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Working Paper 2018:15

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Working Paper 2018:15
November 2018
ISSN 1653-6975

THE RISING RETURN TO NON-COGNITIVE SKILLS*

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16 November 2018

Abstract

We examine the changes in the rewards to cognitive and non-cognitive skill during the time period 1992-2013. Using unique administrative data for Sweden, we document a secular increase in the returns to non-cognitive skill. This increase is particularly pronounced in the private sector, at the upper-end of the wage distribution, and relative to the evolution of the return to cognitive skill. Sorting across occupations responded to changes in the returns to skills. Workers with an abundance of non-cognitive skill were increasingly sorted into abstract and non-routine occupations, for example. Such occupations also saw greater increases in the relative return to non-cognitive skill. This suggests that the optimal skill mixes of jobs have changed over time, that there is sorting on comparative advantage, and that demand-side factors are primarily driving the evolution of the return to non-cognitive skill. Consistent with this, we also show that hikes in offshoring and IT-investments increase the relative reward to non-cognitive skill and the relative intensity of non-cognitive skill usage.

Keywords: Wage inequality, sorting, skill returns, cognitive/non-cognitive skill.
JEL-codes: J24; J31

*First complete draft: 10 March 2017. We thank David Deming, Thomas Lemieux, Anna Sjögren, Jan Stuhler, and Roope Uusitalo as well as seminar participants at the AASLE (Canberra), BeNA Workshop (Berlin), Copenhagen University, IIPF (Tokyo) Nordic Summer Institute in Labor (Aarhus), SOFI, Tinbergen Institute, the UCLS workshop on Industrial Relations (Uppsala), Uppsala University, and the Workshop in Honor of Kjell Salvanes (Bergen) for very helpful comments and suggestions. We also thank Fredrik Heyman for providing information on automation.

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1 Introduction

According to a recent (and exclusively US) literature, the return to cognitive skill fell during the 2000s; see Acemoglu and Autor (2011), Beaudry, Green, and Sand (2016) and Castex and Dechter (2014). Concomitantly, the return to social skill moved in the opposite direction: According to Deming (2017), employment increased more in occupations requiring social skills (in particular since 2000) and wages grew faster in occupations which are intensive in social skills.[1]

In this paper we estimate the long-run trends in the rewards to cognitive and non-cognitive skills. The information on individual cognitive and non-cognitive ability comes from the military draft in Sweden. The draft featured a relatively standard test of cognitive ability (similar to the Armed Forces Qualification Test). Young Swedish men were also scored on their "non-cognitive" ability, i.e., their ability to interact with others and their leadership abilities. By combining the draft data with wage and employment data, we show that there was a secular increase in the return to non-cognitive skill from 1992 to 2013. We also estimate the returns across the quantiles of the wage distribution and examine whether there are changes in the sorting of skill across occupations. We finally ask whether the increase in the relative reward to non-cognitive skill can be tied to the intensity of offshoring and IT-investments.

Our paper is obviously related to the huge literature on skill-biased technical change (e.g., Tinbergen 1974 and Katz and Murphy 1992) as well as the task-based approach (e.g., Autor, Levy, and Murnane 2003 and Acemoglu and Autor 2011). Acemoglu and Autor (2011) show that the 2000s has been distinctively different in the sense that employment in the US grew much slower at the top-end of the wage distribution than during previous decades. A few explanations for this recent development have been put forward in the literature. Beaudry, Green, and Sand (2016) argue that the slowdown in the demand for cognitive skill is due to a boom-to-bust cycle caused by the maturation of information technology (IT). Brynjolfsson and McAfee (2014) have a very different take, where they argue that the advances in computing technology rapidly expands the set of tasks that computers can do; with the advances in computer technology, tasks which used to be performed by cognitively skilled workers are now becoming "routine". Others point out that increasing possibilities for offshoring can have similar effects; with reductions in trade or coordination costs, the world supply of cognitive skill can more easily substitute for the internal supply of cognitive skill (see Hummels, Munch, and Xiang 2018).

Our paper is most closely related to Deming (2017), who focuses on the evolution of the return to social skills. As a starting point he notes that skills that cannot be easily substituted for by technology or trade likely complement these factors. Social skills are

[1] Relatedly, Cortes, Jaimovich, and Siu (2018) argue that the increasing prevalence of women in high-wage occupations is due to an increasing importance of social skills in top-end jobs.

difficult to automate (see also Autor 2015) and production at different sites (generated by offshoring) may require coordination skills. Deming (2017) sets up a model where social skills facilitate trade in tasks and examines the implications of this model, using, among other things, data from the National Longitudinal Study of Youth (NLSY). He documents an increase in the return to social skills across the cohorts covered by NLSY 1979 and NLSY 1997.[2]

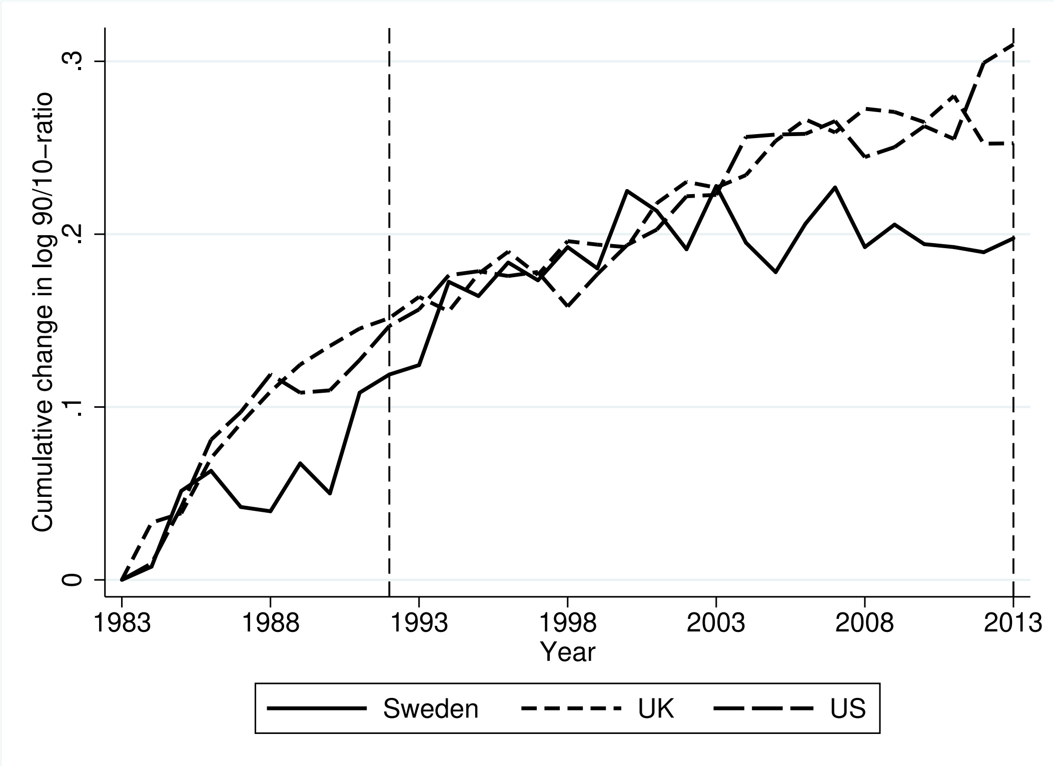
Using unique individual-level data, we document and compare the evolution of the returns to cognitive and non-cognitive skill during the time period 1992-2013. With access to population-wide data on individual skills, that are comparable over time, we provide a more detailed and nuanced picture than has been possible hitherto. We thus explore whether the returns to skills changed differentially across the wage distribution, the exact timing of any changes in the returns to skills, and how the changes in the returns to skills are associated with changes in sorting across occupations and industries. We also directly test whether there are differential effects of offshoring and IT on the returns to non-cognitive and cognitive skills, using a shift-share analysis.

We document six facts, most of which are new to the literature. First, we corroborate one of the key findings in Deming (2017): there is a secular increase in the wage return to non-cognitive skills. From 1992 to 2013, the return to non-cognitive skill in the private sector roughly doubled, from about 7 to 14 percent for a standard deviation increase. Concomitantly, there was much less variation in the return to cognitive skills. Interestingly, the return to cognitive skill has fallen since 2000, a fact that is in line with the literature on the US. Second, the return to non-cognitive skill primarily increased at the top-end of the wage distribution. Third, about half of the increase in the return to non-cognitive skills is across occupations; the occupational component accounts for more of the increase than firms or industries. Fourth, workers who have an abundance of non-cognitive skills are increasingly sorted into occupations that are abstract, non-routine, offshorable, non-automatable, and social; this suggests that optimal skill mixes of given occupations have changed over time. Fifth, across occupations, there is a positive correlation between the increase in the relative return to non-cognitive skill and the relative intensity of non-cognitive skill usage. This suggests sorting on comparative advantage and that the changes in returns come mainly from the demand side. Sixth, offshoring and IT-investments increase the relative return to non-cognitive skill, and the relative intensity of non–cognitive skill use, across industries and occupations. To our knowledge, the five last facts are new to the literature.

The paper unfolds as follows: Section 2 describes the evolution of wage inequality in Sweden since 1992. Section 3 describes the data. Section 4 documents the increase in the return to non-cognitive skill. Section 5 investigates skill sorting into occupations with

[2]For NLSY 1979, Deming (2017) uses two measures of self-reported sociability; for NLSY 1997, he uses two questions capturing extraversion.

Figure 1: 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.

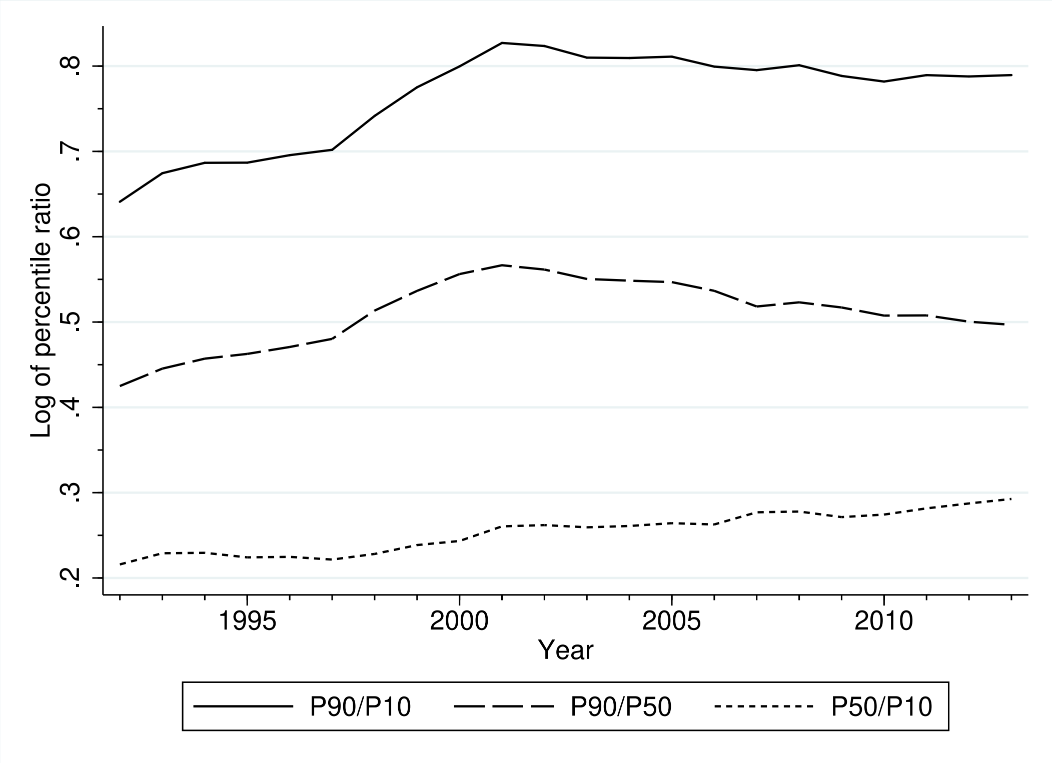
various traits, and examines whether offshoring and IT-investments increase the relative reward to non-cognitive skill. Section 6 concludes.

2 Wage inequality in Sweden

The objective of this section is to provide some context. 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 1 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 2: 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 1 provides the broader picture, Figure 2 closes in on our analysis sample. Since we utilize information from the draft, we focus on men. And since we want changes in the returns to skill to reflect structural changes in the labor market, we focus on prime-aged men (aged 38-42). The availability of the draft data (data are available starting with the cohort born 1951), combined with the age restriction, implies that we can conduct the analysis between 1992 and 2013. Figure 2 thus plots wage inequality among men aged 38-42 over this time period.[3]

A key message of Figure 2 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 1 and 2. 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.

Table 1, inter alia, decomposes the change in the log of the 90/10 ratio between 1995 and 2010 into the components attributable to changes in composition and to changes in the wage structure; Firpo, Fortin, and Lemieux (2009) and Fortin, Lemieux, and Firpo (2011) describe the decomposition method. We are primarily interested in how much changes in the returns to skills contribute to the changes in wage inequality. For that reason we

[3]We describe the wage and draft data in more detail in Section 3. In the sequel, we also show that wage returns to skill are more or less identical in a broader sample of men aged 30-50.

do not include factors that are endogenous to skills, such as education, occupation, and industry. The skill measures come from the military draft. They are measured at age 18 or 19. Individuals are scored on an integer Stanine scale along the cognitive as well as the non-cognitive dimension. The Stanine scale runs from 1 to 9, with a mean of 5 and a standard deviation of 2. The decomposition exercise includes completely flexible indicators for the Stanines, in each of the two skill measures.

Since we focus on men aged 38-42, and since the Stanine skill measures are normalized in the population, changes in composition is not going to be substantial; the only reason skill composition could be important is if the selection on skill into employment would change across the two time points. Consistent with this reasoning, Table 1 shows that changes in the distribution of skills are relatively unimportant.

The lower half of Table 1 shows how changes in the returns to skills contribute to wage inequality. The table shows, for instance, that 43 percent (=3.97/9.29) of the overall increase in wage dispersion can be tied to the increase in returns to non-cognitive skill. Changes in the return to cognitive skill would have *reduced* wage inequality, which is somewhat remarkable given that wage inequality increased.

