Online Appendix for "The Rising Return to Non-cognitive Skill"*

Per-Anders Edin Peter Fredriksson Martin Nybom
Björn Öckert

December 22, 2020

A1 Cognitive and non-cognitive skills

A1.1 What traits are captured by the skill measures?

Here we describe what kind of traits the aggregate measures of cognitive and non-cognitive skills capture. We do so in two ways. First, we correlate the skills with detailed occupational requirements derived from O*NET (section A2.3 describes how we match O*NET with our data). Second, we list occupations that score high on a particular dimension, conditional on the other dimension.

Table A1 contains the results from the first exercise. Column (1) correlates non-cognitive skill with a set of occupational requirements, while holding cognitive skill constant; these occupational requirements are the "Big-5" traits (emotional stability is the inverse of neuroticism). Column (2) conducts the analogous exercise for cognitive skill, holding non-cognitive skill constant. Table A1 shows, for example, that individuals with high non-cognitive skill relative to cognitive skill are sorted into occupations requiring extraversion and emotional stability to a greater extent than individuals with high cognitive skill relative to their non-cognitive skill.

Table A2 contains the results of the second exercise; see Fredriksson, Hensvik, and Skans (2018) for a more detailed characterization along the same lines. The left-hand-panel lists occupations scoring high on the non-cognitive dimension by tercile of the cognitive skill distribution.[1] This panel shows, e.g., that among the occupations in the middle

*Edin: Department of Economics, Uppsala University, UCLS, IFAU, and STIAS (Email: per-anders.edin@nek.uu.se). Fredriksson: Department of Economics, Uppsala University, UCLS, IZA, and IFAU (Email: peter.fredriksson@nek.uu.se). Nybom: Institute for Evaluation of Labour Market and Education Policy (IFAU), UCLS, and SOFI (Email: martin.nybom@ifau.uu.se). Öckert: IFAU, Uppsala University, and UCLS (Email: bjorn.ockert@ifau.uu.se).

[1]Given that the skills are so highly correlated, we think it is more informative to examine the conditional distributions.

Table A1: Partial correlations between skills and occupational skill requirements

	Non-cognitive skill	Cognitive skill
	(1)	(2)
Occupational requirements		
Conscientiousness	0.0989	0.1617
	(0.0042)	(0.0055)
Agreeableness	-0.1895	-0.0112
	(0.0043)	(0.0056)
Emotional stability	0.0990	-0.1253
	(0.0036)	(0.0048)
Extraversion	0.1863	-0.0769
	(0.0032)	(0.0042)
Openness to experience	-0.0434	0.3277
	(0.0033)	(0.0043)
Individual skill		
Cognitive skill	0.2168	
	(0.0011)	
Non-cognitive skill	–	0.3719
	–	(0.0019)
#observations	434,286	434,286
R-squared	0.182	0.238

Notes: Robust standard errors in parentheses. Data on individual skills and occupations are from 2000 and cover males aged 38-42. Occupational requirements are constructed from O*NET; see Black, Grönqvist, and Öckert (2018). All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

range of the cognitive skill distribution, workers in sales occupations and fire fighting score particularly high on non-cognitive ability. For sales persons, the fundamental reason is probably that they are abundant on extraversion which is an important component of the overall non-cognitive score according to Table A1. Fire-fighting is presumably an occupation requiring emotional stability, which according to Table A1 is a trait characterizing individuals who score high on the non-cognitive dimension.

The right-hand-side of Table A2 contains a parallel exercise for cognitive ability. This panel shows, for example, that librarians have an abundance of cognitive skill (0.60 standard deviations above average) but are remarkably low on non-cognitive skill. It also shows that researchers and doctors do well on the cognitive as well as the non-cognitive dimension.

A1.2 Changes in the distribution of skills?

The skill measures we use in the main text are scored on a Stanine scale and hence (approximately) normally distributed in any given cohort of draftees. An interesting (and difficult) question is whether the standardization masks changes in the underlying distribution of skills.

Table A2: Skill endowments across occupations

Top non-cognitive (by tercile of cognitive)		Top cognitive (by tercile of non-cognitive)	
1st tercile of cognitive skill		1st tercile of non-cognitive skill	
Occupation	Score	Occupation	Score
1. Miners (711)	-0.08	1. Librarians (243)	0.60
2. Construction workers (712)	-0.11	2. Craft printing workers (734)	-0.18
3. Health/child/home care workers (513)	-0.15	3. Stock and transport clerks (413)	-0.27
2nd tercile of cognitive skill		2nd tercile of non-cognitive skill	
1. Administrative professionals (248)	0.42	1. Priests (246)	0.82
2. Sales persons (341)	0.41	2. Engineers (311)	0.45
3. Fire fighters and security guards (515)	0.38	3. Photographers, optical/sound operators (313)	0.43
3rd tercile of cognitive skill		3rd tercile of non-cognitive skill	
1. Police officers (345)	0.85	1. University research and teaching (231)	1.14
2. CEOs (121)	0.82	2. Medical doctors (222)	1.14
3. Medical doctors (222)	0.81	3. Physicists, chemists etc. (211)	1.06

Notes: Data pertain to males aged 38-42. Numbers within parentheses are 3-digit ISCO-codes. Small occupations containing less than 50 individuals in our sample (roughly less than 0.06% of the target population) are dropped.

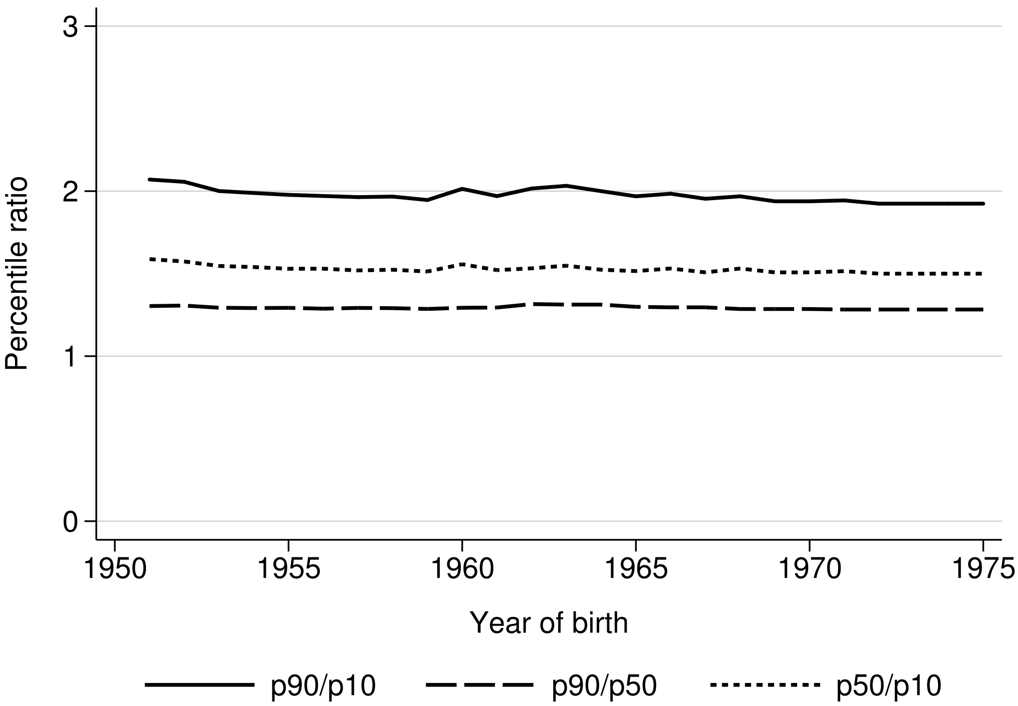
We conduct two robustness checks to address this issue. None of these checks suggest that changes in the distribution of skill are driving the variation in the estimated returns to skills.

A first robustness check is based on the fact that we also have data on the scores on the various cognitive tests. With these data we can examine whether the distribution of cognitive scores changes over time. Figure A1 illustrates how the distribution of cognitive scores have evolved over time. Very little is happening to the distribution of scores over birth cohorts; the 90/10 ratio for instance hovers between 1.9 and 2.1 throughout the time period covered by these data. Below we also show that the return to cognitive skill is essentially the same when we compare raw scores and normalized scores; see Figure A12b.

The above robustness check obviously does not get at changes in the distribution of non-cognitive skill. As a second robustness check, we use data from Finland to measure the changes in the distribution of both kinds of skill. To conduct this exercise we use the paper by Jokela et al. (2017). Their Appendix Table S1 presents anchored cognitive and non-cognitive skills. On the basis of this information, we convert our standardized measures of skill to "actual skill" (assuming that the evolution over cohorts in Finland is an accurate approximation of the corresponding evolution over cohorts in Sweden). We take 1962 to be the base year so that changes in mean skills and dispersion is relative to the 1962 cohort (note that the 1962 cohort is observed in 2002).

