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# ABSTRACT

## The Rising Return to Non-Cognitive Skill*

We examine the changes in the relative 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, which is particularly pronounced in the private sector and at the upper-end of the wage distribution. Workers with an abundance of non-cognitive skill were increasingly sorted into occupations that were intensive in: cognitive skill; as well as abstract, non-routine, social, non-automatable and offshorable tasks. Such occupations were also the types of occupations which saw greater increases in the relative return to non-cognitive skill. Moreover, we show that greater emphasis is placed on noncognitive skills in the promotion to leadership positions over time. These pieces of evidence are consistent with a framework where non-cognitive, inter-personal, skills are increasingly required to coordinate production within and across workplaces.

**JEL Classification:** J24, J31

**Keywords:** wage inequality, sorting, returns to skills, cognitive skills, noncognitive skills

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# 1 Introduction

Most industrialized countries have seen an increase in overall wage inequality. A large (and predominantly US) literature has tied this increase to larger wage-differentials between college and high-school educated labor (see, e.g., Acemoglu and Autor 2011 for a review of the literature).

The canonical model to explain the variation in the college-high school wage premium is one featuring skill-biased technical change (SBTC); see Tinbergen (1974). In models with SBTC, changes in relative wages are driven by the "race" between relative demand and relative supply; they predict that changes in technology will have monotone effects across the skill distribution.

Another class of models separates tasks from skills; see Autor et al. (2003). Changes in technology lead to changes in the relative valuation of tasks, which workers who are differentially skilled are more or less apt to do. This class of models implies that technology need not have monotone effects across the skill distribution. According to the "routinization hypothesis", technology (automation and computers) has replaced workers in the middle part of the skill distribution. As a consequence, we observe job polarization, i.e., greater employment growth at the bottom and top ends of the skill distribution. Both ends of the distribution are populated by workers with skills that are not easily replaced by automated procedures.

A recent paper by Deming (2017) builds on the task-based approach. The basic argument is that technology (e.g., computers) is increasingly substituting for labor also at the high-end of the distribution; computers thus replace cognitively demanding tasks to a greater extent over time. Inter-personal and social skills are more difficult to replace, however. Therefore, we should observe that the labor market increasingly rewards individuals possessing these kinds of social skills. Consistent with this prediction, Deming (2017) shows that occupations demanding social skills have exhibited higher employment growth, in particular since 2000; wage changes at the occupational level are also in line with this prediction.

We provide a direct test of the argument of Deming (2017). In particular, we estimate long-run trends in the returns to cognitive and non-cognitive skills for prime-age individuals. To conduct this exercise we tap unique information derived from the military draft in Sweden. The draft was mandatory for all males in the cohorts we study and was conducted at age 18 or 19. Thus, the data provide pre-market information on a broad set of cognitive and non-cognitive skills for a large sample of Swedish men. The domains covered by the non-cognitive skills include dimensions that should arguably be interpreted as social skills.

By combining the draft information with wage data, we show that there is a secular increase in the returns to non-cognitive skills from 1992 to 2013. During this time period 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; throughout the time period it varied between 11 and 13 percent per standard deviation increase in cognitive skill. Thus, the labor market increasingly values individuals possessing good non-cognitive (inter-personal) skills over time. We further document that the increasing return to non-cognitive skill is particularly pronounced in the upper-end of the wage distribution.

Returns increased differentially *across* occupations. We document greater increases in the relative return to non-cognitive skill in occupations that (initially) were intensive in cognitive skill and characterized by more abstract, non-routine, non-automatable, and offshorable tasks.

We also provide direct evidence on the main mechanism proposed by Deming (2017). We show that non-cognitive skills load more heavily on the probability of obtaining a leadership position over time, while the opposite pattern is found for cognitive skill. This is consistent with the view that it is increasingly important to have non-cognitive skills in order to run complex organizations.

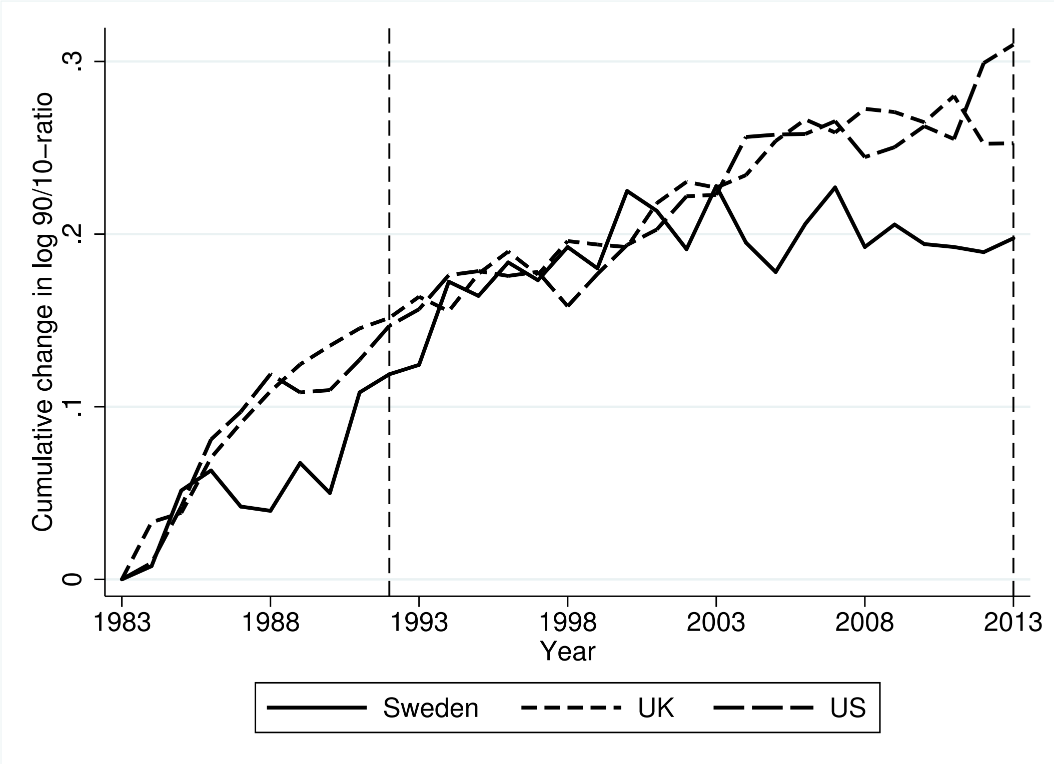
To the best of our knowledge, this is the first study to document and compare long-run trends in the returns to cognitive *and* non-cognitive skills using individual-level data. Most previous work has inferred such information from the typical skill requirements of occupations. Our findings can also complement the recent evidence on stagnating or decreasing returns to cognitive skill in the US (Castex and Dechter, 2014; Beaudry et al., 2016). Our evidence suggests that this decrease could mask a coinciding (and possibly substantial) increase in the valuation of non-cognitive or social skills.

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 presents estimates of the returns to skills at the occupational level and examines whether changes in relative returns affect the allocation of workers with different skills across occupations. And 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

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



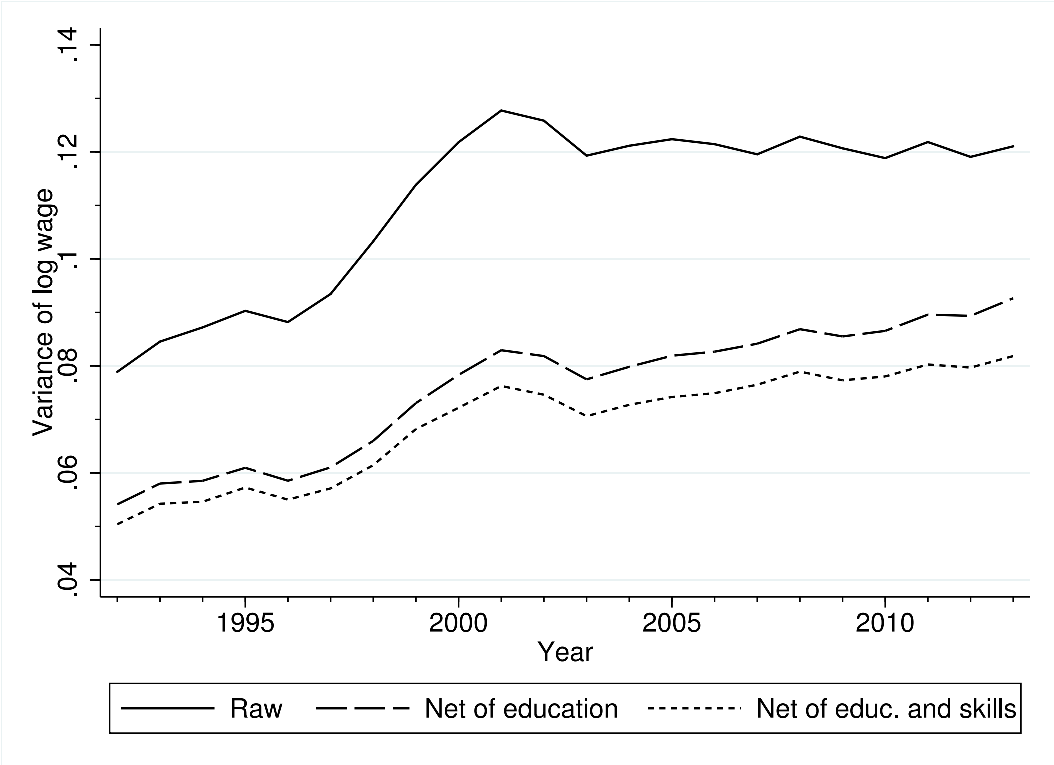

Notes: The data pertain to men and come from the OECD Earnings Distribution Database. For all countries we normalize each series with the log of the 90/10 ratio in 1983. Vertical dashed lines mark the start and end-year of our main analysis.

