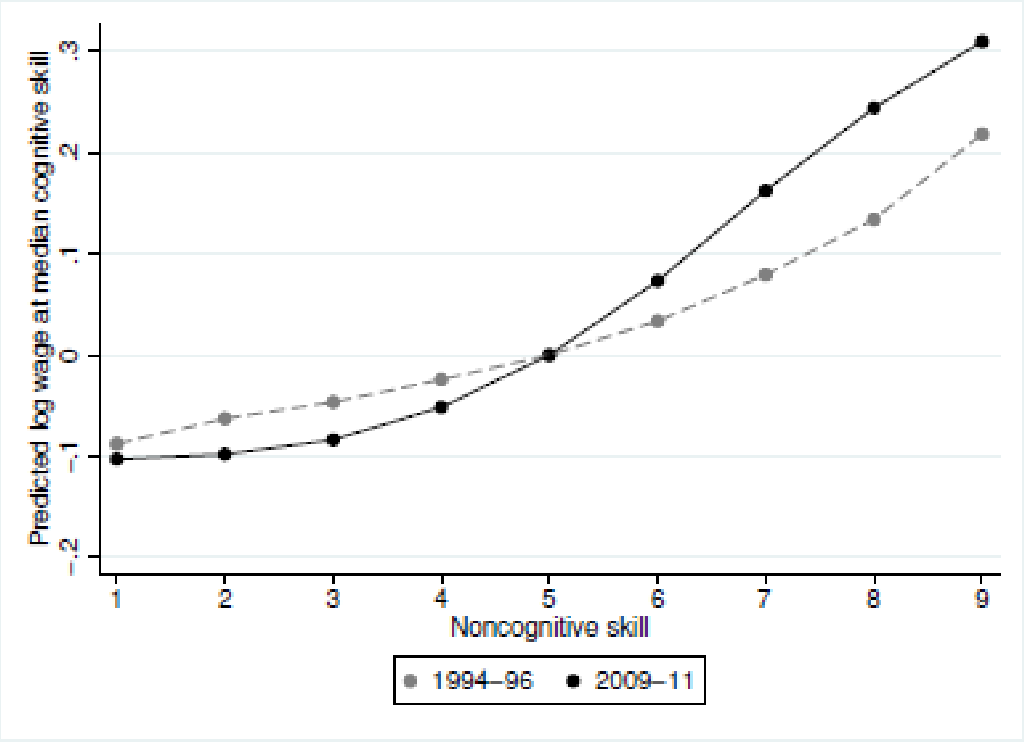
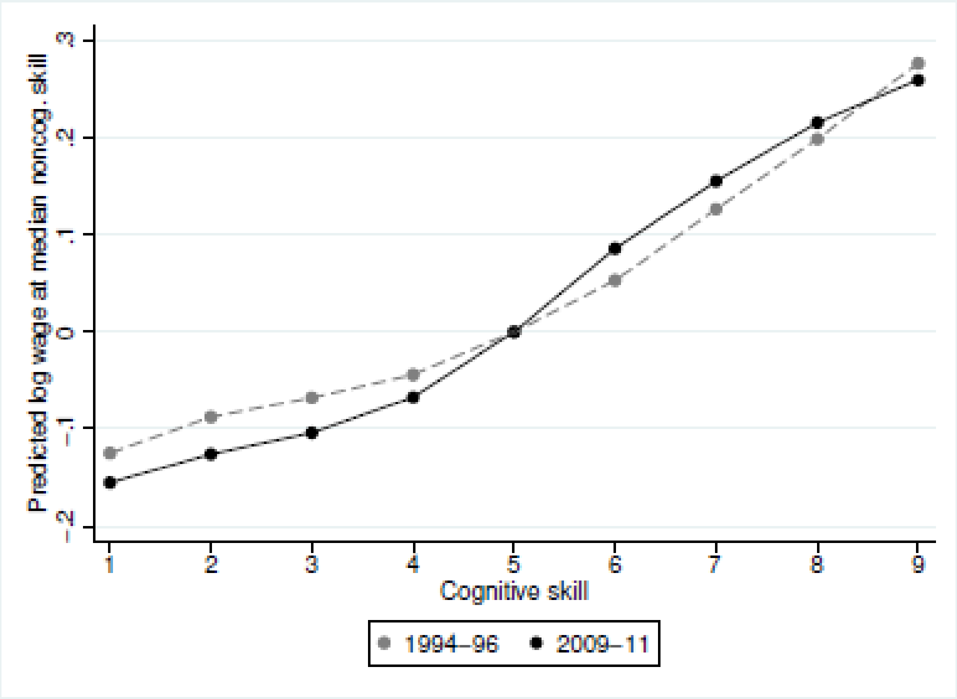


