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The skill-specific impact of past and projected occupational decline[a]

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Abstract

Using very detailed register data on cognitive abilities and productive personality traits for nearly all Swedish males at age 18, we show that employment in the recent past has shifted towards skill-intensive occupations. Employment growth is monotonically skill biased in relation to this set of general-purpose transferable skills, despite the well-known U-shaped ("polarizing") relationship to occupational wage ranks. The patterns coexist because growing low-wage occupations tend to employ workers who are comparably skilled in these dimensions, whereas workers in declining mid-wage occupations instead have less of these general non-manual skills than suggested by their wages. Employment has primarily increased in occupations where workers have larger-than-average endowments of verbal and technical abilities and social maturity. Projections of future occupational decline and automation risks are even more skill-biased, but show similar associations to most of our specific skill-measures. The most pronounced difference is that occupations relying on tolerance to stress are projected to decline in the coming decades.

Keywords: Skills, Polarization, Future of Work

JEL classifications: J21, J31

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1 Introduction

The labor market impact of current and future technological innovations is a key topic in social science and in the public debate. Since Autor et al. (2003), much of the research has analyzed the process through the lens of a task-based framework which emphasizes task- and occupation-specific possibilities of automation. A salient pattern documented across countries and settings is that employment has grown in the highest-paid and the lowest-paid occupations whereas employment has declined in occupations in the middle of the wage distribution (Autor et al. (2003), Goos et al. (2009), Acemoglu and Autor (2011), Goos et al. (2014) and Adermon and Gustavsson (2015)). The finding of such *polarization* is important for understanding the relationship between technical change and wage inequality. The favoured explanation for the pattern is a sharp decline in the demand for routine-intensive tasks, traditionally performed by occupations in the middle of the wage distribution (Autor et al. (2003), Goos et al. (2009), Acemoglu and Autor (2011), Goos et al. (2014), Michaels et al. (2014), Böhm (2015), Cortes (2016)). In this article, we add to this literature by instead characterizing occupations by the skill-set of the employees using very detailed Swedish data on pre-market endowments of traits and abilities. As shown by Fredriksson et al. (2018), the measures capture skills that are valued across the market (i.e. they are general-purpose transferable skills), but they are used with different intensities in different occupations. The data thus allow us to provide new and direct evidence on the relationship between occupational decline and the overall endowments of general skills among workers in each occupation. Furthermore, we are able to document the association between occupational decline and the specific traits and abilities of workers within each occupation. As with most of the literature, this analysis focuses on the evolution in the recent past. But it has been argued that future technological advances will affect a much broader set of tasks, and hence different types of workers, than changes in the recent past (see e.g. Mitchell and Brynjolfsson (2017)). To address this issue, we rely on existing projections about the future occupation-specific impact of technical change and assess if these projections suggest that the association between occupational decline and worker skill types is likely to change in the non-so-distant future.

Our results show that employment growth in the recent past has had a monotonic positive relationship to occupation-specific endowments of general skills, despite of the polarizing relationship to occupational wage ranks. The result implies that growing low-wage jobs require more of these general skills than indicated by their wage ranks, and that declining mid-wage occupations instead motivated their relatively high wages aspects that do not require any of the intellectual traits or abilities captured by our data such as, e.g., manual strength, the ability to cope with hazardous work environments, pure rent-seeking abilities or the ability to perform very specific manual tasks. We further show that occupations which draw on workers with higher-than-average levels of *Social Maturity* (i.e. extroversion, responsibility and independence), *Verbal* comprehension and *Technical* abilities have seen particularly strong growth, whereas occupations where worker skills primarily come in the form of *Psychological Energy* (i.e. the ability to focus) and problem solving abilities in the form of *Inductive* reasoning have declined. The pattern thus varies substantially according to specific traits and abilities even within the broader context of cognitive vs. non-cognitive skills, favoring communication-related components such as verbal comprehension and social maturity over problem-solving components such as inductive reasoning and the ability to focus. Finally, we repeat the analysis after replacing the actual evolution during the past decades by projected occupational employment growth from two different sources. We show that the relationship with both wage ranks (i.e. polarization), overall skill levels (i.e. the monotonic positive association) and skill-composition are similar to the experiences of the recent past for both of these projections, despite the fact that the occupations projected to be affected in the future are different from those affected in the past. This suggests that empirical lessons from the recent past may be informative about the distributional impact of future technological change. The main difference to the past is that the projections suggest that the association between overall skill levels and occupational growth is projected to become even more pronounced and that occupations projected to shrink rely on workers with relatively high endowments of *Emotional Stability* (tolerance to stress) whereas occupations projected to grow instead employ workers endowed with high levels of *Intensity* (i.e. activation without external pressure).

The paper is structured as follows: In Section 2 we give a very brief overview of the relevant literature. Section 3 discusses our data and empirical method. Section 4 presents the main results. Throughout, we focus on the essentials in the main paper and refer all robustness checks and extensions to the appendix. Section 5 concludes.

2 Literature

Since Autor et al. (2003) the literature on technical change has to a large extent analyzed the impact of automation on workers through its impact on the demand for *tasks*. This approach replaced the paradigm of Skill Biased Technical Change, see e.g. Card and DiNardo (2002) for a critical review, which presupposed that technology was factor-augmenting in the sense that new technology caused a rise in demand for well educated workers, and a decline in the demand for low educated workers. The task-based approach notes that some tasks are easier to automate than others suggesting that changes in the demand for labor induced by technological advances are best modeled with a production function where output is produced through performed tasks, some of which can be automated or offshored with the help of technology. The ensuing empirical literature has taken this idea to the data by exploring information on the task-contents of different occupations and related the employment growth of occupations to the potential for automation (Autor et al. (2003), Goos et al. (2009), Acemoglu and Autor (2011), Goos et al. (2014)).[1] A salient finding is that occupations with a large ”routine task” component have declined due to technological advances. The fact that many of these routine jobs are found in the middle of the wage distribution implies that the occupational decline has lead to polarization in terms of employment growth where ”middling” (in the terminology of Goos et al. (2014)) wage occupations have declined and occupations in the higher and lower end of the occupational wage spectrum instead have grown. In terms of wage-evolution the impact is somewhat more intricate since displaced workers from middling-wage jobs will provide additional downward wage pressure on low-wage jobs.

A key insight from the task-based approach is that the link from technical change to worker skills is mediated by the demand for tasks. But knowing which worker characteristics are associated with a negative impact of automation is still of key interest, at least from a policy perspective.[2] A noteworthy feature is that much of the literature note that the wage rank can be considered an all-encompassing measure of skills, and it is thus commonplace to refer to these patterns as a decline in middle-*skilled* jobs and a growth of low- and high-skilled jobs (see e.g. Autor and Dorn (2013) for a discussion). But in order to make progress on the direct impact on different types of workers it is useful to be more specific, and in this paper we therefore differentiate between *skill ranks*, to be precisely defined below, and *wage ranks*.

In another set of related studies, with an objective that is less focused on occupational decline and polarization, researchers have documented the changing market returns to cognitive vs. non-cognitive skills (Deming (2017), and Edin et al. (2017)) suggesting that the market returns to specific skill-types have shifted over time.[3]

When discussing the future impact of technological change it is clear that different types of automation may affect different types of workers and thus have different impacts on the labor market. One way to address this issue is to focus the analysis on particular well-defined types of innovations. An important example is provided the emerging literature on the impact of industrial robots pioneered by Graetz and Michaels (2018) and Acemoglu and Restrepo (2017). The latter analysis uses the task-based approach to tease out the impact of industrial robots on the overall economy and isolate the channels that determine the overall impact on employment.[4]

[1] Adermon and Gustavsson (2015) provide an analysis on Swedish register data similar to ours.

[2] See Cortes (2016) for a thorough investigation of the association between occupational decline and worker demographics.

[3] Other related studies include Cortes (2016) who discusses the the impact on the demand for skills in the framework of a general equilibrium model with endogenous sorting of workers into occupations, but do not use direct measures of worker skills in the empirical application. Böhm (2015) estimates task prices under routine-biased technical change and Graetz and Feng (2016) discusses the role of training requirements for polarization.

[4] Also related is Michaels et al. (2014) who study the interaction between ICT-use and education in a related framework, showing that industries with faster ICT growth have a faster fall in the demand for middle-educated

The fact that new innovations, e.g. relying on machine learning algorithms are likely to affect different segments of the labor markets than past innovations such as industrial robots makes it difficult to know, *ex ante*, to what extent we can extrapolate from recent experiences when discussing the future impact of automation technologies. Indeed, much of the attention of policy makers and the general public has been centered around which tasks are most likely to be automated in the future, and how this will affect different types of workers. As a consequence, public agencies (see e.g. (Nedelkoska and Quintini, 2018)) and groups of researchers in economics and beyond have spend considerable amounts of effort on trying to project which types of tasks are most likely to be automated in the near and distant future. Mitchell and Brynjolfsson (2017) provides a recent discussion regarding the factors that determine the automation potential of different types of tasks. The most well-known examples of occupation-specific projections are probably those of the US Bureau of Labor statistics and Frey and Osborne (2017) which we rely on in this paper.

3 Data and methods

3.1 Outline of the empirical set-up

Our set-up closely follows the conventions in the literature on task-based labor market polarization to facilitate comparisons with earlier studies. We thus rely on occupation-level data for most of the analysis although we verify that the main patterns also are present at the job-level as well.

We rank occupations according to mean wages or skills in a start year (2001 in the baseline) and relate these to the employment growth of the same occupations during a follow-up period (2001-13 in the baseline). The raw wage data and occupation data (*Strukturlonestatistiken*) are drawn from firms' personnel records using a firm-level sampling frame covering about half of all employees every year. The baseline time frame is determined by availability of Swedish data with consistent occupational codes.[5] We also add data on *routine intensity* from Autor and Dorn (2013) and Goos et al. (2014).

We add information from two additional resources: The first is data on worker skills from the Swedish military draft from Fredriksson et al. (2018). Their descriptive data are on the 3-digit occupational level (from 2001) so we use this level of aggregation as our baseline. Our second additional resource is projections of future "automation risks" and occupational employment growth. We draw these from the official 10-year projections published by the US Bureau of Labor Statistics and from the very well-cited study by Frey and Osborne (2017). As

workers.

[5]Our occupational employment data are downloaded from Statistics Sweden's web page, see www.scb.se.

with the rest of our set-up and data, we take these projections at face value.

3.2 Occupation-specific skill endowments

We characterize occupation-specific skill endowments in eight dimensions using data that originates from the Swedish military service conscription. The data include information on four cognitive abilities, assessed through written tests, and four non-cognitive productive traits assessed by trained psychologists during an interview, see Mood et al. (2012) for details about the testing procedure. All of the skills were measured around age 18, i.e. before labor market entry, for 90 percent of all Swedish males born between 1951 and 1976.[6]

We will analyse the skills through a joint composite score, and as separate components. When analysed jointly, the sum of the eight scores provide a broad assessment of each worker's set of intellectual, general purpose, transferable skills. Thus, when referring to *skill ranks* of occupations, we rank occupations based on the average worker endowments of these general skills within each occupation, exactly corresponding to the wage ranks used in the polarization literature. When we analyze the skills separately, we instead rely on the fact that some aspects of the skill vector are more productive in some jobs than in others.

We use these data as processed by Fredriksson et al. (2018) who used the scores to study sorting patterns across jobs and occupations. The processed data capture the average skill endowments in each occupation among workers with at least three years of tenure at the workplace. This zooms in on workers who have settled in their job, which is a useful indicator for having the right skill set for the job-specific tasks, see Fredriksson et al. (2018) for a further discussion.[7] This is potentially important in our context since some transitory workers in low-wage occupations may be over-skilled labor market entrants (or students) passing through the occupations, or young workers involved in an, initially quite volatile, search for an appropriate first match (see e.g. Jovanovic (1979)). To validate the usefulness of the scores, Fredriksson et al. (2018) show that *i)*) all scores are associated with independent wage returns, *ii)*) that workers are sorted into jobs where their coworkers have similar types of abilities, and that *iii)*) workers sort into jobs where the returns to their specific skills are higher than average.[8]

We analyse our skill measures after aggregating them to the level of occupations. This

[6]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 (mean = 0, standard deviation = 1) within each cohort of draftees.

[7]Fredriksson et al. (2018) show that experienced workers who enter new jobs or occupations where tenured workers have a similar skill composition as the entrants earn higher wages and stay longer in these jobs. This suggests that tenured workers' skills reflect the skill requirements of these jobs. In contrast, inexperienced hires are more randomly sorted across jobs and therefore separate more often.

[8]See also Lindqvist and Vestman (2011) for more evidence on the wage and earnings returns to these cognitive- and non-cognitive test scores; Håkanson et al. (2015) for evidence on (changes in) the sorting of workers to firms by cognitive and non-cognitive skills and Edin et al. (2017) for evidence on the changing returns to these cognitive and non-cognitive skills.

alleviates potential concerns regarding random measurement errors that arise when analyzing the data at the individual level (see e.g. the discussion in Edin et al. (2017)).