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 et al. (2014) show that Sweden experienced much slower employment growth between 1993 and 2010 in the middle of the wage distribution than at the low- 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 (the first digitized cohort is born in 1951), combined with the age restriction, implies that we can conduct the analysis between 1992 and 2013. One 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 wage inequality during the 1990s. This increase came to a halt in the early 2000s, and since then there has been no increase in dispersion.

Figure 2 also provides a rough decomposition of the variance of log wages. The dashed line shows residual wage inequality after non-parametrically netting out educational attainment (and age). During the 2000s, there is a a small increase in residual wage inequality; in other words, wage differentials attributed to education seem to have decreased marginally. Part of this decline is likely due to a substantial increase in the supply of college educated individuals among the cohorts born in the 1960s and 1970s.

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




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

The third dotted line shows residual wage inequality after also accounting for a second order polynomial in cognitive and non-cognitive skill. Accounting for these skills, in addition to educational attainment, reduces the trend increase in residual wage inequality only marginally. However, as we show in section 4, this overall picture hides substantial changes in the relative importance of cognitive and non-cognitive skills in the labor market.

# 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 percent of all private sector workers and all public sector workers during 1985-2013.[1] Since we are interested in structural change in the labor market, we focus the analysis on prime-aged individuals aged 38-42. This group of workers are basically insulated from the cyclical variation that affects younger as well as older workers;[2] another advantage of focusing on prime-aged workers is that we can abstract from the fact that life-cycle wage profiles are heterogeneous by skill.

To these wage data we add military enlistment scores. Information from the draft is available for males who did the draft between between 1969 and 1994. During these years, almost all males went through the draft procedure at age 18 or 19, and enlistment scores are available for more than 90 percent of the sample. The availability of the draft data combined with the age restriction means that our analysis is based 25 cohorts of males born between 1951 and 1975.

Linked to these 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; some of our analyses also tap information on education, industry, sector, and firms.

## 3.1 Cognitive and non-cognitive skills

The data from the draft procedure include four different measures of cognitive skills and four measures of non-cognitive skills. We focus on the return to these aggregates.[3] The overall cognitive score is based on four sub-tests measuring: (i) inductive skill (or reasoning), (ii) verbal comprehension, (iii) spatial ability, and (iv) technical understanding. The tests are graded on a scale from 0 to 40 for some cohorts and from 0 to 25 for others. To achieve comparability across cohorts, we standardize the test scores within each cohort of draftees.

[1]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. The sampling is stratified by firm size and industry; small firms in the private sector are underrepresented. The wage measure reflects the wage the employee had during the sampling week expressed in full-time monthly equivalents. It includes all fixed wage components, such as piece-rates, performance pay, and fringe benefits. Overtime pay is not included.

[2]In Appendix A2, we estimate the returns for a population whose age range is wider (30-50) and over a longer period of time. There is more variation in the estimated returns, and this variation is arguably driven by the cycle.

[3]We have also examined the returns to the component skills. Since the returns to cognitive and non-cognitive aggregates convey the main message of the paper, we relegate this analysis to Appendix A4.

The non-cognitive score is based on behavioral questions in a 20-minute interview with a trained psychologist. On the basis of the interview, the draftee is scored along four separate dimensions (see Mood et al. (2012)): (i) social maturity, (ii) psychological energy (e.g., focus and perseverance), (iii) intensity (e.g., activation without external pressure) and (iv) emotional stability (e.g., tolerance to stress). There is also an overall non-cognitive score on a Stanine scale, which ranges from 1 to 9. We standardize the overall score within each cohort of draftees in the same fashion as for the cognitive score.[4]

To get a sense about how the variation in skills accounts for variation in wages, we add the skill measures to a regression with time and age fixed effects. Adding the skill measures increases the adjusted R-squared from 0.18 to 0.35; the corresponding exercise with a detailed set of educational attainment fixed effects increases the adjusted R-squared to 0.36. 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 does quite little to the return to non-cognitive skills, while it weakens the association between cognitive skills and log wages quite substantially.

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 1. Table 1 also shows how the correlations evolved between two separate time points, 1994-96 and 2009-2011. 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). The 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. If a similar explanation would hold in the Swedish context we would thus expect a fall in the correlation between non-cognitive skills and schooling over time (cohorts). This is not something we see in our data; the correlations between years of schooling and skills, as well as the correlation between the two skill types, do increase marginally but not to an extent that they can explain the results we present below.

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

Table 1: Correlations between skills and schooling

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

## 4 The increase in the return to non-cognitive skills

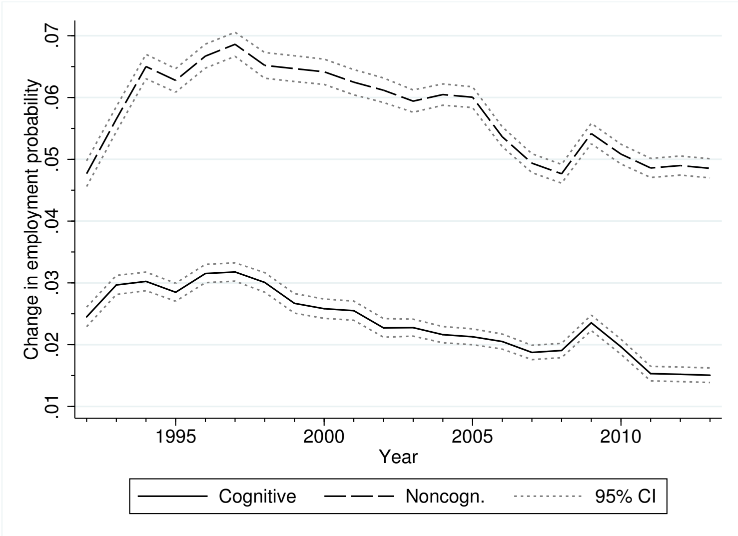
Our primary objective in this section is to estimate the wage return to cognitive and non-cognitive skill at successive points in time. Whether the focus on the wage return is sensible or not depends in part on whether the relationship between employment and skills changes over time.

Figure 3 thus examines the employment and earnings return to skill. Both of these outcomes are defined for the entire population (all males aged 38-42). Figure 3a 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). But there are no major changes over time in the relative importance of cognitive and non-cognitive skills for the probability of being employed, implying that it is likely that we get the same pattern for wages and earnings.

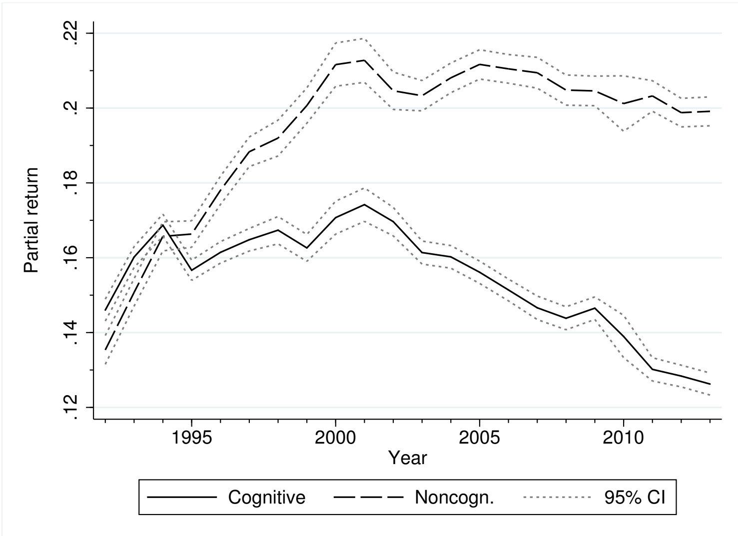
Figure 3b shows the returns in terms of annual earnings. To get an easily interpretable scale, the outcome is defined as the level of individual earnings divided by mean earnings at each time point. Figure 3b shows a striking pattern that we will encounter repeatedly in this paper. During the 1990s the return to non-cognitive skill increased drastically, 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. As we will show below, the relative wage returns evolves over time in a way that is parallel to Figure 3b. In fact, the relative wage return is the main driver of the evolution shown in Figure 3b.