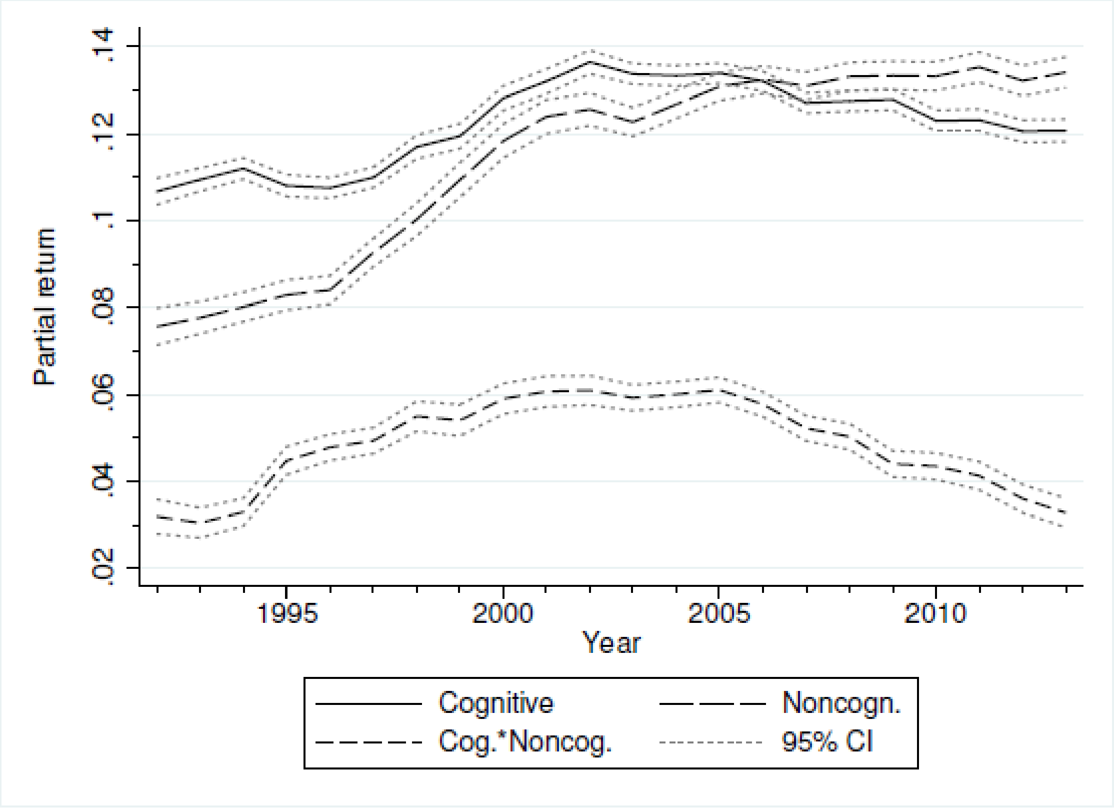
Figure 6: Predicted log wages across the skill distributions



(b) Predicted log wage by bins of cognitive skill

Notes: The figure is based on the model $\ln(wage)_{iat} = \alpha_{at} + \sum_{j=1}^{9} \beta_{jt}^{NC} D_{ij}^{NC} + \sum_{j=1}^{9} \beta_{jt}^{C} D_{ij}^{C} + \epsilon_{iat}$, where, e.g., D_{ij}^{NC} equals unity if the individual score belongs to the jth Stanine of the non-cognitive skill distribution. The figure shows predicted log wages by Stanine bin, at two points in time, holding the other skill fixed.