3.2.1 Cognitive abilities

The data contain four specific scores measuring cognitive abilities from the written tests. The scores capture *verbal* and *technical* comprehension as well as *spatial* and *inductive* abilities. The verbal and technical comprehension tests are examples of what, e.g., Cattell (1987) refers to as "crystallized" intelligence (A^c), while the spatial and inductive tests are examples of "fluid" intelligence (A^f).[9] Crystallized intelligence measures the ability to utilize acquired knowledge and skills and is thus closely tied to intellectual achievement and therefore also malleable through policy interventions. Fluid intelligence, on the other hand, captures the ability to reason and solve logical problems in unfamiliar situations, and should therefore be independent of accumulated knowledge.[10]

Below we define the abilities and list the occupations that are most heavily endowed in each of these as illustrative examples.[11] We first split all occupations according to the overall skill rank and extract the most endowed occupation in the low (LTS), mid (MTS) and high (HTS) overall skill segments respectively:

- *Verbal comprehension* (A^c). Storage workers (LTS), Librarians (MTS), Medical Doctors (HTS).
- *Technical understanding* (A^c). Wood and Paper Processors (LTS), Photographers (MTS), Architects and Engineers (HTS).
- *Spatial ability* (A^f). Furniture Carpenters (LTS), Photographers (MTS), University Research/Teaching (HTS).
- *Inductive skill (reasoning)* (A^f). Storage Workers (LTS), Librarians (MTS) and Medical Doctors (HTS).

3.2.2 Non-cognitive productive traits

The data contain four specific scores measuring productive non-cognitive traits assessed by a trained psychologist. The content of each of these scores are described in great detail in Mood

[9]The concepts of crystallized and fluid intelligence was originally developed by Cattell (1971).

[10]Along these lines, Carlsson et al. (2015) study the relationship between schooling and the cognitive test scores used in this paper. They find that that 10 more days of school instruction raises cognitive scores on the crystallized intelligence tests (verbal and technical comprehension) by approximately one percent of a standard deviation, while the fluid intelligence tests are unaffected.

[11]This description reiterates results from Fredriksson et al. (2018), see their paper for details on actual scores.

et al. (2012) and our interpretation and labeling fully rely on their work.[12]

Below we define the traits and list the occupations that are most heavily endowed in each of these in the low (LTS), mid (MTS) and high (HTS) total skill segments as above:[13]

- *Social maturity* measures extroversion, responsibility and independence. Restaurant Workers (LTS), Nurses (MTS), Medical Doctors (HTS).
- *Emotional Stability* measures tolerance to stress. Miners (LTS), Fire Fighters/Security Guards (MTS), Pilots (HTS).
- *Intensity* measures activation without external pressure. Miners (LTS), Forestry Workers (MTS), Police Officers (HTS).
- *Psychological Energy* measures perseverance and the ability to focus. Dairy Producers (LTS), Placement Officers (MTS) and Medical Doctors (HTS).

3.3 Projections

Our analysis makes use of two sets of projections of the future demand for labor in different occupations. These are drawn from the US Bureau of Labor Statistics and from Frey and Osborne (2017). The two projections differ quite substantially in terms of methodology and aims (see below). For the purpose of this paper, we do not take a stance on which of these projections are more accurate but instead consider them as interesting objects in their own right. We choose the two projections based on the the official status in the case of BLS and the massive impact on the public debate in the case of Frey and Osborne (2017).

The US Bureau of Labor Statistics publishes projections of future employment growth by occupation. These projections are described in detail on the BLS website. The methodology assesses the future share of each occupation within each industry and then aggregates this up after assessing the future total labor demand of each industry. It is stated that ”BLS economists thoroughly review qualitative sources such as scholarly articles, expert interviews, and news stories, as well as quantitative resources such as historical data and externally produced projections.” The analysis incorporates ”judgments about new trends that may influence occupational demand, such as expanding use of new manufacturing techniques like 3D printing that might change the productivity of particular manufacturing occupations, or shifts in customer preferences between different building materials which may affect demand for specific construction occupations.” The assessment thus include factors such as expectations of technological innovations, changes in business practices, reorganizations, off-shoring and cross-industry changes

[12]Nilsson (2017) provides a mapping between these scores and the ”Big Five” personality classifications, see the Appendix, Table A.1 for details.

[13]This description reiterates results from Fredriksson et al. (2018), see their paper for details on actual scores.

in demand. These assessed trends are then aggregated into an assessment of whether labor demand will grow or shrink, and if so, by how much. For each occupation that is expected to change in size, a reason is stated. Examples from the 2016 projections include:

- *”Security guards (All industries): Productivity change - share decreases as improvements in remote sensing and autonomous robots allow security guards to patrol larger physical areas.”*
- *”Chefs and head cooks (Special food services): Demand change - share increases as a greater emphasis is placed on healthier food in school cafeterias, hospitals, and government, requiring more chefs and head cooks to oversee food preparation in these establishments.”*

Edin et al. (2018) use the 1985 version of these projections and verify that they predict occupation-specific employment growth in Sweden between 1985 and 2013.[14]

Our alternative projection is from Frey and Osborne (2017). This paper stresses that the impact of technological change on the labor market is likely to be different in the future because developments relying on artificial intelligence, such as machine learning and mobile robotics, will enable technology to replace labor across a wide range of non-routine tasks. They go as far as to argue that recent advances make it ”possible to automate almost any task, provided that sufficient amounts of data are gathered for pattern recognition”. Instead, only those tasks that are subject to *engineering bottlenecks* are insulated against automation. These are tasks defined by the use of *perception and manipulation*, *creative intelligence*, and *social intelligence*. In the end, their methodology for defining the automation potential starts from The Occupational Information Network (O*NET) data on tasks by occupations and then relies on a combination of subjective assessments by data scientists and a search for “bottleneck-related” task-variables within O*NET.[15]

We use the ensuing automation potentials as transformed into the Swedish occupational classification system by Heyman et al. (2016). To achieve comparability to the case of BLS, we rank the occupations according to their resilience to automation where a high value refers to a resilient occupation, i.e. an occupation with many bottleneck tasks, whereas low values instead indicate occupations that are projected to be relatively easy to automate. It can be noted that (Nedelkoska and Quintini, 2018) show that Sweden and the US have very similar ”automation risks” using a similar strategy as Frey and Osborne (2017) but at a lower level of aggregation.[16]

[14]Despite noise arising from changes in occupational codes, they find that a BLS projection index for the US labor market explains 22 percent of the variation in employment growth across these 28 years in Sweden.

[15]Finger dexterity, Manual dexterity, and Awkward work positions indicate the bottleneck *Perception and manipulation*. Originality and Fine arts indicate the bottleneck *Creative intelligence*, Social perceptiveness, Negotiation, Persuasion and Caring for Others indicate the bottleneck *Social Intelligence*.

[16]The OECD projections are based on the adjusted (relative to Frey and Osborne (2017)) methodology of (Arntz

3.4 Data processing

The level of detail is covering 110 occupations characterized by 3-digits according to the Swedish nomenclature SSYK (closely related to ISCO-88). We exclude military workers. In addition, we pre-screened the data to check for anomalies and excluded cases where the number of employees more than doubled between two adjacent years anytime during the 2001-2013 period. This further excludes ”Higher officials in public services” and ”Manual construction laborers”.[17] These are both tiny occupations and, as we show in the Appendix, including these does not affect any of our results.

Our baseline strategy is to rely on 3-digit occupations. However, in the Appendix we also make use of more detailed definitions of a job by combining occupations and industry groups. We also include robustness results where we change the time-frame, the functional forms, the level of aggregation, weighting and so forth. In the interest of presentation, we will, however, not always refer to the robustness exercises in the running text. When matching the projections to Swedish nomenclatures, we lose a few additional occupations where the cross-walk was unsuccessful.

Descriptive statistics are found in Appendix A. These statistics highlight the distinction between skill-ranks and wage-ranks which we will document more robustly in the empirical analysis below. While the employment decline has been concentrated to occupations in the middle of the wage distribution, worker skills do not show a corresponding pattern. Instead, we find clear examples where workers employed in the declining middle-paying occupations have lower average skills than workers in some of the growing, but low-paying, occupations. Examples of low-skilled, mid-wage declining occupations are ”Extraction and building trades workers”, ”Metal, machinery and related trades workers” and ”Office clerks” Examples of growing low-paid occupations with higher skills are ”Personal and protective service workers” and ”Customer service clerks”.

4 Results

4.1 Wage ranks and skill ranks

Most previous studies have found a U-shaped relationship between occupational employment growth and the initial wage ranks of these occupations. To first replicate this pattern within

and Gregory, 2016) which provide lower levels of average automation risks than Frey and Osborne (2017). As we show in Appendix D, the arising resilience *rank* across occupations is, however, very similar across the Frey and Osborne (2017) assessment for the US and the OECD assessment (building on (Arntz and Gregory, 2016)) for Sweden.

[17] For the former of these, we know that the origin is a restructuring of job titles within the public sector in 2008. For the latter category, we do not have a clear explanation.

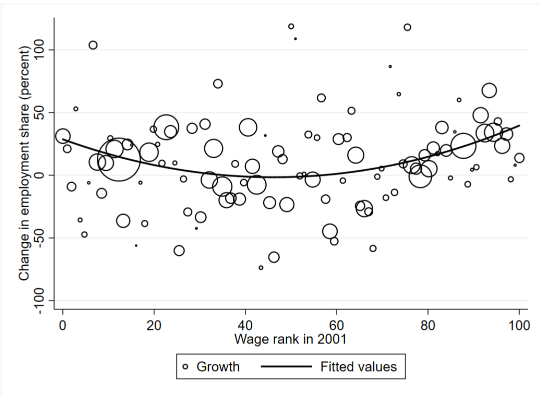
our data, we rank occupations by their wage in 2001 and relate this rank to their employment growth in percent between 2001 and 2013. Panel (a) in Figure 1a shows the expected U-shaped pattern with a decline in the middle-ranked occupations, i.e. *polarization*. The magnitudes are very similar to those found in other studies, e.g. Goos et al. (2009) which also included data for Sweden. This pattern is very robust to alternative treatments of the data as shown by the various robustness checks supplied in Appendix B.1.

Figure 1b replicates the second well-established empirical regularity; occupations that are intensive in *routine tasks* are declining. This relationship is monotonically negative (but of increasing magnitude). Appendix B provide point estimates and further analyses of the interplay between wage ranks and routine intensity to further confirm that stylized facts arise also within our data.[18]

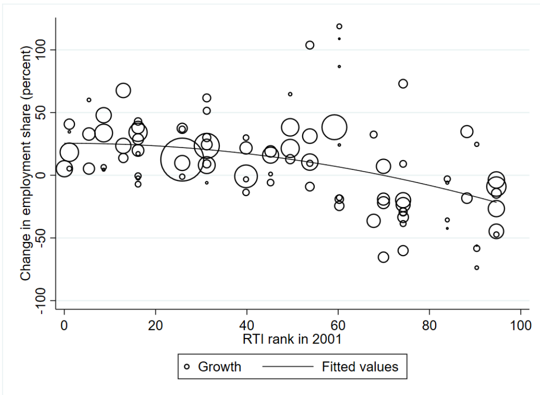
[18] The routine task index is based on Autor, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2006, 2008) mapped into the European occupational classification by Goos et al. (2014). It is constructed from five original DOT task measures combined to produce three task aggregates: the Manual task measure corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination"; the Routine task measure is a simple average of two DOT variables, "set limits, tolerances and standards" measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks; and the Abstract task measure is the average of two DOT variables: "direction control and planning," measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning requirements. From these three measures the Routine Task Intensity (RTI) index is constructed as the difference between the log of Routine tasks and the sum of the log of Abstract and the log of Manual tasks.

Figure 1: Employment growth by occupation 2001 to 2013

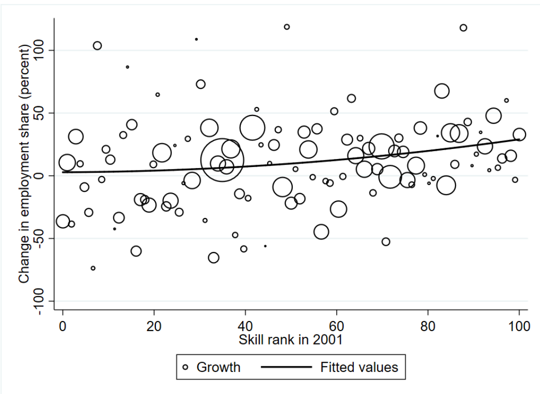
(a) Growth by wage rank



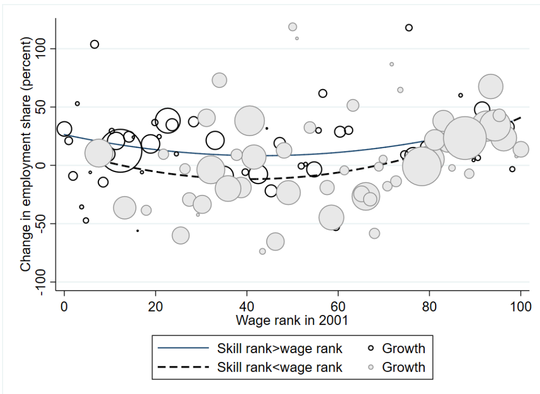
(b) Growth by amount of routine tasks



(c) Growth by skill rank



(d) Growth by skill-to-wage rank ratio



Note: y-axis displays the percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden's official calculations. Each circle is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated according to employment shares in 2001. Panel (a): x-axis ranks occupations according to mean wages in 2001. Panel (b) x-axis ranks occupations according to routine task intensity from Goos et al. (2014). Panel (c) x-axis ranks occupations according to mean overall skill intensity by tenured employees in 2001 as calculated by Fredriksson et al. (2018). Panel (d): x-axis ranks occupations according to mean wages as in Panel (a) but separates occupations according to whether or not the skill rank (as in panel c) is higher than the wage rank (as in panel a). All lines represent predictions from regression equations on the following form:
$EmploymentGrowth_{occupation} = a + b * Rank_{occupation} + c * (Rank_{occupation})^2$, where Rank is defined as the x-axis of the respective panel.

