The skill-specific impact of past and projected occupational decline

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A B S T R A C T

Using population-wide data on a vector of cognitive abilities and productive non-cognitive traits among Swedish male workers, we show that occupational employment growth has been monotonically skill-biased in terms of these intellectual skills, despite a simultaneous (polarizing) decline in middle-wage jobs. Employees in growing low-wage occupations have more of these skills than employees in other low-wage occupations. Conversely, employees in declining, routine-task intensive, mid-wage occupations have comparatively little of these skills. Employees in occupations that have grown relative to other occupations with similar wages have more intellectual skills overall but are particularly well-endowed with the non-cognitive trait “Social Maturity” and cognitive abilities in the “Technical” and “Verbal” domains. Projections from the US Bureau of Labor Statistics about future occupational labor demand do not indicate that the relationship between employment growth and skills is about to change in the near future.

1. Introduction

The changing demand for labor in different segments of the labor market is a key topic in social science and in the public debate. Since Autor et al. (2003), much of the research in this field 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 (Acemoglu and Autor, 2011; Autor et al., 2003; Goos and Manning, 2007; Goos et al., 2009; Goos et al., 2014; Spitz-Oener, 2006 and Adermon and Gustavsson, 2015). The finding of such polarization is important for understanding the relationship between the changing occupational employment structure and wage inequality but it is less informative about the changing demand for different types of skills. In this paper, we generate new evidence on the relationship between changing occupational structure and the demand for skills covering both the cognitive and non-cognitive domains.

The favored explanation in the literature for the polarization patterns of the recent past is that technological change has induced a sharp decline in the demand for routine-intensive tasks traditionally performed by occupations in the middle of the wage distribution (Acemoglu and Autor, 2011; Autor et al., 2003; Böhm, 2020; Cortes, 2016; Goos et al., 2009; 2014; Michaels et al., 2014). In this article, we do not challenge this view, instead we complement it by characterizing occupations by the skill-set of the employees (instead of the tasks they perform) in affected occupations. We present what we believe to be the most detailed description yet of how structural change in the form of occupational decline has altered the demand for different types of skills. The aim is to provide insight to the vivid policy debate regarding which skills will be demanded on the labor markets of the future.

To this end, we use very detailed Swedish skills data for nearly all male Swedish workers. The data capture pre-market endowments of eight different intellectual skill components, where four capture non-cognitive productive traits and four capture cognitive abilities. Each of these specific skills are valued across the market and could be considered as “general-purpose” skills that can be transferred across tasks. But as workers with different skills are sorted into different occupations (see Fredriksson et al. (2018)), the skills map well into the “skill-weights” approach of Lazear (2009) where skills are general, but used in different intensities in different parts of the labor market.

Throughout our paper, we relate the initial (2001) worker endowments of traits and abilities within each occupation to the employment...
growth across time (2001 – 2013). As an important prelude, we first show that the skill-use within occupations has remained stable across time, despite the changing task content documented by, e.g., Spitz-Oener (2006) and Atalay et al. (2020). Furthermore, we show that occupations with high-skilled employees pay higher wages, but, at the same time, there is substantial wage variation across occupations with similar skill levels. The wedge between skills and wages may arise because our skill measures are broad in the intellectual dimension but leave out all other wage-related attributes, e.g., manual strength, the ability to cope with hazardous work environments, rent sharing practices and/or other types of specific knowledge that may be acquired through on-the-job learning.

Our main analysis conveys three main insights: First, employment growth in the recent past has had a **monotonic positive relationship** to occupation-specific endowments of the intellectual skills we measure, despite the polarizing relationship to occupation-specific wages. We show that this result is robust to using other direct skill measures (grades from school for men and women) and to many variations in measurement and definitions - including an analysis of how skills and wages relate to the growth of labor demand at the establishment times occupation level.\(^1\) Our analysis unravels the previously undocumented fact that the low-wage occupations that have grown are those that employ comparatively skilled workers. Conversely, the (routine intensive) occupations in the middle of the wage distribution that have declined are those that employ comparatively low-skilled workers. In other words, labor demand has moved away from average-paying occupations with relatively low-skilled employees to lower-paying jobs with relatively high skilled (within the wage-segment) employees. The fact that workers in mid-wage routine occupations appear to have comparatively low skills in our measured dimensions may help explain why these workers tend to struggle to find new employment after displacement as shown by e.g. Bliena et al. (2021).