Figure 7: Returns to skills and their interaction



4.2 Can the increase be accounted for by sorting?

Table 2: Decomposing the changes in the returns to cognitive and non-cognitive skills

	Cognitive		Non-cognitive	
	Overall change: 0.016		Overall change: 0.052	
	Across	Within	Across	Within
A. Industry	0.012	0.004	0.014	0.038
B. Firm	0.008	0.008	0.016	0.036
C. Occupation	0.009	0.007	0.027	0.025
D. (Occupation×Industry)	0.012	0.004	0.032	0.020

Notes: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist et al. (2017). Appendix A5 outlines the procedure.

5 Occupational sorting and wage-setting

5.1 Sorting on occupational task intensities

- How sorting across occupations relates to cognitive and non-cognitive skills, and how these relations have changed over time.

- Use occupational task/skill intensities as outcomes in a regression model that is otherwise analogous to equation (1), i.e.,

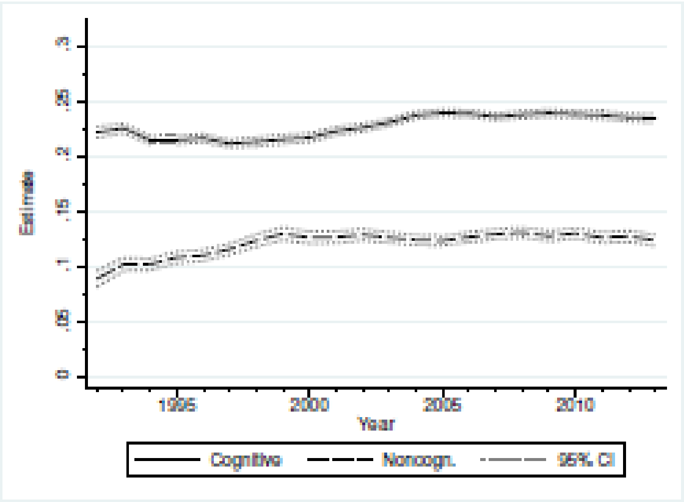
$$T_{iat} = \gamma_{at} + \theta_t^C C_i + \theta_t^{NC} NC_i + \varepsilon_{iat} \qquad (2)$$

where *T* denotes a task (or skill) intensity in the occupation performed by individual *i*.

5.2 The probability of holding a managerial position

Table 2: Decomposing the changes in the returns to cognitive and non-cognitive skills

(a) Initial cognitive skill intensity



(b) Abstract

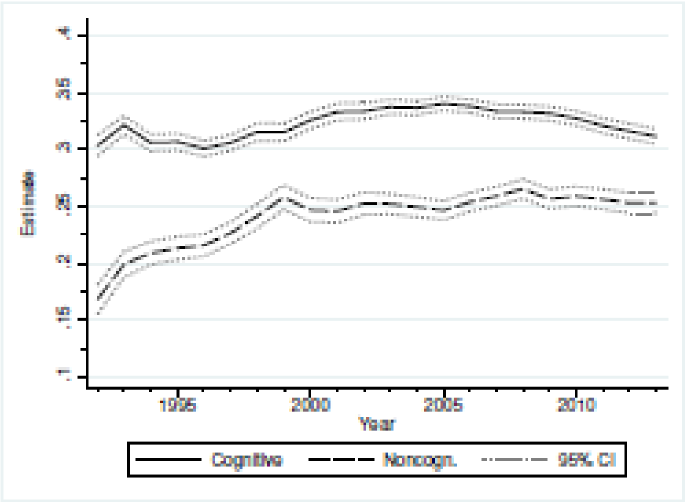


Table 2: Decomposing the changes in the returns to cognitive and non-cognitive skills