Next, we analyse of the relationship between skill ranks and employment growth at the occupational level. We rank the occupations according to *overall skills* measured as the sum of the eight components.[19] As a background, it may be useful to know that the skill-wage correlation at the occupational level is 0.72 which implies a strong positive, but non-deterministic, relationship between the endowments of overall skills and wages.[20]

Furthermore, within our data, the overall skill requirements of occupations remain very stable over time. The inter-temporal correlation in occupation-specific skill endowments between 2001 and 2008, which is the last year for which we have access to the skill data, is 0.96 (see Appendix figure B.3 for details).

Figure 1c documents the relationship between overall skill ranks and employment growth. In clear contrast to Figure 1a, however, we find that the relationship between the skill ranks and employment growth is positive throughout the distribution. The positive slope is statistically significant (see Table B.2 in Apnnedix B), but the quadratic is not.

As with the wage-rank result, this pattern is robust to a number of variations in the model and the used data (e.g. including outliers, interacting occupations by industry, changing base years for measuring skills, using broader start and end periods) as shown in Appendix B.2.[21]

Our results thus imply that the skill-employment association has the opposite sign to the wage-employment association in the lower part of the wage spectrum. To align the results it is instructive to split the sample into occupations according to the relative rank, i.e according to an indicator variable $I = Skill^{rank} > Wage^{rank}$ and show the association between the wage rank and the employment growth separately for the values of this indicator. As shown in Figure 1d, employment has grown much more in occupations where $Skill^{rank} > Wage^{rank}$. This is particularly true in the mid to low part of the wage distribution. For each of these lines, the polarizing pattern remain, but is much weaker than in the aggregate. The quadratic fit is negative (hence, declining occupations) for a long range of *low* skill-to-wage occupations but positive (growing occupations) in the full range for *high* skill-to-wage occupations.

This suggest that the declining mid-wage occupations (on average) motivated their higher wage by factors that are not included in our skill-vector and that the growing low-wage occupations are more intensive in these skills than the wage rank suggests. As an alternative way of illustrating the same pattern, Table 1 shows that occupations with a higher skill rank than wage rank had more employment growth in the lower part of the wage distribution.

The analysis discussed above is performed at the occupational level, but the most immediate consequences of structural change is felt by workers who lose their jobs, regardless of the

[19] Using weights defined by estimated wage returns for each of the eight components give identical results, see Appendix B.1.

[20] As shown in Appendix B.1, the association is stronger in the upper part of the wage distribution which is well in line with results on individual data presented in Lindqvist and Vestman (2011).

[21] The Appendix also discusses the relationships to wage growth known as ”wage polarization” where the results are less clear, both in our setting and the literature in general.

impact at the occupational level. Furthermore, we know that workers are systematically sorted on skills across jobs even within occupations (Fredriksson et al. (2018)). We therefore provide a complementary analysis at the job level, where we define a job as a combination of occupation and establishment. This analysis studies the relationship between initial wage and skill ranks of each job and the subsequent employment growth within these jobs. This set up thus uses job-level employment growth, instead of occupation-level employment growth, as the outcome of interest. The results, shown in Figure 2, suggest that employment growth has a much more positive relationship to skills than to to wages in the lower part of the distribution also at the job-level.

Overall, these results thus imply that the declining mid-wage jobs motivated their wages through other characteristics than those captured by our vector of general-purpose intellectual skills, whereas the growing low-wage jobs instead seems to employ workers with a disproportional abundance of such skills. This transformation of labor demand, from (relatively) high paying jobs with a low need for general intellectual skills to low paying jobs with a high need for such skills, may be particularly bad news for workers who used to be able to earn relatively high rents from very specific manual skills or rent-seeking abilities. A deeper investigation of the nature of these ”lost” earnings attributes has to be left for future research, but a tentative discussion is presented in Appendix B.1 which shows that occupations with higher wage ranks than skill ranks are found in ”high wage firms”, i.e. firms that, in general, pay a higher wage premium to identical workers.

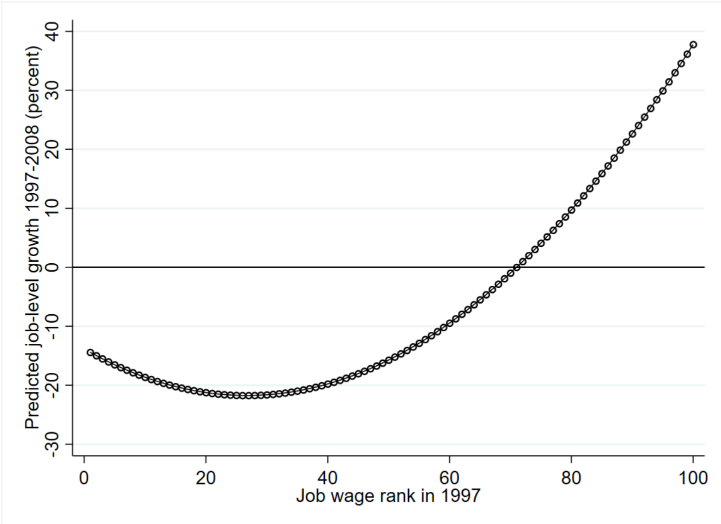
Table 1: Employment growth and the skills-to-wage relationship

	(1) All occupations	(2) Low wage	(3) High wage
	Outcome: Employment growth		
I[$Skill^{rank} > Wage^{rank}$]	9.33	18.56**	8.101
	(5.902)	(8.711)	(9.251)
R-squared	0.031	0.111	0.017

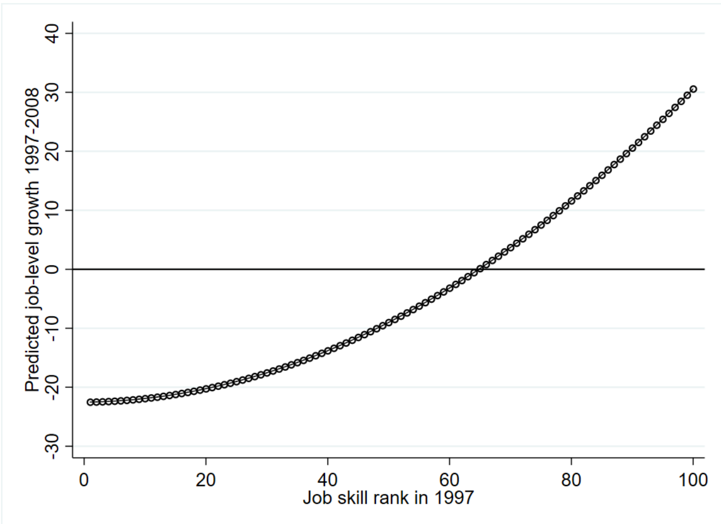
Note: The dependent variable is the percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden’s official calculations. The independent variable is an indicator taking the value one if $Skill^{rank} > Wage^{rank}$ in 2001. Column 1 shows the association for the full sample. In columns (2) and (3) we divide occupations into low- and high wage occupations defined by the median in the distribution of mean wages among tenured male workers. Robust standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Figure 2: Predicted job-level employment growth by wage and skill ranks (1997-2008)

(a) Job-level growth by wage rank



(b) Job-level growth by skill rank



Note: y-axis displays the predicted percent change in employment between 1997 and 2008 by job defined by the combination of an occupation and an establishment obtained from the following equation: $EmploymentGrowth_{job} = a + b * Rank_{job} + c * (Rank_{job})^2$, where Rank is defined as the x-axis of the respective panel. See Appendix B.1. for details on the data construction.

4.2 Specific skill endowments

Our results presented above rely on an overall measure of skills. But our data allow for an analysis of the granularity underlying this aggregate score. Which types of skills are more pronounced among workers in growing vs. shrinking occupations? To analyze this issue, Table 2 shows the relationship between skills and occupational employment growth. We first show the coefficient related to the above discussion on overall skills (column 1), we then redo this analysis controlling for the wage rank with a quadratic term (column 2), and the association is only marginally altered.

We then turn to the eight specific skill measures. The table shows these in the order implied by the point estimates ranging from the most positive to the most negative estimate. Notably, the fit of the model is substantially improved when including the specific skills (adjusted R^2 grows from 0.18 to 0.29 and overall R^2 from 0.20 to 0.35). As is evident, the associations are very different for different scores, and these vary also within the groups of cognitive abilities (indexed by A) and non-cognitive traits (T). The cognitive abilities are separately indicated with (A^c) for the malleable "Crystallized" abilities and (A^f) for the less malleable "Fluid" abilities. The results show that the "Social maturity" trait as well as the crystallized cognitive abilities ("Verbal" and "Technical") have strong positive associations with employment growth, whereas the "Psychological energy" trait and the fluid cognitive abilities (primarily "Inductive") have negative associations with employment growth conditional on the other skills.

As with the results above, we use the web Appendix (B.2) to show that the associations are robust to a number of variations in the estimated model.[22] The Appendix also shows that verbal skills are more important as a predictor in high-wage occupations, whereas social maturity and technical abilities matter more in the low-wage occupations.

[22]The Appendix also shows the corresponding association between occupational skill measures and routine task content. These results suggest that the same occupational skill endowments associated with occupational growth/decline, are the same endowments associated with lower/higher amount of routine tasks.

Table 2: Determinants of employment growth 2001-2013

	(1)	(2)	(3)
	Overall skills		Specific skills
Panel A: *Overall skills:*			
Skill rank	0.263**	0.331**	
	(0.104)	(0.155)	
Panel B: *Specific skills:*			
Social maturity (T)			1.479*
			(0.809)
Verbal (A^c)			1.427**
			(0.579)
Technical (A^c)			1.050**
			(0.436)
Emotional stability (T)			0.599
			(0.718)
Intensity (T)			0.035
			(0.223)
Spatial (A^f)			-0.642
			(0.532)
Psychological energy (T)			-1.422*
			(0.821)
Inductive (A^f)			-1.974***
			(0.674)
Wage rank		-1.418***	-1.935***
		(0.359)	(0.436)
Wage rank^2		0.013***	0.016***
		(0.004)	(0.004)
Observations	107	107	107
R-squared	0.068	0.200	0.354
Adjusted R-squared	0.059	0.177	0.287

Note: Dependent variable is percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden's official calculations. Each observation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Regressions are weighted according to employment shares in 2001. Skill rank is a rank of occupations according to mean overall skill intensity by tenured employees in 2001 as calculated by Fredriksson et al. (2018). Wage rank instead ranks occupations according to mean wages in 2001. *Specific skills* rank occupations according to skill intensity in each dimension during 2001 as calculated by Fredriksson et al. (2018). The skills are ordered according to estimate size. The different types of skills are highlighted by: T = Non-Cognitive Trait, A^c = Crystallized (malleable) Cognitive Ability and A^f = Fluid (less malleable) Cognitive Ability. Interpretation of non-cognitive traits are according to Mood et al. (2012) which provides further details on the tests. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

4.3 Occupational employment projections

Finally, we turn to the projected future. As noted in the introduction, much of the concerns regarding the labor market impact of future automation rest on the fear that the not-so-distant future will have an impact on the labor market that is fundamentally different from these experiences. The challenges for doing empirical research on future processes are obvious and fundamental. To make progress on this front, we rely on the existing projections of future occupational declines that were described in the data section. We rank the occupations according to projections to get a comparable metric. Figure 3a plots the association between BLS projections and wage ranks. It suggests a continued hollowing out of employment in the middle of the wage distribution. But as we shown for the past above, there is a monotonically positive relationship between overall skills and future growth (Figure 3b). In Figures 3c and 3d we show that we get a very similar pattern when we replace the BLS projections with those from Frey and Osborne (2017). In Panel A of Table 3, we show the regression coefficients and compare the results to that of the recent past. As is evident, the skill-bias is projected to increase in the future. This implies that the occupational decline is projected to continue to favor more skill-intensive jobs also in the future.

In the foot of Table 3 we show that the predictions are related, but different. The correlation is 0.46. Furthermore, it is shown that the correlations between each projection and the employment growth in the recent past is positive (0.22 for Frey and Osborne and 0.34 for BLS), but in both cases substantially lower than across the two sets of projections.[23]

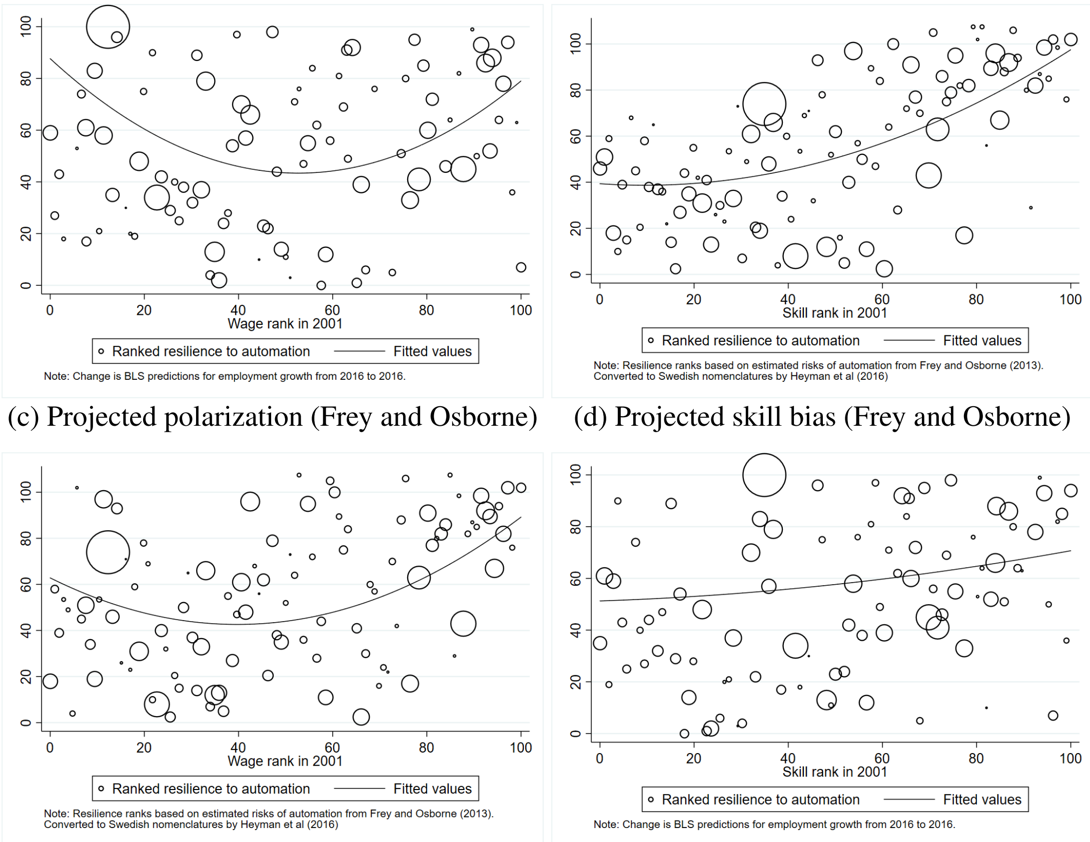
Panel B shows the relationship between the projections and the eight sub-components of our skill-vector. The results, again, show that the two projections produces a very similar picture despite the large differences in methodology and scope. The results imply that occupations that (currently) rely on workers with *Social Maturity* and *Verbal comprehension* are projected to continue to grow. Meanwhile, the decline in occupations employing workers with heavy endowments of *Inductive* reasoning are projected to continue to fall, the results for *Psychological energy* are less clear. Thus, in terms of skill-demand, the projections jointly suggest (again, despite their different scopes and methods) that the process of occupational decline will continue on a similar path as it has in recent decades. The main difference, that arise in both projections, is a decline in occupations relying on *Emotional Stability* (i.e. tolerance to stress) and a growth in occupations relying on *Intensity* (i.e. activation without pressure). Robustness checks related to these results are presented in Appendix B.3.