Figure 3: Employment and earnings returns

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




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




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

As indicated above our main analysis focuses on wages. We thus estimate wage regressions of the following kind

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

where $C$ and $NC$ denote cognitive and non-cognitive skill, respectively, and $\alpha_a$ 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 ($\beta_t^C$ and $\beta_t^{NC}$) are plotted in Figure 4; Figure 4a pertains to the entire labor market, while Figure 4b zooms in on the private sector.[5]

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 et al. (2016), who document that employment growth in cognitively demanding occupations slowed down markedly during the 2000s.

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 4b).[6] 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.[7]

## 4.1 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?

To answer the first question, we estimate quantile regressions corresponding to equation (1); see Figures 5a and 6b. 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).

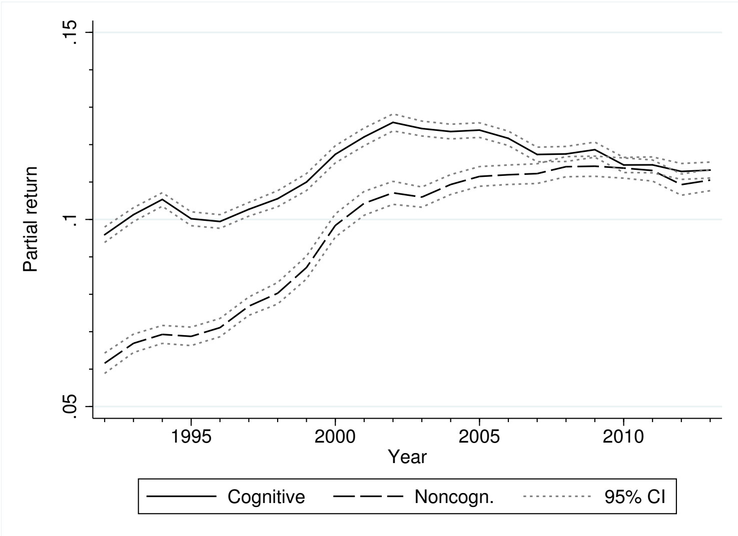
[5]Throughout we correct our estimates for measurement error using the reliability ratios estimated by Grönqvist et al. (2017). In Appendix A5 we show that our conclusions are unaffected by allowing the measurement error to be time-varying.

[6]By contrast, in the public sector, the returns to both types of skills have moved largely in parallel. Between 1992 and 2005 the returns increased by 3-4 percentage points; from 2005 and onwards, the returns fell by 1-2 percentage points.

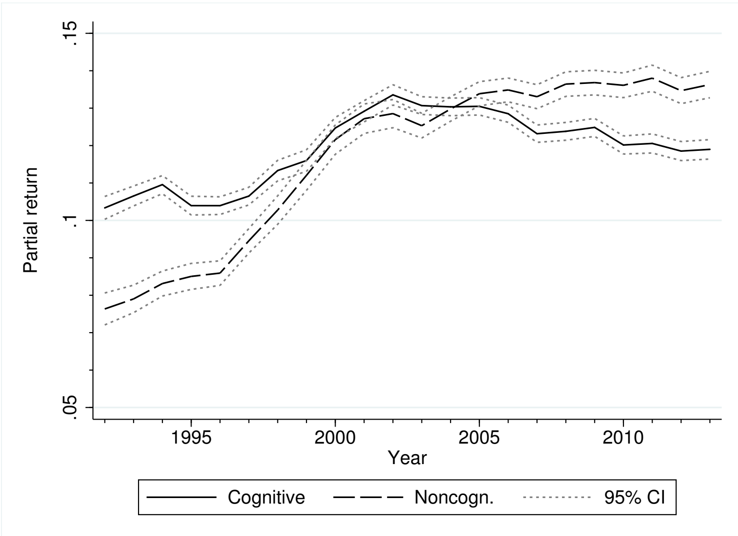
[7]Figure A3 shows the estimated bivariate (as opposed to the partial) returns to skills. The increase in the return to non-cognitive skill is even more striking when not conditioning on the other skill.

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

(a) All workers



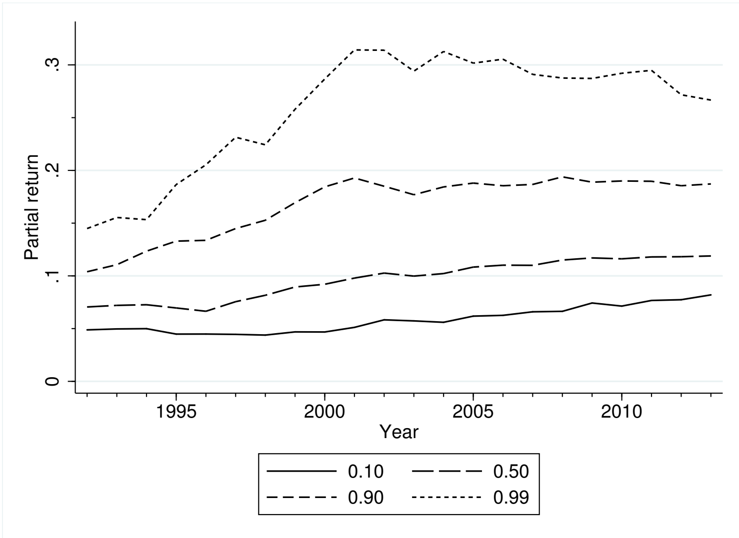

(b) Private sector workers

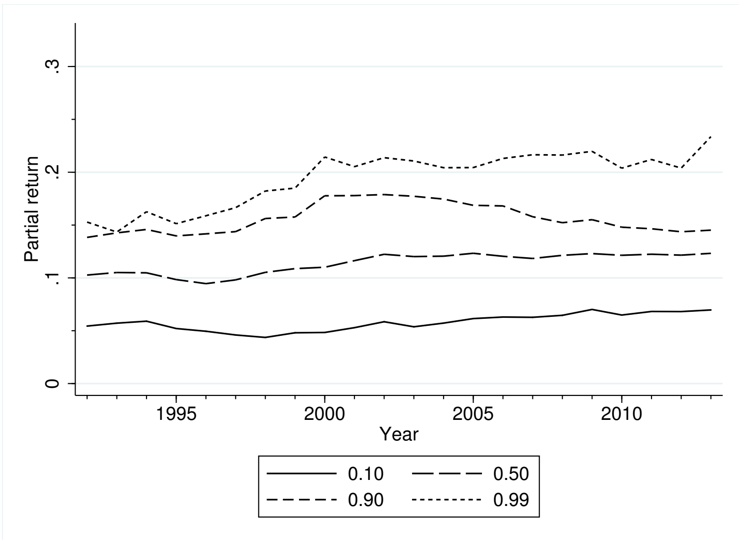



Notes: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist et al. (2017). Appendix A5 outlines the procedure.