The second and third columns decompose the 90/10 into the 90/50 and 50/10 ratios. The lower half of the table shows that the increase in the return to non-cognitive skill can account for 60 percent (=2.85/4.73) of the rise in wage inequality at the upper end of the distribution; at the lower-end of the distribution, the rise in the return to non-cognitive skill accounts for 25 percent (=1.12/4.56) of the increase in dispersion. Subsequently we show that the increase in the return to non-cognitive skill is particularly pronounced at the very top of the distribution. The second and third columns also illustrate that the increase in the return to cognitive skill is concentrated around the median of the distribution, which is why cognitive skill contributes to the reduction of inequality in the upper part of the distribution.

Changes in the returns to skills which are uniform across the wage distribution do not have any impact on changes in wage inequality. In the remainder of the paper we mainly focus on the changes in average returns over time. But we also present quantile regression estimates which reinforce the conclusion from Table 1. The return to non-cognitive skill increased more at the top-end of the distribution than at the bottom of the distribution. The return to cognitive skill, on the other hand, primarily increased around the median of the distribution.

3 Data

We use data from administrative wage registers collected by Statistics Sweden and test scores from the Swedish War Archives. The complete wage data contain information on (full-time equivalent) wages for a very large sample of establishments covering almost 50

Table 1: Decomposition of the change in inequality, 1995-2010

	Inequality measure		
	ln(90/10)	ln(90/50)	ln(50/10)
Unadjusted change	0.0929	0.0473	0.0456
	(0.0021)	(0.0020)	(0.0011)
Composition effects attributable to:			
Cognitive skill	-0.0072	-0.0054	-0.0017
	(0.0005)	(0.0004)	(0.0002)
Non-cognitive skill	-0.0103	-0.0074	-0.0028
	(0.0004)	(0.0004)	(0.0001)
Total composition	-0.0170	-0.0126	-0.0044
	(0.0008)	(0.0006)	(0.0002)
Wage structure effects attributable to:			
Cognitive skill	-0.0187	-0.0318	0.0131
	(0.0032)	(0.0033)	(0.0017)
Non-cognitive skill	0.0397	0.0285	0.0112
	(0.0037)	(0.0034)	(0.0016)
Constant	0.1011	0.0703	0.0256
	(0.0064)	(0.0064)	(0.0032)
Total wage structure	0.1096	0.0616	0.0496
	(0.0019)	(0.0020)	(0.0010)

Notes: Decompositions using RIF-regressions as described in Firpo, Fortin, and Lemieux (2009) and Fortin, Lemieux, and Firpo (2011). 1995 refers to 1994-96 and 2010 to 2009-11. The distribution of characteristics in 1994-96 are reweighted to correspond to the distribution in 2009-11 (the base year is unimportant). The relationship between wages and skills is allowed to be non-linear; in particular, we include indicators for the (nine) stanines of cognitive and non-cognitive skills, respectively. We have not adjusted these estimates for measurement error in cognitive and non-cognitive skills. For that reason, the importance of skills is likely underestimated. The regressions also include indicators for age (not shown) but since we focus on males aged 38-42 these have only a minimal effect on the estimates. Bootstrapped standard errors in parentheses (100 replications).

percent of all private sector workers and all public sector workers during 1985-2013.[4]

To these wage data we add military enlistment test scores. Complete information from the draft is available for males who were drafted between 1969 and 2000. During these years, almost all males went through the draft procedure at age 18 or 19, and enlistment scores are available for 90-95 percent of the sample.[5]

Linked to the data there is also information on educational attainment, occupation, and plants. We make frequent use of the occupational information, as well as the task content of different occupations from O*NET; some of our analyses also tap information on education, industry, sector, and firms. The occupational information is available from 1995 and onwards. At some points in the paper we examine changes between two time points. In these analyses, 1995 is always the starting point and we choose 2010 as the end point.[6]

Since we are interested in structural change in the labor market, we focus the analysis on prime-aged individuals; this group of workers is basically insulated from the cyclical variation that affects younger as well as older workers. Our main analysis is based on workers aged 38-42. As shown in the previous section, the evolution of wage inequality for this age group is representative of the evolution of inequality among a broader set of prime-aged workers. In Section 4 we also show that the returns to skills evolve in the same way for workers aged 38-42 as they do for workers aged 30-50. The advantage of basing the main analysis on workers aged 38-42 (rather than individuals aged 30-50) is that this group is observed throughout the time period (1992-2013).[7] Given the availability of draft data (the first available draft cohort is born in 1951) we would miss older workers in the early part of the period; for the later part of the time period coverage of the draft data is lower for younger workers. For workers aged 38-42, on the other hand, we are able to hold the age composition constant non-parametrically which is an advantage since returns to skills vary by age (Nybom, 2016). The availability of the draft data, combined with the age restriction in our main analysis, means that our analysis is based on 25 cohorts of males born between 1951 and 1975.

[4]Wage and occupation information is collected during a measurement week (in September-November) each year, conditional on being employed for at least one hour during the sampling week. Sampling is stratified by firm size and industry; small firms in the private sector are underrepresented. We do not use the sampling weights in the regressions; note that the essence of the results does not change with weighting – see section A8. The wage measure reflects the wage the employee had during the sampling week expressed in full-time monthly equivalents. It includes all wage components, such as regular pay, piece-rates, performance pay, and fringe benefits. Overtime pay is not included, however.

[5]There is more recent information, but the share taking part in the draft declines rather quickly for those born during the 1980s. For the cohort born 1983, around 60 percent of the male population took part in the draft.

[6]Choosing 2013 as the end point does not change the results.

[7]In Appendix A4, we present results for the population aged 30-50 during 1985-2013. This time window incorporate the severe crisis hitting Sweden in the late 1980s; for Sweden, this "unemployment crisis" was more severe than the Great Recession. Appendix A4 shows that there is more variation in the estimated returns, and this variation is arguably driven by the cycle, but that the long-run trends are similar.

The data from the draft procedure include an overall measure of cognitive skill and a corresponding measure of overall non-cognitive skill. The overall cognitive score is based on four sub-tests measuring: inductive skill (or reasoning); verbal comprehension; spatial ability; and technical understanding. Overall cognitive skill is reported on an integer Stanine scale, which varies from one to nine.[8] There is a slight drift in the Stanines over cohorts and, therefore, we re-standardize the cognitive score such that it has zero mean and unit standard deviation within each birth cohort.[9]

The evaluation of non-cognitive ability is based on a procedure that was adopted in 1969 and it was kept unchanged throughout our sample period (Lindqvist and Vestman 2011). The evaluation procedure consists of a 25-minute interview with a certified psychologist; the interview centers around a number of pre-specified behavioral topics. On the basis of the interview, the draftee gets an overall score on a Stanine scale. We standardize the overall score within each birth cohort in the same fashion as for the cognitive score.[10]

The overall non-cognitive score reflects social maturity, psychological energy (e.g., focus and perseverance), intensity (e.g., activation without external pressure), and emotional stability (e.g., tolerance to stress); see Mood, Jonsson, and Bihagen (2012). Social skills are important in the overall non-cognitive score and an explicit objective of the interview is to identify individuals who are unable to function in a group (see Lindqvist and Vestman 2011 for a more detailed description of both tests). Consistent with this, Appendix A1 shows that individuals who score particularly high on non-cognitive skill tend to be sorted into occupations requiring extraversion and emotional stability to a greater extent than individuals scoring particularly high on cognitive ability.

Table A3 in the Appendix summarizes the data. It shows for instance that 92 percent of the target population is employed, that the employed population is positively selected in terms of skill, and that those sampled in the wage register (employees), have slightly higher earnings than the average employed individual (which includes the self-employed).

To get a sense of how the variation in skills accounts for variation in wages, we add the skill measures (linearly) to a regression with time and age fixed effects. Adding the skill measures increases the adjusted R-squared from 0.18 to 0.41. The corresponding exercise with a detailed set of educational attainment fixed effects (distinguishing seven attainment levels) increases the adjusted R-squared to 0.36; the two skill measures thus explains a

[8]The Stanines are normally distributed with a mean of 5 and a standard deviation of 2. The data also contain the raw scores on each subtest. We prefer to use the Stanine score, since we only have the Stanine score for non-cognitive skill.

[9]In Figure A4 we allow the mean and the dispersion of the skill distributions to vary over time. This has no implications for our conclusions.

[10]Lindqvist and Vestman (2011), Håkansson, Lindqvist, and Vlachos (2015), Hensvik and Skans (2016), Nybom (2016), Black, Grönqvist, and Öckert (2017), and Fredriksson, Hensvik, and Skans (2018), are examples of studies that have used these data previously. Jokela et al. (2017) presents an interesting analysis of how non-cognitive ability has evolved over cohorts in the Finnish context.

Table 2: Correlations between skills and schooling

	Men age 38-42		
	1995	2010	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

Notes: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Appendix A7 outlines the procedure. 1995 refers to 1994-96 and 2010 to 2009-11

greater fraction of the variance of wages than the seven educational attainment fixed effects. Adding skills (again linearly) to the regression with educational attainment fixed effects increases adjusted R-squared from 0.36 to 0.44. On average between 1992 and 2013, a standard deviation increase in cognitive skill is associated with an increase in wages of about 11.4 percent, while a similar increase in non-cognitive skill is associated with a wage increase of about 9.8 percent, in a model that does not include educational attainment. When we add educational attainment the associations with the skill dimensions become weaker: the "returns" are reduced to 6.6 (cognitive skill) and 7.9 percent (non-cognitive skill). Thus, adding educational attainment fixed effects weakens the association between cognitive skills and log wages substantially, but does not reduce the return to non-cognitive skills as much.

The previous remark suggests that the correlation between cognitive skills and educational attainment is higher than the correlation between non-cognitive skills and education – and it is, see Table 2. Table 2 also shows how the correlations evolved between two separate time points, 1995 and 2010. These two time points span 15 years and roughly correspond to the lows and the highs in the returns to skills over time (see next section). One reason for showing these results at separate time points is to provide evidence on whether the association between skills and education has changed over time; Castex and Dechter (2014) argue that the fall in the return to ability in the US is tied to a strong increase in the correlation between ability and schooling over time. Table 2 shows that such an explanation has limited potential in our context. The correlations between years of schooling and the two skills, as well as the correlation between the two skill types, increase marginally but not to an extent that they can explain the results we present below.[11]

[11]Subsequently, we will document an increase in the return to non-cognitive skill. If a Castex and Dechter (2014) type of explanation would hold in the Swedish context, we would expect a fall in the correlation between non-cognitive skills and schooling over time (cohorts). This is not something we see in our data.

4 The increase in the return to non-cognitive skills

Our primary objective in this section is to estimate the wage return to cognitive and non-cognitive skill at successive points in time. Section 4.1 presents the main results of this exercise.

Whether the focus on the wage return is sensible or not depends in part on whether the relationship between employment and skills changes over time. Section 4.2, inter alia, illustrates that the earnings returns to skill evolves in the same way as the wage returns, suggesting that changes in the wage returns to skill are driving the evolution of the earnings returns. Section 4.2 also addresses the question of whether our main results are sensitive to the chosen age range (and they are not) and a number of other important robustness checks.[12]

Section 4.3 then examines whether the returns to skill has changed at particular points in the distribution and Section 4.4 decomposes the changes in the returns to skills into firms, industries, and occupations, respectively.

4.1 Main results

Our main analysis focuses on wages. We thus estimate wage regressions of the following kind

$$\ln(wage)_{iat} = \alpha_{at} + \beta_t^c s_i^c + \beta_t^n s_i^n + \epsilon_{iat} \tag{1}$$

where s^c and s^n denote cognitive and non-cognitive skill, respectively, and α_a an age fixed effect. These regressions are run separately by time point for the population of males aged 38-42. The estimates of the returns to each skill component (β_t^c and β_t^n) are plotted in Figure 3; Figure 3a pertains to the entire labor market, while Figure 3b zooms in on the private sector.[13]

The increase in the wage return to non-cognitive skill during the second half of the 1990s is remarkable. Between the mid 1990s and the early 2000s, the return increased by 6-7 percentage points. The return to non-cognitive skill continues to rise after 2000, but at a much slower pace. The return to cognitive skill also increased during the second half of the 1990s. But this increase is much less dramatic, and after the turn of the century, the return to cognitive skill actually falls. The fall in the return to cognitive skills is consistent with Beaudry, Green, and Sand (2016), who document that employment growth in cognitively demanding occupations slowed down markedly during the 2000s.

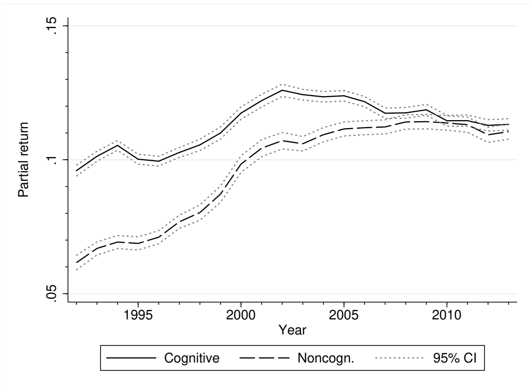
The slow-down in the increase in the return to non-cognitive skill during the 2000s is

[12] Among other things, we discuss whether the results are driven by changes in the returns over cohorts and whether weighting changes the main results. None of these issues are fundamental in any way.

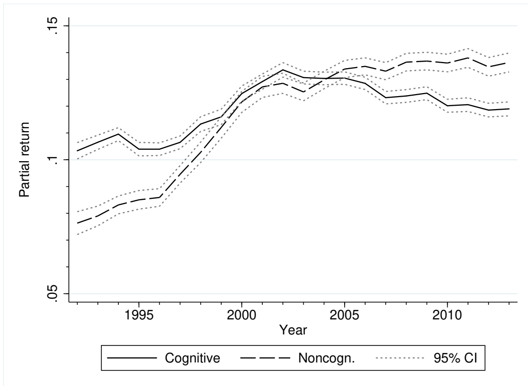
[13] Throughout we correct our estimates for measurement error using the reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). In Appendix A7 we show that our conclusions are unaffected by allowing the measurement error to be time-varying.