Figure A2 presents the results. The black lines in the figure show the results of correcting the skill measures using the data from Finland. These adjusted lines basically lie on top of the lines corresponding to our baseline estimates. Adjusting the estimates

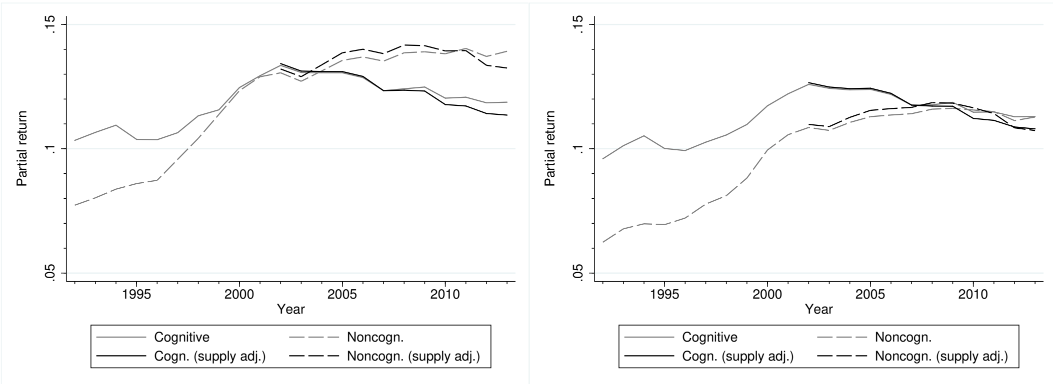
Figure A1: The distribution of cognitive scores, men born 1951-75



Notes: There has been one minor revision of the test during the time frame covered by these cohorts. To link data when a new test is introduced, we have used equipercentile equating. In practice we thus take the last cohort with the old test and compare it to the first cohorts with the new test. The test score for a given percentile with the new test is then assumed to equal the score at the same percentile with the old test.

Figure A2: Returns estimated using variable skill distributions, 1992-2013

(a) Private sector workers (b) All workers



Notes: For all cohorts born 1962 or later we impute changes in the standard deviation of each skill using the summary statistics on anchored cognitive and non-cognitive skills in Appendix Table S1 in Jokela et al. (2017). We use 1962 as the base year so that the changes in skill means and skill dispersion over cohorts are relative to this cohort.

for changes in skill supplies across cohorts thus seems unimportant.

A1.3 Measurement error in the skill measures

Grönqvist, Öckert, and Vlachos (2017) show that measurement errors plague the measures of cognitive and non-cognitive skills to a considerable degree. In their paper, they present two ways of estimating the reliability ratio. In one approach, they use information on the individuals themselves at two different ages (age 13 and age 18). In another approach, they use information on brothers to estimate the reliability ratio. These two approaches yield very similar results. We use their results for brothers which suggest that the reliability ratio for cognitive skill is 73 percent, while the reliability ratio for non-cognitive skill is 50 percent.

We use these estimates to correct the estimates of the respective returns, in a way that we outline below. The measurement error approach becomes a bit non-standard because we use standardized variates in our analysis. If the measurement errors are classical, the measurement error ridden coefficients (b^j) relate to the true coefficients β^j through the formula (see Griliches 1986)

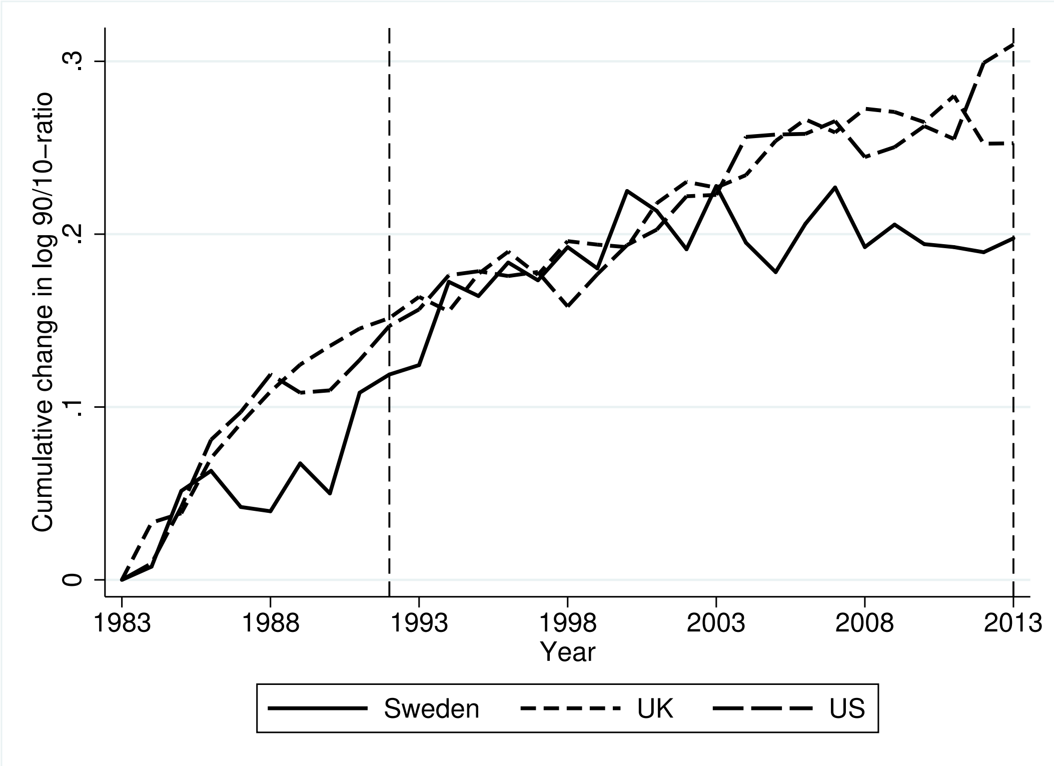
$$b^j = \frac{\beta^j}{\sqrt{\gamma^j}(1-\rho^2)}\left[\gamma^j - \rho^2 + \frac{\beta^k}{\beta^j}(1-\gamma^k)\rho\right],\ j,k = c,n\ j \neq k$$

where ρ denotes the correlation between skill j and skill k and γ^j denotes the conventional reliability ratio:

$$\gamma^j = \frac{VAR(X^j)}{VAR(X^j) + VAR(V^j)},\ j = c,n$$

where X^j denotes the correctly measured non-standardized variables and V^j the mea-

Figure A3: Changes in earnings inequality, men, 1983-2013



Notes: The data pertain to annual earnings for prime-aged 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.

surement error.

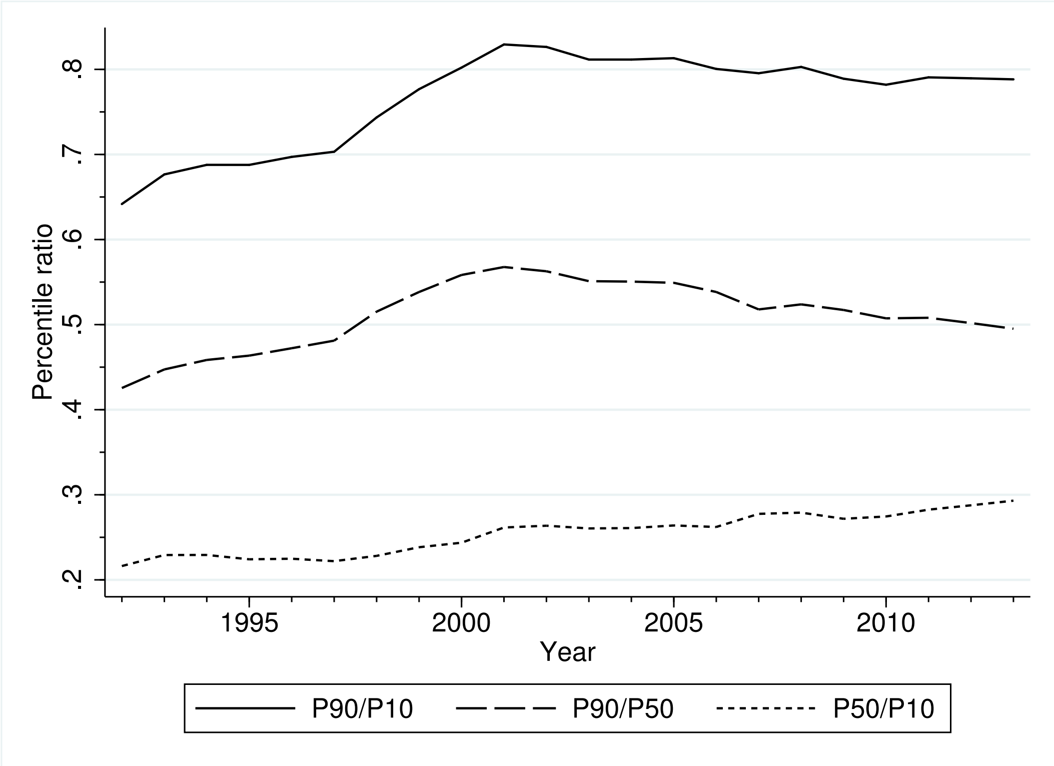
A2 Descriptive statistics

A2.1 Wage inequality in Sweden

It is well known that wage inequality is low in Sweden. But like the vast majority of industrialized countries, inequality has increased markedly since the early 1980s. Figure A3 shows the changes in earnings inequality (the 90/10-ratio) among men in Sweden, the UK, and the US between 1983 and 2013. Over the entire time period, earnings inequality has increased by 20-30 log points in these three countries. During the first 20 years of the observation window (1983-2003), the increase in inequality is virtually identical in the three countries. Between 2003 and 2013 earnings dispersion continued to rise in the UK and the US, while the increase came to a halt in Sweden

In addition to sharing the increase in wage inequality with almost all developed countries, Sweden has seen job polarization like the rest of Western Europe and the US. Goos, Manning, and Salomons (2014) show that Sweden experienced much slower employment growth between 1993 and 2010 in the middle of the wage distribution than at the low-

Figure A4: Wage inequality among men aged 38-42, 1992-2013



Notes: The sample only includes individuals with valid draft scores.