(c) Routine (d) Automation

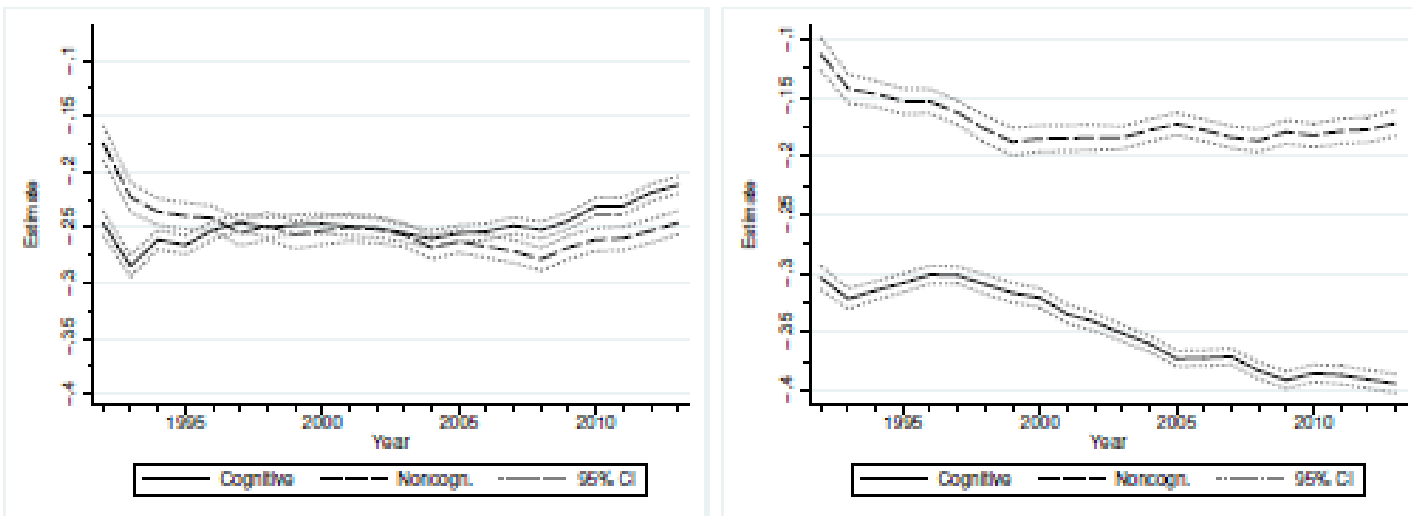
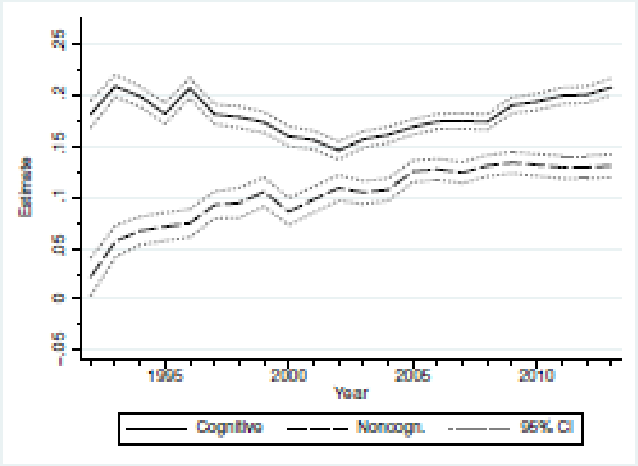
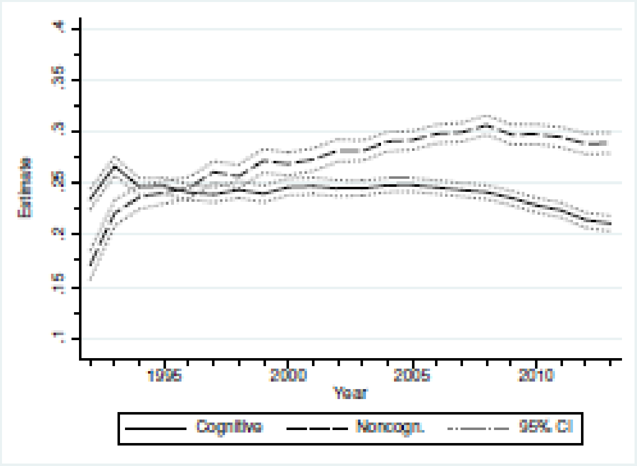