Figure 3: The returns to cognitive and non-cognitive skills, 1992-2013

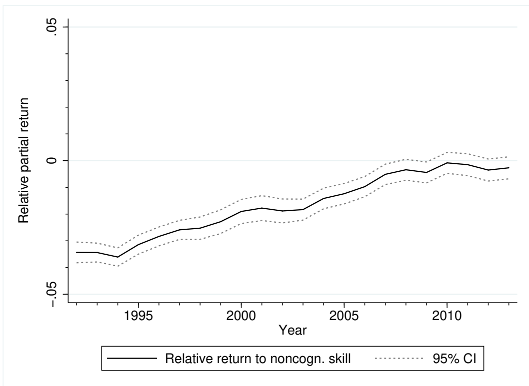
(a) All workers



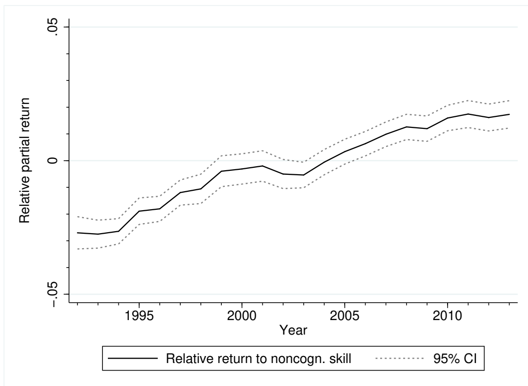
(b) Private sector workers



(c) All workers, relative return



(d) Private sector workers, relative return



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). Appendix A7 outlines the procedure.

to some extent driven by the evolution of the overall skill premium. Figure 3c instead shows the evolution of the relative return to non-cognitive skill, i.e., $\beta_t^n - \beta_t^c$. As shown by Figure 3c, there is a secular, and steady, increase in the relative return to non-cognitive skills throughout the time period. In this respect, the development during the 2000s is not different from the development during the 1990s.

When we estimate the return separately by sector we find that it is mainly the private sector that drives the evolution of the relative return to non-cognitive and cognitive skills (see Figure 3b). From here on we focus mainly on the private sector, since the development in the private sector is driven by market forces to a greater extent than in the public sector.[14] Figure 3d shows a steady increase in the relative return to non-cognitive skill in the private sector. Over the entire time-period, the relative reward to non-cognitive skills rose by some 5 percentage points.

4.2 Robustness

This section examines a number of potential caveats of our main results. Section 4.2.1 considers differential selection into employment with respect to skill over time. Section 4.2.2 examines the importance of the chosen age range and Section 4.2.3 reports on a number of other robustness checks.

4.2.1 Employment and earnings

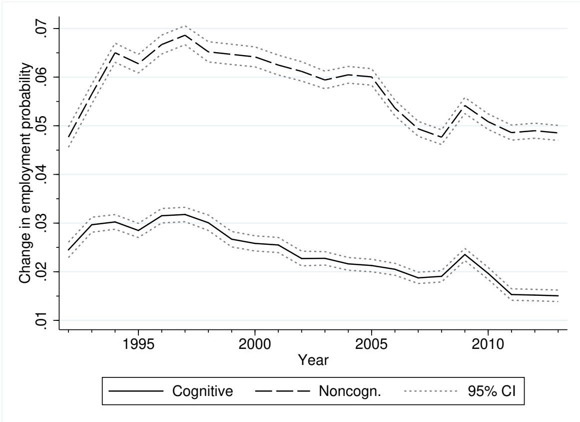
A potential concern with our main results is that the selection into employment with respect to skill might change over time. Figure 4 thus examines the overall employment and earnings returns to skill. Both of these outcomes are defined for the entire population of males aged 38-42. Figure 4a shows that the selection into employment depends on non-cognitive skill to a greater extent than cognitive skill (this was first documented by Lindqvist and Vestman 2011). The figure also shows that prime-aged males are relatively insulated from the business cycle; in the Great Recession, for instance, the coefficients on cognitive and non-cognitive skill increased moderately, by 0.5 percentage points. Overall, there are no major changes over time in the importance of cognitive and non-cognitive skills for the probability of being employed, which implies that the changes at the employment margin are not distorting our main result.[15]

[14]Figure A3 shows the estimated bivariate (as opposed to the partial) returns to skills. The increase in the return to non-cognitive skill is even more striking when not conditioning on cognitive skill.

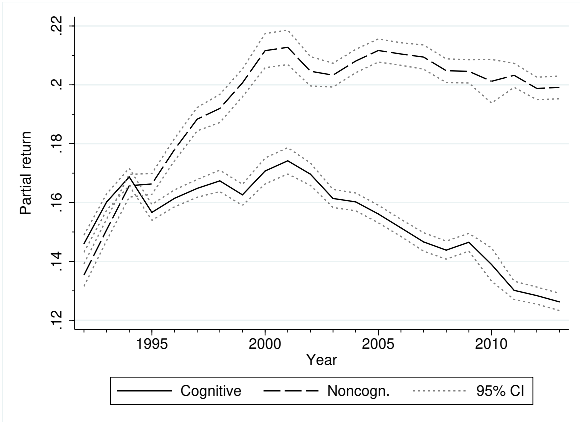
[15]The changes that we do see in the relationship between employment and skills is arguably tied to the evolution in the overall employment rate for this age category. Between 1992 and 1994 (when we see an increase in the association between employment and both skill measures), the employment to population ratio among 35-44 year-olds declined from 91 to 85 percent. Between 1994 and 2013 (when there is a trend decline in the relationship between employment and both skill measures) there is a secular increase in the employment to population ratio from 85 percent to 91 percent. Notice also that the relative importance of non-cognitive and cognitive skill for selection into employment evolves in broadly the same way over time; therefore it is highly unlikely that the employment evolution can explain the trend increase in

Figure 4: Employment and earnings returns

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



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



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). Appendix A7 outlines the procedure.

Figure 4b shows the returns in terms of annual earnings. To get an easily interpretable scale, the outcome is defined as (the level of) individual earnings divided by mean earnings at each time point. Figure 4b, which should be compared to Figure 3a, shows a striking increase in the earnings return to non-cognitive skill during the 1990s; during this time-period the return to non-cognitive skill increased by some 6-7 percentage points. This increase came to a halt during the 2000s. However, relative to the evolution of the return to cognitive skill (which has fallen since 2000), it is clear that non-cognitive skills are increasingly rewarded throughout the time period. Compared to the evolution of relative wage returns, Figure 4b displays a very similar time pattern. We thus conclude that Figure 3 is not distorted by changes in the selection into employment by skill over time.[16]

4.2.2 Age, cohort, and time

Another potential concern is that the results are particular to the chosen age-range. What if we would broaden the age range to include males aged 30-50? Broadening the age range introduces the complication that the sample is not entirely 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:

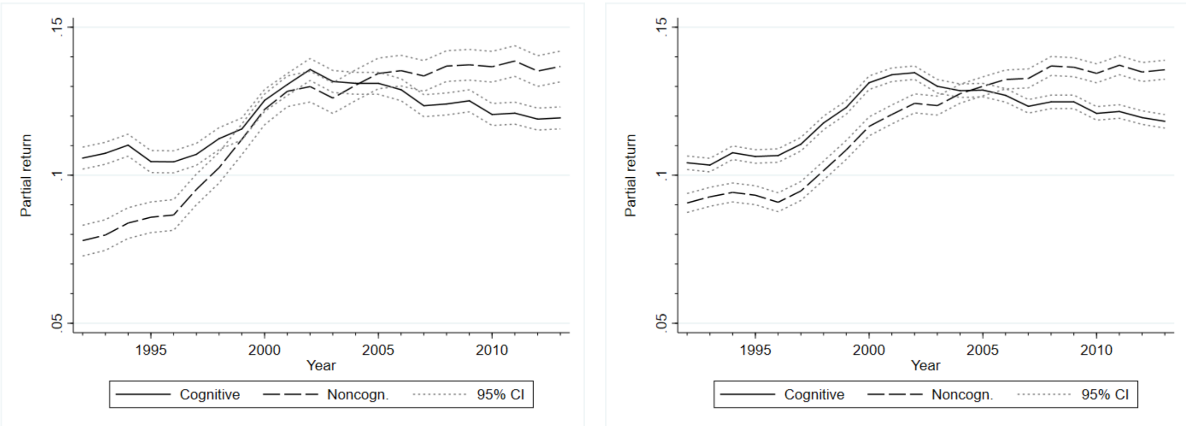
$$\ln(wage)_{iat} = \sum_{t=1992}^{2013} (\alpha_t + \beta_t^c s_i^c + \beta_t^n s_i^n) + \sum_{a=30}^{50} (\alpha_a + \lambda_a^c s_i^c + \lambda_a^n s_i^n) + \varepsilon_{iat}, \tag{2}$$

the relative return to non-cognitive skill documented in Figure 3d. Notice finally that the employment evolution during the time period when we see the big increase in the return to non-cognitive skill (say between 1995 and 2005) would arguably have contributed to lower the return to non-cognitive skill.

[16]In addition to estimating the earnings return (where selection is not an issue), we have considered bounding the coefficients on cognitive and non-cognitive skill using the procedure in Lee (2009). However, Lee's procedure is not directly implementable since it is designed for a binary treatment rather than a continuous variable.

Figure 5: 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). Appendix A7 outlines the procedure. Age fixed effects and interactions between age and skills included. Levels are normalized to age 40.

The notation is basically the same as in equation (1). 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 5 shows the results; Figure 5a reproduces our main results; while Figure 5b shows the results for men aged 30-50. Overall, the two figures are very much alike. Consistent with 5a, Figure 5b shows a strong rise in the return to non-cognitive skill while the return to cognitive skill falls somewhat between 2000 and 2013.

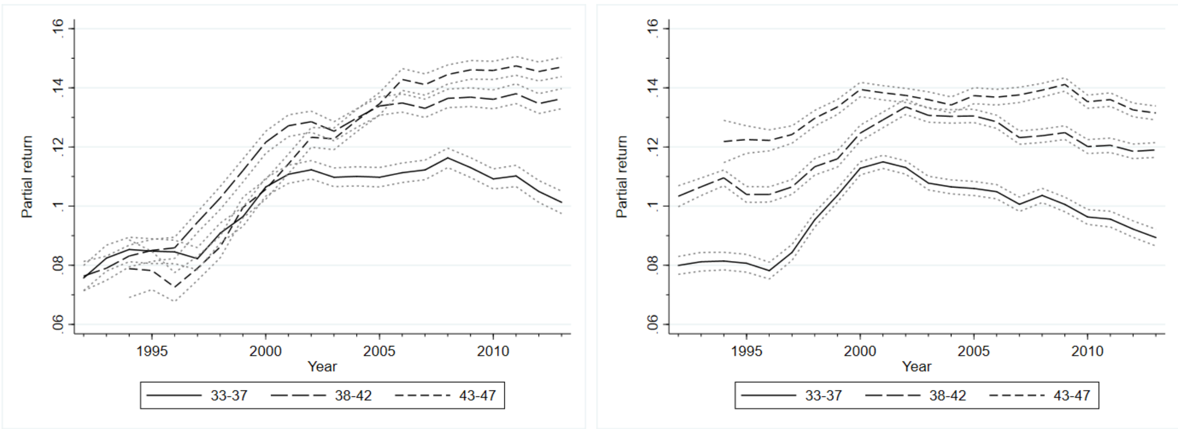
An additional concern related to age is that age, cohort, and time are not simultaneously identified. Since we hold age constant, cohort varies one-for-one with time. The question is whether there are cohort-specific skill returns that conflate our interpretations of the results. To examine this question 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 6 shows the results. Figure 6a shows the returns to non-cognitive skills across the three age-groups, while Figure 6b does the same thing for cognitive skills. 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).

In Figure 6a there is little to suggest that the remarkable increase during the 1990s is driven by changing returns to non-cognitive skills across cohorts. Regarding the returns to cognitive skill, there is one notable difference across the age groups; the return to

Figure 6: The returns to skills across different age groups, 1992-2013

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



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). Appendix A7 outlines the procedure.

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.

4.2.3 Other robustness checks

Here we report briefly on some other robustness checks. The full details of these checks are available in the Appendix.

Measurement error Typically, measurements of cognitive and non-cognitive skill are plagued with some form of error. We have dealt with these measurement errors by using the reliability ratios estimated in Grönqvist, Öckert, and Vlachos (2017), who report that the reliability ratio is 0.73 and 0.50 for cognitive and non-cognitive skill, respectively. The fact that we standardize the variables implies that we reduce the impact of the measurement error a bit, but the measurement error problem is complicated by the fact that cognitive and non-cognitive skills are correlated.[17] In Appendix A7, we present the measurement error corrections which are applicable in our setting. For cognitive skill, the correlation-adjusted reliability ratio is 0.95; for non-cognitive skill, the corresponding reliability ratio is smaller, 0.73.

We apply the same reliability ratios to correct for measurement error during the entire time period. A potential concern, however, is that the measurement error varies over time. Even though the same type of tests were used throughout the entire time period,

[17] In particular, the standardization implies that the bivariate reliability ratios are equal to the square root of the original reliability ratios.

finer details may have changed, implying that measurements are differentially informative over time. To address this concern we use the brothers of the individuals included in our sample. By utilizing information on the brothers, we implement a straightforward instrumental variables procedure that allows the measurement error to vary over time. Figure A5 shows that allowing for time-varying measurement error has no implications for our conclusions.

Weighting strategy The wage data are collected via stratified sampling. Our baseline regression strategy does not adjust for stratified sampling. Part of the reason for not doing so, is that we do not have exact information on the stratification weights. Rather we have weights that adjust for non-response as well as stratification. These weights are sometimes very large and appear to weight units that are not necessarily representative heavily with the result that there is an implausible amount of year-to-year variation in the estimated returns. Whether we weight or not does not affect our overall conclusions, however.[18]

Figure A6b shows the results when we weight the regression using the weights available in our data. Over the entire time period the return to non-cognitive skill increases from 7-8 percent in the beginning of the time period to around 13 percent towards the end of the period. The return to cognitive skill varies between 11 and 13 percent over the entire time period, and the return to this particular skill seems to have fallen during the 2000s.

A longer time frame An interesting question is whether the increase in the return to non-cognitive skill is the continuation of a trend that started earlier (say in the 1980s). In an attempt to answer this question we estimate a regression analogous to equation (2) for the 1985-2013 time period. Unfortunately, the analysis is complicated by the unemployment crisis starting around 1990. The crisis coupled with the fact that we can only estimate the equations for relatively young individuals lead to significant variability in the returns during the time period (1985-1991) that we add to the analysis; see Figure A2. With that said, it seems that the wage return to non-cognitive skill was relatively flat before the onset of our observation window. In 1985, the return was close to 8%, which is comparable to the return around 1994-95.