Figure 5: Quantile regression estimates, 1992-2013

(a) Non-cognitive skills



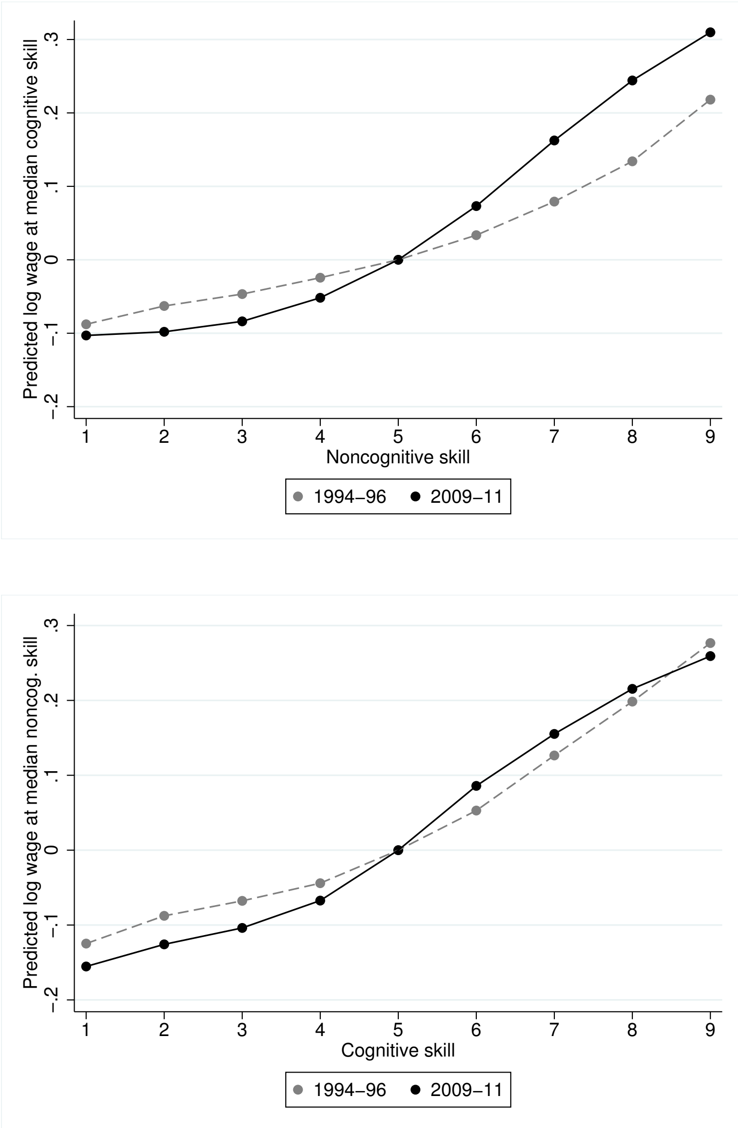

(b) Cognitive skills

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

Figures 6a and 7b pursue a similar theme by estimating the returns flexibly across the skill distribution at two points in time, (around) 1995 and 2010. The underlying skill scores are on a Stanine scale, ranging from 1 to 9. We use this information to construct indicators for belonging to a particular Stanine and estimate wage regressions at the two points in time. Figure 6a 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. Nothing much seems to have happened over time; see Figure 7b.

Figure 6: Predicted log wages across the skill distributions

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



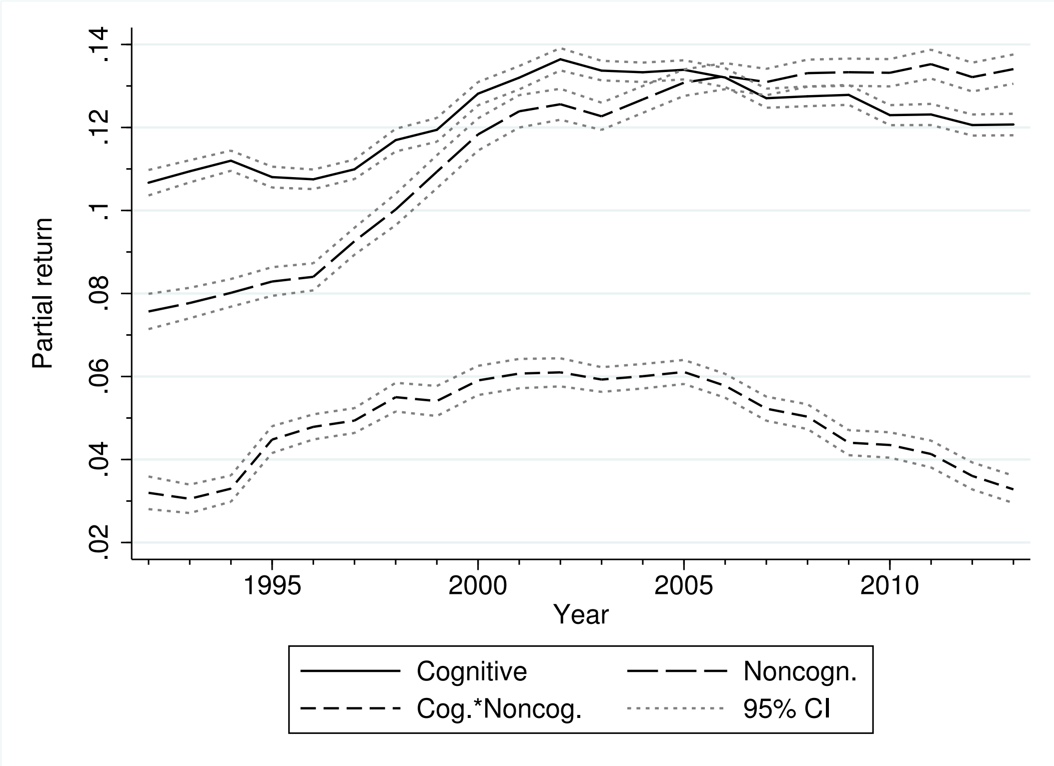

(b) Predicted log wage by bins of cognitive skill

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

Figure 7 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 7, the interaction between cognitive and non-cognitive skill is always significantly positive.[8] However, there are no drastic changes over time. The interaction term is about as important in 2010 as it was in 1995.

[8]Note that Deming (2017) also finds a positive interaction between cognitive and social skills using data from NLSY (the 1979 cohort).

Figure 7: Returns to skills and their interaction




## 4.2 Can the increase be accounted for by sorting?

We begin our exploration into the possible explanations for the increase in the return to non-cognitive traits by examining whether the increase is tied to restructuring and sorting across industries, occupations, and firms. Table 2 decomposes the changes in the return to skills into across- and within-components. The overall increases between 1994-96 and 2009-11 are 1.6 percentage points for cognitive skills and 5.2 percentage points for non-cognitive skill.

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: 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 about 40 percent of the overall increase in the return to non-cognitive skill.

In Appendix Table A1 we conduct an analogous decomposition exercise for two sub-periods: the period of the great expansion in returns (1995-2002) and the period where the returns changed more modestly (2002-2010). It turns out that the occupation-by-industry interaction can account for around two thirds of the increase in the return to non-cognitive skill during 1995-2002, but only 40 percent of the (smaller) increase during 2002-2010.

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

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

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

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. In particular the occupational dimension was a key component during the period of the remarkable increase in the return to non-cognitive skill.

# 5 Occupational sorting and wage-setting

We now turn our attention to the occupational level. The basic idea is that the two types of skills are differentially valuable across occupations. Workers will thus sort across occupations according to comparative advantage. 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 occupations; see Rosen (1978) (which in turn builds on Roy 1951 and Mandelbrot 1962).[9]

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.

[9]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 et al. (2011) also estimate models of occupational wage-setting.

This section examines occupational sorting and occupational wage-setting. Sections 5.1 and 5.2 pertain to sorting across occupation. Section 5.3 estimates wage returns at the occupational level and asks how these returns are correlated with the supply of skills.

## 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. To conduct this exercise, we use occupational task/skill intensities as outcomes in a regression model that is otherwise analogous to equation (1), i.e.,

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

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

Figure 8 shows the result of estimating equation ((2)) for various skill/task intensities. 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 8a-b); conversely, such individuals are increasingly escaping routine and automatable tasks over time (see Figures 8c-d).

Figures 8e-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. Over the entire time period, a standard deviation increase in non-cognitive skill is associated with working in an occupation that is around 0.12 higher in terms of offshorability or the use of social skills.

## 5.2 The probability of holding a managerial position

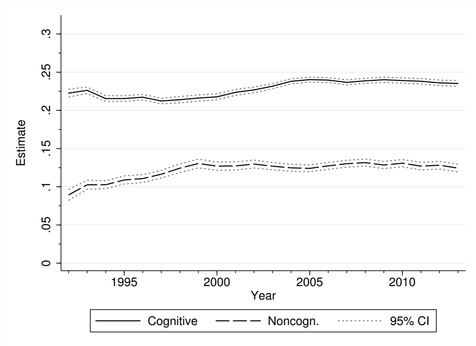
In Section 4.2 we documented that the return to non-cognitive skill primarily increased at the top-end of the wage distribution. Here we zoom in on the probability of holding a managerial position. Managers are particularly interesting in the current context. It is obviously a high-wage and abstract occupation; it also requires inter-personal skills, and perhaps increasingly so, as emphasized by Deming (2017).

Figure 9 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.[10] During the same time-period

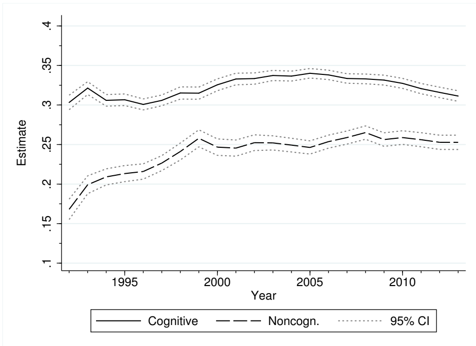
[10] We exclude 1992 and 1993 in this analysis since we lack occupation data for these years.