Table 2: Decomposing the changes in the returns to cognitive and non-cognitive skills

(e) Offshorability

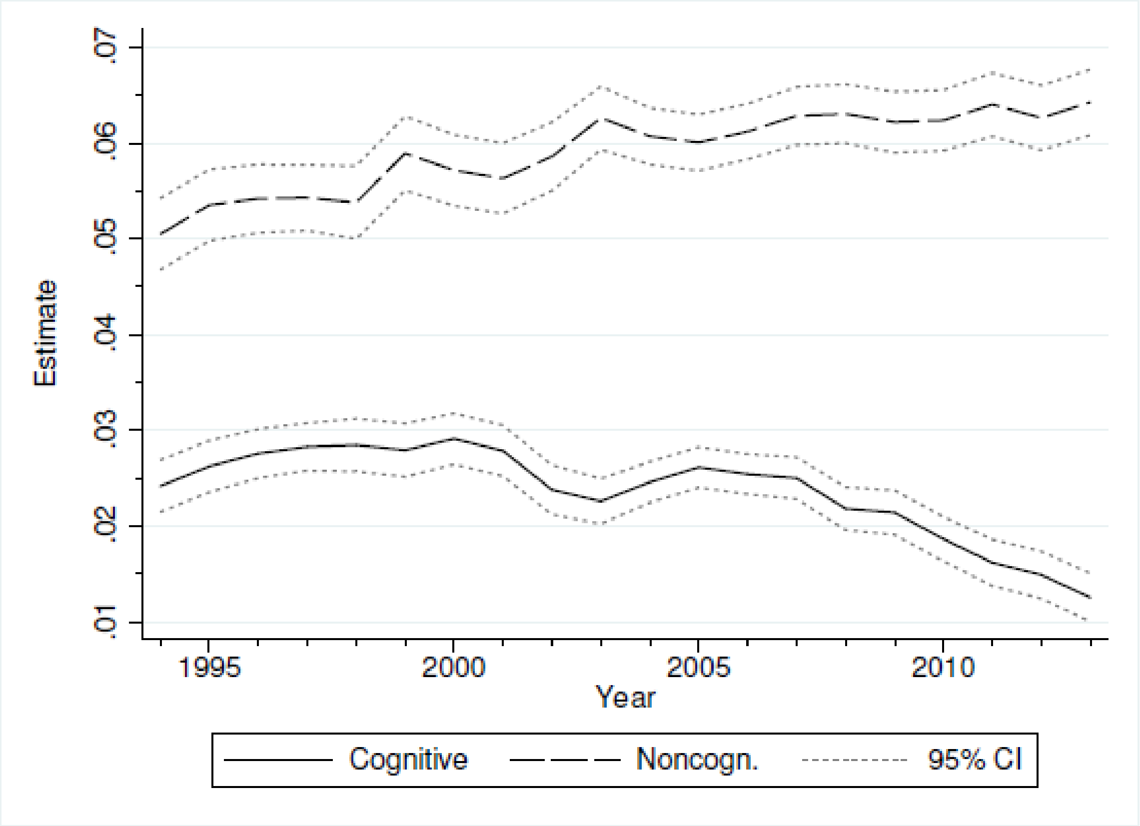


(f) Social



Notes: Occupational information has been matched to the O*NET database to obtain job requirements. The classification of Abstract, Routine, and Offshorable jobs follows Acemoglu and Autor (2011) and the classification of occupations requiring social skills comes from Deming (2017). We thank Fredrik Heyman for providing the information on automatable occupations.