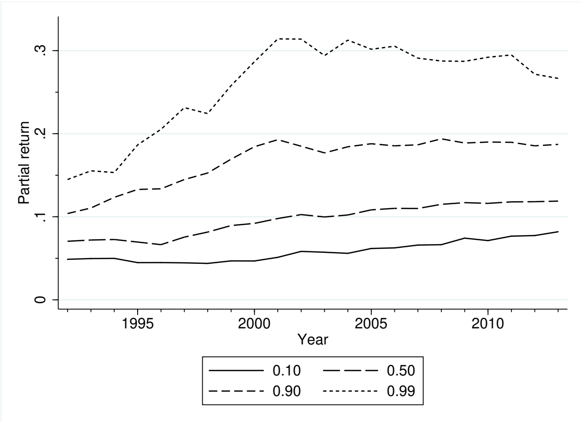
4.3 Non-linearities in the return to skills

In this section we ask two questions: In what part of the wage distribution did the return to non-cognitive skills increase? Are there significant complementarities between cognitive and non-cognitive skills, and have they changed over time?

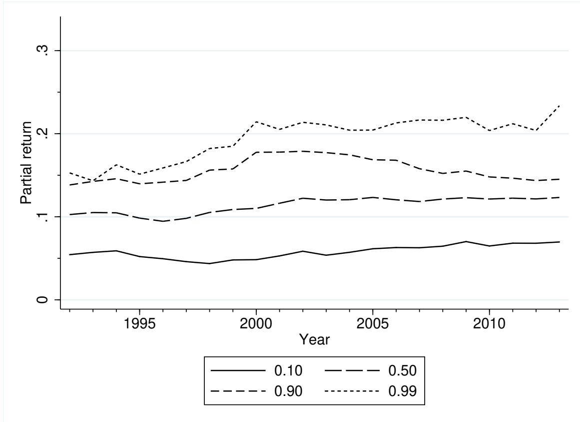
[18]Note also that the earnings returns to skill (which are estimated for the full population) evolve in the same wage as the unweighted wage estimates, suggesting again that weighting is unimportant for our overall conclusion.

Figure 7: Quantile regression estimates, 1992-2013

(a) Non-cognitive skills



(b) Cognitive skill



Notes: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Appendix A7 outlines the procedure.

The first question relates to the analysis of inequality in Section 2. The results in Table 1 suggest that the changes in the return to non-cognitive skill contributed to increase inequality, while changes in the return to cognitive skill contributed to lowering inequality.

As a first pass on the question of where the returns to skill primarily changed, we estimate quantile regressions corresponding to equation (1); see Figures 7a and 7b. In general, the returns to both types of skills are higher towards the upper end of the wage distribution. It is also clear that the big increase in the return to non-cognitive skill occurred at the very top of the wage distribution (from the 90th percentile and above). For cognitive skills, on the other hand, the gap between the returns at the 90 percentile and the 50th percentile is reduced – primarily because there is an increase over time in the return at the median. Overall, Figure 7 corroborates the findings from Table 1.

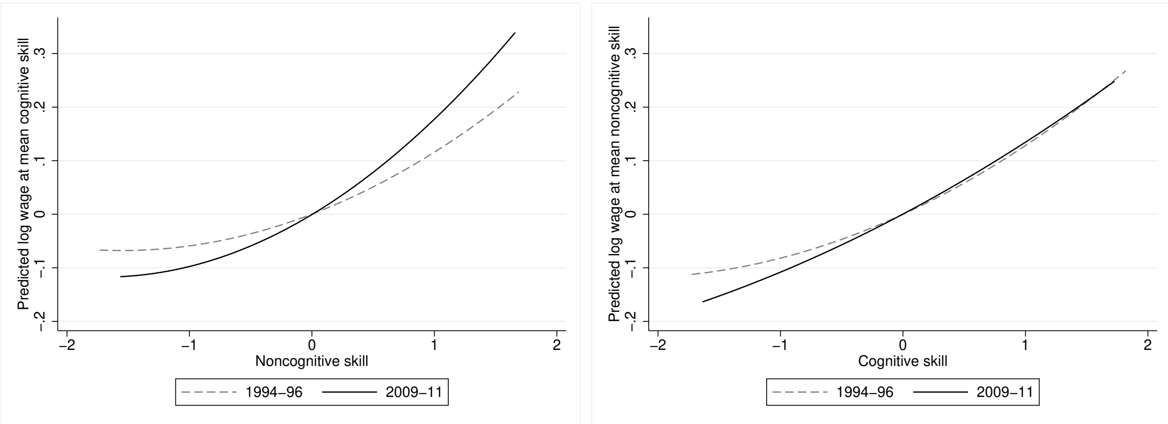
Figures 8a and 8b pursue a similar theme by allowing the returns to skill to vary across the skill distribution at two points in time, 1995 and 2010. To do this, we simply include a second-order polynomial in each of the two skills in the regression (more flexible specifications do not change the results). Figure 8 shows that the reward to having non-cognitive skills at the top-end of the distribution increased markedly between the two points in time. The picture is very different for cognitive skills. The wage-skill gradient increases somewhat between the two points in time, but this primarily happens at the bottom of the skill distribution; see Figure 8b.

Figure 9 turns to the second question, i.e., the complementarities between the two types of skills. We examine this question by adding a linear interaction between the two skills to the model outlined in equation (1). As shown by Figure 9, the interaction between cognitive and non-cognitive skill is always significantly positive.[19] However, there are no

[19]Note that Deming (2017) also finds a positive interaction between cognitive and social skills using data from NLSY.

Figure 8: Predicted log wages across the skill distributions

(a) Predicted log wage by non-cognitive skill (b) Predicted log wage by cognitive skill



Notes: The changes in the returns to skills are calculated between 1995 (1994-96) and 2010 (2009-11). All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Appendix A7 outlines the procedure.

drastic changes over time. The interaction term is about as important in 2010 as it was in 1995.

4.4 Decomposition of the changes in returns

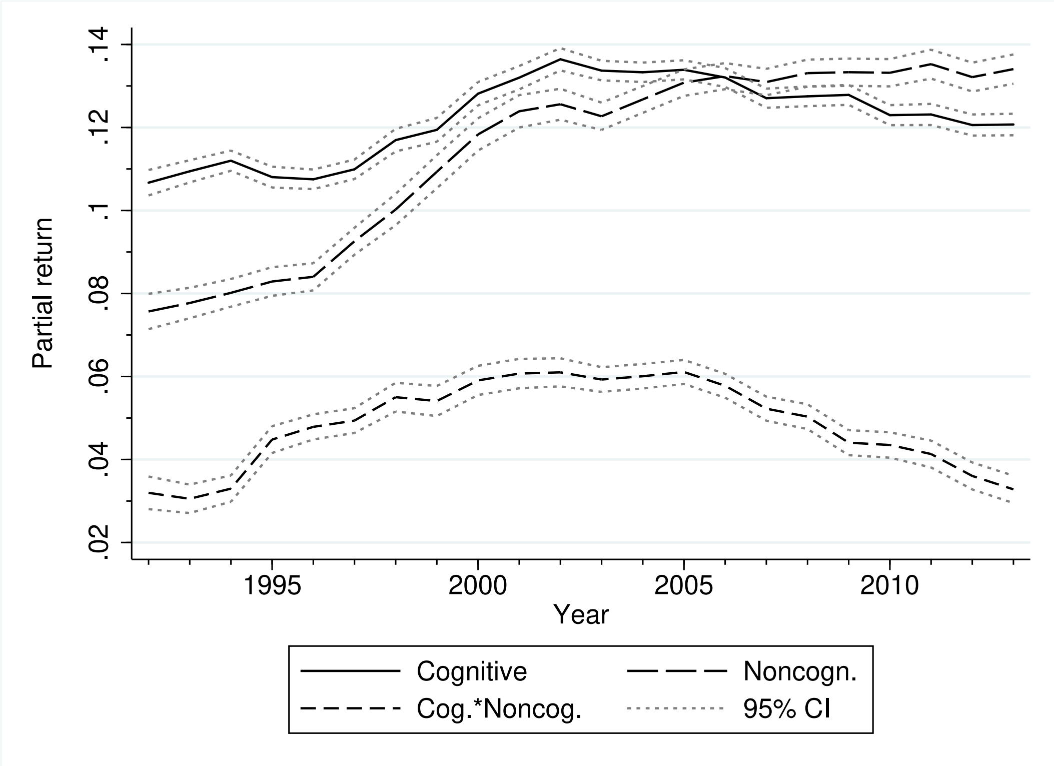
What factors can account for the remarkable increase in the return to non-cognitive traits? We begin our search for possible explanations by examining whether the increase is tied to restructuring and sorting across industries, occupations, and firms. Table 3 decomposes the changes in the return to skills into across- and within-components. The overall increases between 1995 and 2010 are 1.6 percentage points for cognitive skills and 5.2 percentage points for non-cognitive skill.[20]

Panel A shows the results of adding a detailed set of three-digit level industry dummies (distinguishing some 230 different industries) to equation (1). By doing so, we do away with most of the increase in the return to cognitive skill; by contrast, most of the increase in the return to non-cognitive skill is due to the within component. In panel B we add (some 6,700) firm fixed effects to the regression. Again, most of the increase in the return to non-cognitive skill is within firm, while the opposite is true for the increase in the return to cognitive skill.

Panels C and D consider the occupational dimension. Panel C begins by adding fixed effects by detailed three-digit occupations (about 110 unique occupations). This is the first instance where sorting matters for the change in the return to non-cognitive skill:

[20] A concern with Table 3 may be that the "Across-components" are exaggerated because some cells are small (in particular firms may be an issue). Table A4 shows that it is unlikely that this is an issue. The results are identical when we compare the larger and broader sample of men aged 30-50 with our baseline sample of men aged 38-42.

Figure 9: 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). Appendix A7 outlines the procedure.

about half of the increase in the return is due to sorting *across* occupations. Panel D allows occupational sorting to differ across two-digit industries (by including some 2,700 fixed effects). By doing so, we reduce the change in the return to non-cognitive skill further. But the within component still accounts for almost 40 percent of the overall increase in the return to non-cognitive skill.

We conclude from this simple exercise that to understand the increase in the return to non-cognitive skill the most promising avenue is along the occupational dimension. We thus turn to this dimensions next.

Table 3: 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: The changes in the returns to skills are calculated between 1995 (1994-96) and 2010 (2009-11). All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Appendix A7 outlines the procedure.

5 Occupational sorting and wage-setting

Here we examine occupational sorting and the wage-returns to skills at the occupational level. The basic idea is that the two types of skills are differentially valuable across tasks. Workers will thus sort across tasks (or occupations) according to their comparative advantage in performing them. Since each worker comes with a particular bundle of skills, however, there is no reason to expect the returns to skill to be equalized across tasks and occupations; see Rosen (1978) (which in turn builds on Roy 1951 and Mandelbrot 1962).[21]

Suppose now that there is a change in how the labor market values a particular task. Since differentially skilled workers have differential ability to conduct the particular task, workers reallocate across jobs (and occupations) in response to the change in the underlying returns. This supply response implies that it will be difficult to identify the underlying change in the return to skills. But since skills are bundled, we will still be able to trace some of the change in the returns to skills.

This section begins by documenting occupational sorting; see Section 5.1. Section 5.2 estimates wage returns at the occupational level and asks how changes in these returns are correlated with changes in the skill intensities of occupations. Section 5.3 turns to the occupational-by-industry level and asks whether offshoring and IT-investments affects the relative return to non-cognitive skill.

5.1 Sorting on occupational task intensities

This section examines how sorting across occupations relates to cognitive and non-cognitive skills, and how these relations have changed over time.[22] To conduct this exercise, we use (standardized) occupational task and skill intensities as outcomes in a regression model that is otherwise analogous to equation (1), i.e.,

$$Task_{iat} = \gamma_{at} + \theta_t^c s_i^c + \theta_t^n s_i^n + \varepsilon_{iat} \tag{3}$$

where $Task_{iat}$ denotes the task (or skill) intensity in the occupation performed by individual i.[23]

Figure 10 shows the result of estimating equation (3) for various task/skill intensities.

[21]The returns to skills only get equalized across occupations if the skill mixes are sufficiently different across workers to accommodate the differences in skill requirements across occupations. Firpo, Fortin, and Lemieux (2011) also estimate models of occupational wage-setting.

[22]In the Appendix we examine how the probability of being a manager relates to cognitive and non-cognitive skills over time. Figure A7 shows that non-cognitive skills are becoming increasingly important over time, while cognitive skills are becoming less important over time.

[23]To obtain the task intensities we start by matching information from the O*NET database onto occupations. We then apply the classification of Abstract, Routine, and Offshorable tasks from Acemoglu and Autor (2011), the classification of task requiring social skills from Deming (2017), and a classification of automatable tasks (which was provided by Fredrik Heyman) to obtain the occupational task intensities. The task intensities for a given occupation do not vary over time.

With respect to non-cognitive skill, most of the action takes place during the 1990s; note that this is also the time period when the return to non-cognitive skill increased the most. The general pattern is that individuals that score high on the non-cognitive skill dimension are increasingly sorted into occupations involving cognitively demanding and abstract tasks during the 1990s (see Figures 10a-b); conversely, such individuals are increasingly escaping routine and automatable tasks over time (see Figures 10c-d).

Figures 10e-f pertain to sorting into occupations that are either offshorable or intensive in the use of social skill. Here the pattern is slightly different than in the previous figures. The difference is that the increase in the loading on non-cognitive skills continues through the 2000s. A standard deviation increase in non-cognitive skill is associated with working in an occupation that is around 0.12 higher in terms of either offshorability, or the use of social skills, in 2013 compared with 1992.

The changes in the sorting patterns documented in Figure 10 imply that the optimal skill mix of any given occupation has changed over time. Occupations that demanded mainly abstract skills, for example, in the beginning of the time period have to some extent shifted to emphasize non-cognitive skills by the end of the time-period. In the remainder of section 5 we examine possible explanations for changes in the sorting pattern and the changes in the returns to cognitive and non-cognitive skills.