The second insight is that occupational decline is systematically related to workers' specific **comparative advantages**. We find important differences across different types of cognitive and non-cognitive skills. There has been a particularly strong growth in occupations employing workers with higher-than-average levels of the non-cognitive skill **social maturity** (i.e. extroversion, responsibility and independence) - and **two** of the four cognitive skills - **verbal comprehension and technical ability**. These results suggest that the labor demand increased in occupations that rely on social communication and technical abilities. We also show that these skills tend to be used less in routine-task intensive occupations. At the other end of the scale, occupations where workers primarily rely on **psychological energy** (a non-cognitive trait capturing perseverance and the ability to focus) and **inductive reasoning** (a cognitive ability related to pattern recognition) have declined. These results complement Edin et al. (2022) who document a secular increase in the wage returns to non-cognitive skills relative to cognitive skills. Our results suggest that the key empirical difference in terms of occupational decline is not between occupations that rely on cognitive vs. non-cognitive skills, but between occupations that rely on different types of cognitive and non-cognitive skills. Our results are thus more aligned with Deming (2017) who found that labor demand is shifting towards a combination of communication-related skills (in our case social and verbal ability) and math-skills (in our case, more specifically, technical abilities.)

The third insight is more tentative. We cautiously interpret our results as suggesting that the evolution in the recent past may be informative about the skill-specific demand for labor also in the not-so-distant future. As in most of the literature, our main analysis focuses on the recent past. But since it has been argued that future technological advances will affect a much broader set of tasks, and hence different types of workers (see e.g. Mitchell and Brynjolfsson (2017)), we end the paper by providing results on the relationship between observed occupational skills and **projected future** occupational employment growth from the US Bureau of Labor Statistics. We show that the overall skill level and the same specific skills that were positively related to past employment growth are positively related to future employment growth according to the BLS projections. Thus, the BLS projections do not indicate that empirical lessons from the recent past should be invalid when discussing the skill-specific impact of future changes in labor demand as has been argued by Mitchell and Brynjolfsson (2017) and others. On the contrary, the current trends are likely to continue if (and we acknowledge that this is a big “if”) the BLS projections are reasonably accurate, as they have been in the past; see Edin et al. (2018).

We complement this analysis with an even more tentative analysis where we use assessments of how difficult tasks in different occupations are to automate based on “engineering bottlenecks” as computed by Frey and Osborne (2017) and three measures of task-replacing patents within each occupation taken from Webb (2019). The results suggest that skilled occupations are more likely to be insulated from automation by more “engineering bottlenecks” and covered by fewer task-replacing patents related to Robots and Software. For AI-patents the picture is somewhat different as these tend to be related to high-wage tasks as noted by Webb (2019) and these tasks are also more skill intensive on average. But we show that skilled occupations are less exposed to AI-patents **conditional on the wage**. Thus, although high-wage jobs are in general more exposed to AI-patents, our results imply that tasks-replacing AI-patents are more likely to negatively affect jobs that pay high wages for other reasons than those related to our vector of cognitive and non-cognitive skills.\(^2\)

The paper is structured as follows: Section 2 reviews the literature. Section 3 presents the data and the methods. Section 4 presents the results. Section 5 concludes the paper. Throughout, we focus on delivering the key insights in the main paper. Robustness checks and extensions are found in the appendix, or in our supplementary web appendix.

### 2. Literature

Since Autor et al. (2003) the literature on occupational decline has analyzed the impact of automation on workers through the lens of models where automation alters 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, causing a rise in the demand for well-educated workers and a decline in the demand for low-educated workers. The task-based approach argues 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. The precise nature of the tasks determines if they can be automated or offshored with the help of technology.