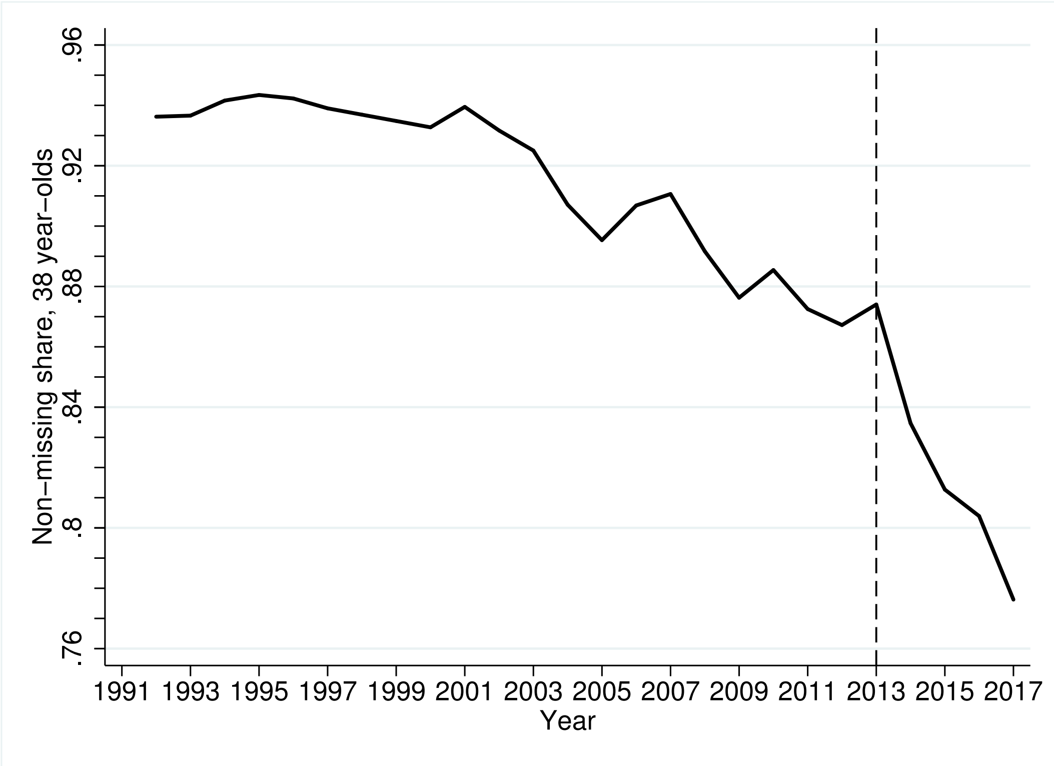
and high-end of the distribution (see also Adermon and Gustavsson 2015).

While Figure A3 provides the broader picture, Figure A4 closes in on our analysis sample (men aged 38-42). A key message is that the changes in wage inequality in our analysis sample tracks the changes in overall inequality in the Swedish labor market well; compare Figures A3 and A4. Again we see a substantial increase in overall wage inequality during the 1990s. This increase came to a halt in the early 2000s. Since then there has been no increase in the 90/10 ratio, but the 90/50 and 50/10 moved in opposite directions.

A2.2 Individual data

The analysis in our paper is based on all men with non-missing cognitive and non-cognitive scores. Figure A5 shows the fraction of men aged 38 with information on draft scores from 1992 to 2017; the dashed line indicates the end of our main analysis period. Throughout the time period we use in the main text, i.e., 1992-2013, the coverage rates never fall below 88 percent, and most of the time it is well above 90 percent. Figure A5 also shows a distinct fall in the coverage rates between 2014 and 2017, from 88% in 2013 to 79% in 2017. This fall is particularly pronounced for individuals at the low end of the distribution. In the bottom decile of the wage distribution, the coverage fell by 14 percent between 2014 and 2017; overall it fell by 10 percent. Selection into test-taking it thus a bigger concern during 2014-17, and therefore our main analyses discards this time period. In Figure A11a, we show estimates of the returns to skills during 1992-2017 for the entire target population (men aged 38-42). The returns to both skills drop by a log point between 2014 and 2017. However, Figure A11b, which presents estimates for men aged 41-42, demonstrates that for non-cognitive skill, in particular, this decline is likely an artifact coming from the sharp reduction in the coverage rates during 2014-17.

Figure A5: Fraction of men with complete draft scores



Notes: The figure is based on men born 1954-1979 who were aged 38 between 1992-2017. The substantial fall in the coverage rate in 2014 occurs for the cohort born 1976. The dashed vertical line indicates the end of our main analysis period.

Table A3 shows descriptive statistics for various sub-samples of individuals observed in 2011-13 with valid draft scores. Column (1) shows average skills and labor market outcomes (employment and annual earnings) among men aged 30-50 in 2011-13, who did both tests at age 18 or 19.[2] 92 percent of these men were employed according to Statistics Sweden's register-based definition of employment. This registered employment rate is based on income statements from employers and self-employment income; the objective is to emulate employment in November according to the Labor Force Surveys (where individuals are coded as employed if they have worked one hour during the measurement week).

Column (2) considers the population age 38-42. This subset of individuals have a

[2]The respective scores are standardized within each birth cohort for the population with a non-missing value along a particular dimension. Those being evaluated along the non-cognitive dimension are slightly positively selected in terms of their cognitive skill. This is the reason why the mean of the cognitive score, for example, is 0.05 in column (1).

marginally higher connection to the labor market; the employment rate is 1 percentage point higher, and annual earnings 4 percent higher, in column (2) compared with column (1). Column (3) focuses on the subset of the population in column (2) who are employed (according to the definition used by Statistics Sweden). This raises average earnings by construction. Column (3) also shows that the employed are positively selected in terms of skills.

Column (4) considers the subset of individuals in column (3) who are observed in the wage register. The wage register covers employees, and thus the self-employed are not included. As such, it samples employees with more stable employment than the population register. For these two reasons, earnings is higher in the wage sample than among those who are registered as employed according to the population register.

The wage data are collected by stratified sampling of (around 50% of workers in) the private sector. Stratification is based on firm size, with the largest private sector firms being sampled with unit probability, and private sector firms with fewer than 10 employees being sampled with 3% probability. Unfortunately we do not have information on the exact stratification weights. Rather we have information on the "final weights" which reflect the combined influence of sampling probabilities and response rates. Non-response rates are sometimes high, resulting in very high weights, implying that certain observations might be very influential when trying to estimate other moments than the mean. For that reason our baseline approach is to present unweighted estimates. In Section A3.8 we illustrate that the weighted regression yields the same trends as the unweighted one. While the trends are the same, there is more year-to-year volatility in the weighted estimates. The year-to-year variability presumably comes from the adjustment for non-response; we do not find this variability particularly plausible and, therefore, focus on the unweighted estimates.

For descriptive statistics, the weighted means are preferable, however. Thus, Table A3 also presents the weighted means for the key variables in brackets. The weighted means show that employees in the wage register have slightly higher skills than those who are coded as employed in the population register.

Column (5), finally, focuses on employees in the private sector. The weighted means illustrate that earnings and wages are slightly higher (2%) in the private sector than in the overall economy. A comparison of columns (4) and (5) also reveal that those working in the public sector are more skilled on average.

A2.3 Occupational traits

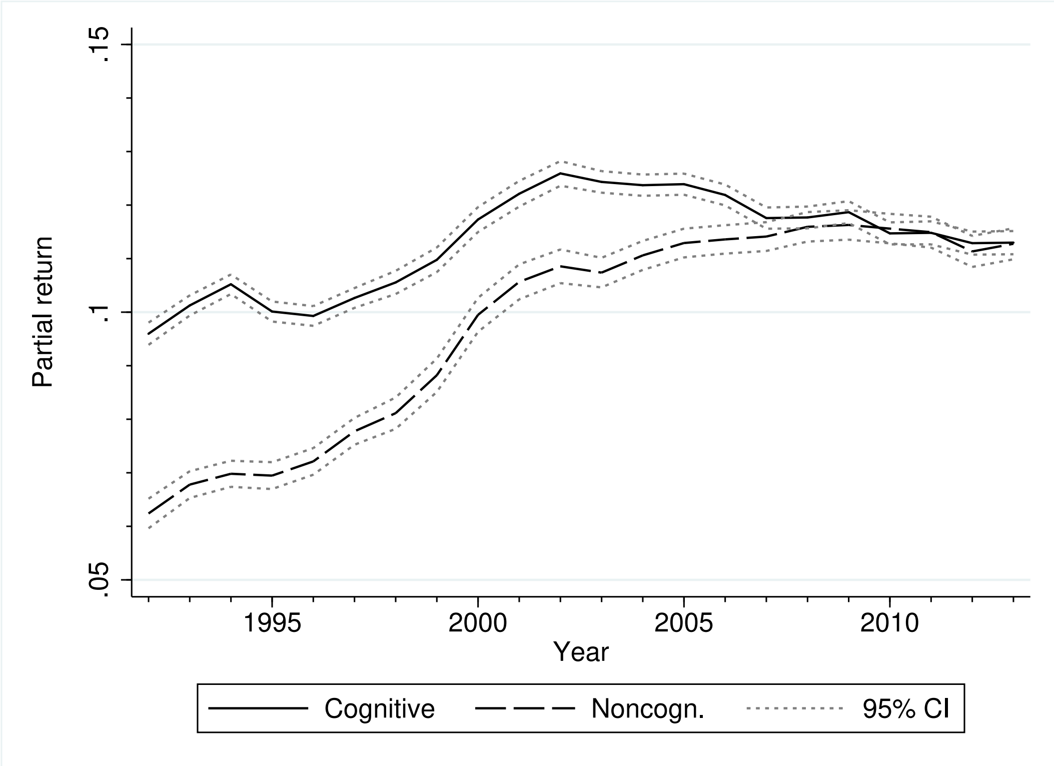
We make frequent of information about the task content of occupations from O*NET. To link the O*NET information to the Swedish occupational classification we used the following steps. First, we merge the occupational codes (SOC 2000) in O*NET version