5.2 Demand or supply?

A first question is whether the demand or the supply side was the origin of the increase in the relative return to non-cognitive skill. In particular, we estimate the change in the relative return to non-cognitive skill between two points in time, 1995 and 2010.[24] If $T = 1$ indicates the latter time point, we estimate the regression

$$\ln(wage)_{iajt} = \alpha_{ajt} + \phi^c_{j0}(s^c_i + s^n_i) + \lambda^n_{j0}s^n_i + \phi^c_{j1}\left[T \times (s^c_i + s^n_i)\right] + \lambda^n_{j1}\left[T \times s^n_i\right] + \epsilon_{iajt}, \quad (4)$$

where i indexes individuals, a age, j occupations, and t time. The coefficient of main interest is $\lambda^n_{j1} = (\beta^n_{j,2010} - \beta^c_{j,2010}) - (\beta^n_{j,1995} - \beta^c_{j,1995})$, which measures the change in the *relative* return to non-cognitive skill between the two time points. Since the underlying model is one of selection on comparative advantage (see Rosen 1978), we mainly focus on changes in the relative returns. This focus also allows us to net out the effects of overall changes in skill demand and skill supply.[25]

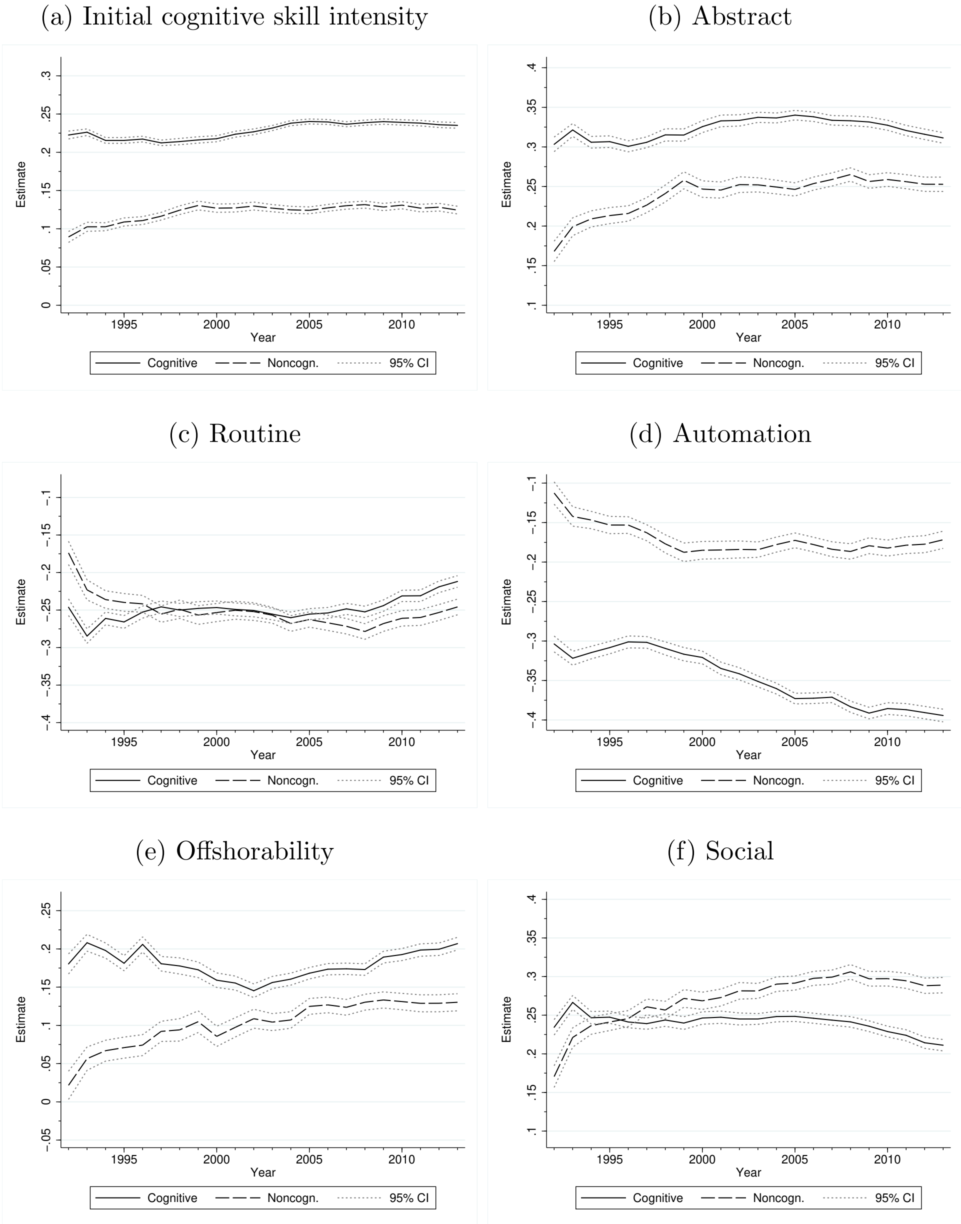
We also calculate the changes in relative skill intensity by occupation, i.e., $\Delta(s^n_j - s^c_j)$.[26]

[24] To increase precision we pool three years centered around each of the two time points; 1995 thus refers to to 1994-96, while 2010 refers to 2009-11.

[25] Note, however, that the results for non-cognitive skills are not particularly sensitive to normalizing by the change in the return to cognitive skill.

[26] By focusing on relative skill intensity, we partial out the evolution of cognitive skill in a way that is

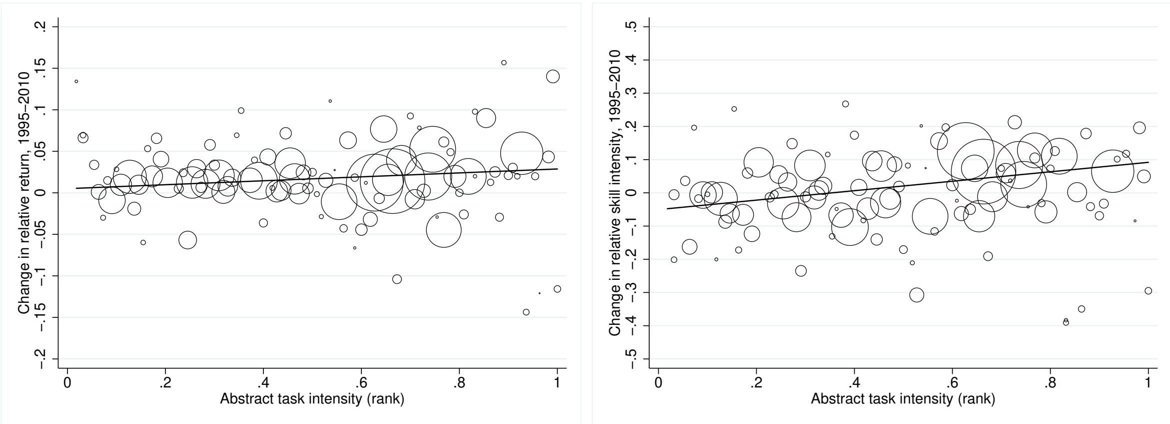
Figure 10: Sorting into occupations characterized by their task intensities



Notes: Panel (a) characterizes occupations on the basis of cognitive skill as measured in the draft. For panels (b), (c), (e), and (f) 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. Confidence bands are based on robust standard errors.

Figure 11: Changes in relative returns and relative skills by abstract task content

(a) Relative returns (b) Relative skills



Notes: The slope of the regression line in panel (a) is 0.024 (SE = 0.0003) and the slope in panel (b) is 0.142 (SE = 0.0008). To increase visibility we have removed a small number of outlier occupations comprising less than one percent of the data.

We then ask whether changes in relative returns seem to correlate negatively or positively with changes in relative skill intensities. If the demand side is the principal origin of the shocks affecting the returns to skills, we would expect relative returns and relative skill intensities to be positively correlated; if, on other hand, the shocks come mainly from the supply side, we would expect a negative correlation between relative returns and relative skill intensities.

Rather than doing the analysis separately for each occupation, we find it more informative to present the results by occupational task intensities (whether the occupation is, e.g., abstract, routine, or offshorable). Figure 11 presents estimates of the changes in relative returns (panel a) and relative skills (panel b) in terms of the abstract task content of the occupation. Returns to non-cognitive skills have increased more in abstract occupations, and individuals employed in such occupations also possess these skills to a greater extent.

Figure 11 thus suggests that the reasons for the increase in the return to non-cognitive skills should primarily be traced to the demand side.[27] Our favored interpretation is that the demand for non-cognitive skills increased primarily in abstract occupations (or high-wage occupations more generally). This increase in demand caused a relative supply response in which individuals who were relatively abundant in non-cognitive skill reallocated to occupations with high abstract task content. This labor supply response mitigates the increase in returns to non-cognitive skills, although not completely since cognitive and non-cognitive skills are bundled within each individual.

akin to the wage regression. It is more difficult to interpret the evolution of cognitive/non-cognitive skill intensity per se since the two types of skills are positively correlated; Table A5 shows that the correlation between the two skills across occupations is 0.9.

[27]If we relate the change in the relative return to the change in relative skill intensity directly, the coefficient estimate is 0.018 with a standard error of 0.001.

Table 4 illustrates how changes in relative returns and changes in relative skills relate to occupational task intensities more broadly.[28] We have ranked occupations on the basis of their amount of abstract, routine, or social task content as well as whether the occupations are privy to automation or offshoring. The first row of Table 4 shows the regression estimates corresponding to Figure 11; see columns (1) and (2) (notice that each entry to the table comes from a separate regression).[29] It shows that the relative return to non-cognitive skill increased by 2.4 percentage points more in the most abstract occupation compared to the least abstract occupation. Compared to the least abstract occupations, the most abstract occupations also saw relative skill intensities rise by 14 percent of a standard deviation.

Table 4 also illustrates that the relative return increased more in non-routine occupations relative to routine occupations, and that individuals with an abundance of non-cognitive skill are increasingly entering non-routine occupations over time. Occupations that are routine are also privy to automation, and we basically observe the same pattern for automatable occupations as for routine occupations.[30]

The lower half of Table 4 shows that the relative return to non-cognitive skill increased more in offshorable occupations than in non-offshorable occupations. This is in line with the hypothesis that the possibility to offshore a task may be to the advantage of individuals scoring relatively high on the non-cognitive dimension; in the next subsection, we test this hypothesis explicitly. The last row shows that the relative return to non-cognitive skills also increased more in occupations that are intensive in social tasks relative to those that are not.

Overall, the first two columns of Table 4 document a remarkably systematic pattern. Whenever there is evidence of an increase in the relative return to non-cognitive skills, we observe an increase in the relative intensity of non-cognitive skill, and vice versa. This is further evidence of sorting on the basis of changes in returns, and strongly suggests that demand-side factors are driving the change in relative returns and relative skill intensities.

5.3 The impact of offshoring and IT

The previous subsection indicates that the explanations for the increase in the return to non-cognitive skill should be sought on the demand-side. Here we test two potential explanations that have been proposed in the literature – one pertains to offshoring, the other to IT-investments.

A recent literature suggests that offshoring may be to the detriment of workers who are

[28] The analysis of relative skill intensities is obviously related to the analysis in Figure 10. Results may, in principle, differ since column (2) of Table 4 is a slightly more restrictive version of Figure 10.

[29] For completeness, Table 4 also shows how the changes in the returns to cognitive skills relate to occupational characteristics, see column (3).

[30] When interpreting the results it should be kept in mind that many of these occupational dimensions are highly correlated; Table A5 in the Appendix, inter alia, reports the correlations.

Table 4: Changes in returns and skills across tasks

Ranked (0/1) task intensity	Δ(relative return)$_j$ (1)	Δ(relative skill intensity)$_j$ (2)	Δ(cog. return)$_j$ (3)
Abstract	0.024	0.142	0.021
	(0.000)	(0.001)	(0.000)
Routine	-0.019	-0.156	-0.026
	(0.000)	(0.001)	(0.000)
Automatable	-0.019	-0.075	0.002
	(0.000)	(0.001)	(0.000)
Offshorable	0.010	0.134	0.010
	(0.000)	(0.001)	(0.000)
Social	0.010	0.152	0.032
	(0.000)	(0.001)	(0.000)

Notes: The dependent variable in the column (1) is $\lambda^n_{j1} = (\beta^n_{j,2010} - \beta^c_{j,2010}) - (\beta^n_{j,1995} - \beta^c_{j,1995})$, while the dependent variable in column (3) is $\phi^c_{j1} = (\beta^c_{j,2010} - \beta^c_{j,1995})$; see equation (4). The dependent variable in column (2) is $\Delta(s^n_j - s^c_j)$.. The results come from separate regressions for each cell and 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.

cognitively skilled, but to the advantage of workers who are skilled along the non-cognitive dimension.[31] Increases in offshoring may come from shifts in location comparative advantage (say because of an increase in the relative abundance of cognitive skills in China or India) or because of changes in trade or coordination costs. Independently of the underlying reason, offshoring, by definition, implies disaggregating production at different sites. When production increasingly takes place at different sites one would expect the demand for coordination skills to increase (see Deming 2017). Since non-cognitive ability captures such skills, offshoring may increase the relative return to non-cognitive skills. Consistent with this, Hummels et al. (2014) find that wage gains in response to offshoring occurs in occupations requiring communication skills, while wage losses occur in occupations requiring natural science (engineering, for example).

With respect to IT, technological advancements (computing technology, in particular) may be replacing tasks that are intensive in cognitive skill. Brynjolfsson and McAfee (2014) argue, for example, that increases in computing power expand the set of tasks that machines can perform. Tasks that require interpersonal skills are more difficult to replace by machines, however. Technological advancements may therefore push the relative return to non-cognitive skill upwards over time.