Figure 9: The relationship between skills and probability of being a manager



Notes: All estimates are corrected for measurement error using reliability ratios of 0.73 for cognitive skill and 0.50 for non-cognitive skill; see Grönqvist et al. (2017).

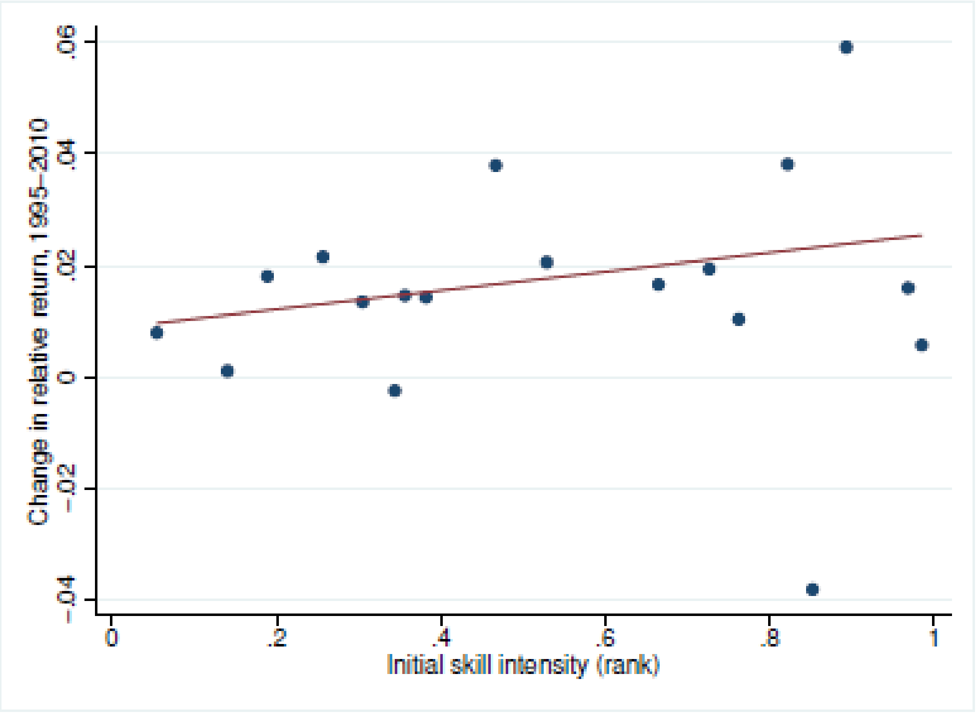
5.3 Occupational wage setting

Occupational wage-setting

- Estimate the returns at the occupational level and then ask whether the estimated returns correlate with skill supply.
- Note that this analysis is bound to be descriptive since, with skill responses to changes in the underlying returns, it is not possible to estimate the "true" change in the return to skills at the occupational level. The fundamental input to the evidence presented in this section come from occupational wage regressions of the form