The empirical literature has taken this insight 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 or offshoring (Acemoglu and Autor, 2011; Aderon and Gustavsson, 2015; Autor et al., 2003; Goos and Manning, 2007; Goos et al., 2009; 2014). A salient finding is that occupations with a large “routine task” component have declined due to technological advances. The literature has thus converged upon the conclusion that technology and automation have been important factors shaping the changing nature of labor demand. The fact that many of the routine jobs that have been automated

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\(^1\) In addition, each of our eight skill components has a monotonically positive relationship to employment growth.

\(^2\) The results regarding the associations between technological resilience and specific skill components are more mixed and depend on the exact measure of resilience (bottlenecks vs. patents). In particular, all patents classes (Robots, Software and AI) tend to be related to occupations that rely more on technical skills.
were found in the middle of the wage distribution implies that the occupational decline has caused polarisation in terms of employment growth. Polarization in this context implies that middle-wage occupations have declined whereas occupations at the higher and lower end of the occupational wage spectrum have instead grown. The impact on occupational wages is more intricate since displaced workers from middle-wage jobs will provide additional downward wage pressure on low-wage jobs, and since the wage effects will be related to the composition of employees (Böhm, 2020; Böhm et al., 2019).

In the literature, the wage rank is often interpreted as an all-encompassing measure of skills, and it is thus commonplace to refer to polarization 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 impact on different types of workers it is useful to have a more direct definition of “skills”. We argue that deriving a better understanding of the precise traits and abilities that are associated with an occupational decline is of key importance. In particular, this aspect may be relevant for policy makers since traits and abilities can be changed through interventions within the educational system (Carlsson et al., 2015). In this paper, we therefore use external measures of skills, to be precisely defined below. These measures allow us to contrast the occupation-level wage rank commonly used in the literature to similarly defined measures of the occupation-level skill rank.3

Parts of our analysis focus on the changing demand for specific skills. Here, the most related is probably Deming (2017) who studies the changing demand for social skills and math skills. The focus is, however, slightly different as we are interested in understanding the changing allocation of labor demand across occupations (as in the polarization literature) whereas Deming (2017) focuses on the changing wage returns to different skills. Other studies focusing on the changing wage returns to skills (rather than employment shares) have documented the changing market returns to cognitive vs. non-cognitive skills, see Edin et al. (2022). A closely related study in terms of methods is Cortes et al. (2017) which presents a thorough investigation of the association between occupational decline and worker demographics, but without precise measures of skills. Other related studies include Cortes (2016) studying the demand for skills in a general equilibrium model, Böhm (2020) which presents estimates of task prices under routine-biased technical change and Feng and Graetz (2020) which shows how training requirements relate to polarization.4 A main addition relative to all of these papers is that we are able to use much richer data to study the changing demand for skills across a wide set of dimensions.

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 and organizations such as the OECD (see e.g. Nedelkoska and Quintini (2018)) and groups of researchers in economics and beyond have spent considerable effort trying to project which types of tasks are most likely to be automated in the near and distant future. See e.g. Mitchell and Brynjolfsson (2017) for a discussion regarding factors that may determine the automation potential of different types of tasks in the future.

3 A booming recent literature, see e.g. Deming and Kahn (2018) and Atalay et al. (2020) for early examples, analyzes skill demand as advertised in job postings. Our approach is different as we are using direct measures of employee skills.

4 For the impact of industrial robots see Graetz and Michaels (2018) and Acemoglu and Restrepo (2020). See also Michaels et al. (2014) for a study of the interaction between ICT-use and education.

The most well-known example of occupation-specific projections are probably those made by the US Bureau of Labor statistics which we rely on as the main projection in this paper. Other assessments have more specifically focused on different aspects of technology and automation. Here, Frey and Osborne (2017), Arntz et al. (2016), Nedelkoska and Quintini (2018) and Webb (2019) use different approaches to the same general aim. We discuss their methods and the critique raised against some of these studies in more detail in the data section. But already here it is useful to note that both the employment projections and the automation assessments focus on the evolution within existing occupations, a process which is obviously very difficult to predict. An even harder question, however, is what the tasks performed in completely new occupations will be, as these may fall outside of existing occupational classifications. The projections have very little to say about this important aspect - and so will our own analysis.