To test these two hypotheses we move to the occupation-by-industry level. We examine whether increases in offshoring, for example, affect the relative return to non-cognitive skill. To address this question, we must take into account that offshoring may be en-

[31]Hummels, Munch, and Xiang (2018) survey the literature on the labor market effects of offshoring.

dogenous to the wage structure. To deal with endogeneity, we construct a shift-share instrument a la Bartik (1991) and estimate reduced-form equations.[32] In particular, we examine whether hikes in intermediate imports at the industry level (our measure of offshoring) had the effect of increasing the relative return to non-cognitive skills more (or less) in occupations that are offshorable. We thus take data from two time points, 1995 and 2010 and run the regression:

$$\begin{aligned} \ln(wage)_{ijst} = \alpha_{jst} + \phi^c_j(s^c_i + s^n_i) + \lambda^n_j s^n_i + \phi^c_{st}(s^c_i + s^n_i) + \lambda^n_{st} s^n_i \\ +\mu^c \left[O_j \times D^o_{st} \times (s^c_i + s^n_i)\right] + \eta^n \left[O_j \times D^o_{st} \times s^n_i\right] + \epsilon_{ijst} \end{aligned} \quad (5)$$

Equation (5) allows the return to cognitive and the relative return to non-cognitive skill to vary by the shift-share instrument ($O_j \times D^o_{st}$), where O_j measures the offshorability of the occupation and D^o_{st} is an indicator variable equalling unity for industries (s) which saw above median increases in log intermediate imports.[33] Notice that the specification of the wage regression is very flexible. For instance, it includes occupation-by-industry-by-time fixed effects (α_{jst}), which take care of the main effects of offshorability of the occupation and the change in intermediate imports ($O_j \times D^o_{st}$). Moreover, it allows the return to cognitive and non-cognitive skills to vary freely by occupation (j) and industry-by-time ($s \times t$).

We run a parallel analysis for skill-intensities at the occupation-by-industry-by-time level. We thus examine whether the intensity of non-cognitive skill, relative to cognitive skill, increased more in cells that were more likely to be hit by an offshoring shock according to our shift-share instrument. We thus run the regression

$$s^n_{ijst} - s^c_{ijst} = \alpha_j + \alpha_{st} + \pi \left[O_j \times D^o_{st}\right] + \varepsilon_{ijst} \quad (6)$$

Table 5 reports the results of estimating equations (5) and (6). Data on intermediate imports come from the STAN-database maintained by the OECD. Note that focusing on intermediate imports implies that we sample individuals working in the manufacturing sector. Column (2) of Table 5 corresponds directly to equation (5), while column (4) corresponds to equation (6); columns (1) and (3) report the results of slightly more parsimonious specifications.

Column (4) suggests that the relative intensity of non-cognitive skill increased more in occupation-by-industry cells that were more likely to experience increases in offshoring.

[32] Unfortunately, we cannot implement an instrumental variables approach since we have no information on exposure to intermediate imports in the firms where the individuals are employed.

[33] A couple of comments regarding the specification may be in order. First, from a qualitative point of view, it does not matter whether we include a dummy for industries that saw above median increases in log intermediate imports or whether we use log intermediate imports directly in the equation; we have a preference for the current specification since the results are less dependent on extreme changes in intermediate imports. Second, without changing anything of substance (apart from the standard errors) we could aggregate the key measures of exposure to intermediate imports to the occupational level.

Table 5: The effects of offshoring

	Returns		Skill intensities	
	(1)	(2)	(3)	(4)
Offshoring $[O_j \times D^o_{st}]$			0.0353	0.0365
			(0.0161)	(0.0145)
interacted with overall skill	-0.0028	-0.0039		
$[O_j \times D^o_{st} \times (s^c_i + s^n_i)]$	(0.0017)	(0.0018)		
interacted with non-cognitive skill	0.0110	0.0111		
$[O_j \times D^o_{st} \times s^n_i]$	(0.0032)	(0.0032)		
Fixed effects				
occupation			√	√
industry			√	
time			√	
industry×time	√			√
occupation×time	√			
occupation×industry×time		√		
Skill interactions				
industry×time	√	√		
occupation	√	√		
#observations	153,879	153,879	153,879	153,879

Notes: Standard errors (reported in parentheses) are robust in columns (1) and (2) and clustered by occupation×industry×time in columns (3)-(4). All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017); Appendix A7 outlines the procedure. Data on intermediate imports come from the STAN database. The classification of offshorable jobs follows Acemoglu and Autor (2011).

Analogously, the relative return to non-cognitive skill increases with offshoring. The difference in the growth of log intermediate imports between industries having $D^o_{st} = 1$ and industries where $D^o_{st} = 0$ is 0.485. Hit by an offshoring shock of this magnitude, the return to non-cognitive skill would grow by half a percentage points more in occupations where the offshorability of tasks is a standard deviation higher than average. This corresponds to a quarter of the variation of the relative return to non-cognitive skill across occupation-by-industry cells; see Table 3.[34] Interestingly, column (2) suggests that the return to cognitive skill is negatively affected by increases in offshoring.

The analysis of the effects of IT-investments is analogous to the effects of offshoring. We thus examine whether hikes in IT-investments at the industry level had the effect of increasing the relative return to non-cognitive skill more (or less) in occupations that are intensive in abstract tasks; in other words we take abstract occupations as demanding primarily cognitive skills.[35] We run the regression:

[34]Table 3 shows that the relative return to non-cognitive skill grew by 2 percentage points (=3.2-1.2) across occupation-by-industry cells

[35]This is also true in the data. Table A5 shows that cognitive skill intensity correlate most strongly with abstract task intensity of the occupational traits we consider (abstract, routine, automatable, offshorable, and social).

$$\begin{aligned}\ln(wage)_{ijst} = \alpha_{jst} + \phi^c_j(s^c_i + s^n_i) + \lambda^n_j s^n_i + \phi^c_{st}(s^c_i + s^n_i) + \lambda^n_{st} s^n_i \\ +\omega^c \left[A_j \times D^{IT}_{st} \times (s^c_i + s^n_i)\right] + \tau^n \left[A_j \times D^{IT}_{st} \times s^n_i\right] + \epsilon_{ijst}\end{aligned} \tag{7}$$

Equation (7) allows the return to cognitive and the relative return to non-cognitive skill to vary by the shift-share instrument ($A_j \times D^{IT}_{st}$), where A_j measures the intensity of abstract tasks in the occupation and D^{IT}_{st} is an indicator variable equalling unity for industries (s) which saw above median increases in log IT-investments. Again, occupation-by-industry-by-time fixed effects (α_{jst}) take care of the main effects of A_j as well as D^{IT}_{st}, and the returns to cognitive and non-cognitive skills are allowed to vary freely by occupation (j) as well as industry-by-time ($s \times t$).

For relative skill intensities we estimate

$$s^n_{ijst} - s^c_{ijst} = \alpha_j + \alpha_{st} + \rho\left[A_j \times D^{IT}_{st}\right] + \varepsilon_{ijst} \tag{8}$$

Table 6 reports the results; column (2) corresponds to equation (7) and column (4) to equation (8). Data on IT-investments come from EU KLEMS and cover a broader set of industries – the entire private sector – than the data on intermediate imports.

Column (4) of Table 6 suggests that the relative intensity of non-cognitive skill increased more in occupation-by-industry cells that were more likely to experience an increase in IT-investments. Moreover, column (2) shows that the relative return to non-cognitive skill rises with IT-investments. The difference in the growth of log IT-investments between industries having $D^{IT}_{st} = 1$ and industries where $D^{IT}_{st} = 0$ is to 1.219. Hit by an IT shock of this magnitude, the relative return to non-cognitive skill would grow by 0.9 percentage points more in occupations where the intensity of abstract tasks is a standard deviation higher than average. This magnitude corresponds to some 40 percent of the variation in the relative return to non-cognitive skill across occupation-by-industry cells. The return to cognitive skill is, however, unrelated to IT-investments according to the estimates in columns (2).

At this stage, it is of course relevant to ask whether it is primarily offshoring or IT-investments that are driving the changes in relative returns and relative skill intensities. In principle we can answer this question by examining the set of industries used in Table 5. In the Appendix (see Table A6) we report results from regressions where we include our measures of offshoring *and* IT-investments simultaneously. Since the correlation between offshorable and abstract occupations is fairly weak (roughly 0.2), it does not matter so much if we include our shift-share instruments one at a time or both at once.

The upshot of the analyses presented in this sub-section is that the increase in the return to non-cognitive skill can be tied to offshoring and to IT-investments. The effects of offshoring may reflect the combination of outside cognitive skill supply displacing internal cognitive skill supply to some extent, as well as the demand for coordination skills

Table 6: The effects of IT-investments

	Returns		Skill intensities	
	(1)	(2)	(3)	(4)
IT-investments $\left[A_j \times D_{st}^{IT}\right]$			0.0664	0.0619
			(0.0115)	(0.0115)
interacted with overall skill	0.0024	-0.0011		
$\left[A_j \times D_{st}^{IT} \times (s_i^c + s_i^n)\right]$	(0.0019)	(0.0020)		
interacted with non-cognitive skill	0.0093	0.0070		
$\left[A_j \times D_{st}^{IT} \times s_i^n\right]$	(0.0036)	(0.0036)		
Fixed effects				
occupation			$\surd$	$\surd$
industry			$\surd$	
time			$\surd$	
industry×time	$\surd$			$\surd$
occupation×time	$\surd$			
occupation×industry×time		$\surd$		
Skill interactions				
industry×time	$\surd$	$\surd$		
occupation	$\surd$	$\surd$		
#observations	327,481	327,481	327,481	327,481

Notes: Standard errors (reported within parentheses) are robust in columns (1) and (2) and clustered by occupation×industry×time in columns (3)-(4). All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017); Appendix A7 outlines the procedure. Data on IT-investments come from the EU-KLEMS database. The classification of abstract jobs follows Acemoglu and Autor (2011).

increasing along with outsourcing, since outsourcing implies disaggregating production to different sites. The effect of IT-investments is consistent with the view that machines replace (what used to be) high-cognitive tasks to a greater extent than tasks where non-cognitive (or social) skills are important.

6 Conclusions

We have examined the changes in the relative rewards to cognitive and non-cognitive skills during the time period 1992-2013. Using unique administrative data for Sweden, including high-quality data on cognitive and non cognitive skills from the mandatory military draft at age 18, we have documented a secular increase in the wage returns to non-cognitive skill for prime-aged men. This increase occurred primarily in the private sector and at the upper-end of the wage distribution. In the private sector, the partial return to non-cognitive skill (i.e., the return conditional on cognitive skill) roughly doubled over the time period: it increased from around 7 to 14 percent per standard deviation increase in non-cognitive ability.

Meanwhile, the return to cognitive skills was stable; over the entire time-period, it varied between 11 and 13 percent per standard deviation increase in cognitive ability. Interestingly, between 2000 and 2013, the return to cognitive skill fell by almost 2 percentage points. This is consistent with Beaudry, Green, and Sand (2016), who document that employment growth in cognitively demanding occupations slowed down markedly during the 2000s, and Castex and Dechter (2014), who document a mild negative trend in the return to cognitive ability in the US. Thus, the labor market appears to increasingly value individuals possessing high non-cognitive relative to cognitive skills over time.

We have also provided evidence of changes in occupational sorting. During the time-period of observation, workers with an abundance of non-cognitive skill were increasingly sorted into occupations that were intensive in abstract, non-routine, social, non-automatable and offshorable tasks. Such occupations also saw greater increases in the relative return to non-cognitive skill. This suggests sorting on comparative advantage and that the optimal skill mixes of any given occupation has changed over time.

In a recent paper, Deming (2017) argues that technology is increasingly substituting for labor also at the high-end of the distribution, thus replacing cognitively demanding tasks to a greater extent over time. Inter-personal and social skills are more difficult to replace, however, such that the labor market should increasingly reward individuals possessing these kinds of social skills. Both our individual- and occupational-level results are consistent with Deming (2017). We also directly test the hypotheses that offshoring and IT-investments favor individuals with an abundance of non-cognitive skill. Using variation across industries and occupations, we show that offshoring and IT-investments increase the return to non-cognitive ability relative to the return to cognitive ability.

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Appendix

A1 Cognitive and non-cognitive skills

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. 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 that individuals with high non-cognitive skills relative to cognitive skills are sorted into occupations requiring extraversion and emotional stability to a greater extent than individuals with high cognitive skills relative to their non-cognitive skills.

Table A1: Partial correlations between skills and occupational skill requirements

	Non-cognitive skill	Cognitive skill
	(1)	(2)
Occupational requirements		
Conscientiousness	0.0980	0.1616
	(0.0042)	(0.0088)
Agreeableness	-0.1899	-0.0172
	(0.0043)	(0.0056)
Emotional stability	0.0995	-0.1232
	(0.0036)	(0.0047)
Extraversion	0.1847	-0.0708
	(0.0032)	(0.0042)
Openness to experience	-0.0432	0.3245
	(0.0033)	(0.0042)
Individual skill		
Cognitive skill	0.2213	
	(0.0011)	
Non-cognitive skill	–	0.3733
	–	(0.0019)
#observations	446,161	446,161
R-squared	0.184	0.240

Notes: Robust standard errors in parentheses. Data are from 2000 and cover males aged 38-42. Occupational requirements are constructed from O*NET; see Black, Grönqvist, and Öckert (2017). All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Appendix A7 outlines the procedure.

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-

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)	-0.07	1. Librarians (243)	0.61
2. Workers in animal production (612)	-0.09	2. Library assistants (414)	0.07
3. Construction workers (712)	-0.11	3. Precision workers (731)	-0.06
2nd tercile of cognitive skill		2nd tercile of non-cognitive skill	
1. Sales persons (341)	0.40	1. Priests (246)	0.81
2. Fire fighters and security guards (515)	0.38	2. Laboratory technicians (324)	0.49
3. Safety inspectors (315)	0.30	3. Electrical/Construction Engineers (311)	0.44
3rd tercile of cognitive skill		3rd tercile of non-cognitive skill	
1. Police officers (345)	0.84	1. University research and teaching (231)	1.14
2. Medical doctors (222)	0.81	2. Medical doctors (222)	1.14
3. CEOs (121)	0.80	3. Physicists, chemists etc. (211)	1.06

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

panel lists occupations scoring high on the non-cognitive dimension by tercile of the cognitive skill distribution. This panel shows, e.g., that among the occupations in the middle 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 (0.61 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.

A2 Descriptive statistics

Here we describe the data in more detail than in the main text. Table A3 shows descriptive statistics for various sub-samples of individuals observed in 2009-11. As a starting point we sample all individuals who have either done the cognitive test battery or have been evaluated along the non-cognitive dimension. We then standardize the respective scores within each birth cohort. Column (1) shows average skills and labor market outcomes (employment and earnings) among men aged 30-50 in 2009-11, who did both tests at age 18 or 19.[36] 91 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 marginally higher connection to the labor market; the employment rate is 1 percentage point higher, and earnings 4 percent higher, in column (2) than in column (1). Column (3) focuses on the subset of the population in column (2) who are employed (according to the definition of 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 A8 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 in the private sector than in the

[36] Conditioning on a non-cognitive score being available is the reason why the mean of the cognitive score is 0.02. Those being evaluated along the non-cognitive dimension are slightly positively selected in terms of their cognitive skill.