Figure 8: Sorting into occupations characterized by their task intensities

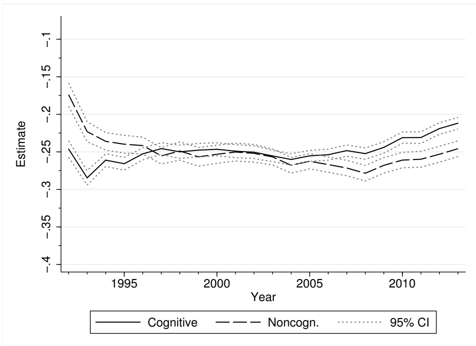
(a) Initial cognitive skill intensity



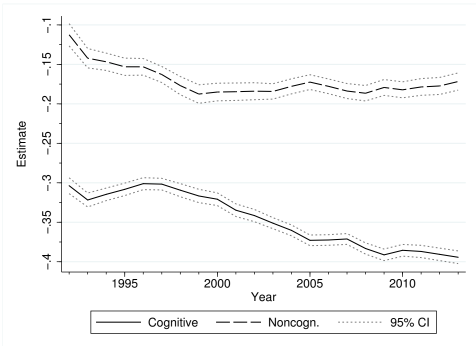

(b) Abstract



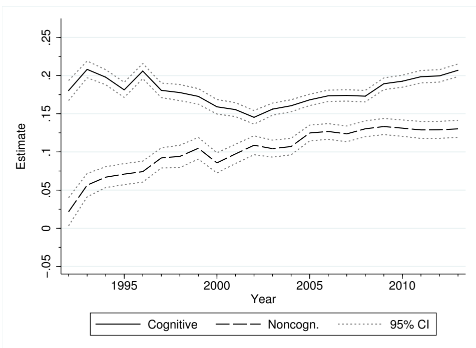

(c) Routine



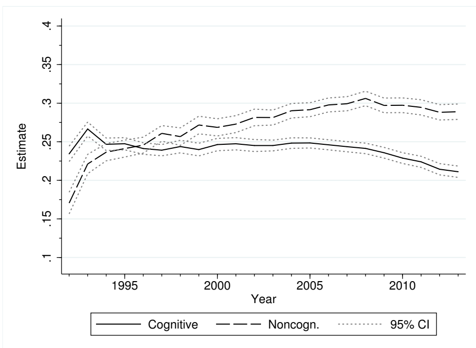

(d) Automation




(e) Offshorability




(f) Social

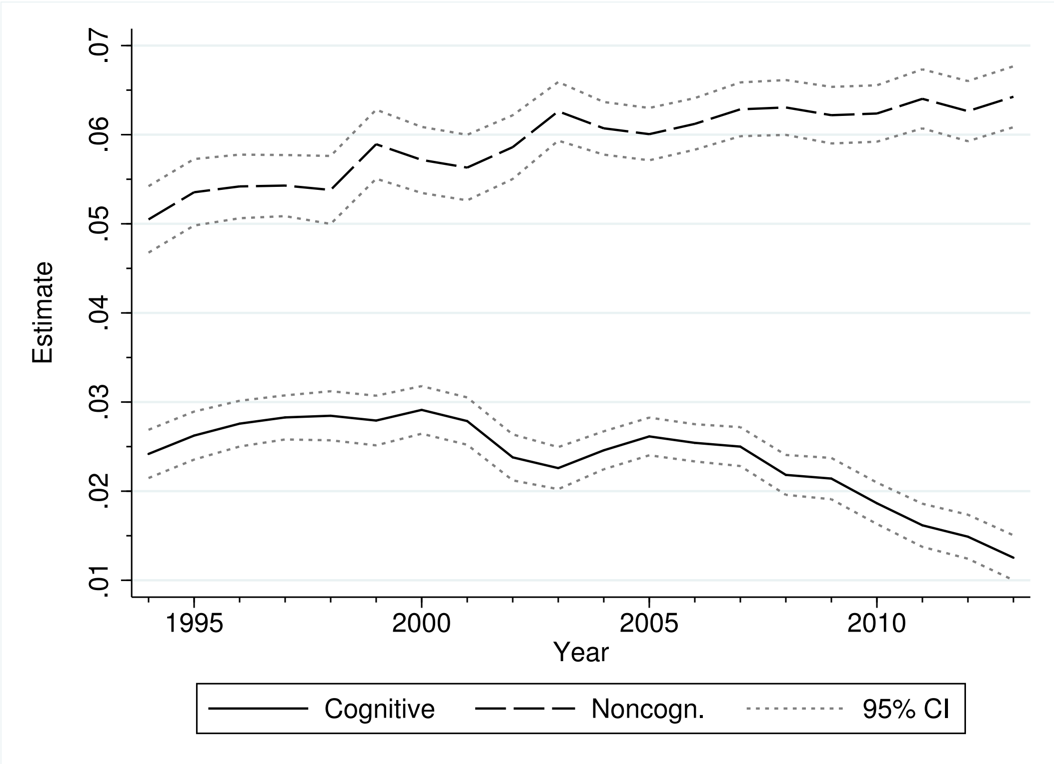



Notes: Occupational information has been matched to the O*NET database to obtain job requirements. The classification of Abstract, Routine, and Offshorable jobs follows Acemoglu and Autor (2011) and the classification of occupations requiring social skills comes from Deming (2017). We thank Fredrik Heyman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

the importance of cognitive skills fell by roughly the same magnitude.[11]

A plausible explanation for the increased importance of non-cognitive skills is that leadership positions demand more inter-personal skills over time. This evidence is thus in line with the framework proposed by Deming (2017).

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




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

### 5.3 Occupational wage setting

We now turn to models of occupational wage-setting. We thus estimate the returns at the occupational level and then ask whether the estimated returns correlate with skill supply. Note that this analysis is bound to be descriptive since, with skill responses to changes in the underlying returns, it is not possible to estimate the "true" change in the return to skills at the occupational level.

The fundamental input to the evidence presented in this section come from occupational wage regressions of the form

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

where $i$ indexes individuals, $a$ age, $j$ occupation, and $t$ year. From these estimates we

[11]Interestingly, the importance of non-cognitive skills for holding managerial positions have grown even more in the public sector.

calculate the changes in the relative returns, i.e., $\Delta RR_j = \Delta(\beta_j^{NC} - \beta_j^{C})$ between 1994-96 and 2009-11. We focus on changes in the relative returns since we want to net out changes in the overall demand for skills.[12] We also calculate the changes in relative skill intensity by occupation, i.e., $\Delta RS_j = \Delta(\ln \bar{NC}_j - \ln \bar{C}_j)$.

### 5.3.1 Are non-cognitive skills replacing cognitive skills?

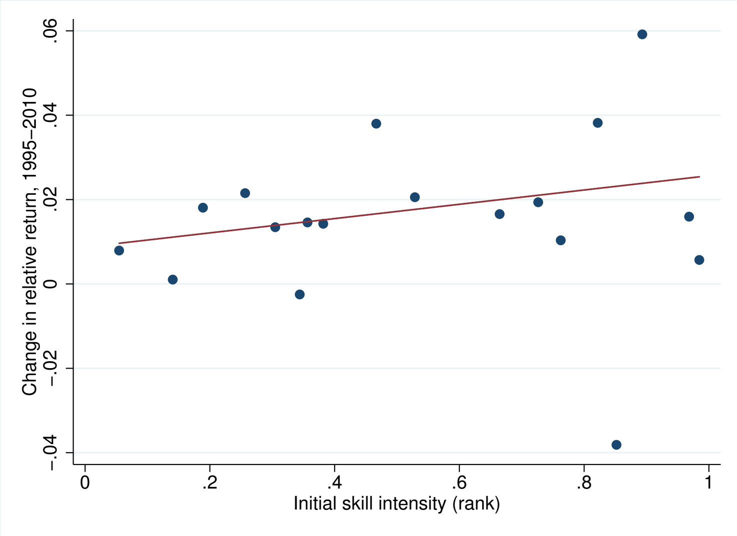
As an initial exercise we relate changes in relative returns ($\Delta RR_j$) and relative skill intensities ($\Delta RS_j$) to the initial intensity of cognitive skills in an occupation. Given the patterns documented in Section 4, we expect to see relative returns, and relative skill supplies, to increase more in occupations that were initially intensive in cognitive skills. This prediction is based on the observation that the return to non-cognitive skill primarily increased at the upper-end of the wage distribution, where we tend to find occupations that are intensive in cognitive skill.