Table A3: Descriptive statistics, men, 2011-13

	(1)	(2)	(3)	(4)	(5)
Age group	30-50	38-42	38-42	38-42	38-42
Population	All	All	Employed	Employed	Employed
Register	Pop. register	Pop. register	Pop. register	Wage register	Wage register
Sector	All	All	All	All	Private sector
Employed	0.92	0.93	1.00	1.00	1.00
Annual earnings (1000 SEK)	398.20	413.25	442.16	472.01	498.87
[weighted mean]				[458.56]	[468.32]
(SD)	(305.75)	(280.15)	(268.52)	(257.63)	(284.86)
Cognitive skill	0.05	0.04	0.07	0.17	0.12
[weighted mean]				[0.09]	[0.05]
(SD)	(0.98)	(0.98)	(0.97)	(0.97)	(0.98)
Non-cognitive skill	0.02	0.02	0.06	0.12	0.08
[weighted mean]				[0.06]	[0.03]
(SD)	(0.98)	(0.99)	(0.96)	(0.96)	(0.94)
Log wage				10.49	10.53
[weighted mean]				[10.46]	[10.48]
(SD)				(0.33)	(0.35)
Private sector				0.71	1.00
Blue-collar worker					0.35
White-collar worker					0.65
Managerial occ.				0.09	0.11
Other high-skill occ.				0.54	0.48
# observations	2,755,257	692,237	644,187	288,581	204,877
[sum of weights]				[532,153]	[448,449]

Notes: All columns condition on non-missing cognitive and non-cognitive scores as well as non-missing employment and earnings. Individuals have non-missing employment information if they are alive and Swedish residents in 2011-13. Weighted means are in brackets; standard deviations (based on non-weighted data) are reported in parentheses for non-binary variables.

Figure A6: Wage returns to skills for all employed workers



Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

14.0 to ISCO88, using a crosswalk table produced by The National Crosswalk Center. Second, we take the employment-weighted average of the job attributes in O*NET, using US occupational employment statistics. Third, we translate the Swedish occupational classification into the ISCO88 using a crosswalk table from Statistics Sweden. Fourth, we match the data sources together. We are able to do this for occupations at the 3-digit level and the result is an O*NET characterization of all 114 occupations at the 3-digit level in the Swedish occupational classification.

Table A4 provides the correlation between various occupational traits in our data.

A3 Additional estimates of the returns to skill

A3.1 Returns to skill for private and public sector workers

Figure A6 shows the evolution of the wage returns to skill for all employed workers. Since the vast majority of prime-aged men is employed in the private sector, this figure delivers a similar message as Figure 1 of the main text. The main difference between the two is that the level of the return to non-cognitive skill appears to be lower in the public sector. However, we see the same stark increase the reward to non-cognitive ability from 1992 to 2013.

Table A4: Correlation matrix, occupational data

	ΔRR_j	ΔRS_j	$\ln(w_{j,95})$	$\Delta Empl.sh._j$	$s^c_{j,95}$	$s^n_{j,95}$	Abstract	Routine	Automation	Offshorability	Social
ΔRR_j	1.000										
ΔRS_j	0.028	1.000									
$\ln(w_{j,95})$	0.095	0.454	1.000								
$\Delta Empl.share_j$	-0.034	-0.036	0.173	1.000							
$s^c_{j,95}$	0.173	0.535	0.850	0.221	1.000						
$s^n_{j,95}$	0.067	0.544	0.877	0.216	0.897	1.000					
Abstract	0.106	0.392	0.852	0.298	0.818	0.872	1.000				
Routine	-0.091	-0.449	-0.610	-0.256	-0.636	-0.773	-0.683	1.000			
Automation	-0.221	-0.221	-0.747	-0.347	-0.775	-0.697	-0.801	0.544	1.000		
Offshorability	0.066	0.448	0.463	0.056	0.439	0.374	0.209	-0.313	-0.148	1.000	
Social	-0.013	0.399	0.719	0.255	0.640	0.822	0.773	-0.829	-0.569	0.389	1.000

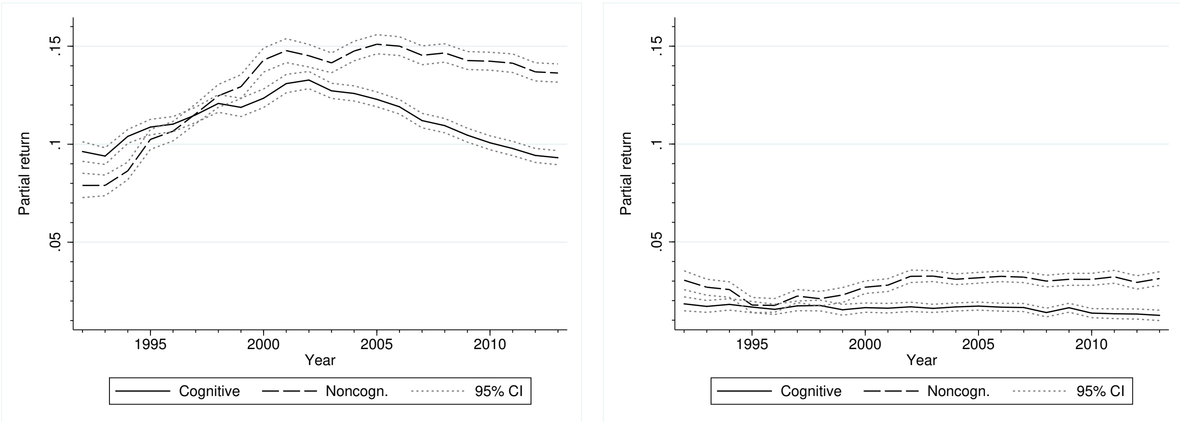
Notes: All correlations are weighted by the number of individuals in each occupation cell. $\Delta Empl.share_j$ is measured for the entire population (rather than just men aged 38-42). $\Delta RR_j = (\beta^n_{j,2012} - \beta^c_{j,2012}) - (\beta^n_{j,1995} - \beta^c_{j,1995})$ denotes the change in the relative return by occupation and $\Delta RS_j = \Delta(s^n_j - s^c_j)$ the change in relative skill intensity by occupation. All changes are between 1995 and 2012. The remainder of the notation is as in the main text.

A3.2 Returns by worker status

Figures A7a and A7b shows returns estimated by worker status (white-collar and blue-collar workers). The increase in the returns almost exclusively occurs in white-collar occupations. This is consistent with the result that the return to non-cognitive skill increased the most at the upper-end of the wage distribution; see Figure 5 of the main text.

Figure A7: Returns by worker status, 1992-2013

(a) White-collar workers (b) Blue-collar workers



Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

A3.3 Age, cohort, and time

A potential concern is that the results are particular to the chosen age-range. What if we broaden the age range to include males aged 30-50? Broadening the age range introduces the complication that the sample is not balanced in terms of age over time. To deal with this issue we must impose more structure on the estimated equation. We thus estimate the panel data model:

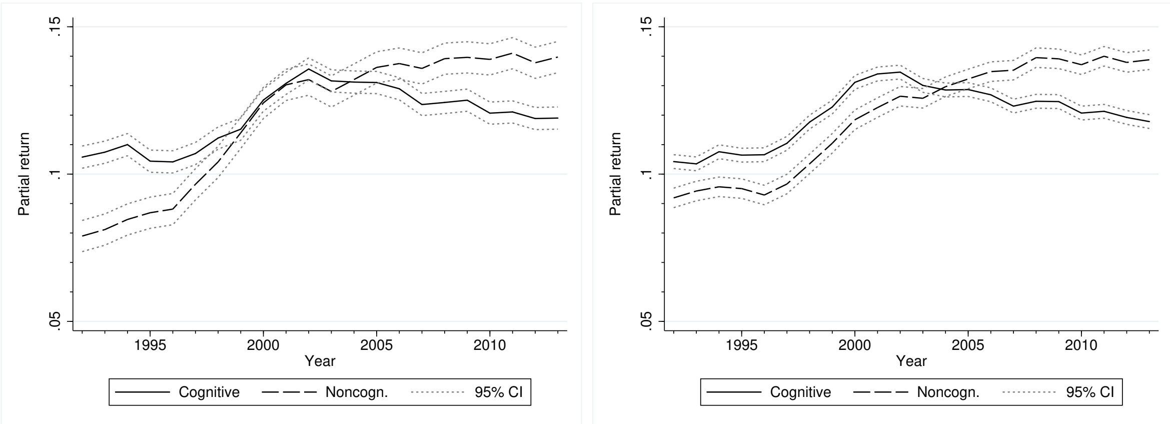
$$\ln(wage)_{iat} = \sum_{t=1992}^{2013} (\alpha_t + \beta_t^c s_i^c + \beta_t^n s_i^n) + \sum_{a=30}^{50} (\alpha_a + \lambda_a^c s_i^c + \lambda_a^n s_i^n) + \varepsilon_{iat}, \tag{A1}$$

The notation is basically the same as in equation (1) of the main text. Relative to equation (1) we assume that the effect of age does not vary over time; we also include the skill-age interactions λ_a^c and λ_a^n, to deal with the fact that the age range varies over time. We normalize the age fixed effects and skill-age interactions to age 40, such that the estimates have the same reference age as our main analysis.

Figure A8 shows the results; Figure A8a reproduces our main results; while Figure A8b shows the results for men aged 30-50. Overall, the two figures are very much alike. Consistent with A8a, Figure A8b shows a strong rise in the return to non-cognitive skill

Figure A8: The returns to skills for different age ranges, 1992-2013

(a) Ages 38-42 (b) ages 30-50



Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure. Age fixed effects and interactions between age and skills are included. Estimates of the returns are normalized to age 40.

while the return to cognitive skill falls somewhat between 2000 and 2013.