Table A3: Descriptive statistics, men, 2009-11

	(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	0.91	0.92	1.00	1.00	1.00
Annual earnings (1000 SEK)	362.86	377.43	408.12	438.56	460.49
[weighted mean]				[425.94]	[434.06]
(SD)	(311.94)	(350.41)	(348.48)	(423.96)	(486.94)
Cognitive skill	0.02	0.02	0.06	0.15	0.11
[weighted mean]				[0.08]	[0.04]
(SD)	(0.99)	(0.99)	(0.98)	(0.98)	(0.99)
Noncognitive skill	0.00	0.00	0.05	0.10	0.06
[weighted mean]				[0.06]	[0.03]
(SD)	(0.99)	(0.99)	(0.97)	(0.96)	(0.95)
Log wage				10.41	10.44
[weighted mean]				[10.38]	[10.39]
(SD)				(0.33)	(0.35)
Private sector				0.73	1.00
Blue-collar worker					0.37
White-collar worker					0.63
Managerial occ.				0.09	0.10
Other high-skill occ.				0.51	0.45
# observations	2,865,257	731,832	673,421	313,732	228,243
[sum of weights]				[569,050]	[483,561]

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 2009-11. Weighted means are in brackets; standard deviations (based on non-weighted data) are reported in parentheses for non-binary variables.

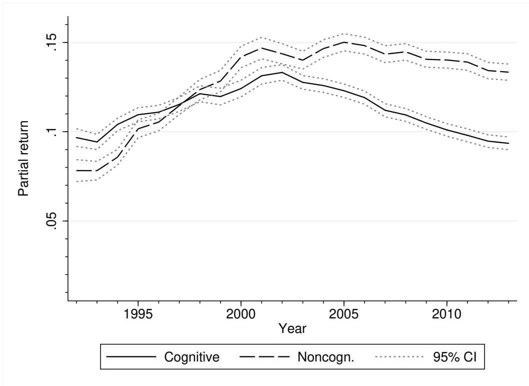
overall economy. A comparison of columns (4) and (5) also reveal that those working in the public sector are more skilled on average.

A3 Returns by worker status

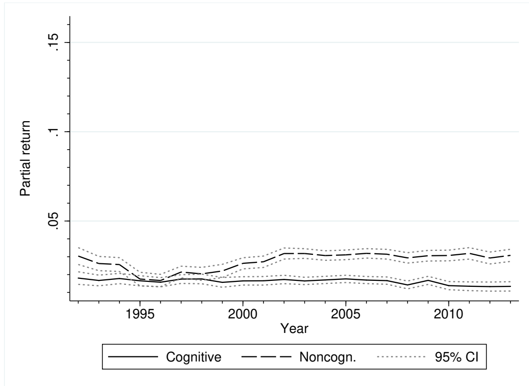
Figures A1a and A1b shows returns estimated by worker status (white-collar and blue-collar workers). It is clear that the increase in the returns almost exclusively occurs in white-collar occupations. This is consistent with the result that the return to non-cognitive skill increased the most at the upper-end of the wage distribution; see Figure 7, panels (a) and (b).

Figure A1: Returns by worker status, 1992-2013

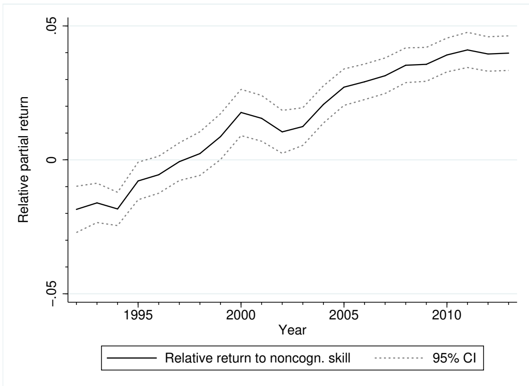
(a) White-collar workers



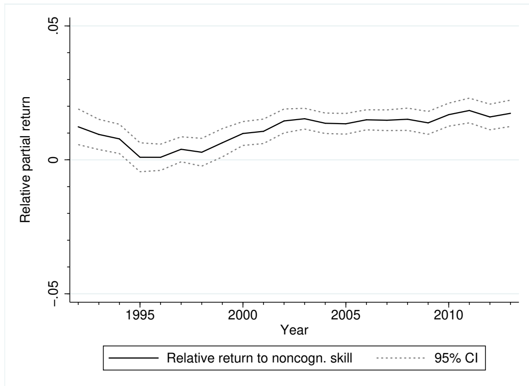
(b) Blue-collar workers



(c) White-collar workers, relative returns



(d) Blue-collar workers, relative returns



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). Appendix A7 outlines the procedure.

A4 Estimates of returns between 1985-2013

Here we provide estimates for the population aged 30-50 during the time-period 1985-2013. To do so we impose some additional structure and estimate a panel data model which is analogous to equation (2):

$$\ln(wage)_{iat} = \sum_{t=1985}^{2013} (\alpha_t + \beta_t^c s_i^c + \beta_t^n s_i^n) + \sum_{a=30}^{50} (\alpha_a + \lambda_a^c s_i^c + \lambda_a^n s_i^n) + \varepsilon_{iat}, \tag{A1}$$

We normalize the model to age 40, such that the estimates have the same reference age as our main analysis.[37]

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 A2a and A2b report a sub-set of the results. In interpreting these results, note

[37] 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.

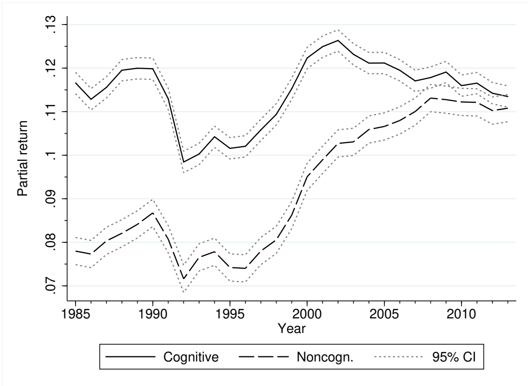
that Sweden was hit by the most severe unemployment crisis since the Great Depression in the early 1990s. In just a few years, unemployment among men aged 25-54, for example, went from 1.3% (in 1990) to 8.4% (in 1993). Like all cyclical downturns, this shock hit the bottom end of the skill distribution 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 A2a). 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 A2b 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 A2a. Thus we are more inclined to believe that Figure A2b reflects structural change in the labor market, at least for the skilled segment of the market.

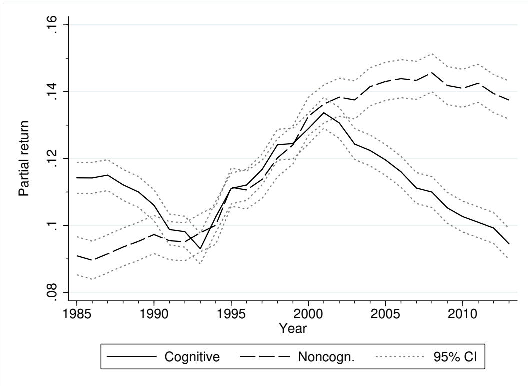
The estimates in Figure A2b can be compared to A1a. Since the evolution of the estimates in the two figures is similar for the period when the two approaches can be compared, it seems that the panel approach delivers reliable estimates (with the caveat that it is more sensitive to cyclical changes since 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 A2a prior to 1990.

Figure A2: Panel estimates of returns, 1985-2013 (ages 30-50)

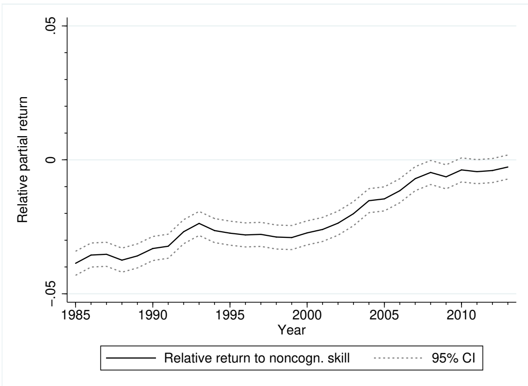
(a) All workers



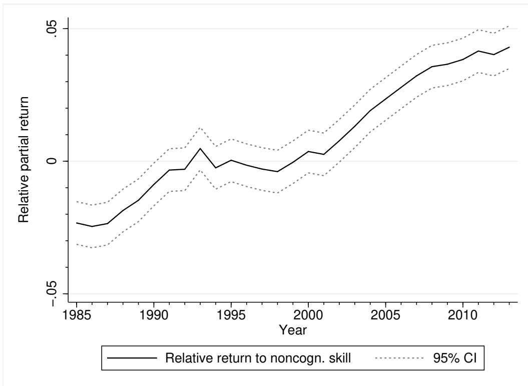
(b) White-collar workers



(c) All workers, relative returns



(d) White-collar workers, relative returns



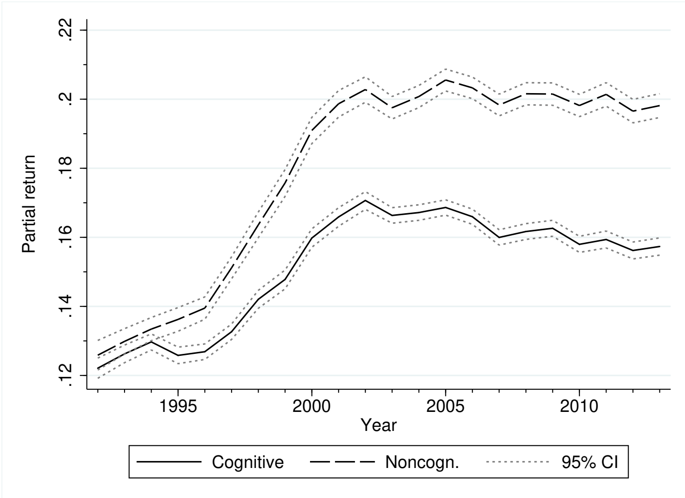
Notes: Confidence bands are based on robust standard errors. All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Appendix A7 outlines the procedure.

A5 Returns estimated from bivariate regressions

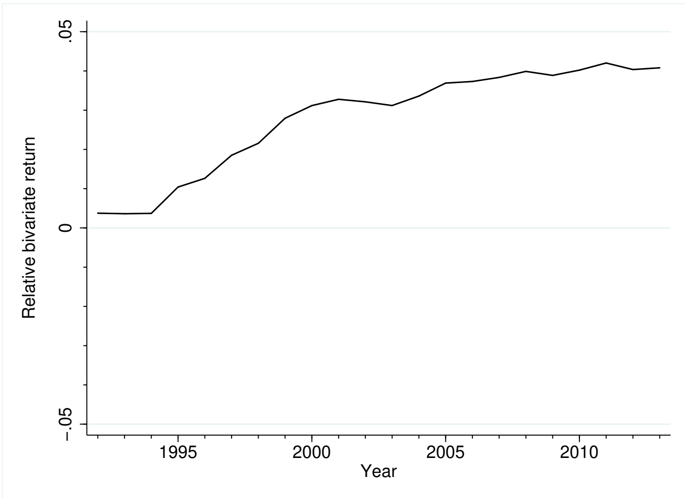
Figure A3 shows the results of separate regressions of log wages on cognitive and non-cognitive skill, respectively. This does not change the overall flavor of our results. Nevertheless, it is noteworthy that the bivariate return to non-cognitive skill is much higher than the return obtained by partialing out the variation in cognitive skill.

Figure A3: Returns to skills (bivariate regressions)

(a) Bivariate returns, private sector



(b) Difference in bivariate returns, private sector



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. Private sector only. Confidence bands in panel (a) are based on robust standard errors.

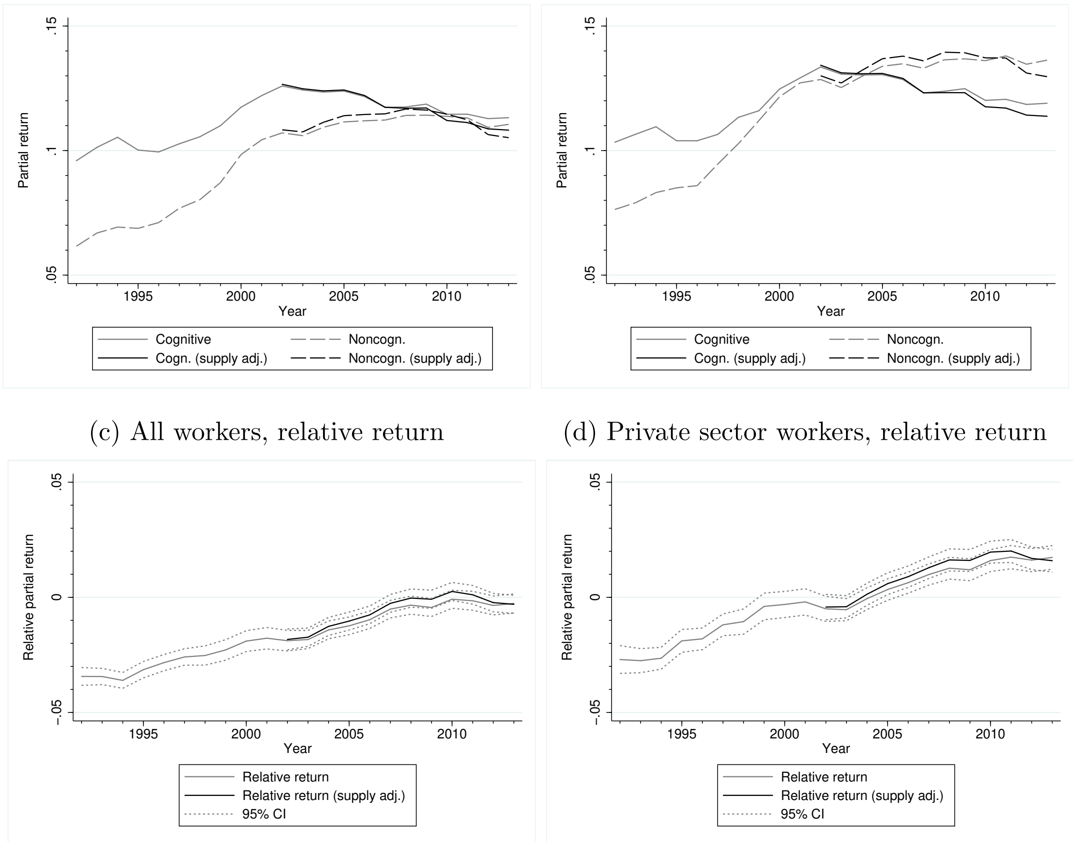
A6 Sensitivity to time-variant skill distributions

Here we present an attempt to measure the absolute changes in skill supplies (rather then standardizing the skill measures as in the main text). 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.