3. Data and methods

3.1. Outline of the empirical set-up

Our set-up closely follows the conventions in the polarization literature in order to facilitate comparisons with earlier studies. For replication, we first rank occupations according to mean wages in a start year (2001) and relate these to the employment growth of the same occupations during a follow-up period (2001-13). The raw wage and occupation data (Strukturlonstatistiken) are based on a stratified sample covering half of all employees in Sweden. The (baseline) time frame is the longest possible with consistent 3-digit occupational codes.5 For replication purposes, we also relate our analysis to data on routine intensity from Autor and Dorn (2013) and Goos et al. (2014).

For our main analysis, we use information on worker skills as assessed during the mandatory military enlistment. Except where otherwise explicitly noted, our use of the term skills refers to these enlistment data.

Our final set of resources is projections of future occupational employment growth. Here, we use the official 10-year projections published by the US Bureau of Labor Statistics. We complement this analysis by using assessments of future “automation risks” based on “engineering bottlenecks” from Frey and Osborne (2017), and data on patent exposure from Webb (2019).

3.2. Occupation-specific skill endowments

We characterize occupation-specific skill endowments in eight dimensions using data from the Swedish military enlistment. The data include four cognitive abilities, assessed through written tests, and four non-cognitive productive traits assessed by trained psychologists during an interview. (We discuss the components below in detail.) The skills were assessed around the age of 18, i.e. before labor market entry and before potential entry into higher education, for 90 percent of all Swedish males born between 1951 and 1976.6

We first analyze the skills through a joint overall score, and then as eight separate components. The overall score sums the eight scores to provide the broadest possible assessment of each worker’s complete set of “intellectual” skills. When referring to skill ranks of occupations, we

5 To some extent this matches well into the standard approach to measuring job-polarization which tends to use weights based on the employment shares in the start year and therefore, by construction, put a low weight on the nature of new occupations when assessing how a changing occupational structure is affecting the wage distribution.

6 Our occupational employment data are downloaded from Statistics Sweden’s web page, see www.scb.se.

7 Since the reporting scales changed during the sample period, we standardize the test scores (mean = 0, standard deviation = 1) within each cohort of draftees to ensure comparability.
rank occupations based on the mean skill endowments of the workers, corresponding to the wage ranks used in the polarization literature. The fact that we analyze our skill measures after aggregating them to the level of occupations alleviates the 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. (2022)).

When we analyze the eight components separately, we start from the presumption that some aspects of the skill vector are more productive in some jobs than in others. We use the data as processed by Fredriksson et al. (2018) who analyzed the data with a completely different aim – they study hiring and separation patterns across jobs and occupations in the cross-section, with a focus on labor market experience. 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. 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). 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 To ensure comparable metrics, we use the same set of workers when ranking occupations according to wages, but this is not important for the results.

3.2.1. The four dimensions of cognitive ability

The first two cognitive scores in our raw data capture verbal and technical comprehension. The remaining two measure spatial ability which is a standard IQ-test component related to the ability to process spatial relations (e.g. “metal folding”) and inductive ability, i.e. the ability to identify patterns in data. For illustrative purposes, Table 1 lists the occupations where workers are most (and least) endowed with each type of cognitive ability. We show three columns, one for each tercile of the occupational (overall) skill intensity. The table shows, e.g. that librarians are particularly endowed with verbal comprehension and inductive reasoning whereas photographers tend to have large amounts of technical understanding and spatial ability.9

3.2.2. The four dimensions of non-cognitive productive traits

As part of the enlistment, a specially trained psychologist meets with the subject to assess his non-cognitive productive traits during a structured interview.10 The purpose of the interview is to quantify the subject’s endowments of four useful non-cognitive traits. Social maturity measures extraversion, responsibility and independence. Emotional stability measures tolerance to stress. Intensity measures the assessed ability to activate without external pressure. Psychological energy measures the assessed perseverance and the ability to focus.

Table 2 lists examples of occupations where workers are endowed with large and small amounts of each type of non-cognitive productive trait. The table shows, e.g., that nurses are particularly endowed with social maturity whereas protective service workers are endowed with emotional stability and intensity and health professionals have high levels

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8 Håkanson et al. (2021) study changes in the sorting of workers to firms by cognitive and non-cognitive skills and Edin et al. (2022) study the changing returns to cognitive and non-cognitive skills.