[23] Examples of occupations that are projected to be exposed to automation in the future, while having proved resilient in the past, include Sales persons, Clerks and Drivers.

Figure 3: Projected job polarization and skill-bias

(a) Projected polarization (BLS) (b) Projected skill bias (BLS)

(c) Projected polarization (Frey and Osborne) (d) Projected skill bias (Frey and Osborne)



Note: Panels (a) and (b) BLS: y-axis displays the ranked employment change as projected by the US Bureau of Labor statistics transposed into Swedish occupational codes by the authors. Panels (c) and (d) Frey and Osborne: ranked change as projected by Frey and Osborne (2017) transposed into Swedish occupational codes by Heyman et al. (2016). Each circle is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated according to employment shares in 2001. Panels (a) and (c): x-axis ranks occupations according to mean wages in 2001. Panels (b) and (d): x-axis ranks occupations according to mean overall skill intensity by tenured employees in 2001 as calculated by Fredriksson et al. (2018). All lines represent predictions from regression equations on the following form: $ProjectedEmploymentGrowth_{occupation} = a + b * Rank_{occupation} + c * (Rank_{occupation})^2$, where Rank is defined as the x-axis of the respective panel.

Table 3: Determinants of past and projected employment growth 2001-2013

Growth:	(1) Past	(2) Projected: BLS	(3) Projected: Frey & Osborne
	Panel A: Relationship with overall skills		
Skill rank	0.331**	0.647***	0.788***
	(0.155)	(0.180)	(0.182)
Observations	107	91	103
R-squared	0.200	0.274	0.344
	Panel B: Relationship with specific skills		
Social maturity (T)	1.479*	2.246**	2.121**
	(0.809)	(1.030)	(0.911)
Verbal (A)	1.427**	1.754**	2.125*
	(0.579)	(0.751)	(1.077)
Technical (A)	1.050**	0.001	0.674*
	(0.436)	(0.547)	(0.405)
Emotional stability (T)	0.599	-1.733**	-3.049***
	(0.718)	(0.777)	(0.693)
Intensity (T)	0.0348	0.698**	0.966***
	(0.223)	(0.317)	(0.223)
Spatial (A)	-0.642	0.158	-0.135
	(0.532)	(0.619)	(0.530)
Psychological energy (T)	-1.422*	-0.945	0.176
	(0.821)	(1.091)	(1.005)
Inductive (A)	-1.974***	-1.723**	-2.288*
	(0.674)	(0.773)	(1.307)
Observations	107	91	103
R-squared	0.354	0.419	0.557
Correlations:			
Past growth	1	0.341	0.219
BLS	0.341	1	456
Frey & Osborne	0.219	0.456	1

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Dependent variables are the change in employment defined as follows: Column (1) The recent past: percent change in actual growth between 2001 and 2013 by occupation according to Statistics Sweden's official calculations. Column (2) Projected BLS: ranked change as projected by the US Bureau of Labor statistics transposed into Swedish occupational codes by the authors. Column (3) Projected Frey and Osborne: ranked change as projected by Frey and Osborne (2017) transposed into Swedish occupational codes by Heyman et al. (2016). Each observation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Regressions are weighted according to employment shares in 2001. Skill rank is a rank of occupations according to mean overall skill intensity by tenured employees in 2001 as calculated by Fredriksson et al. (2018). Model also controls for initial wage rank with squares. Wage rank ranks occupations according to mean wages in 2001. *Specific skills* rank occupations according to skill intensity in each dimension during 2001 as calculated by Fredriksson et al. (2018). The skills are ordered according to estimate size in Column (1). The different types of skills are highlighted by: T = Non-Cognitive Trait, A^c = Crystallized (malleable) Cognitive Ability and A^f = Fluid (less malleable) Cognitive Ability. Interpretation of non-cognitive traits are according to Mood et al. (2012) which provides further details on the tests. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

5 Conclusions

In this paper, we present a new way of characterizing the skill requirements within occupations and relate these requirements to occupation-specific employment trends, in the past and projected future. Overall, the results provides, what we believe to be, an important addition to the stock of knowledge regarding the relationship between occupational employment shifts, wage polarization, and skill demand.

Our results show that occupational employment shifts are skill-biased towards a composite measure of general-purpose transferable intellectual skills, despite the non-linear relationship to wages. The reason is that growing low-wage occupations are more intensive in these skills than their wage ranks suggest and the converse is true for the declining mid-wage occupations. Focusing on the lower half of the wage distribution, the results thus suggest that labor demand has moved away from average-paying jobs with a low need for general intellectual skills towards low-paying jobs with a high need for such skills. This process may explain why workers in declining occupations in the middle of the wage distribution appear to suffer from long-term adverse employment effects (see e.g. Edin et al. (2018)) as the transition into low-wage jobs may demand more in terms of general skills than these workers possess, despite of the fact that their pre-displacement jobs were relatively well paid.

The difference between the skill-rank and wage-rank results arises because our skill measures are broad in the intellectual dimension but leave out a set of residual unobserved wage-related attributes such as, e.g., manual strength, the ability to cope with hazardous work environments, pure rent-seeking abilities and knowledge that is specific enough to not be captured by any of our general skill measures. For natural reasons, we need to leave an exploration of the relative importance of these unobserved earnings-related factors aside for the purpose of this article; our results strongly suggest that future research on the granularity of these residual components and their role in the decline of middling-wage occupations is of first-order importance.

Our second key insight is that the underlying patterns are far from uniform across skill types, even within the broader cognitive vs. non-cognitive aggregates that have been emphasized in the related literature on the changing worker-level returns to skills (see Deming, 2017, and Edin et al 2018). In particular, we note that growing occupations are relatively dense in *Verbal* comprehension and *Social Maturity* (i.e. extroversion), both of which are related to human communication (and thus perhaps could be labeled ”soft”). Occupations that are dense in *technical abilities* have also grown. In contrast, we see and a reduction in employment within occupations where workers are relatively well-endowed in terms of the ability to focus (measured as *Psychological Energy*) and *Inductive* reasoning, i.e. problem-solving skills. Notably, and somewhat on the positive side from a policy perspective, both of the cognitive abilities that have seen an increased demand are in the set of (crystallized) abilities that previous research have identified as being more malleable since they measure the ability to utilize acquired knowledge and skills, see e.g. Cattell (1987).

We further show that existing projections, drawn from two very different sources, suggest that the patterns of the recent past may be reasonably representative of the near future. This is true even though, as is well known, the same projections suggest that future technology will affect a very different set of occupations. The relative growth of occupations that (currently) relies on more skilled workers is projected to continue, perhaps even more distinctly than in the past. The main consistent projected change is a decline in occupations that employ workers with higher than average tolerance to stress and a projected growth in jobs that employ workers with the ability to activate without external pressure. However, since three out of four of the attributes that defined winners and losers in the recent past will continue to do so in the projected future, the overall impression is that the same types of workers that gained in the recent past will be the winners in the near future. On the positive side, this suggest that policy makers striving to design educational systems to favor the acquisition of skills that are useful at the future labor market may draw guidance from the evolution in the recent past.

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Appendix

Abstract

This appendix provides additional information about the data as well as supplementary analyses and additional results. The appendix is structured in the order of the main paper.

Appendix A Supplements to Section on ”Data and methods”

The non-cognitive skill measures capture the workers’ individual traits according to four dimensions and in the paper we give a brief description of their interpretation. But to give some additional flavor to their nature it may be useful to highlight how these traits relate to the ”Big Five” characteristics that are standard measures of personality types used in psychology. Table A.1 restates an overview of the relationship from Nilsson (2017) who should be given full credit for the content. The matrix highlights that ”Social Maturity” mostly captures Extraversion but also some elements of Conscientiousness and Openness/non-conformity. ”Emotional Stability” is mostly related to Neuroticism. ”Intensity” is a mixture of Conscientiousness and Openness. Finally, ”Psychological Energy” is most strongly related to Conscientiousness.

Table A.1: Mapping between the cognitive and non-cognitive skills and the ”big five”

Social maturity		Intensity	
Extraversion	(E)	The capacity to activate oneself without external pressure	(C)
Having friends	(E)	The intensity and frequency of free time activities	(O)
Taking responsibility	(C)		
Independence	(O*)		
Phsychological energy		Emotional stability	
Perseverance	(C)	Disposition to anxiety	(N)
Ability to fulfill plans	(C)	Ability to control and channel nervousness	(-N)
To remain focused	(C)	Tolerance of stress	(-N)

Notes: The table shows how the four items that define the non-cognitive ability test-score from the military enlistment psychologist interview maps into the Big Five traits of Personality inventory. This theory classifies traits into five broad categories. Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N). The four non-cognitive sub-scales do not match the Big Five traits perfectly. The independence undercategory is interpreted as the alternative interpretation of Openness (O*) which is “non-conformity”. The table (and note) is based on Nilsson (2017).

Table A.2 shows summary statistics for the used sample. While most of our analysis uses occupational characteristics at the 3-digit level here we list mean employment shares, growth and skill/wage ranks aggregated to the 2-digit level as in Goos et al. (2014). Following Goos et al. (2014), we order occupations by their mean wage rank and report the initial employment share (col 1), and the percentage point change in employment share between 2001-2013 (col 2). In addition, columns (3) and (4) give the overall skill and wage rank for each occupation group. It is notable from the table that the highest paying occupations tend to have higher employment growth, and higher skill levels in the pool of employees. Comparing the skill levels of middle and low paying occupations this correlation seems less clear and there are several occupations in the lower part of the wage distribution that have higher skill rank than wage rank. In the following sections, we will explore in more detail how the skills and wages of occupations relate to employment growth.

Table A.2: Summary statistics

	(1)	(2)	(3)	(4)
Occupation ranked by wage	Empl. share in 2001	Empl. growth	Overall skill rank	Wage rank
Highest paying occupations:				
Legislators and senior officials	0.03	8.14	89.62	99.06
Corporate managers	3.58	35.07	90.57	96.54
Physical, mathematical and engineering science professionals	4.0	23.22	92.45	91.04
Life science and health professionals	1.97	32.86	88.68	87.11
Other professionals	6.10	19.14	77.36	80.50
General managers	1.80	5.32	66.04	80.19
Physical and engineering science associate professionals	5.22	6.91	74.15	77.17
Middle paying occupations:				
Teaching professionals	.05	14.18	83.21	62.26
Other associate professionals	.09	25.41	69.46	55.07
Other craft and related trades workers	.015	39.70	28.30	54.45
Machine operators and assemblers	.03	24.88	44.81	51.42
Life science technicians and related associate professionals	.03	7.66	69.10	50.94
Subsistence agricultural and fishery workers	.05	34.40	25	48.82
Extraction and building trades workers	.04	-24.66	33.96	42.92
Metal, machinery and related trades workers	.00	-40.76	33.49	37.03
Teaching associate professionals	.02	8.46	55.66	36.32
Stationary-plant and related operators	.06	-16.72	17.09	36.06
Office clerks	.09	-24.17	44.97	34.12
Sales and services elementary occupations	.02	-1.82	6.60	33.49
Low paying occupations:				
Customer service clerks	.02	8.40	52.36	30.19
Personal and protective service workers	.16	19.18	45.28	27.74
Models, salespersons and demonstrators	.04	38.41	41.51	22.64
Precision, handicraft, printing and related trades workers	.00	-21.62	19.34	19.10
Market-oriented skilled agricultural and fishery workers	.01	29.12	41.32	16.60
Drivers and mobile-plant operators	.04	29.31	3.96	7.55

Note: Statistics are for the used sample but aggregated from the 3-digit to the 2-digit occupational level. Employment growth are for 2001-2013.