Figure A4: Returns estimated using variable skill distributions, 1992-2013

(a) All workers (b) Private sector workers

(c) All workers, relative return (d) Private sector workers, relative return



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. Confidence bands in panels (c) and (d) are based on robust standard errors.

Figure A4 presents the results. The slightly darker 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 for changes in skill supplies across cohorts thus seems unimportant.

A7 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. Their analysis suggest that the reliability ratio for cognitive skills is 73 percent, while the reliability ratio for non-cognitive skills 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)

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

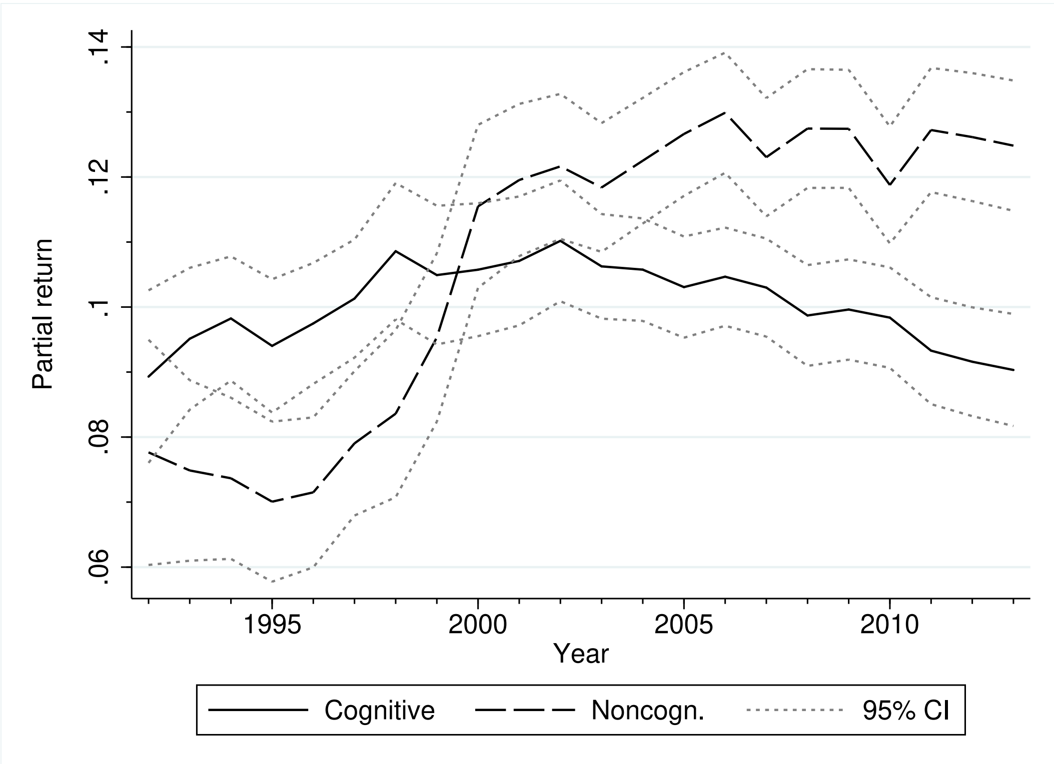
where ρ denotes the correlation between skill j and skill k and γ^j denotes the conventional reliability ratio:

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

where X^j denotes the correctly measured non-standardized variables and V^j the measurement error.

A potential concern associated with our approach is that measurement errors may change over time and (hence) cohorts. To examine whether this is a concern, we used skills for brothers as instruments for own skills. Figure A5 shows the results; they should be compared to Figure 3a of the main text. Such a comparison reveals that none of our conclusions change by taking a time-varying measurement error into account.

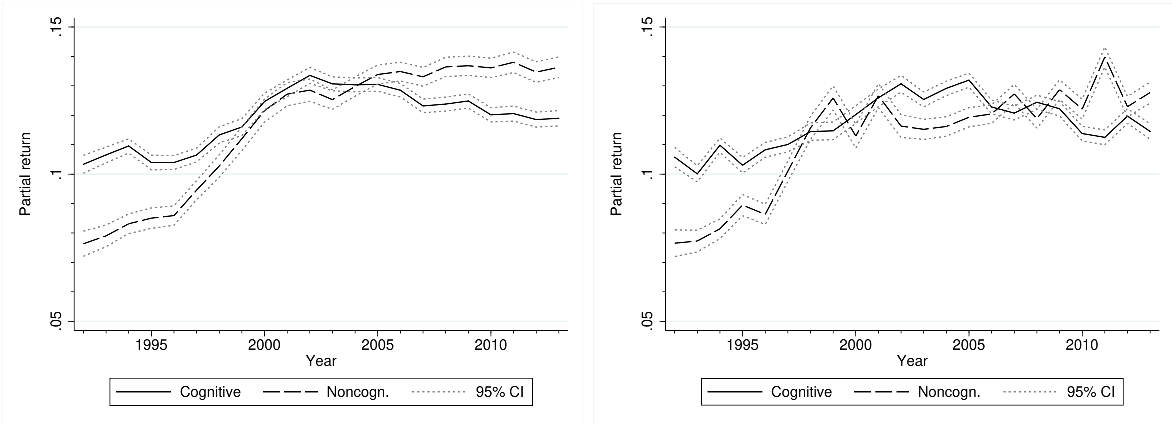
Figure A5: IV estimates using brothers' skills as instruments for own skills



Notes: Confidence bands are based on robust standard errors.

Figure A6: 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). Appendix A7 outlines the procedure.

A8 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 A6 compares the unweighted and the weighted estimates. It shows that for the trend changes that we emphasize it does not matter whether we weight or not. 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.

A9 Decomposition of the returns in 2009-11

Table A4 examines whether the age range appears to matter for the decomposition results in Table 3 of the main text. We compare a broader age-category (ages 30-50) to our baseline age range (38-42) in 2009-11 (since in 2009-11 all cohorts in the age range 30-50 have been observed in the draft). Table A4 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.

A10 Additional descriptives

Table A5 provides the correlation matrix at the occupational level.

Table A4: Decomposition of the returns to skill 2009-11, 30-50 year-olds vs. 38-42 year-olds

	A. Ages 30-50			
	Cognitive		Non-cognitive	
	Across	Within	Across	Within
A. Industry	30%	70%	21%	79%
B. Firm	36%	64%	28%	72%
C. Occupation	61%	39%	53%	47%
D. Occupation×Industry	69%	31%	60%	40%
	B. Ages 38-42			
A. Industry	31%	69%	22%	72%
B. Firm	38%	62%	28%	72%
C. Occupation	63%	37%	55%	45%
D. Occupation×Industry	70%	30%	62%	38%

A11 The probability of holding a managerial position

In Section 4.3 we documented 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 skills, and perhaps increasingly so, as hypothesized by Deming (2017).

Figure A7 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 skills increased by 1.5 percentage points.[38] During the same time-period the importance of cognitive skills fell by almost the same magnitude.

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

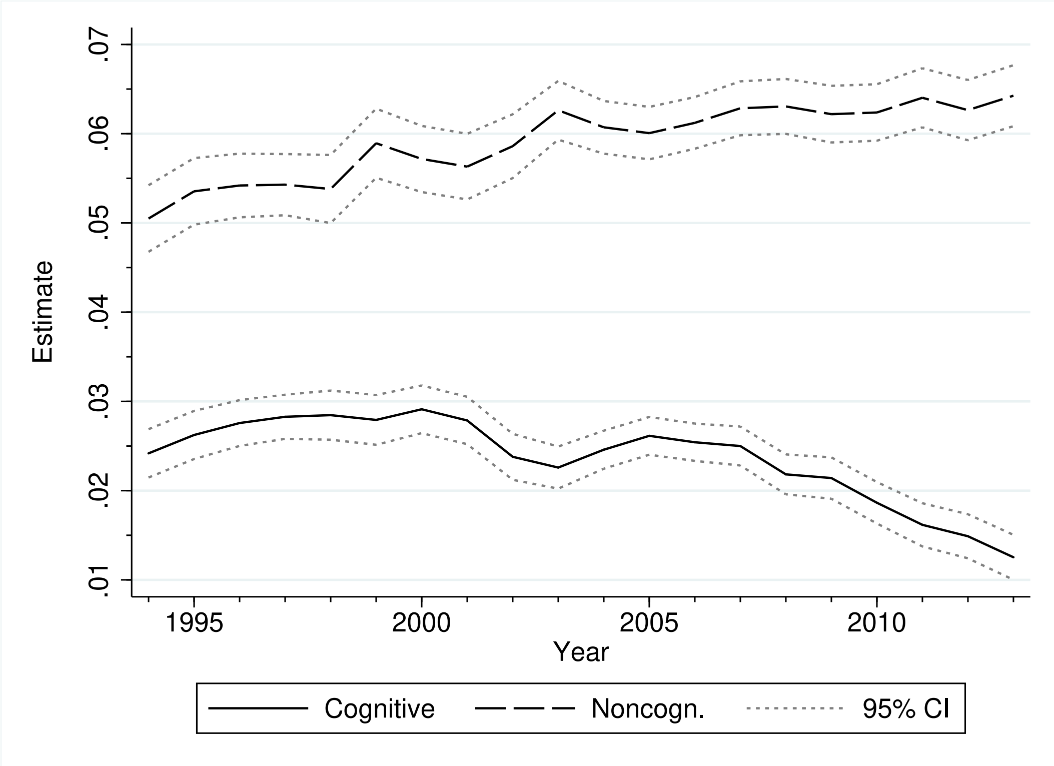
[38] We exclude 1992 and 1993 in this analysis since we lack occupation data for these years.

Table A5: Correlation matrix

	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	0.038	1.000									
$\ln(w_{j,95})$	0.178	0.425	1.000								
$\Delta Empl.\,share_j$	-0.021	-0.073	0.147	1.000							
$s^c_{j,95}$	0.158	0.516	0.846	0.173	1.000						
$s^n_{j,95}$	0.120	0.517	0.870	0.174	0.898	1.000					
Abstract	0.201	0.354	0.849	0.230	0.819	0.870	1.000				
Routine	-0.139	-0.461	-0.601	-0.232	-0.637	-0.774	-0.682	1.000			
Automation	-0.209	-0.216	-0.748	-0.308	-0.773	-0.699	-0.800	0.550	1.000		
Offshorability	0.094	0.504	0.453	0.047	0.427	0.360	0.199	-0.298	-0.137	1.000	
Social	0.092	0.414	0.718	0.204	0.648	0.825	0.775	-0.827	-0.577	0.381	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). ΔRR_j denotes the change in the relative return by occupation and ΔRS_j the change in relative skill intensity by occupation. All changes are between 1995 and 2010. The remainder of the notation is as in the main text.

Figure A7: The relationship between skills and probability of being a manager



Notes: Confidence bands in panels (c) and (d) are based on robust standard errors.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, Öckert, and Vlachos (2017).

A12 More on the effects of offshoring and IT

Here we present the results of including offshoring and IT simultaneously for the sample used in Table 5. Table A6 report the results from a specification corresponding to column (2) of Table 5. For easy reference, columns (1) and (4) reproduce the results of columns (2) and (4) in Table 5.

Columns (2) and (5) of Table A6 report the reduced form effects of the IT-instruments. The effect on relative skill intensities is comparable for the set of manufacturing industries examined here, relative to the entirety of the private sector examined in Table 6. The impact on skill returns is very different in some respects. While it is true that IT-investments increase the relative return to non-cognitive skill in both samples, the increase in the manufacturing sector comes almost exclusively from a fall in the return to cognitive skill. For the broader set of industries included in the private sector, the increase in the relative return stems from a rise in the return to non-cognitive skill.

Columns (3) and (6) finally shows the reduced form effects of the offshoring and IT instruments simultaneously. This leaves the impacts of offshoring virtually unaffected. The estimated coefficients on the IT instruments fall slightly in absolute value, and precision

Table A6: The effects of offshoring and IT

	Returns			Skill intensities		
	(1)	(2)	(3)	(4)	(5)	(6)
Offshoring $[O_j \times D^o_{st}]$				0.0365		0.0362
				(0.0145)		(0.0144)
interacted with overall skill	-0.0039		-0.0033			
$[O_j \times D^o_{st} \times (s^c_i + s^n_i)]$	(0.0018)		(0.0018)			
interacted with non-cognitive skill	0.0111		0.0105			
$[O_j \times D^o_{st} \times s^n_i]$	(0.0032)		(0.0032)			
IT-investments $\left[A_j \times D^{IT}_{st}\right]$					0.0191	0.0079
					(0.0394)	(0.0387)
interacted with overall skill		-0.0170	-0.0159			
$\left[A_j \times D^{IT}_{st} \times (s^c_i + s^n_i)\right]$		(0.0060)	(0.0060)			
interacted with non-cognitive skill		0.0182	0.0143			
$\left[A_j \times D^{IT}_{st} \times s^n_i\right]$		(0.0110)	(0.0111)			
Fixed effects						
occupation				√	√	√
industry×time				√	√	√
occupation×industry×time	√	√	√			
Skill interactions						
industry×time	√	√	√			
occupation	√	√	√			
#observations	153,879	153,879	153,879	153,879	153,879	153,879

Notes: Standard errors (reported within parentheses) are robust in columns (1)-(3) and clustered by occupation×industry×time in columns (4)-(6). All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist, Öckert, and Vlachos (2017). Appendix A7 outlines the procedure.

is reduced somewhat. But overall there are only minor changes relative to columns (2) and (5).