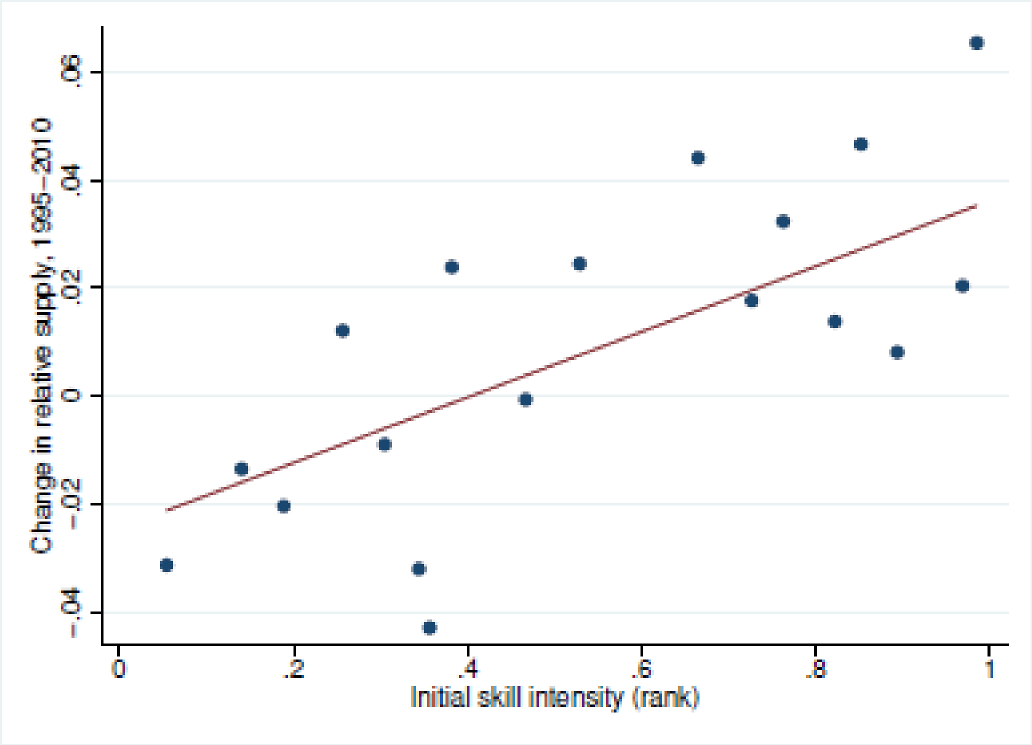
$$\ln(wage)_{iajt} = \alpha_{ajt} + \beta^{C}_{jt} C_i + \beta^{NC}_{jt} NC_i + \epsilon_{iajt}, \qquad (3)$$

Figure 10: Changes in relative returns and relative skill intensities across occupations



(a) Changes in relative return by initial cognitive skill

Figure 10: Changes in relative returns and relative skill intensities across occupations



(b) Changes in relative skill by initial cognitive skill

Table 3: Occupational changes in relative returns and skill intensities

	Dependent variable:				
	ΔRR_j	ΔRR_j	ΔRS_j	ΔRS_j	ΔRR_j
	(1)	(2)	(3)	(4)	(5)
Initial cognitive skill (ranked 0/1)	.017	.034	.061	.045	
	(.000)	(.001)	(.000)	(.001)	
Change in relative supply (ΔRS_j)					.049
					(.002)
Control for initial non-cognitive skill	No	Yes	No	Yes	No

Notes: All estimates are weighted by the number of individuals in each occupation cell. Robust standard errors in parentheses.

Table 4: Changes in relative returns and skills across tasks

Rank (0/1) of initial task intensity	ΔRR_J	ΔRS_J
Abstract	0.024	0.050
	(0.000)	(0.000)
Routine	-0.019	-0.058
	(0.000)	(0.000)
Automatable	-0.019	-0.024
	(0.000)	(0.000)
Offshorable	0.010	0.049
	(0.000)	(0.000)
Social	0.010	0.054
	(0.000)	(0.000)

Notes: All estimates are weighted by the number of individuals in each occupation cell. Robust standard errors in parentheses. Occupational information has been matched to the O*NET database to obtain job requirements. The classification of Abstract, Routine, and Offshorable jobs follows Acemoglu and Autor (2011) and the classification of occupations requiring social skills comes from Deming (2017). We thank Fredrik Heyman for providing the information on automatable occupations.