Appendix B Supplements to Section on "Results"

B.1 Supplements to Subsection "Wage Ranks and Overall Skills"

The first empirical point made in the paper is that the polarizing relationship between occupational wage ranks and employment growth is present also in our used data. The second point is that the relationship to the routine index (RTI) of Autor et al. (2003) is present in the data as expected. Both of these points are made in Figure 1 in the paper. In Table B.1 we show the point estimates related to Figure 1a (in column 1) and Figure 1b (in column 2). The table further shows that the RTI index explains much of the relationship to wage ranks (columns 3 and 4) and, in the final column (5), it documents that the relationship between occupational decline and RTI index also holds within the middle of the wage-rank distribution.

Table B.1: Stylized facts: Job polarization and routine tasks

	(1)	(2)	(3)	(4)	(5)
Dep. var:	Empl. growth	RTI	RTI	RTI	RTI
Sample	All jobs	All jobs	All jobs	All jobs	Middle wage jobs
Wage rank	-1.312***			-0.385	
	(0.340)			(0.415)	
Wage rank^2	0.014***			0.004	
	(0.003)			(0.004)	
RTI rank		0.006	-0.510***	-0.461***	-0.902***
		(0.364)	(0.095)	(0.112)	(0.204)
RTI rank^2		-0.005			
		(0.004)			
Observations	107	94	94	94	30
R-squared	0.162	0.310	0.288	0.295	0.372

Note: The RTI index is only available at the 2-digit level. They are not available for all occupations, which explains the lower number of observations in columns (2), (3) and (4).
*** p<0.01, ** p<0.05, * p<0.1

In Figure B.1, we show that the relationship between employment growth and wage ranks is robust to a number of different alterations of the used data and the estimated model:

1. In the top left panel (a): We generate more *detailed occupational cells* by interacting 3-digit occupations and with 10 industry indicators when defining the occupations.

2. In the top right panel (b): We *include the two occupations* ”Higher officials in public services” and ”Manual Construction Laborers” which were excluded in the main analysis since the data appeared flawed in these occupations due to changes in collection methods (more than doubled in size across two adjacent years).

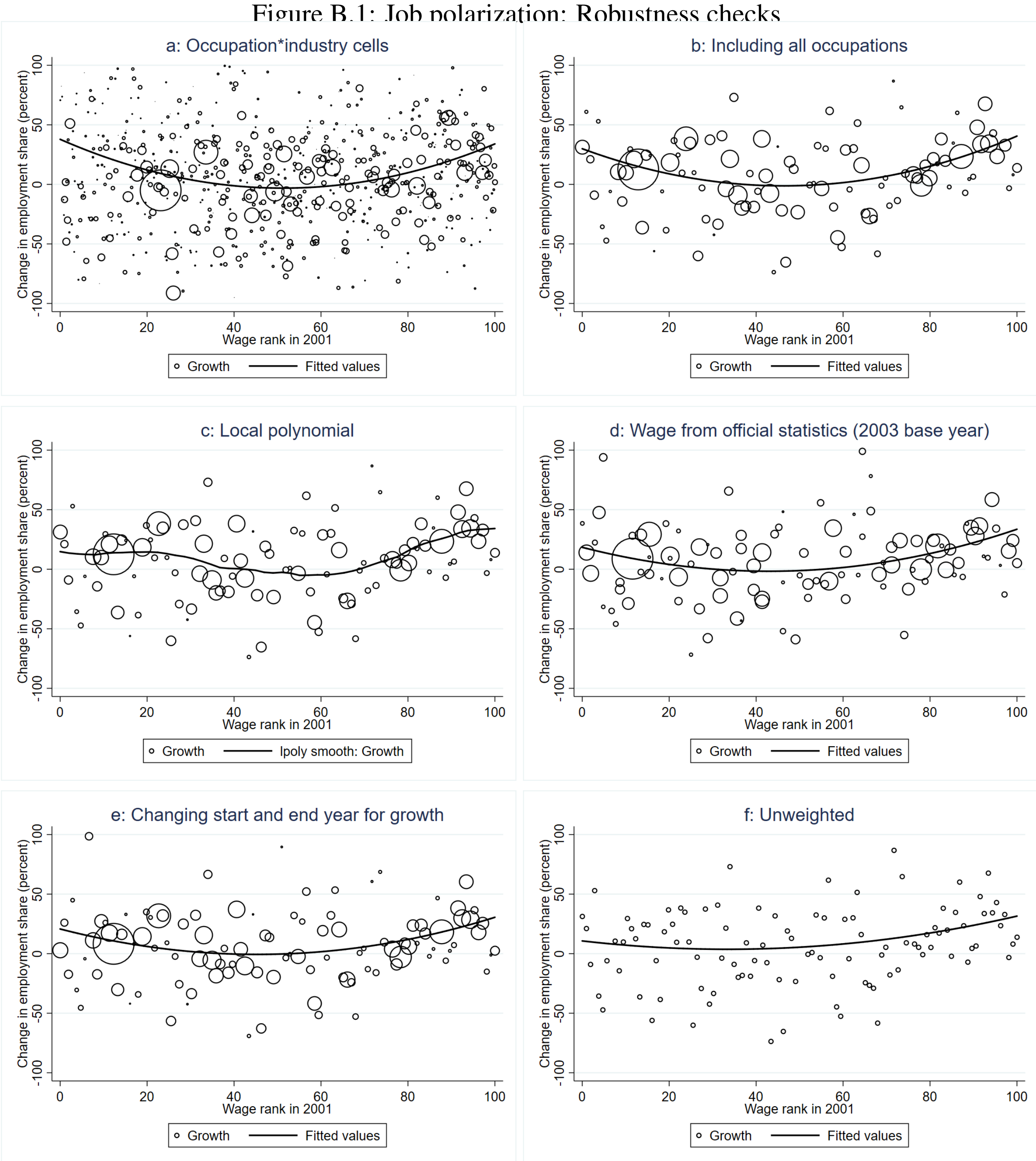
3. In the middle left panel (c): We use a smoothed local polynomial instead of the quadratic functional form employed in the baseline to ensure that the patterns are not forced onto the data from a too restrictive *functional form*.

4. In the middle right panel (d): We use *wages in official statistics* to rank the occupations instead of within-sample wages for tenured males. These data thus do include females and short tenured males as well. These data also use sample weights that should correct for under-sampling of small establishments in the micro data. Due to data availability, we use 2003 as the base year for this analysis.

5. In the lower left panel (e): We *vary the start and end point* of the analysis. Here we average over the three first and the three last years respectively to ensure that the results are not idiosyncratically related to the specific years used in the main analysis.

6. In the lower right panel (f): We show the *unweighted* relationship between the 2001 wage rank and employment growth. This contrasts to the main analysis which, following the standards in the literature, are weighted according to the relative sizes of the different occupations in the start year.

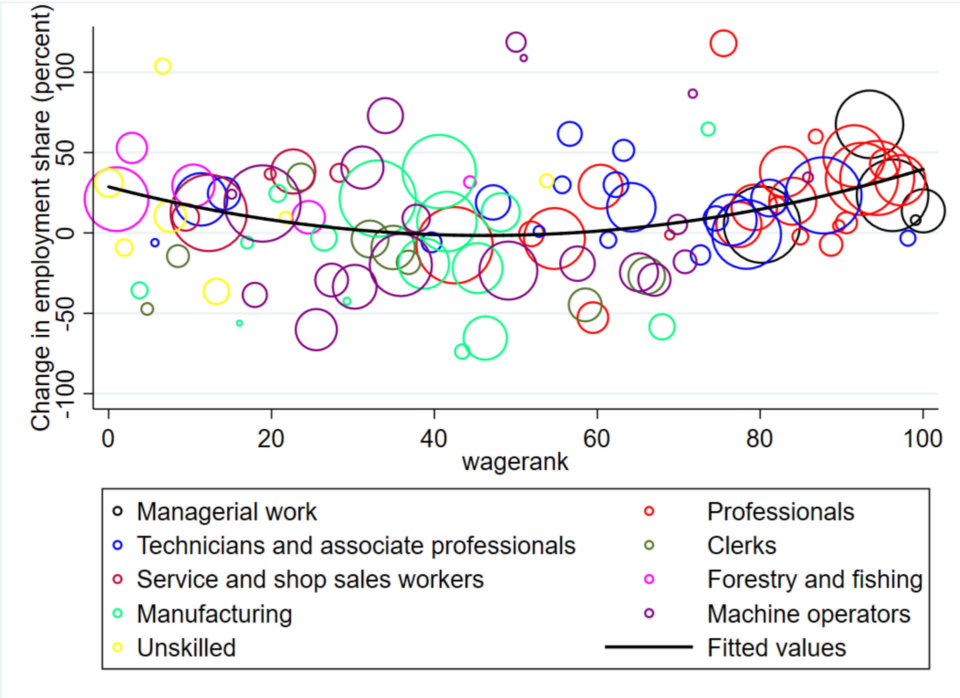
Figure B.1: Job polarization: Robustness checks



Note: The Figure shows the relationship between employment growth when we vary the sample and variable definitions. In (a), we use the combination of 3-digit occupation and broad industry (10 groups) to define a job; in (b) we include the occupations excluded in our main sample when estimating the quadratic; in (c) we use a local polynomial; in (d), we use wages in official statistics instead of within-sample wages for tenured males (due to data availability, we use 2003 as the base year for the analysis). In (e), we use the average of the first/last three years as the start/end year when calculating employment growth. Finally in (f) we show the unweighted relationship between the 2001 wage rank and employment growth. Each circle is a 3-digit occupation (except in a) according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated as employment shares in the start year when applicable.

A further point of interest is the relationship between occupational decline and different broad categories of occupations. Figure B.2 therefore illustrates the polarization pattern while highlighting the different 1-digit occupation groups. As is evident from the figure, many of the declining occupations are found in manufacturing jobs and by machine operators. Growing low-wage jobs are instead drawn from a more mixed set of groups.

Figure B.2: Contribution to polarization by broad occupation groups



Note: y-axis displays the percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden's official calculations. Each circle is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated according to employment shares in 2001. x-axis ranks occupations according to mean wages by tenured employees in 2001. The line represents prediction from the regression equation: $EmploymentGrowth_{occupation} = a + b * Rank_{occupation} + c * (Rank_{occupation})^2$, where Rank is defined as the x-axis.

After validating the stylized facts the paper goes on to show its main results by focusing on the relationship between employment growth and occupational skills. The first main result is shown in Figure 1c in the main paper and it displays a monotone relationship between occupational employment growth and occupational skill ranks. The estimates corresponding to Figure 1c in the main paper are shown in table form in Table B.2. The table also shows that the square term is insignificant. Panel B examines whether the results seem sensitive to the way we measure the overall skill-intensity of an occupation. Instead of using the sum of the eight talents, we use a weighted sum where the weights correspond to the market wage return of each skill at age 35, reported in Fredriksson et al. (2018). The estimates look very similar.

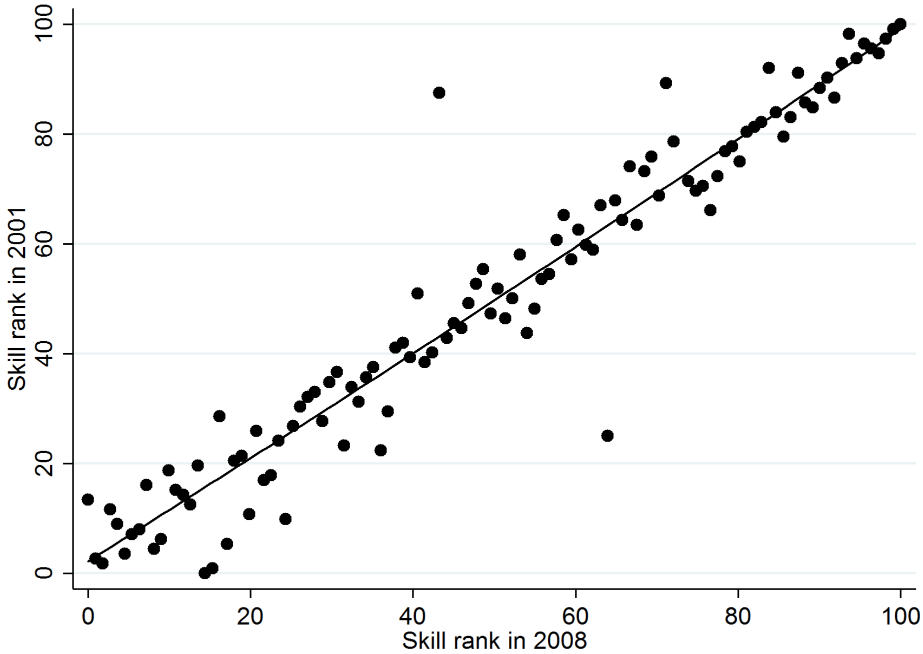
Figure B.3 further verifies that the skill-rank of occupation is stable over time. It shows that there is a strong correlation between occupational skill rank in 2001 and 2008, which is the last year for which we have access to the skill data. The estimated slope coefficient is 0.96.

Table B.2: Relationship between skill rank and employment growth

	(1)	(2)	(3)
Panel A:Overall skills as sum of talents			
Skill rank	0.263**	0.331**	0.603
	(0.104)	(0.155)	(0.383)
Skill rank^2			-0.003
			(0.004)
Wage rank		-1.418***	-1.522***
		(0.359)	(0.375)
Wage rank^2		0.013***	0.015***
		(0.004)	(0.004)
R-squared	0.068	0.200	0.205
Panel B: Overall skills as weighted sum of talents			
Skill rank	0.258**	0.303*	0.539
	(0.105)	(0.161)	(0.405)
Skill rank^2			-0.003
			(0.004)
Wage rank		-1.398***	-1.490***
		(0.358)	(0.375)
Wage rank^2		0.013***	0.014***
		(0.004)	(0.004)
R-squared	0.064	0.193	0.197
Observations	107	107	107

Note: The dependent variable is the percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden's official calculations. Each occupation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Column (1) shows the linear relationship between occupational skill rank and employment growth. Column (2) shows the relationship conditional on *wagerank* and *wagerank*^{2}. Column (3) shows the quadratic relationship conditional on *wagerank* and *wagerank*^{2}. Panel A measures overall skills as the sum of the eight skills. Panel B weights the different skill components by their average wage returns at age 35. The weights are reported in Table 1 in Fredriksson et al. (2018). All regressions are weighted by the occupation employment shares in 2001. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure B.3: Stability in occupational skill rank 2001-2008



Note: Each dot represent a 3-digit occupation. Slope coefficient: 0.9629.