9 In the web appendix, we show further descriptive statistics that relate skill intensities to employment size.

10 The process and contents of the measure are described in great detail in Mood et al. (2012) and our interpretation and labeling of the skills rely on their work.
Table 2
Most and least skilled occupations - Non-cognitive skills.

<table>
<thead>
<tr>
<th>Overall skills</th>
<th>Low</th>
<th>Middle</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Maturity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most intensive occ.</td>
<td>Mining</td>
<td>Nurses</td>
<td>Senior officials</td>
</tr>
<tr>
<td>Skill rank</td>
<td>21</td>
<td>64</td>
<td>90</td>
</tr>
<tr>
<td>Wage rank</td>
<td>74</td>
<td>64</td>
<td>99</td>
</tr>
<tr>
<td>Least intensive occ.</td>
<td>Manufacturing workers</td>
<td>Librarians</td>
<td>Computer professionals</td>
</tr>
<tr>
<td>Skill rank</td>
<td>1</td>
<td>38</td>
<td>67</td>
</tr>
<tr>
<td>Wage rank</td>
<td>13</td>
<td>5</td>
<td>81</td>
</tr>
<tr>
<td>Emotional Stability</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most intensive occ.</td>
<td>Builders</td>
<td>Protective service workers</td>
<td>Fishery workers</td>
</tr>
<tr>
<td>Skill rank</td>
<td>32</td>
<td>56</td>
<td>82</td>
</tr>
<tr>
<td>Wage rank</td>
<td>41</td>
<td>28</td>
<td>44</td>
</tr>
<tr>
<td>Least intensive occ.</td>
<td>Helpers and cleaners</td>
<td>Handicraft workers</td>
<td>Computer professionals</td>
</tr>
<tr>
<td>Skill rank</td>
<td>1</td>
<td>44</td>
<td>67</td>
</tr>
<tr>
<td>Wage rank</td>
<td>8</td>
<td>16</td>
<td>81</td>
</tr>
<tr>
<td>Intensity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most intensive occ.</td>
<td>Textile workers</td>
<td>Protective services workers</td>
<td>Police officers</td>
</tr>
<tr>
<td>Skill rank</td>
<td>31</td>
<td>56</td>
<td>86</td>
</tr>
<tr>
<td>Wage rank</td>
<td>4</td>
<td>28</td>
<td>75</td>
</tr>
<tr>
<td>Least intensive occ.</td>
<td>Restaurant helpers</td>
<td>Librarians</td>
<td>Religious professionals</td>
</tr>
<tr>
<td>Skill rank</td>
<td>3</td>
<td>38</td>
<td>81</td>
</tr>
<tr>
<td>Wage rank</td>
<td>1</td>
<td>5</td>
<td>85</td>
</tr>
<tr>
<td>Psychological Energy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most intensive occ.</td>
<td>Animal producers</td>
<td>Business agents</td>
<td>Health professionals</td>
</tr>
<tr>
<td>Skill rank</td>
<td>27</td>
<td>63</td>
<td>100</td>
</tr>
<tr>
<td>Wage rank</td>
<td>10</td>
<td>57</td>
<td>97</td>
</tr>
<tr>
<td>Least intensive occ.</td>
<td>Manufacturing workers</td>
<td>Librarians</td>
<td>Computer professionals</td>
</tr>
<tr>
<td>Skill rank</td>
<td>1</td>
<td>38</td>
<td></td>
</tr>
<tr>
<td>Wage rank</td>
<td>13</td>
<td>5</td>
<td>81</td>
</tr>
</tbody>
</table>

Note: The table shows the most and least skill intensive occupations in each dimension of our non-cognitive skill measures, where we split occupations into low- (col 1), middle- (col 2) and high (col 3) skilled occupations according to the mean overall skill intensity by tenured employees in 2001. The table also shows, for each occupation, the rank in the overall skill and wage distribution.