Figure 10 provides a graphical illustration. It shows that changes in the relative return to non-cognitive skill were greater in occupations that initially were intensive in cognitive skill. Similarly, occupations that initially were intensive in cognitive skill became relatively more intensive in non-cognitive skill over time. There is thus sorting on relative returns, but this sorting is not sufficient to completely undo the increase in the underlying return.

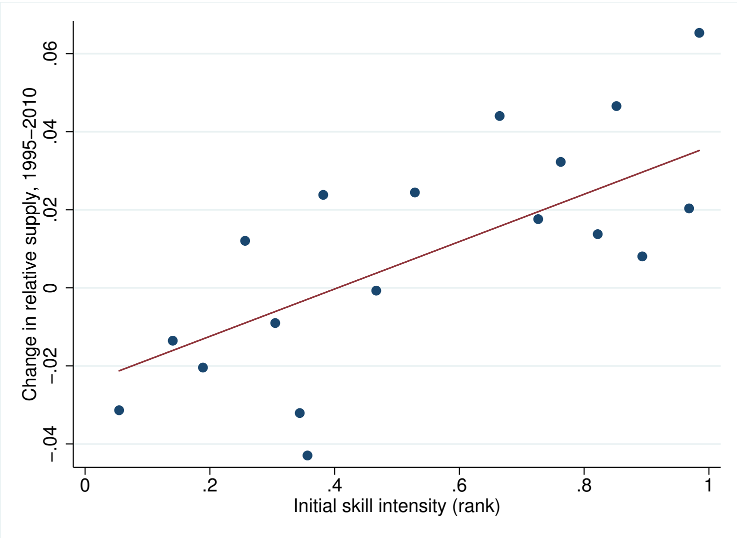
Our favored interpretation of these results is that the demand for non-cognitive skills increased primarily in high-cognitive occupations. This increase in demand caused a relative supply response in which individuals who were relatively abundant in non-cognitive skill reallocated to occupations which were initially intensive in cognitive skill. The 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.

[12] The underlying model is one of selection on comparative advantage. So from this point of view it makes sense to focus on (changes in) relative returns. Also, note that the results are not sensitive to normalizing by the change in the return to cognitive skill.

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




(a) Changes in relative return by initial cognitive skill




(b) Changes in relative skill by initial cognitive skill

Table 3 summarizes the relationships between changes in returns, changes in skill supply, and initial skill intensity. Column (1) shows the results for the change in relative returns (which corresponds to Figure 10a). The estimate implies that in the most cognitively demanding occupations the relative return to non-cognitive skill increased by 1.7 percentage points more than in the least cognitively demanding occupations. Column (2) demonstrates that this result become stronger when we control for non-cognitive skill intensity; note also that the estimate in column (2) is unaffected by controlling for the initial wage rank of the occupation.

Column (3) shows the supply relationship corresponding to Figure 10b. Occupations that initially were the most cognitively demanding saw the relative supply of non-cognitive skills increase by 6.1 percent more than the least cognitively demanding occupations. Column (4) illustrates that this holds also when we control for initial non-cognitive skill.

Column (5) of Table 3 proceeds by characterizing the relationship between relative returns and relative supplies. As indicated above, we think that the fundamental driving force of these changes are shocks to labor demand. With this interpretation, the results in column (5) provide evidence on a labor supply relationship. Interpreted literally, the estimates imply that the relative supply of non-cognitive skills increases by 50 percent in occupations where the relative return increased by 2 percentage points (which corresponds to the change in the relative return to non-cognitive skill across occupations; see Table 2). Relative skill supply thus seems highly elastic, which is natural given that we have data at a relatively finely grained occupational level. During the time period featuring the most dramatic changes in the return to non-cognitive skill, i.e., during 1995-2002, the relative skill response is half the size of the estimate for the entire time period, plausibly because of a shorter time period to adjust to changes in returns.

Table 3: Occupational changes in relative returns and skill intensities

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

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

### 5.3.2 Other occupational dimensions

Occupations can of course be characterized in many ways, other than cognitive skill intensity; see Figure 8, for instance. Table 4 shows how changes in relative returns and changes in relative skills relate to occupational task intensities. We have thus ranked occupation 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. When interpreting the results it should be kept in mind that many of these occupational dimensions are highly correlated; Table A2 in the Appendix, inter alia, reports the correlations.

By and large, these estimates line up with our expectations. The relative return to non-cognitive skills increased more in occupations that are abstract relative to non-abstract and non-routine relative to routine. Such occupations are also intensive in cognitive skills and tend to be high-wage occupations. Occupations that are routine are also privy to automation, and we basically observe the same pattern for automatable occupations as for routine occupations.

The most interesting contrast, perhaps, is between offshorable and non-offshorable occupations. Offshorable occupations tend to be high-wage occupations but less so than if an occupation is abstract or non-routine. Here the evidence suggests 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 poses an increasingly greater threat for cognitively able individuals relative to individuals scoring high along the non-cognitive dimensions.

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.

Table 4 also provides further evidence on sorting on the basis of changes in returns. Whenever there is evidence of an increase in the relative return to non-cognitive skills, we observe an increase in the relative supply of non-cognitive skill, and vice versa.

Table 4: Changes in relative returns and skills across tasks

| Rank (0/1) of initial task intensity | $\Delta RR_j$ | $\Delta RS_j$ |
|---|---|---|
| Abstract | 0.024 | 0.050 |
| | (0.000) | (0.000) |
| Routine | -0.019 | -0.058 |
| | (0.000) | (0.000) |
| Automatable | -0.019 | -0.024 |
| | (0.000) | (0.000) |
| Offshorable | 0.010 | 0.049 |
| | (0.000) | (0.000) |
| Social | 0.010 | 0.054 |
| | (0.000) | (0.000) |

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

# 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, among white-collar workers, 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 skill.

Meanwhile, the return to cognitive skills was relatively stable; it varied between 11 and 13 percent per standard deviation increase in cognitive skill during the time period. The stability over time in the return to cognitive skills is broadly consistent with Beaudry et al. (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. In fact, between 2000 and 2013, the return to cognitive skill fell by almost 2 percentage points. 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: cognitive skill; as well as abstract, non-routine, social, non-automatable and offshorable tasks. Such occupations were also the types of occupations which 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). His argument receives additional support from the fact that non-cognitive skills load more heavily on the probability of obtaining a leadership position over time. This is consistent with the view that it is increasingly important to have non-cognitive skills in order to run complex organizations.

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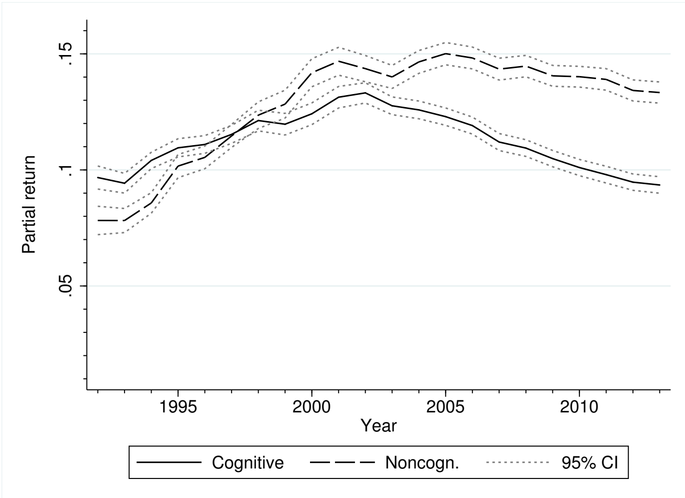
# Appendix

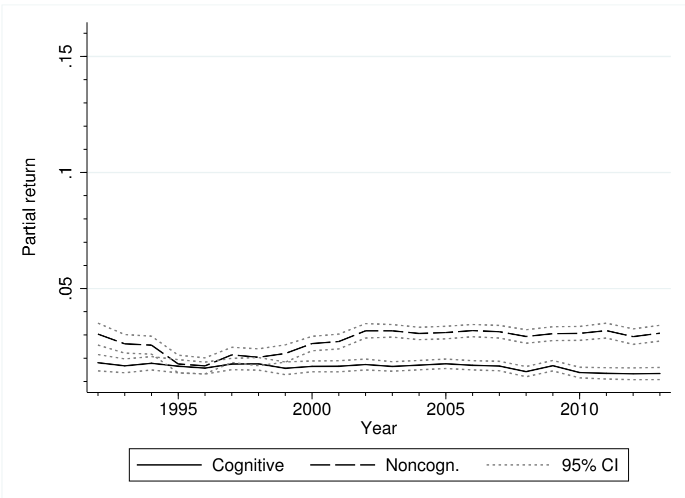
## A1 Returns by worker status

Figures A1a and A2b 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 Figures 5a and 6b.