The relationship between wage rank and skill rank

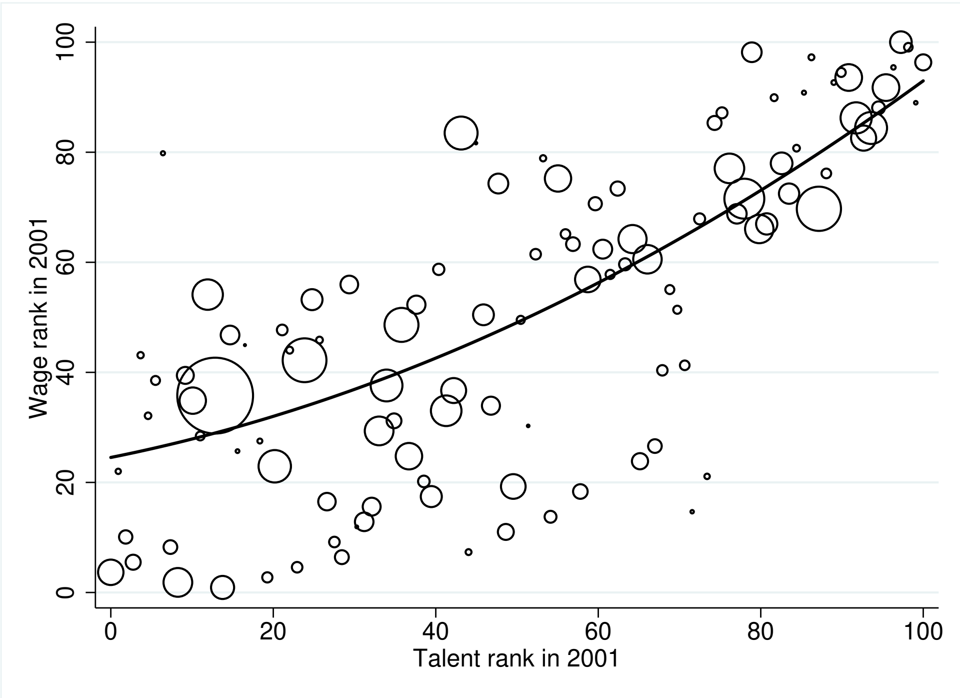
Since this result is very different from the patterns related to the wage ranks, we here let Figure B.4 show how the wage ranks and skill ranks are associated at the occupational level. As is evident, there is a strong positive relationship but also with some non-trivial variation around the prediction line.

Data and functional form

We next show that the relationship between skill ranks and employment growth is robust to the same variations as we exposed the wage-rank results to in Figure B1 above, i.e. *detailed occupational cells (a)*, *including the two excluded occupations (b)* and *smoother functional form (c)*. The one panel which differs from Figure B1 is the middle right panel (d), where we show results from using *lagged skill endowments (from 1997)* instead of using skills from the same year as the start year of the growth calculation (2001).[1] We then proceed as in Figure B1 by showing results *varying the start and end point of employment growth (e)* and by showing the *unweighted relationship (f)*.

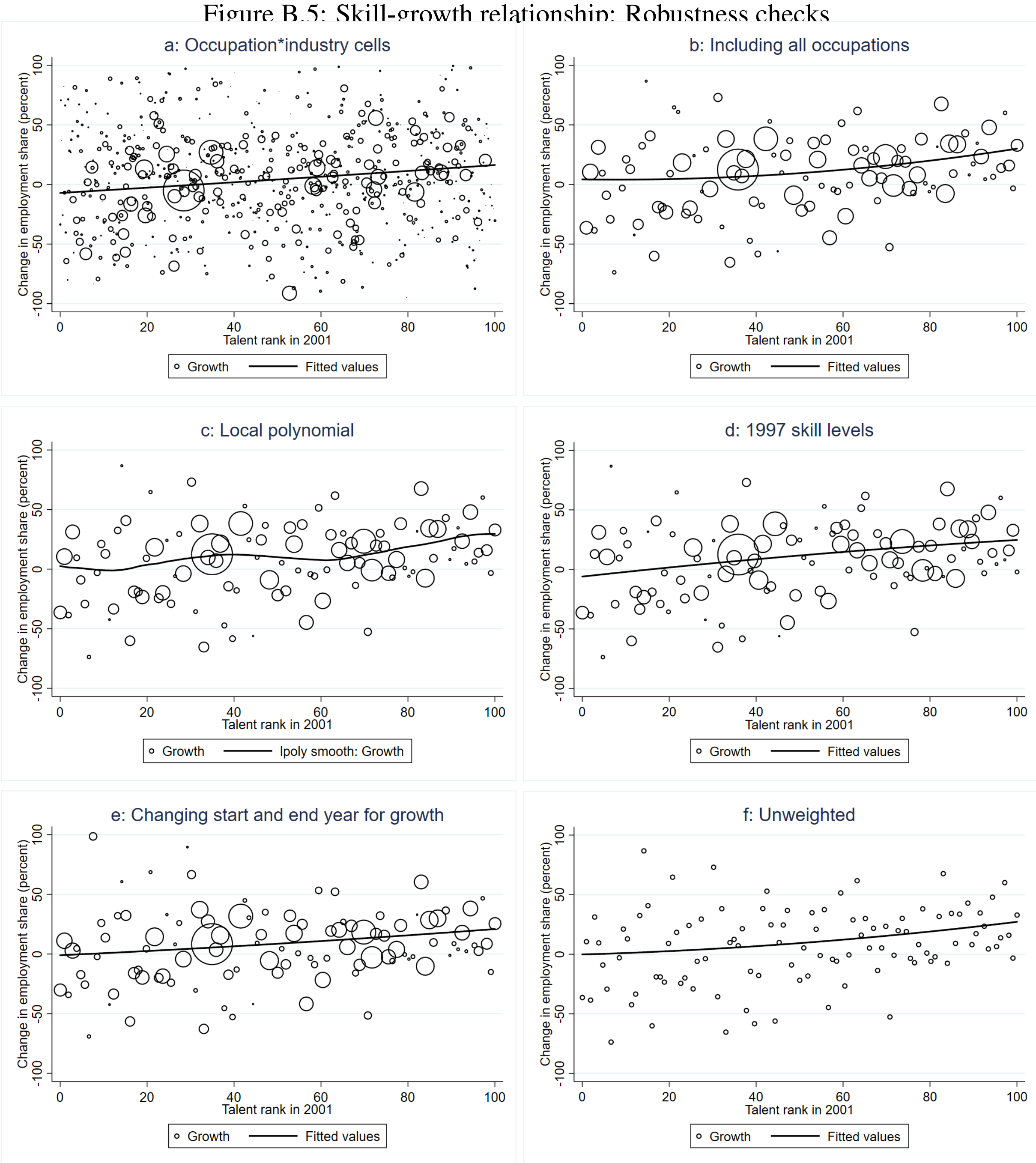
[1]This replaces the use of official wages in Figure B1 above which has no correspondence for skills.

Figure B.4: Correlation between 2001 occupational skills and wages.



Note: Each dot represent a 3-digit occupation. Circle sizes represent weights, calculated as employment shares in 2001.

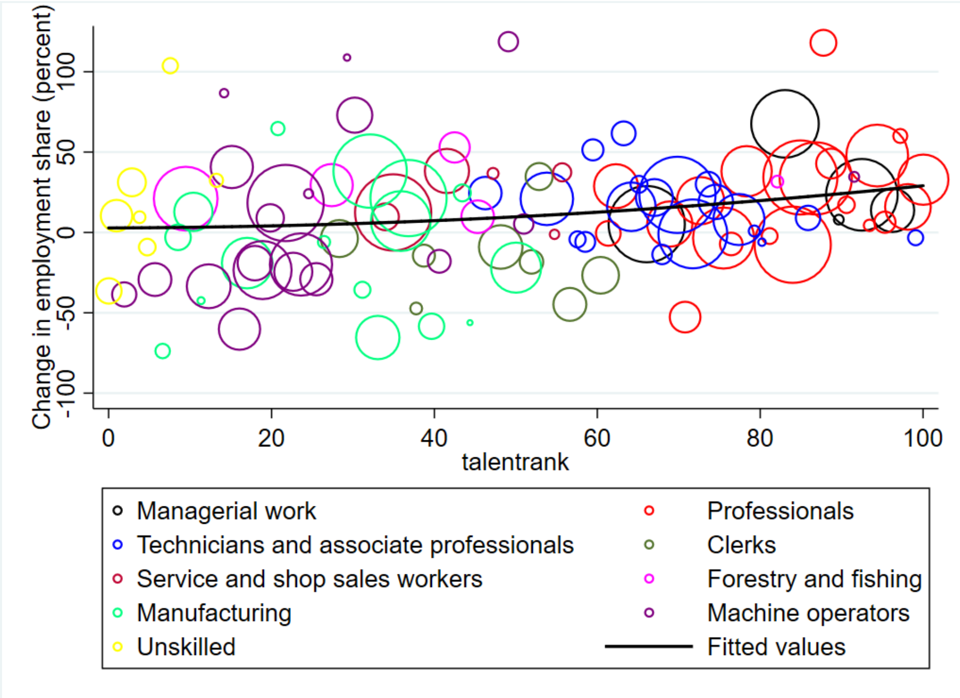
Figure B.5: Skill-growth relationship: Robustness checks



Note: The Figure shows the relationship between employment growth and overall skills when we vary the sample and variable definitions. In (a), we use the combination of 3-digit occupation and broad industry (10 groups) to define a job; in (b) we include the occupations excluded in our main sample when estimating the quadratic; in (c) we use a local polynomial; in (d), we use a different base year (1997) for calculating the occupational skill-level. In (e), we use the average of the first/last three years as the start/end year when calculating employment growth. Finally in (f) we show the unweighted relationship between the 2001 wage rank and employment growth. Each circle is a 3-digit occupation (except in a) according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated as employment shares in the start year when applicable.

As with the wage ranks and figure Figure B.2 above, it is useful to document the the relationship between skill ranks, occupational decline and different broad categories of occupations. Figure B.6 therefore illustrate the skill biased patterns while highlighting the different 1-digit groups. As is evident from the figure, many of the lowest skilled jobs are in the ”unskilled” category. This group was much more dispersed in Figure B.2 above.

Figure B.6: Contribution to skill-growth relationship by broad occupation groups



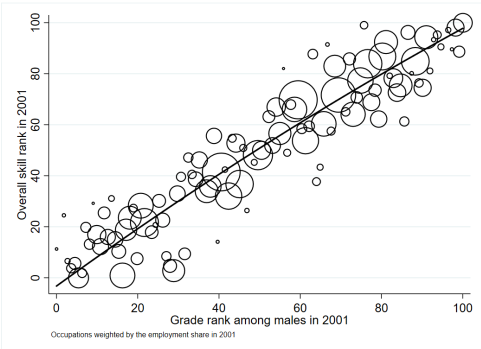
Note: y-axis displays the percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden’s official calculations. Each circle is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated according to employment shares in 2001. x-axis ranks occupations according to mean overall skill intensity by tenured employees in 2001 as calculated by Fredriksson et al. (2018). The line represents prediction from the regression equation: $EmploymentGrowth_{occupation} = a + b * Rank_{occupation} + c * (Rank_{occupation})^2$, where Rank is defined as the x-axis.

Grades instead of military skill tests

We further reassess our results using high school school grade point average as our measure of overall skills. These grades have the advantage of being available for both men and women, but the disadvantages of mostly capturing cognitive skills (regressing GPA on cognitive and non-cognitive skills, using individual level data, gives regression coefficients of 0.66 and 0.22 for cognitive and non-cognitive skills respectively) and having a mechanical relationship to educational opportunities through admissions system. The main disadvantage is, however, that GPA does not lend itself to the decomposition that we perform in the rest of the paper. For the main analysis, it is, however, a reasonable alternative measure. Our analysis of grades in Figure B.7 has four panels components: First, panel (a), shows that the association between grade ranks and our baseline overall skill rank among males is very strong, second in panel (b) we show that the association remains potent also if analyzing male conscription tests relative to female grades within the same occupations. In the lower panels we instead relate the GPA directly to employment growth, separately for males and females. Both of these associations are monotonically positive for males (panel c) as well as females (panel d). If anything, the curvature is the opposite of the polarization (i.e. a more positive slope in the lower part of the distribution).