3.2.3. Data processing

Our baseline analysis first divides the economy into 110 occupations characterized by 3-digits according to the Swedish nomenclature SSYK (similar to ISCO-88). Then, 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 between the 2001–2013 period. This further excludes “higher” officials in public services and “manual construction laborers”, both of which are tiny occupations. To ensure the robustness of our main results, we present robustness tests related to these choices in the appendix.

The routine task index used in the paper is based on Autor et al. (2003) and David et al. (2006) mapped into the European occupational classification by Goos et al. (2014). The 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.

3.3. Projections and assessed resilience to specific technologies

In our interpretation, much of the interest by researchers and policy-makers in the changing nature of labor demand stems from concerns about how labor demand will change in the future. The standard way of addressing this issue is to study the evolution in the recent past. At the same time, many scholars argue that changes in the near future will be very different from those in the recent past. Therefore, we find it useful to extend our analysis by studying the changes in skill-demand that are implied by existing projections of a future occupational decline, even though we do not know how accurate these projections will turn out to be.

Our main tool is projections of future employment growth by occupation published by the US Bureau of Labor Statistics (BLS). These projections, described in detail at the BLS website, are best summarized as forward-looking expert assessments of future employment structures based on expectations of technological innovations, changes in business practices, reorganizations, off-shoring and cross-industry changes in demand. The method first assesses the future demand in each industry (partly using formal statistical models) and then assesses the future share of each occupation within each industry using:

“... a conceptual framework which divides industry employment between occupations based on expected, structural changes in the demand for those occupations within a given industry. To project these changes in occupational demand, 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. These reviews identify structural changes in the economy which are expected to change an occupation’s share of industry employment.”

The analysis thus incorporates forward-looking informed expert judgments about new trends that may influence occupational demand, such as new manufacturing techniques or shifts in customer prefer-
ence.\textsuperscript{14} This process results in an assessment of whether labor demand will grow or shrink, and if so, by how much. For occupations that are expected to change in size, a reason is stated. Examples from the 2016 projections that illustrate some of the factors that are considered are presented below:

- "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 cafes, hospitals, and government, requiring more chefs and head cooks to oversee food preparation in these establishments."

Although it may appear near impossible to predict future employment changes, we note that BLS projections in the past have had a strong relationship to long-run trends on the Swedish labor market as shown by Edin et al. (2018) who use the 1985 version of these projections and verify that they predict occupation-specific employment growth in Sweden between 1985 and 2013. Despite noise arising from changes in occupational codes, they find that a BLS projection index for the US labor market in 1985 explains 22 percent of the variation in employment growth across the coming 28 years in Sweden.

The BLS projections constitute a close relative to our data on actual developments in the recent past as they aim at covering future changes in labor demand, irrespective of the underlying source. They thus serve as our main tool for assessing the skill-composition in those occupations that are most likely to grow in the future. But most concerns about the future seem to focus on the role of technology, a factor that the literature has highlighted as central for the occupational decline in the recent past. Therefore, we also complement the BLS-projections with assessments of the occupation-specific resilience to labor replacing technological innovations (automation).

The first assessment of resilience is drawn from Frey and Osborne (2017). This paper argues that developments relying on artificial intelligence will enable technology to replace labor across a wide range of non-routine tasks and argues that AI will make it "possible to automate almost any task, provided that sufficient amounts of data are gathered for pattern recognition". They count the tasks that are insulated against automation because of engineering bottlenecks. Their methodology starts from 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 the O’NET database. Bottleneck-related tasks relate to finger dexterity, manual dexterity, awkward work positions, originality and fine arts, social perception, negotiation, persuasion, and caring for others. The importance of (the interplay between) these respective tasks is determined by their ability to predict a subjective measure of automation by computer scientists.\textsuperscript{15} The paper drew much attention because it claimed that automation will replace many jobs in the near future, and that the new displaced jobs will be very different from those jobs displaced in the recent past. As pointed out by Arntz et al. (2016) and Nedelkoska and Quintini (2018), it is very likely that Frey and Osborne (2017) paint an overly simplified picture of the occupations and their associated tasks, in particular as they assume that there is no task substitution within occupations. These critical papers provide adjusted versions of the Frey and Osborne (2017) methodology and find substantially lower levels of average automation risks. However, we will only use the data to rank occupations based on the assessed resilience to automation of the tasks in each occupation (many bottlenecks = high resilience) and this ranking is very closely related to the critical assessments by Nedelkoska and Quintini (2018).\textsuperscript{16} Even though it seems highly implausible that the overall rates of automation suggested by Frey and Osborne (2017) are accurate, their data may still be informative about whether or not an occupation is associated with many tasks that are difficult to automate.\textsuperscript{17}