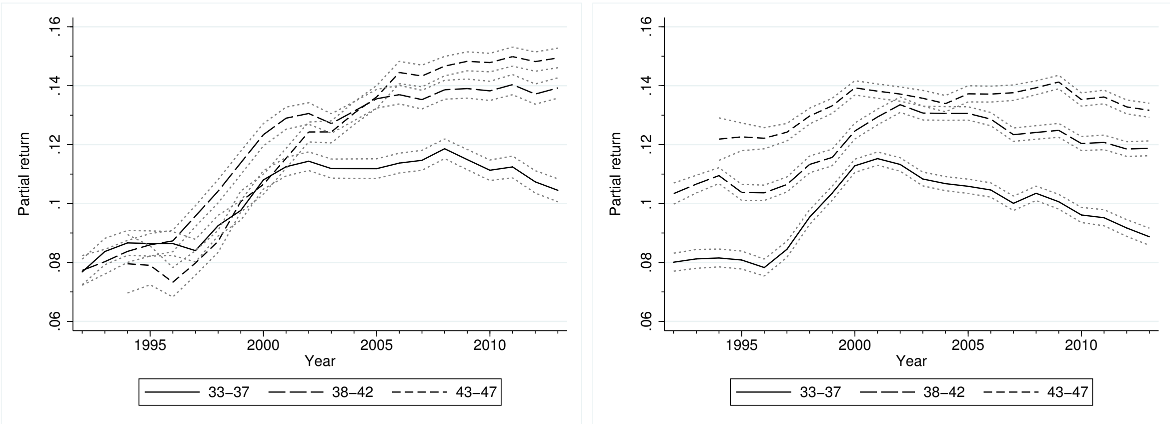
An additional concern related to age is that age, cohort, and time are not simultaneously identified. Since we hold age constant, cohort varies one-for-one with time. The question is whether there are cohort-specific skill returns that conflate our interpretations of the results. To examine this question we take three age groups 33-37 year-olds, 38-42 year olds, and 43-47 year-olds and allow the returns to skill at each particular time point to vary across the three age-groups. If the evolution over time is broadly similar across the three age groups (who are born in different years at a given point in time), this suggests that the skill returns vary over time rather than over cohort.

Figure A9 shows the results. Figure A9a shows the returns to non-cognitive skill across the three age-groups, while Figure A9b does the same thing for cognitive skill. Notice that we can only estimate the returns for the oldest age-group between 1994 and 2013 (given that the draft data start with the cohort born 1951). Notice also that the evolution for the youngest cohort during 2009-13 should be taken with a due grain of salt, since it is for these cohorts we observe the reduction in the coverage rates discussed in connection to Figure A5.

In Figure A9a there is little to suggest that the remarkable increase during the 1990s is driven by changing returns to non-cognitive skill across cohorts. Regarding the returns to cognitive skill, there is one notable difference across the age groups; the return to cognitive skill is markedly lower for the youngest age group in the beginning of the time period. It is difficult to know the exact reason for this. One conjecture is that relatively young and cognitively skilled individuals suffered particularly during the unemployment crises starting around 1990. The three age groups all have in common, however, that the return to cognitive skill stagnated during the 2000s.

Figure A9: The returns to skills across different age groups, 1992-2013

(a) Returns to non-cognitive skill (b) Returns to cognitive skill



Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

A3.4 A longer time frame

What happens to our estimates when we extend the time period? To answer this question, we provide estimates for the population aged 30-50 during the time-period 1985-2013 using equation (A1). Again, we normalize the model to age 40, such that the estimates have the same reference age as our main analysis.[3]

We conduct the analysis for two reasons. First, it would be interesting to provide estimates for a longer time-frame than our main analysis. Second, it illustrates the advantages of focusing on an age group that is insulated from the cycle.

Figures A10a and A10b report a sub-set of the results. In interpreting these results, note that Sweden was hit by the most severe unemployment crisis since the Great Depression in the early 1990s. In just a few years, unemployment among men aged 25-54, for example, went from 1.3% (in 1990) to 8.4% (in 1993). Like all cyclical downturns, this shock hit the bottom end of the skill distribution to a greater extent than the top end. The employed population thus became more selected in terms of skills, and we expect the returns to skills in the employed population to decline. This is also what we see in the population of all workers during the beginning of the 1990s (see Figure A10a). The cyclical variation contaminates the picture and it becomes more difficult to distill the variation in returns that is due to structural change.

In Figure A10b we zoom in on a skilled segment of the labor market: white-collar workers in the private sector. Here we do not see the cyclical variation that distorts Figure A10a. Thus we are more inclined to believe that Figure A10b reflects structural change in the labor market, at least for the skilled segment of the market. Figure A10b suggests that the reward to non-cognitive ability was relatively stable prior to 1992. It is

[3]Notice that the included ages vary over time. Given that the first draft cohort is born 1951, the year 1985 includes individuals aged 30-34.

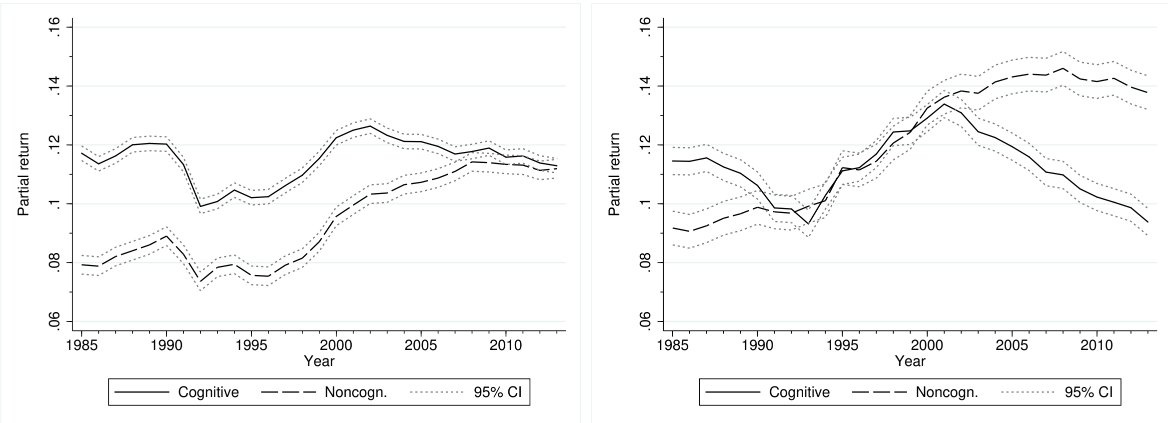
after 1992, that we see the big increase in the return to non-cognitive skill.

The estimates in Figure A10b can be compared to A7a. Since the evolution of the estimates in the two figures is similar for the period when the two approaches can be compared, it seems that the panel approach delivers reliable estimates (with the caveat that it is more sensitive to cyclical changes since in includes younger workers to a greater extent). We therefore conclude that the return to non-cognitive skill appears to have hovered around 8% prior to the start of our analysis period; see Figure A10a prior to 1990.

Figure A10: Panel estimates of returns, 1985-2013 (ages 30-50)

(a) All workers

(b) White-collar workers



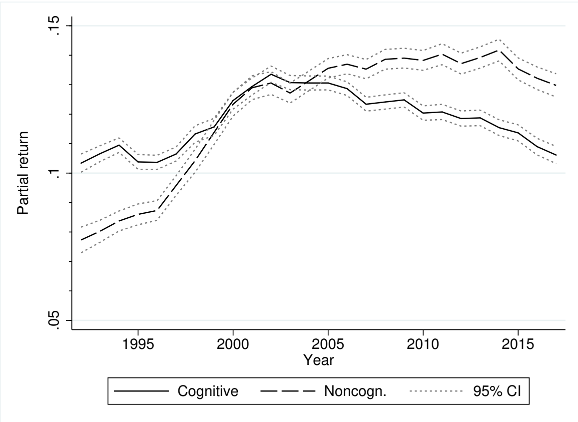
Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

In addition to the estimating the panel data model above, we also add more recent years (2014-2017) in an analysis supplementing our main analysis. Our main analyses exclude these additional years, since the coverage rates start to decline rather drastically during 2014-2017; see Figure A5. For completeness, Figure A11 shows estimates of the returns to skills for 1992-2017. Panel (a) shows that the returns to both types of skills fell by one log-point during 2014-2017, for our target population (men aged 38-42).[4] However, for non-cognitive skill, in particular, this decline is an artifact of the sample getting increasingly selected for these last years. Panel (b) illustrates this by showing estimates for men aged 41-42, an age group which was largely unaffected by the fall in the coverage rates; the return to non-cognitive skill did not change during 2013-2017, while the trend decline in the return to cognitive skill continued through 2013-2017.

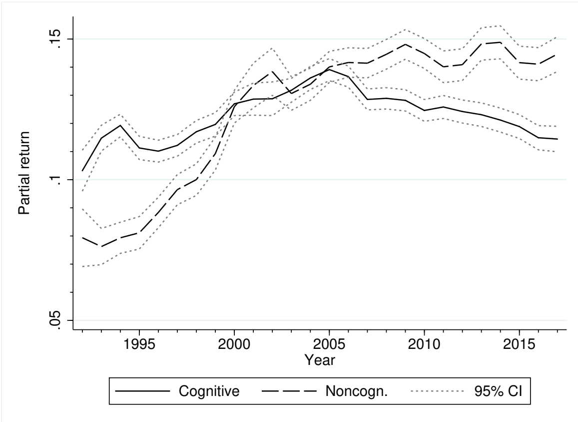
[4]We have tried to deal with the fall in the coverage rates during 2014-17 using various forms of weighting procedures. For example, we have made sure that coverage rates are the same across the wage distribution over time. These weighting procedures do not have much effect on the estimates. However, if selection into observed draft scores are based unobserved characteristics correlated with outcomes, it is unlikely that the weighting procedures will be able to deal with the fundamental selection problem.

Figure A11: Returns to skills 1992-2017

(a) Men aged 38-42



(b) Men aged 41-42



Notes: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure. Confidence bands in panel b) are based on robust standard errors.