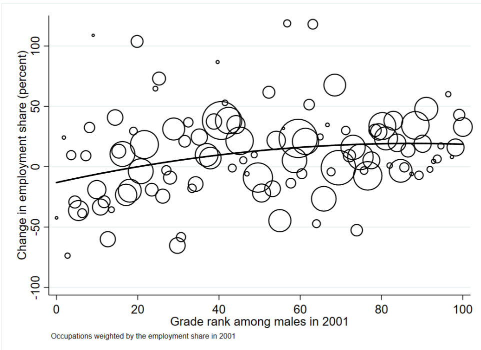
Figure B.7: Alternative skill measure: High school grades

(a) Male skill rank- male grade rank

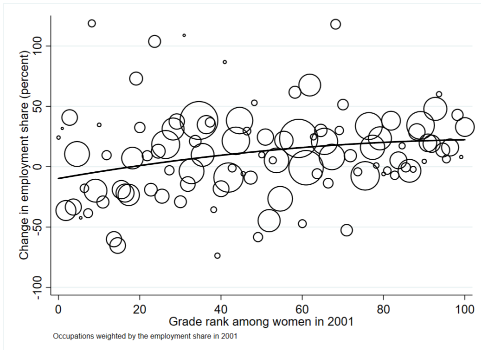


(b) Male skill rank- female grade rank

(c) Grade-growth relationship -tenured men



(d) Grade-growth relationship -tenured women



Note: Each circle is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated according to employment shares in 2001. Panel (a) and (b): y-axis ranks occupations according to mean overall skill intensity by tenured male employees in 2001 as calculated by Fredriksson et al. (2018). Panel (a) x-axis ranks occupations according to mean high school grade point average by tenured male employees in 2001. Panel (b): x-axis ranks occupations according to mean high school grade point average by tenured female employees in 2001. Panel (c) and (d): y-axis displays the percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden's official calculations. Panel (c): x-axis displays the grade rank of occupations based on tenured males. Panel (d): x-axis displays the grade rank of occupations based on tenured females.

Why are the results for skill-ranks different from wage ranks?

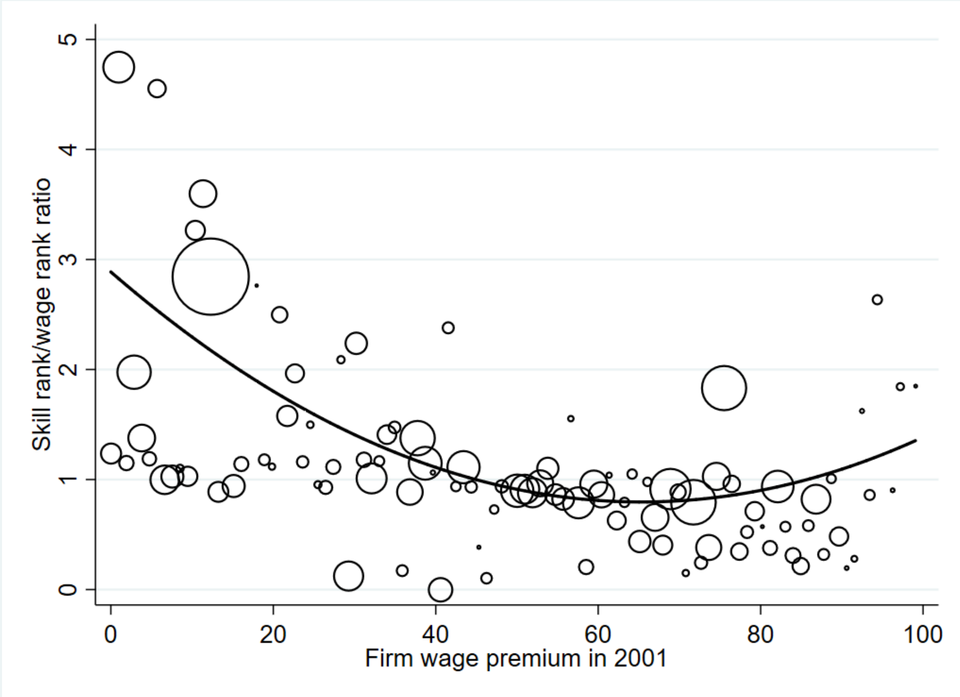
As noted in the paper, the difference between the skill-rank and wage-rank results arises because our skill measures are broad in the intellectual dimension but leave out a set of residual unobserved wage-related attributes such as, e.g., manual strength, the ability to cope with hazardous work environments, pure rent-seeking abilities and knowledge that is specific-enough not be captured by any of our skill measures. A deeper investigation has to be left for future research, but in order to explore the role for firm-side explanations (i.e. those related to factors such as hazardous work environments and/or rent-seeking abilities) we have tentatively explored the relationship between the $Skill^{rank} > Wage^{rank}$ indicator to measures of firm-level wage premiums. The question we ask is if occupations that are ranked higher in terms of skills than in terms of wages are more likely to be found in "high wage firms" defined as firms that, in general, pay higher wages to identical workers.

To get our measure of firm wage premiums we follow the literature and decompose log wages into person effects and firm effects (estimated at the establishment level, using the term "firm effects" for simplicity), according to the AKM-model of (Abowd et al., 1999) :

$$Y_{it} = \theta_i + \psi_{k(i,t)} + X_{it}\beta + \varepsilon_{it}, \tag{B.1}$$

where Y_{it} is the log wage of worker i in year t, θ_i is a fixed effect for individual i, $\psi_{k(i,t)}$ is the fixed effect for the employing establishment at year t, $X_{it}\beta$ is a set of control variables (age square and cube and year dummies). We estimate the model on our full micro data set which covers 1997 to 2009. The estimated firm (ψ) effects are the measures of interest. After estimating them, we aggregate them to the occupational level using the distribution of occupations across firms during our start year in 2001. Figure B.8 shows the association between the $Skill^{rank}$ to $Wage^{rank}$ ratio and firm effects across the distribution of firm effects. The clearest message that arises from the figure is that occupations that are associated with low-wage firms have much higher $Skill^{rank}$ to $Wage^{rank}$ ratio than occupations in in high-wage firms. In Table B.3, we show the same pattern in a more compact way by instead regressing occupation-averaged firm-effects on an indicator for $Skill^{rank} > Wage^{rank}$. The conclusion is very similar.

Figure B.8: Correlation between firm wage premium and the $Skill^{rank}$ to $Wage^{rank}$ ratio



Note: Each circle is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated according to employment shares in 2001. y-axis displays the relationship between the $Skill^{rank}$ and the $Wage^{rank}$ of an occupation. x-axis ranks occupations according to the firm wage premium captured by the estimated firm (ψ) effects from eq. (B.1).

Table B.3: Employment growth and the skills-to-wage relationship

	(1) All occupations	(2) Low wage	(3) High wage
AKM establishment effect rank	-0.011***	-0.010***	-0.008***
	(0.002)	(0.003)	(0.003)
R-squared	0.342	0.337	0.268
Observations	107	53	54

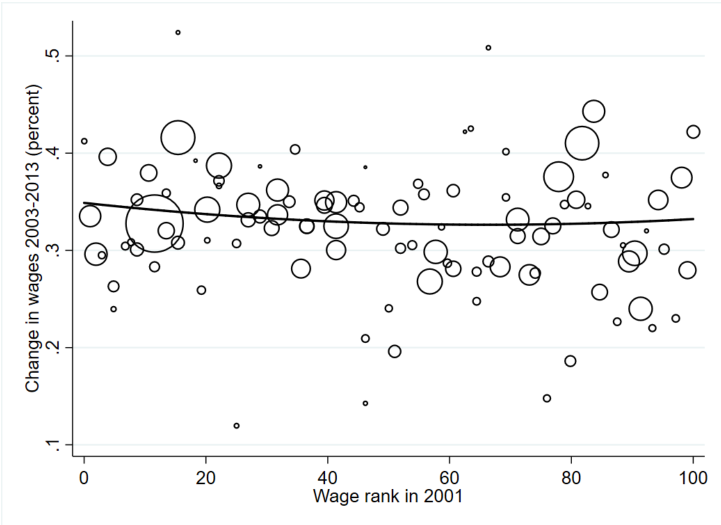
Note: The dependent variable is an indicator variable taking the value one if $Skill^{rank} > Wage^{rank}$ and zero otherwise, by occupation according to Statistics Sweden's official calculations The independent variable is the firm wage premium captured by the estimated firm (ψ) effects from eq. (B.1). Column 1 shows the association for the full sample of occupations. In columns (2) and (3) we divide occupations into low- and high wage occupations defined by the median in the distribution of mean wages among tenured male workers. Robust standard errors are reported in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Skill ranks, wage ranks and ”Wage Polarization”

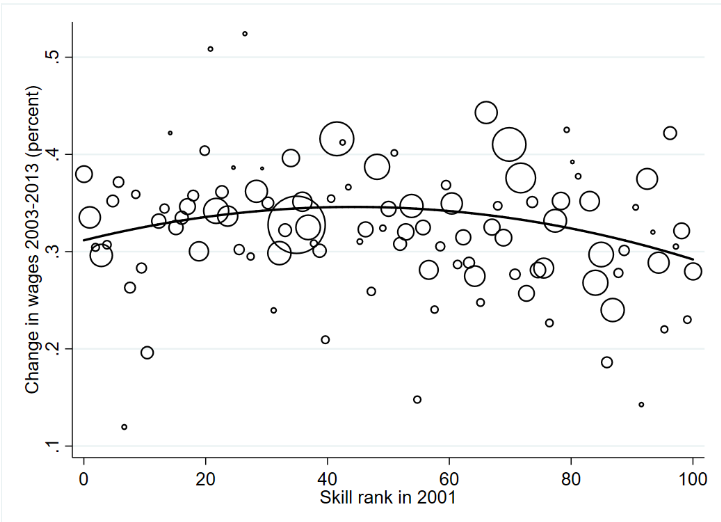
The concept of *wage polarization* refers to the growth of wages at the top and bottom of the wage rank distribution (see e.g. Acemoglu and Autor (2011)). Here, the results have been less uniform in the previous literature, which is expected since displaced workers from the middle of the wage distribution may put additional supply pressure on the low-wage occupations which may cause these wages to fall even if the demand has a secular increase. In Figure B.9, we show how wage growth in 2003 (for data availability reasons) to 2013 are related to wage ranks and skill ranks in 2001. The results show no indications of wage polarization in Sweden during the period. The patterns for skill ranks are, however, disassociated from wage ranks again since wage growth appears to have been particularly pronounced in middle skilled occupations.

Figure B.9: Wage polarization

(a) Percentage growth of wages along the 2003 wage distribution



(b) Percentage growth of wages along the 2003 skill distribution



Note: Each circle is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Circle sizes represent weights, calculated according to employment shares in 2003. Panel (a) and (b): y-axis displays the percent change in wages between 2003 and 2013 by occupation according to Statistics Sweden's official calculations. Panel (a) x-axis ranks occupations according to mean overall wage by tenured male employees in 2001. Panel (b) y-axis ranks occupations according to mean overall skill intensity by tenured male employees in 2001 as calculated by Fredriksson et al. (2018).

Disappearing jobs

Figure 2 in the paper presents a complementary analysis at the job level where we define *jobs* as occupations within establishments, following Fredriksson et al. (2018). We relate initial job-level wage and skill ranks to future employment growth within surviving and re-sampled establishments. We focus on surviving re-sampled establishments to avoid having to make assumptions about reasons for not being sampled in the outcome year (true exit vs. falling out of sample frame). We define our used sample as follows:

- First, we calculate mean wages and skills of male incumbent workers in each *job* during our first year of data (1997). This data include 53,015 distinct jobs.
- Second, we add the total number of paid employees (males and females) to each job.
- Third, we keep establishments that are sampled in 2008 as well. 32,336 distinct jobs remain.
- Fourth, we add the job-level employment in 2008. If a job observed in 1997 does not exist within the sampled establishment in 2008, we assume that the job disappeared in the meantime (i.e. we set N=0 in the final year). In total, 6,859 out of our 32,336 jobs disappeared (21 percent) within our sample of ongoing establishments.
- Fifth, we calculate the employment growth rate from 1997 to 2008 for each of the 32,336 jobs.
- Sixth, we calculate a set of weights according to the initial share of the total employment within our 32,336 jobs in 1997. This exactly mimics the occupational-level analysis.

The ensuing data gives us growth rates with a mean of 14 percent and a median of -25 percent. The minimum is -100 percent (job exit) and the max is 22,733 percent. As a robustness check, we have dropped the top one percentile in the growth distribution (new max being 733 percent), which did not change the results in any substantive way. As in the main analysis, we rank the jobs according to wages and skills and relate second order polynomials of these ranks to employment growth within these jobs.

B.2 Supplements to Subsection "Specific Skill Endowments"

Table 2 in the paper displays the paper's second main result. This result shows how the endowments of different types of specific skills are related to occupational employment growth. There is substantial heterogeneity between the skill-types within the broader aggregates of cognitive abilities and non-cognitive traits that have been emphasized in much of the earlier literature.

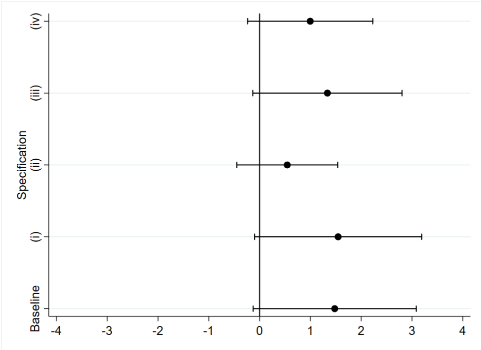
Figure B.10 shows that the results are robust to a number of variations of the model. To highlight that the results provide similar rankings, we show the results in panels that display pairs of the most positive (top) and negative (bottom) associations among the two sets of cognitive abilities and non-cognitive traits respectively. The panels first show the baseline estimates of Table 2. In variation (i), we include the two occupations excluded in our main sample; in (ii), we use the alternative base year (1997) for calculating the occupational skill-level. In (iii), we use the average of the first/last three years as the start/end year when calculating employment growth and in (iv) we show the unweighted relationship between the 2001 wage rank and employment growth.

We further add two sets of analyses to complete the picture. First, in Table B.4, we show the associations separately for low-wage occupations and high-wage occupations (splitting by the median). The results are concurring overall although most of the action for Social Maturity (positive) and Psychological Energy (negative) arise in the low-wage part whereas the positive impact of Verbal abilities only is significant for high-wage jobs. The negative impact of Inductive ability arise in both parts of the wage-rank distribution.