Figure A1: Returns by worker status, 1992-2013

(a) White-collar workers




(b) Blue-collar workers

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

## A2 Estimates of returns between 1985-2013

Here we provide estimates for the population aged 30-50. To do so we impose some additional structure and estimate the panel data model:

$$\ln(wage)_{iat} = \sum_{t=1985}^{2013} \left(\alpha_t + \beta_t^C C_i + \beta_t^{NC} NC_i\right) + \sum_{a=30}^{50} \left(\alpha_a + \lambda_a^C C_i + \lambda_a^{NC} NC_i\right) + \varepsilon_{iat}, \quad \text{(A1)}$$

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 $\gamma_a^C$ and $\gamma_a^{NC}$, since we are pooling a wider age range than in our main analysis. We normalize the model to age 40, such that the estimates have the same reference age as our main analysis.[13]

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 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 A2(a). The cyclical variation contaminates the picture and it becomes more difficult to distill the variation in returns that is due to structural change.

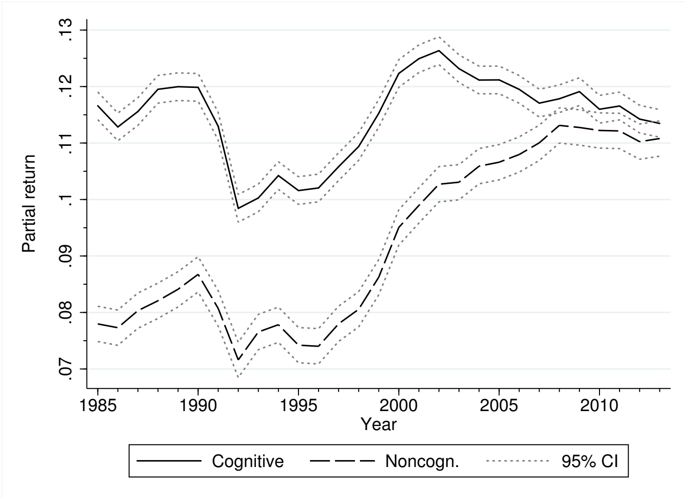
In Figure A2(b) we zoom in on a skilled segment of the labor market: white-collar workers in the private sector. Here we do not see the cyclical variation that distorts Figure A2(a). Thus we are more inclined to believe that Figure A2(b) reflect structural change in the labor market, at least for the skilled segment of the market.

The estimates in Figure A2(b) 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, we conclude that the panel approach seems to deliver 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 A2(a) prior to 1990.

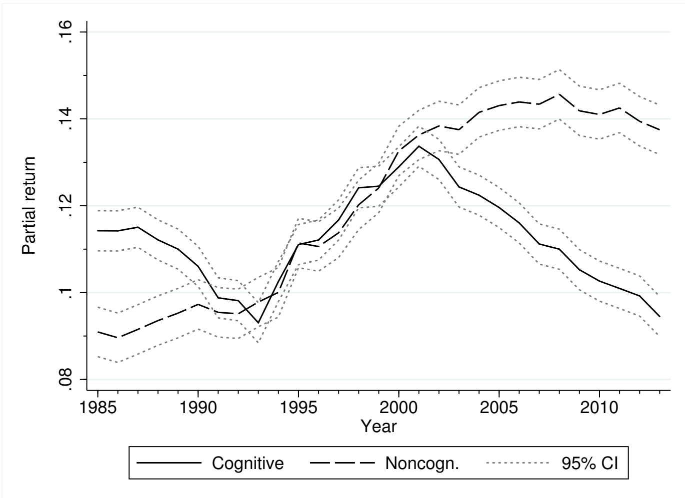
[13] Notice that the included ages vary over time. Given that the first draft cohort is born 1951, the year 1985 includes individuals aged 30-34.

Figure A2: Panel estimates of returns, 1985-2013

(a) All workers, aged 30-50




(b) White-collar workers, private sector, aged 30-50, 1985-2013

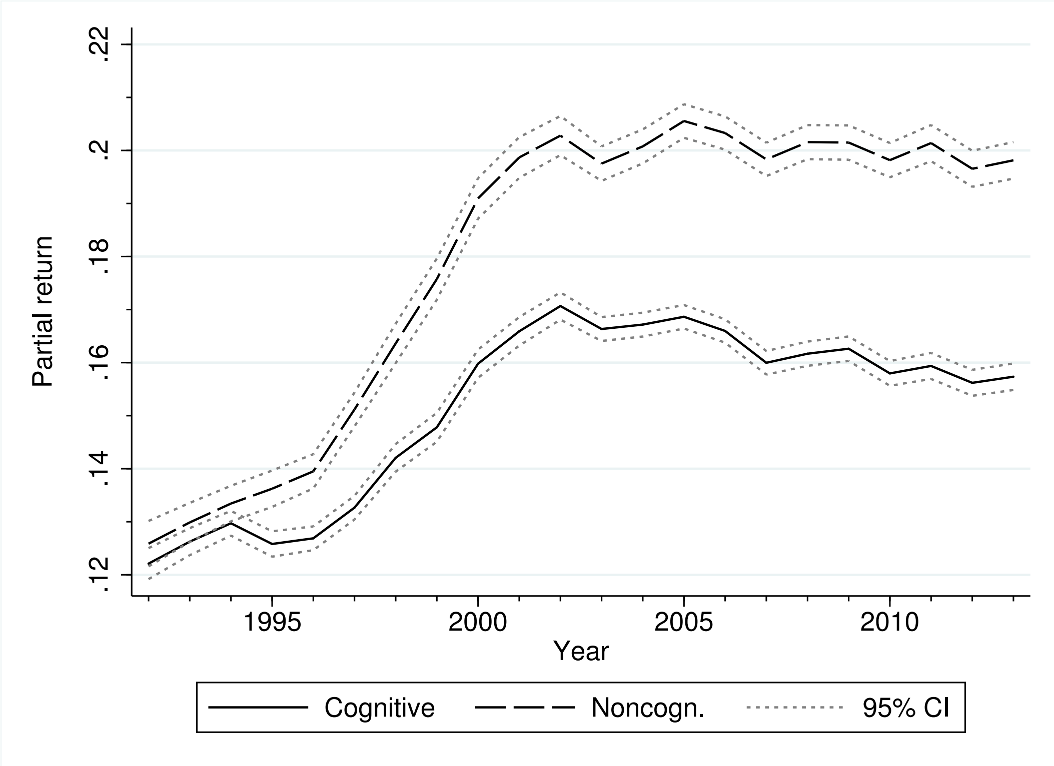



Note: All estimates are corrected for measurement error using reliability ratios estimated by Grönqvist et al. (2017). Appendix A5 outlines the procedure.

# A3 Returns estimated from bivariate regressions

Figure A3 shows the evolution of the returns to the various sub-components of the overall cognitive and non-cognitive skill aggregates.

Figure A3: Returns to skills (bivariate regressions)



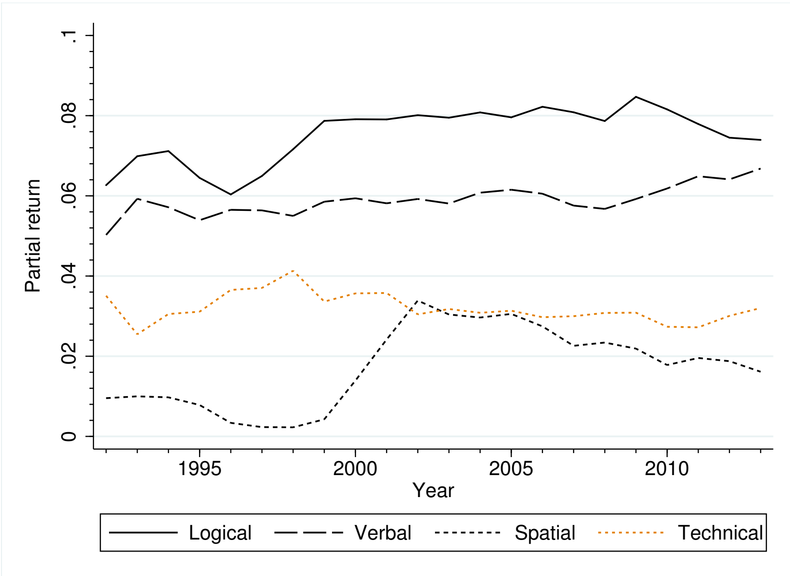

Note: Estimated from separate regressions of log wage on cognitive or non-cognitive skill, respectively. All scores adjusted by the constant reliability ratios for general cognitive and noncognitive skill, respectively. Private sector only.