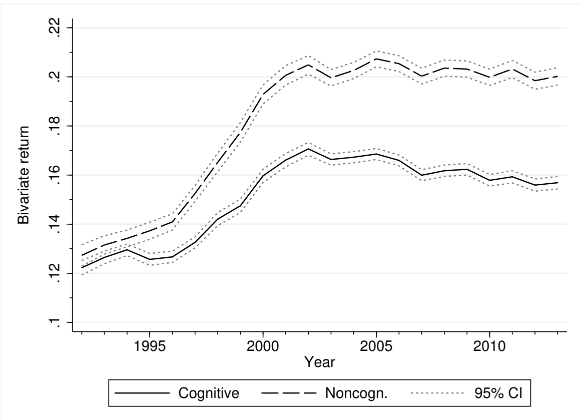
A3.5 Bivariate returns

Figure A12a shows the results of separate regressions of log wages on cognitive and non-cognitive skill, respectively. This does not change the overall flavor of our results. Nevertheless, it is noteworthy that the bivariate return to non-cognitive skill is much higher than the return obtained by partialling out the variation in cognitive skill.

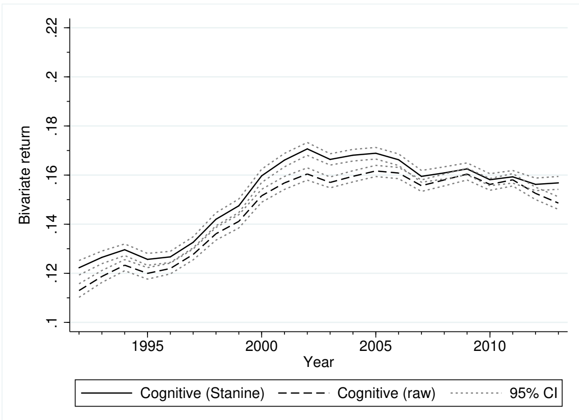
Figure A12b provides a comparison of estimates of the (bivariate) return to cognitive skill for raw scores and standardized scores. The levels are slightly different (the difference is less than a percentage point), but the evolution over time is broadly the same.

Figure A12: Bivariate returns to skills

(a) Both skills – normalized scores

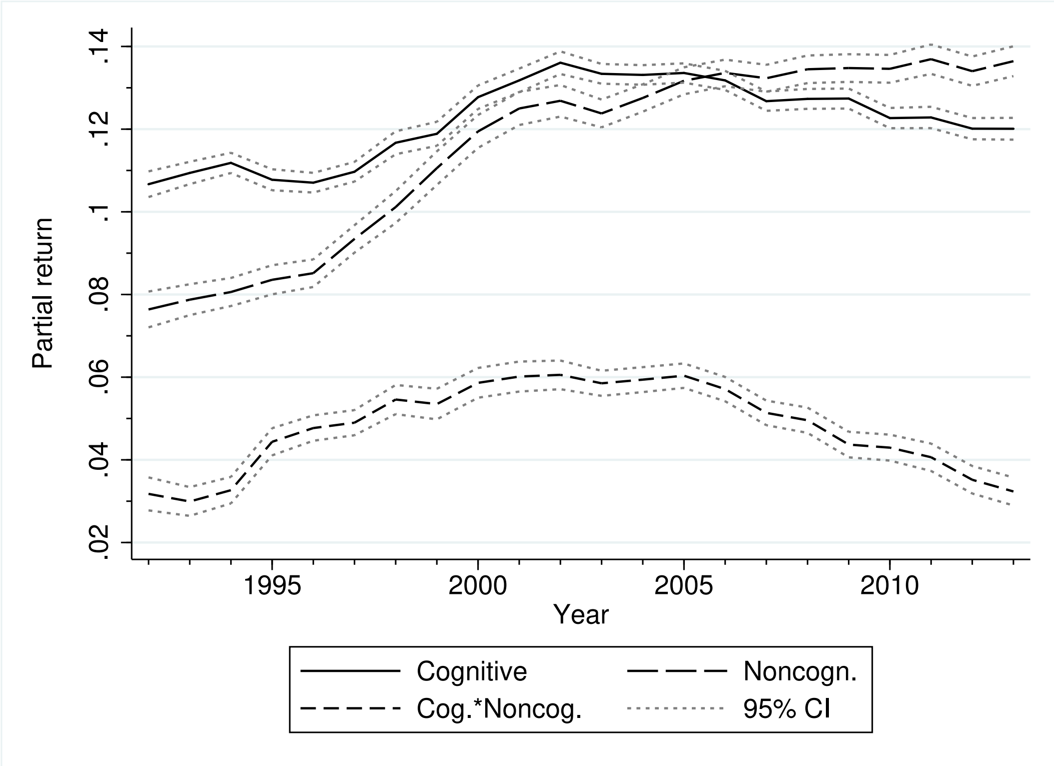


(b) Cognitive skill – raw/normalized scores



Notes: Estimated from separate regressions of log wage on cognitive or non-cognitive skill, respectively. All scores are adjusted by the constant reliability ratios for general cognitive and non-cognitive skill, respectively. Confidence bands are based on robust standard errors.

Figure A13: Returns to skills and their interaction



Notes: Confidence bands are based on robust standard errors. The estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

A3.6 Skill complementarity

An interesting question is whether the two types of skills are complementary, and whether the complementarity evolves over time. Figure A13 shows the results of adding a linear interaction between the two skills to the basic wage regression. Similar to Deming (2017), we find that the interaction between cognitive and non-cognitive skill is always significantly positive. However, there are no drastic changes over time. The interaction term is about as important towards the end as in the beginning of the time period.

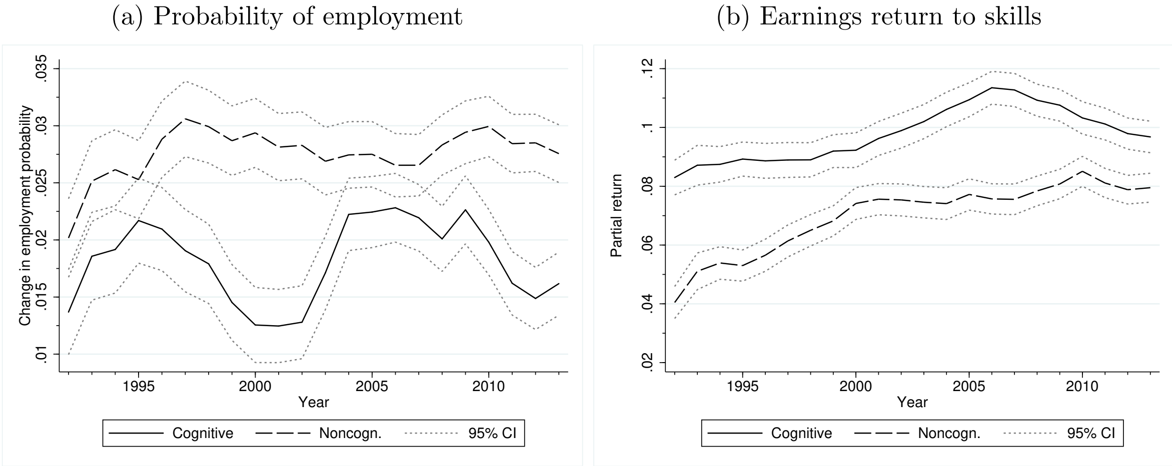
A3.7 Employment and earnings returns for females

Is the increase in the return to non-cognitive skill particular to men? Here we demonstrate that the answer to this question is no.

To estimate the earnings returns to skill we use women with brothers who have done the draft. We convert the reduced form relationship between female earnings and the skills of their brothers to an interpretable scale using estimates of the brother correlation in our data and the relative sister/brother to brother/brother correlation in skills from Grönqvist, Öckert, and Vlachos (2017).

Figure A14 presents the results. Panel (a) shows the results for employment while panel (b) pertains to earnings. Compared to Figure 2 in the paper, the earnings returns

Figure A14: Employment and earnings returns for females



Notes: Confidence bands are based on robust standard errors. To convert the estimates of the reduced form relationship between female earnings and the skills of their brothers to an interpretable scale, we have used estimates of the brother correlations in skills in our data and the relative sister/brother to brother/brother correlation in skills from Grönqvist, Öckert, and Vlachos (2017). The brother correlation is 0.48 for cognitive skill and 0.34 for non-cognitive skill. The relative sister/brother to brother/brother correlation is 0.92 for cognitive skill and 0.93 for non-cognitive skill.

to skills are lower for women than for men. But for women and men alike we see an increase in the return to non-cognitive skill over the time period. Over the entire time period the earnings return to non-cognitive skill increased by 4-5 percentage points.