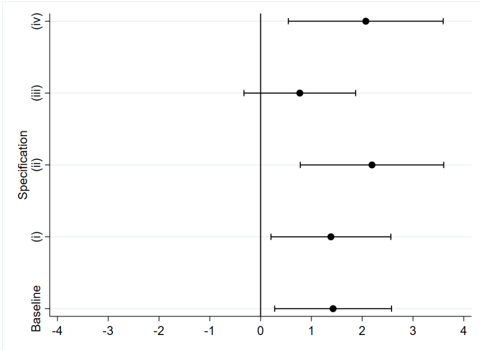
Our second additional element relates the skills to the routine index (RTI). Table B.5 repeats Table 1 of the paper with the RTI as the outcome. The link appears consistent, the routine jobs that we know are declining more are also employing workers that are less heavily endowed with skills such as social maturity and technical abilities and have more inductive abilities.

Figure B.10: Specific skills-robustness checks

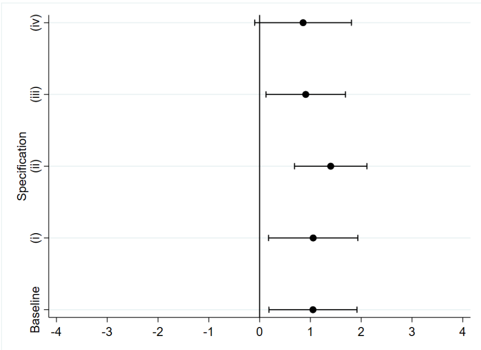
(a) Social maturity



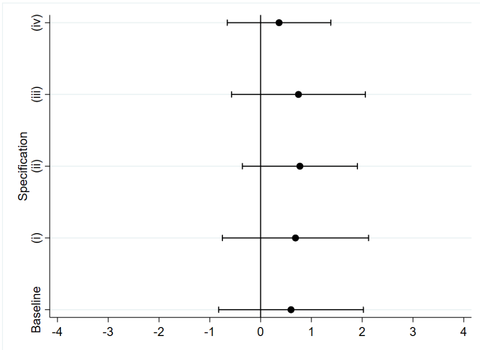
(b) Verbal skills



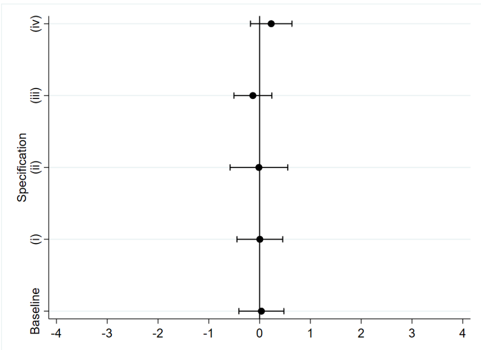
(c) Technical skills



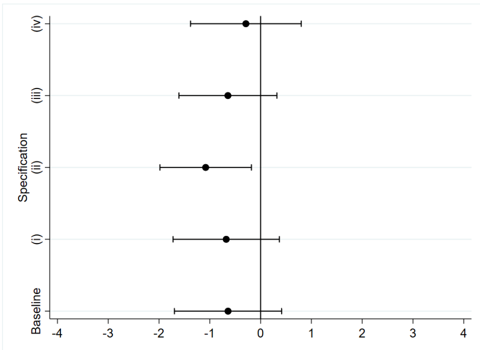
(d) Emotional stability



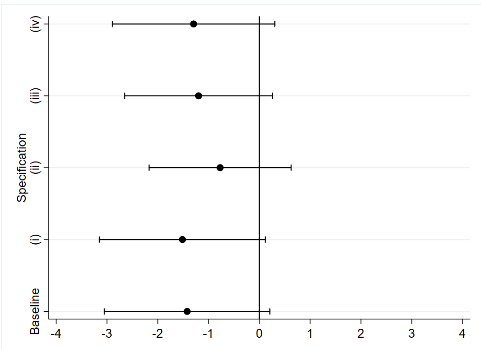
(e) Intensity



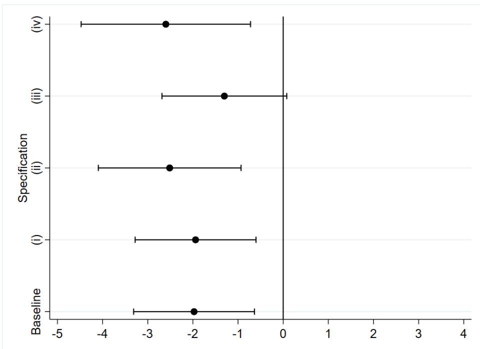
(f) Spatial skills



(g) Phsychological energy



(h) Inductive skills



Note: Figures show relationships between employment growth and specific skills when we vary the sample and variable definitions. The output come from 5 regressions, one per specification. Baseline replicates the estimate from Table 2 in the paper. In (i), we include the two occupations excluded in our main sample when estimating the quadratic; in (ii), we use a different base year (1997) for calculating the occupational skill-level. In (iii), we use the average of the first/last three years as the start/end year when calculating employment growth and in (iv) we show the unweighted relationship between the 2001 wage rank and employment growth.

Table B.4: Employment growth and specific skills in low and high wage jobs

	(1) All jobs	(2) Low wage	(3) High wage
Social maturity (T)	1.479*	2.842**	0.052
	(0.809)	(1.066)	(1.913)
Verbal (A)	1.427**	2.413	1.902**
	(0.579)	(1.584)	(0.807)
Technical (A)	1.050**	1.257***	0.928
	(0.436)	(0.425)	(0.987)
Emotional stability (T)	0.599	0.0610	0.394
	(0.718)	(0.814)	(1.437)
Intensity (T)	0.035	0.172	0.0770
	(0.223)	(0.259)	(0.497)
Spatial (A)	-0.642	-0.664	-0.517
	(0.532)	(0.537)	(1.059)
Psychological energy (T)	-1.422*	-2.065**	-0.289
	(0.821)	(0.937)	(1.863)
Inductive (A)	-1.974***	-3.563*	-2.217*
	(0.674)	(1.823)	(1.225)
Observations	107	53	54
R-squared	0.354	0.435	0.388
Flexible control for wage rank	Yes	Yes	Yes

Note: T = Productive Trait, A = Cognitive Ability. The dependent variable is the percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden's official calculations. Each occupation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Column (1) shows the linear relationship between occupational specific skill rank and employment growth. In columns (2) and (3) we divide occupations into low- and high-wage occupations defined by the median in the distribution of occupation mean wages. All regressions are weighted by the occupation employment shares in 2001. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table B.5: Determinants of routine task content

	(1)	(2)	(3)
	Overall skills		Specific skills
Skill rank	-0.010***	-0.003	
	(0.003)	(0.007)	
Social maturity (T)			-0.089**
			(0.035)
Verbal (A)			-0.031
			(0.027)
Technical (A)			-0.053**
			(0.023)
Emotional stability (T)			0.034
			(0.024)
Intensity (T)			-0.002
			(0.010)
Spatial (A)			0.0374
			(0.026)
Psychological energy (T)			0.031
			(0.031)
Inductive (A)			0.062*
			(0.035)
Wage rank		0.053***	0.070***
		(0.018)	(0.020)
Wage rank^2		-0.001***	-0.001***
		(0.000)	(0.000)
Observations	94	94	94
R-squared	0.075	0.235	0.471

Note: T = Productive Trait, A = Cognitive Ability. The dependent variable is the rank of an occupation according to the routine task intensity (RTI) from Goos et al. (2014). Each occupation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Column (1) shows the linear relationship between occupational specific skill rank and RTI. Column (2) accounts for the wage rank and column (3) replaces the overall skills with specific skills (T = Productive Trait, A = Cognitive Ability). All regressions are weighted by the occupation employment shares in 2001. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

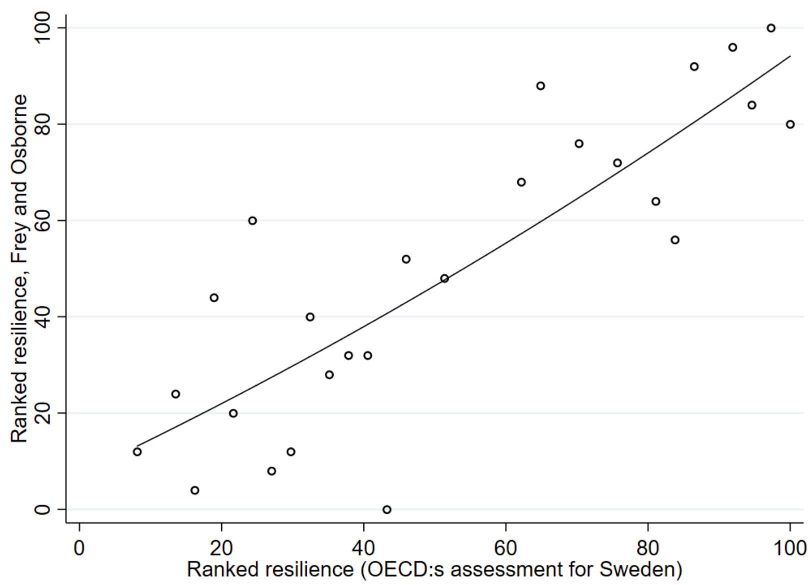
B.3 Supplements to Subsection ”Occupational Employment Projections”

The final set of results in the paper relates the skill measures to projections about future resiliance to to automation and general occupational decline. The results are presented in Figure 3 and Table 2 of the paper. In Table B.6, we show the estimated parameters related to polarization in the past and the projected future corresponding to Figure 3 in the main paper.

In the analysis of the main paper, we rely on projections related to the US that we cross walk to Sweden. To ensure the validity of these cross-walks, we have also analyzed data from the OECD where they have redone the Frey and Osborne (2017)-type of resilience calculations for each country using data from the PIAAC assessments of tasks within each job. These samples are fairly limited in scope (relative to the data used in this paper) so it is difficult to use them at a very detailed occupational level. But, using data at the 2-digit industry level, the ranked assessments for Sweden appear very well-aligned with the ranked assessments for the US from Frey and Osborne (2017). The associations are shown in Figure B.11.

Figure B.11: Correlation between US projections and OECD:s Sweden-specific projection

(a) OECD-Frey & Osborne



Note: y-axis ranks occupations according to the projected resilience to automation in Frey and Osborne (2017) for the US. x-axis ranks occupations according to the projected resilience to automation in Nedelkoska and Quintini (2018) for Sweden. The Sweden-specific projections are calculated using the same task-based approach as in Frey and Osborne (2017), using individual-level survey data (from PIAAC) on the content of tasks in different occupations. The level of observation is the 2-digit industry.

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Table B.6: Past and projected job polarization

Empl. growth:	(1) Past	(2) Projected: BLS	(3) Projected: Frey & Osborne
Wage rank	-1.312***	-1.680**	-0.975
	(0.340)	(0.728)	(0.644)
Wage rank^2	0.014***	0.016**	0.012**
	(0.003)	(0.006)	(0.006)
Observations	107	91	103
R-squared	0.162	0.156	0.166

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.7: Determinants of past and projected employment growth 2001-2013

	(1)	(2)	(3)
Growth:	Past	Projected: BLS	Projected: Frey & Osborne
	Panel A: Relationship with overall skills		
Skill rank	0.290**	0.647***	0.788***
	(0.167)	(0.180)	(0.182)
Observations	107	91	103
R-squared	0.224	0.274	0.344
	Panel B: Relationship with specific skills		
Social maturity (T)	1.151*	2.246**	2.121**
	(0.779)	(1.030)	(0.911)
Verbal (A)	1.648**	1.754**	2.125*
	(0.585)	(0.751)	(1.077)
Technical (A)	1.004**	0.001	0.674*
	(0.417)	(0.547)	(0.405)
Emotional stability (T)	0.846	-1.733**	-3.049***
	(0.741)	(0.777)	(0.693)
Intensity (T)	-0.046	0.698**	0.966***
	(0.244)	(0.317)	(0.223)
Spatial (A)	-0.667	0.158	-0.135
	(0.516)	(0.619)	(0.530)
Psychological energy (T)	-1.254*	-0.945	0.176
	(0.860)	(1.091)	(1.005)
Inductive (A)	-2.198***	-1.723**	-2.288*
	(0.662)	(0.773)	(1.307)
Observations	107	91	103
R-squared	0.406	0.419	0.557
Correlations:			
Past growth	1	0.341	0.219
BLS	0.341	1	0.456
Frey & Osborne	0.219	0.456	1

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Dependent variables are the ranked change in employment defined as follows: Column (1) The recent past: actual growth between 2001 and 2013 by occupation according to Statistics Sweden's official calculations. Column (2) Projected BLS: as projected by the US Bureau of Labor statistics transposed into Swedish occupational codes by the authors. Projected Frey Osborne: as projected by Frey and Osborne (2017) transposed into Swedish occupational codes by Heyman et al. (2016). Each observation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Regressions are weighted according to employment shares in 2001. Skill rank is a rank of occupations according to mean overall skill intensity by tenured employees in 2001 as calculated by Fredriksson et al. (2018). Model also controls for initial wage rank with squares. Wage rank ranks occupations according to mean wages in 2001. *Specific skills* rank occupations according to skill intensity in each dimension during 2001 as calculated by Fredriksson et al. (2018). The skills are ordered according to estimate size in Column (1). The different types of skills are highlighted by: T = Non-Cognitive Trait, A^c = Crystallized (malleable) Cognitive Ability and A^f = Fluid (less malleable) Cognitive Ability. Interpretation of non-cognitive traits are according to Mood et al. (2012) which provides further details on the tests. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

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