# A4 Returns to disaggregate skills

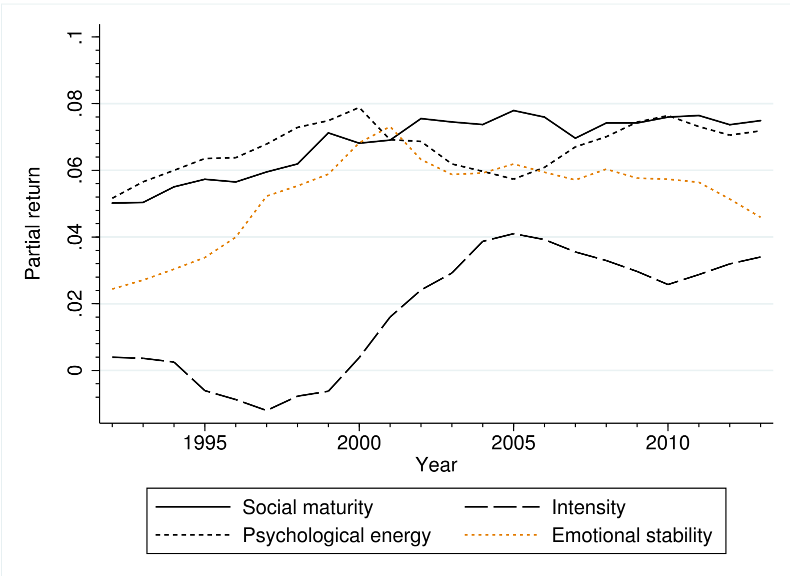
Figure A4 shows the evolution of the returns to the various sub-components of the overall cognitive and non-cognitive skill aggregates.

Figure A4: Returns to disaggregate skills

(a) Disaggregate cognitive skills




(b) Disaggregate non cognitive skills




Note: Estimated from equation including all four cognitive sub-scores and all four non cognitive sub-scores. All scores adjusted by the constant reliability ratios for general cognitive and noncognitive skill, respectively. Private sector only.

# A5 Measurement error in the skill measures

Grönqvist et al. (2017) show that measurement errors plague the measures of cognitive and non-cognitive skills to some extent. 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, one can show that the measurement error ridden coefficient ($b^j$) relates to the true coefficient $\beta^j$ through the formula

$$b^j = \frac{\beta^j}{\sqrt{\gamma^j}} \left[ \frac{\gamma^j - R^2_{jk}}{1 - R^2_{jk}} \right], \; j = C, NC$$

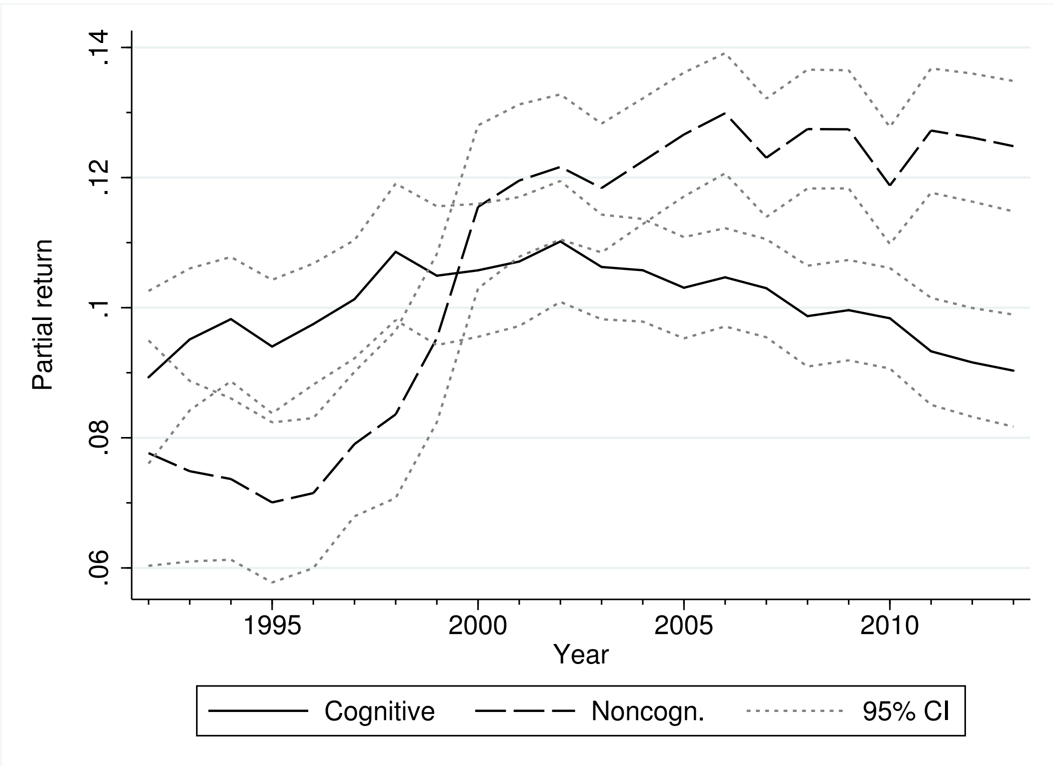
where $R^2_{jk}$ denotes the fraction of explained variance in the regression of skill $j$ on skill $k$ and $\gamma^j$ denotes the conventional reliability ratio . $\gamma^j$ thus equals

$$\gamma^j = \frac{VAR(X^j)}{VAR(X^j) + VAR(V^j)}, \; j = C, NC$$

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 4a 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



# A6 Additional descriptives

Table A1 decomposes the changes in the returns into two time periods, 1995-2002 and 2002-2010

Table A1: Decomposing changes in returns 1995-2002 and 2002-2010

| | Cognitive | | Non-cognitive | |
|---|---|---|---|---|
| | Overall change: 0.025 | | Overall change: 0.042 | |
| | Across | Within | Across | Within |
| A. Industry | 0.016 | 0.009 | 0.013 | 0.029 |
| B. Firm | 0.015 | 0.010 | 0.013 | 0.029 |
| C. Occupation | 0.021 | 0.003 | 0.026 | 0.016 |
| D. (Occupation×Industry) | 0.022 | 0.002 | 0.028 | 0.014 |

(a) 1995-2002

| | Cognitive | | Non-cognitive | |
|---|---|---|---|---|
| | Overall change: -0.009 | | Overall change: 0.010 | |
| | Across | Within | Across | Within |
| A. Industry | -0.004 | -0.005 | 0.001 | 0.009 |
| B. Firm | -0.007 | -0.002 | 0.003 | 0.007 |
| C. Occupation | -0.013 | 0.004 | 0.000 | 0.010 |
| D. (Occupation×Industry) | -0.011 | 0.002 | 0.004 | 0.006 |

(b) 2002-2010

Table A2 provides the correlation matrix at the occupational level.

Table A2: Correlation matrix

| | $\Delta RR_j$ | $\Delta RS_j$ | $\ln(w_{j,95})$ | $\Delta Empl.sh._j$ | $C_{j,95}$ | $NC_{j,95}$ | Abstr. | Rout. | Autom. | Offsh. | Social |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\Delta RR_j$ | 1.000 | | | | | | | | | | |
| $\Delta RS_j$ | 0.043 | 1.000 | | | | | | | | | |
| $\ln(w_{j,95})$ | 0.178 | 0.352 | 1.000 | | | | | | | | |
| $\Delta Empl.share_j$ | -0.021 | -0.043 | 0.147 | 1.000 | | | | | | | |
| $C_{j,95}$ | 0.158 | 0.459 | 0.846 | 0.173 | 1.000 | | | | | | |
| $NC_{j,95}$ | 0.120 | 0.468 | 0.870 | 0.174 | 0.898 | 1.000 | | | | | |
| Abstract | 0.201 | 0.302 | 0.849 | 0.230 | 0.819 | 0.870 | 1.000 | | | | |
| Routine | -0.139 | -0.430 | -0.601 | -0.232 | -0.637 | -0.774 | -0.682 | 1.000 | | | |
| Automation | -0.209 | -0.167 | -0.748 | -0.308 | -0.773 | -0.699 | -0.800 | 0.550 | 1.000 | | |
| Offshorability | 0.094 | 0.462 | 0.453 | 0.047 | 0.427 | 0.360 | 0.199 | -0.298 | -0.137 | 1.000 | |
| Social | 0.092 | 0.369 | 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. The remainder of the notation is as in the main text.