A3.8 Weighted regressions

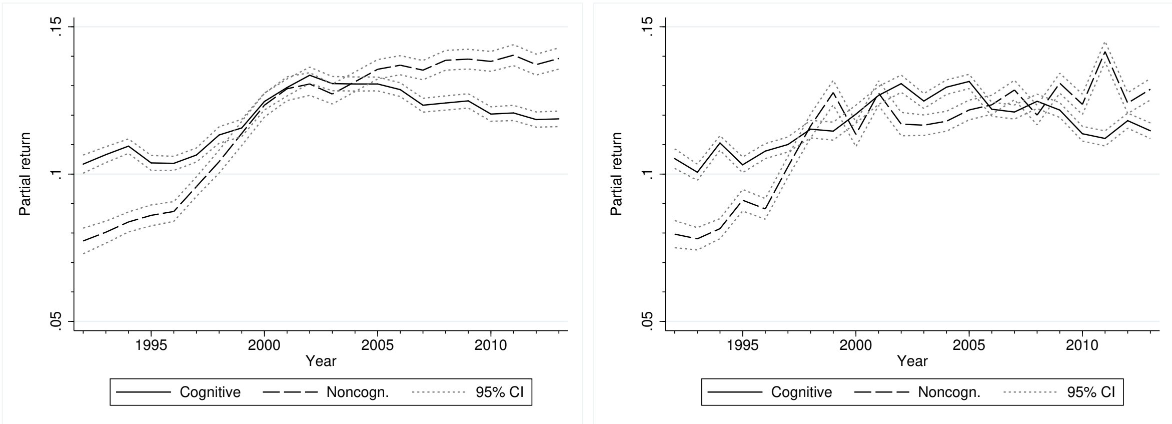
As mentioned above the wage data include weights that correct for stratified sampling and nonresponse. Our baseline approach is to present unweighted estimates. But it is of course natural to ask what would have happened had we used the weights. Figure A15 compares the unweighted and the weighted estimates. It shows that it does not matter whether we weight or not, for the trend changes that we emphasize. Thus, the return to (a standard deviation increase in) non-cognitive skill rose from 7.5% in the early 1990s to around 13% towards the end of time period. The return to cognitive skill varied between 10 and 13 percent over the entire time period. There is more year-to-year volatility in the weighted estimates. Since we find this volatility implausible we have a preference for the unweighted estimates.

A3.9 The college wage premium

As a complement to Figure 4 of the main text, Figure A16 presents the evolution of the college wage premium (dashed line) and the share of the population with at least college attainment (solid line). The college wage premium increased by around 10 log points between 1992 and 2000; between 2000 and 2013, however, the premium declined

Figure A15: The returns to skills, 1992-2013, unweighted and weighted estimates

(a) Unweighted estimates (b) Weighted estimates



Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

by the same magnitude. The decline in the premium seems to be driven by a surge in the supply of college educated men starting around 2000; from 2000 until 2013 the share of college-educated men increased by almost 6 percentage points.

A4 Additional results

A4.1 Decomposition of the returns in 2011-13

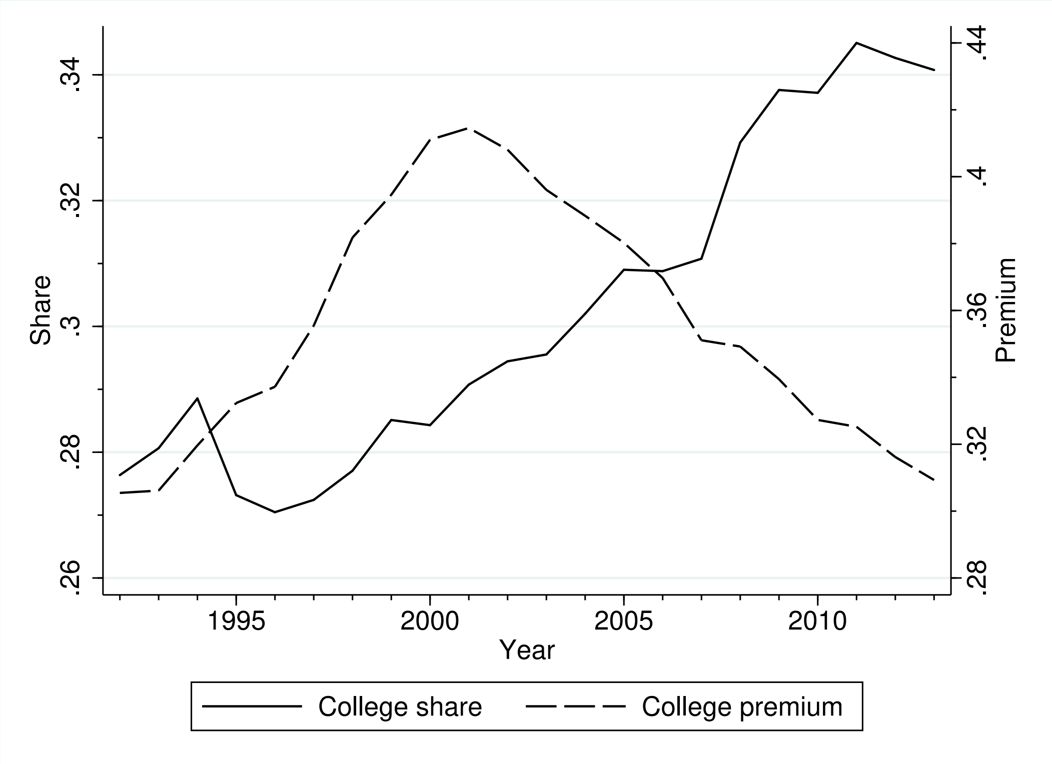
Table A5 examines whether the age range matters for the decomposition results in Table 2 of the main text. We compare a broader age-category (ages 30-50) to our baseline age range (38-42) in 2011-13 (since in 2011-13 all cohorts in the age range 30-50 have been observed in the draft). Table A5 illustrates that the results for the broader age range is basically identical to the more narrow age range; compare the across and within components in panel A with those in panel B.

A4.2 The probability of holding top positions

A4.2.1 Managers

In Section 3.4 of the paper we document that the return to non-cognitive skill primarily increased at the top-end of the wage distribution. Here, we zoom in on the probability of holding a managerial position. Managers are particularly interesting in the current context. It is obviously a high-wage and abstract occupation; it also requires inter-personal skill, and perhaps increasingly so, as hypothesized by Deming (2017).

Figure A16: Share with college attainment and college wage premium



Notes: The college wage premium is estimated for the private sector. The "college share" refers to the fraction of the employed in the private sector with at least college education.

Figure A17 shows that the probability of holding a management position loads more heavily on the non-cognitive component over time. Between 1994 and 2013, the loading on non-cognitive skill increased by 1.5 percentage points.[5] During the same time-period the importance of cognitive skill fell by almost the same magnitude. Considering that the average probability of holding a managerial position is 11%, these changes are rather substantial.

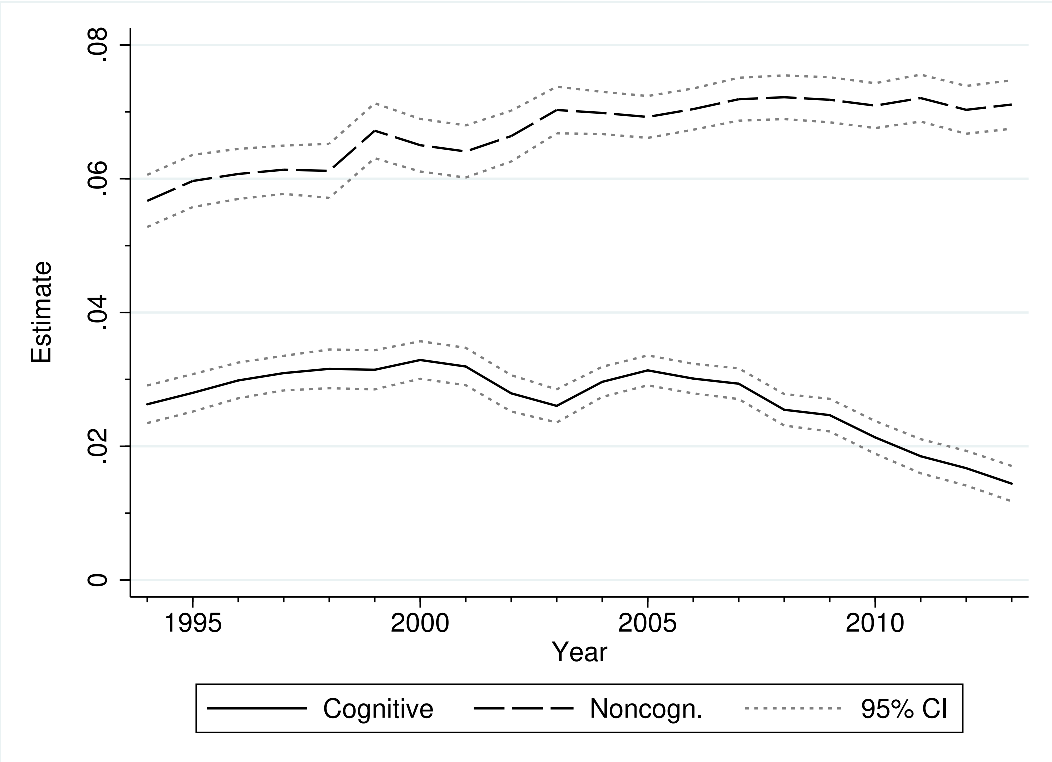
One possible explanation for the increased importance of non-cognitive skill is that leadership positions demand more inter-personal skill over time, because such skills are increasingly required to coordinate production across different sites; see Deming (2017).

[5]We exclude 1992 and 1993 in this analysis since we lack occupation data for these years.

Table A5: Decomposition of the returns to skills, 30-50 year-olds vs. 38-42 year-olds

	Cognitive		Non-cognitive	
	Across	Within	Across	Within
	A. Ages 30-50			
A. Industry	30%	70%	18%	82%
B. Firm	37%	63%	26%	74%
C. Occupation	59%	41%	51%	49%
D. Occupation×Industry	68%	32%	59%	41%
	B. Ages 38-42			
A. Industry	29%	71%	19%	81%
B. Firm	37%	63%	27%	73%
C. Occupation	61%	39%	53%	47%
D. Occupation×Industry	69%	31%	61%	39%

Figure A17: The relationship between skills and probability of being a manager

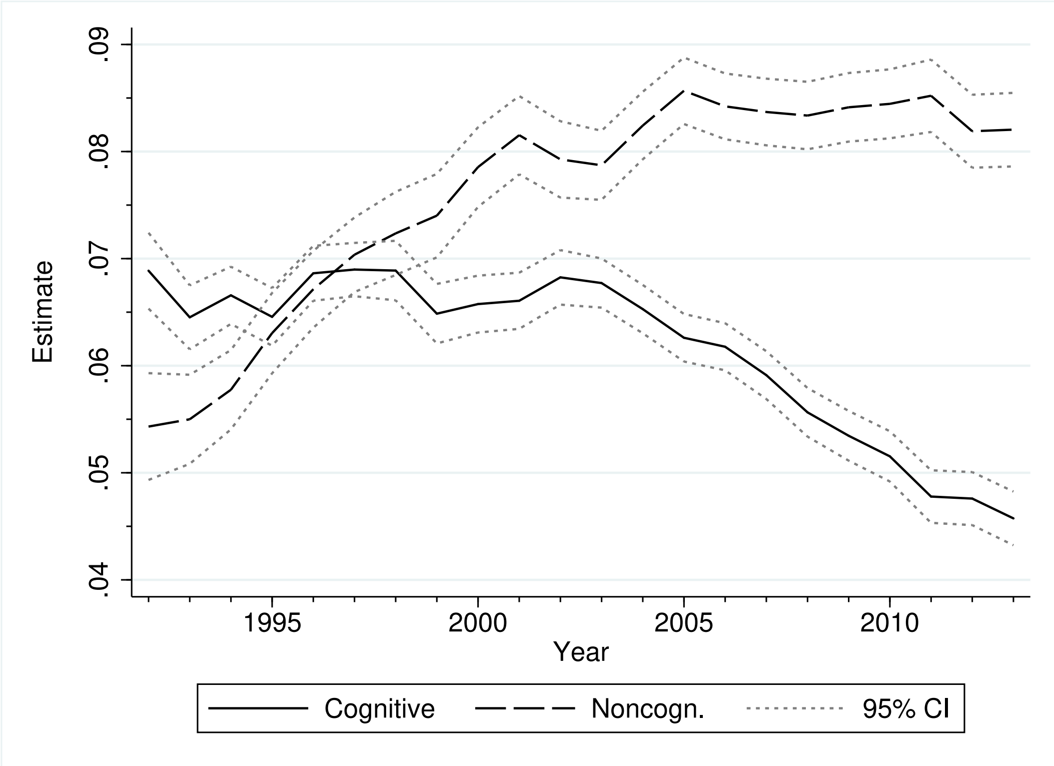


Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

A4.2.2 Top decile of the wage distribution

An analogous exercise is to examine how the two types of skills predict the probability of earning top wages. Figure A18 shows a stark increase in the importance of non-cognitive skill. Over the entire time-period, the loading on non-cognitive skill increased by almost 3 percentage points, while the association with cognitive skill fell by 2.5 percentage points. Again, these changes are very large in relative terms.

Figure A18: Probability of belonging to the top-decile of the wage distribution



Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

A4.3 Changes in occupational sorting and occupational returns

Here we provide some additional detail on the analysis in Section 4. Fundamentally, the purpose of this analysis is to account for the variation in skill returns and skill use across occupations or occupation-by-industry cells. The results in Table 3 come from running regressions (A2) and (A3) using data from two points in time, 1995 and 2012

$$s^n_{iajt} - s^c_{iajt} = \tau_{at} + \tau_{aj} + \rho\left[D_t \times T_{ijt}\right] + \varepsilon_{iajt} \tag{A2}$$

$$\begin{aligned} \ln(wage)_{iajt} = \alpha_{at} + \alpha_{aj} + \alpha_{jt} + \phi^c_j(s^c_i + s^n_i) + \lambda^n_j s^n_i + \phi^c_t(s^c_i + s^n_i) + \lambda^n_t s^n_i + \\ \theta^c\left[D_t \times (s^c_i + s^n_i) \times T_{ijt}\right] + \theta^n\left[D_t \times s^n_i \times T_{ijt}\right] + \epsilon_{iajt} \end{aligned} \tag{A3}$$

where i indexes individuals, a age, j occupations, and t time. $D_t = 1$ indicates 2012 and T denotes task intensity in the occupation where the individual is employed at time t (task intensities are fixed across occupations but individuals may change occupations over time).

Running the regression in, e.g., equation (A3) to estimate θ^n is equivalent to a two-stage procedure where we estimate the change in the relative return to non-cognitive skill across occupations – $\Delta(\text{relative return})_j = (\beta^n_{j,2012} - \beta^c_{j,2012}) - (\beta^n_{j,1995} - \beta^c_{j,1995})$ – in a the first-stage, and then relate these estimates to task intensities in a second stage. Estimating equation (A3) directly has the advantage that we do not have to adjust the standard errors for prior estimation of the change in relative return.

The results in Panel A of Table 4 are based on the regressions

$$s^n_{ijst} - s^c_{ijst} = \alpha_j + \alpha_{st} + \pi \left[O_j \times D^o_{st}\right] + \varepsilon_{ijst} \tag{A4}$$

$$\begin{aligned} \ln(wage)_{ijst} = \alpha_{jst} + \phi^c_j(s^c_i + s^n_i) + \lambda^n_j s^n_i + \phi^c_{st}(s^c_i + s^n_i) + \lambda^n_{st} s^n_i \\ + \mu^c \left[O_j \times D^o_{st} \times (s^c_i + s^n_i)\right] + \eta^n \left[O_j \times D^o_{st} \times s^n_i\right] + \epsilon_{ijst} \end{aligned} \tag{A5}$$

where notation is essentially the same as in the main text. The coefficient η^n in equation (A5) is the same as the coefficient η in equation (5) of the paper. Again, estimating η^n in equation (A5) directly is equivalent to a two-stage procedure where we first estimate the relative return by occupation, industry, and time in a first stage, and then estimate equation (5) of the main text in a second stage. From an inference point of view, it is convenient to estimate (A5). However, equation (5) provides more intuition.

The results in Panel B of Table 4 come from regressions with a completely analogous structure as (A4) and (A5). The only difference is that we replace $[O_j \times D^o_{st}]$ with $\left[A_j \times D^{IT}_{st}\right]$.

A concern with Table 3 is that it only provides information on the bivariate relationship between changes in occupational returns to skills and a particular task intensity. But some task intensities are highly correlated, making it difficult to attribute the relationship to one particular task rather than another. What if we consider more than one task intensity simultaneously? Table A6 shows the results of including social task intensity and abstract task intensity at the same time. The specification is essentially equivalent to equation (A3), although slightly more parsimonious in that we replace $\alpha_{at} + \alpha_{aj} + \alpha_{jt}$ with $\alpha_a + \alpha_j + \alpha_t + \gamma \left[D_t \times T_{ijt}\right]$; we can thus provide estimates of how task returns change over time. Table A6 reports the estimates on the time interactions; the results can be compared to Deming (2017), Table V, column (4

Table A6 shows that the return to doing social tasks increased in general on the labor market. In line with Table 3, but in contrast to Deming, it also illustrates that the relative return to non-cognitive skill increased in the most abstract occupations. In line with Deming, we find that the reward to non-cognitive ability did not increase more in occupations characterized by high social task intensity.

Table A6: Changes in the returns to skills and tasks, 2012 relative to 1995

	Dep var: ln(wage)
Abstract task intensity (rank)	0.000
	(0.007)
Social task intensity (rank)	0.106
	(0.007)
Overall skill	0.005
	(0.002)
Non-cognitive skill	0.012
	(0.004)
Overall skill×Abstract task intensity	-0.046
	(0.008)
Non-cognitive skill×Abstract task intensity	0.023
	(0.014)
Overall skill×Social task intensity	0.044
	(0.008)
Non-cognitive skill×Social task intensity	0.003
	(0.015)
#observations	362,573

Notes: The table resorts the coefficients on tasks interacted with time (2012 relative to 1995), as well as the interactions between skills, tasks and time. The regressions also include controls for cognitive (non-cognitive) skill, age, occupation, and time fixed effects, the main effects of abstract and social task intensity, and the interactions between cognitive (non-cognitive) skill and abstract (social) task intensity, respectively. The classification of Abstract jobs follows Acemoglu and Autor (2011) and the classification of occupations requiring social skill comes from Deming (2017). Standard errors (reported within parentheses) are clustered on individuals. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Section A1.3 outlines the procedure.

References

Acemoglu, Daron and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol. 4B, edited by David Card and Orley Ashenfelter, chap. 12. North-Holland, 1043–1171.

Adermon, Adrian and Magnus Gustavsson. 2015. "Job Polarization and Task-Biased Technological Change: Evidence from Sweden, 1975–2005." *Scandinavian Journal of Economics* 117 (3):878–917.

Black, Sandra E., Erik Grönqvist, and Björn Öckert. 2018. "Born to Lead? The Effect of Birth Order on Non-cognitive Abilities." *Review of Economics and Statistics* 100 (2):274–286.

Deming, David. 2017. "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics* 132 (4):1593–1640.

Fredriksson, Peter, Lena Hensvik, and Oskar Nordström Skans. 2018. "Mismatch of Talent: Evidence on Match Quality, Entry Wages, and Job Mobility." *American Economic Review* 108 (11):3303–3338.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104 (8):2509–2526.

Griliches, Zvi. 1986. "Economic Data Issues." In *Handbook of Econometrics*, vol. 3, edited by Zvi Griliches and Michael D. Intriligator, chap. 25. North-Holland, 1465–1514.

Grönqvist, Erik, Björn Öckert, and Jonas Vlachos. 2017. "The Intergenerational Transmission of Cognitive and Non-cognitive Abilities." *Journal of Human Resources* 52 (4):887–918.

Jokela, Markus, Tuomas Pekkarinen, Matti Sarvimäki, Marko Terviö, and Roope Uusitalo. 2017. "Secular Rise in Economically Valuable Personality Traits." *Proceedings of the National Academy of Sciences* 115 (25):6527–6532.