Our second set of assessments regarding resilience to technology are provided by Webb (2019). That paper analyzes patent titles and texts from Google Patents public data, matched to data on tasks from O’Net, in order to measure the exposure of each occupation to labor replacing technologies. The patent titles identify what each patent can do, and then match verb-noun pairs from these titles to descriptions of tasks within occupations. In essence, a patent is labor-replacing in a specific occupation if the patent description includes “do” “this” (e.g. “revise “paper”) and the occupation description also contains “do” “this”. Labor replacing patents are then grouped into three categories: robotics (capturing industrial robots, e.g. to “move object” or “clean instrument”), software (e.g. to “record data” or “control display”) and AI (machine learning algorithms, e.g. “neural networks”). We will use each of these assessments to illustrate the association between different types of labor replacing-patents and the skill use within each of the occupations. Webb (2019) shows that robotics patents are mostly related to low-wage occupations, software patents are more concentrated in the middle of the wage distribution, whereas AI patents are mostly related to tasks in high wage occupations. As for the other measures, we rank occupations by resilience to automation (few patents = high resilience) where a high value refers to a resilient occupation.

4. Results

4.1. Background results on wages, skills, tasks and employment growth

Our main analysis relates initial skill intensities to changes in employment at the occupational level. But as a prelude, we document two important, but novel, empirical regularities. The first is the high persistence in skill intensities within occupations across time. Fig. 1a shows that the average skills of workers in occupations during 2001 explain (in a statistical sense) 97 percent of the corresponding variation across occupations in 2013. This stability is important because it suggests that occupations do appear to rely on similar types of workers in different years, despite the well-documented process of task changes within occupations, see e.g. Spitz-Oener (2006) and Atalay et al. (2020).

The second crucial pattern is illustrated in Fig. 1b. The figure shows that occupations with highly skilled workers tend to pay higher wages on average. But wages clearly vary for other reasons as well. The figure displays a considerable wage variation across occupations with similarly skilled workers. In a statistical sense, the skill intensity explains 64 percent of the variation in wages across occupations. The remaining “unexplained” variation is important since we will show below that wages and skills have different relationships to employment growth, in particular at the lower end of the distributions. The figure includes a 45-degree line along which occupations are equally ranked in terms of skills and wages. Occupations above (on-the left side of) this line have a higher wage rank than “expected” from their skills. Equivalently, they have a lower skill rank than expected from their wages. In some of the analyses that follow below, we will separately study occupations that are on the two sides of the 45-degree line.

\textsuperscript{14} Frey and Osborne (2017) describe the BLS projections as being “... based on historical staffing patterns...”. This description appears inaccurate at least for this more recent period as illustrated by the quote above.

\textsuperscript{15} The ensuing weights are estimated through a Machine Learning algorithm.

\textsuperscript{16} In the web appendix we show that data from Nedelkoska and Quintini (2018) for Sweden provide similar rankings of “automation risks” across occupations as Frey and Osborne (2017).\textsuperscript{17} In practice, we use the automation potentials as transformed into Swedish occupations by Heyman et al. (2016) and 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. Recent research by Gardberg et al. (2020) shows that the predictions are associated with past occupation-specific employment growth in Sweden. Scholl and Hanson find a stable (over time) positive relationship between the measure and automation.
Next, we show that two of the most well-known empirical regularities emphasized in the earlier literature are present in our data as well. Most previous studies have found a U-shaped relationship between occupational employment growth and the initial wage ranks of these occupations. We replicate this pattern in Fig. 2a. The figure 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, e.g., Goos et al. (2009), which also included data for Sweden.\textsuperscript{18}

Furthermore, Fig. 2b replicates a second well-established empirical regularity; occupations that are intensive in routine tasks according to the measures in Goos et al. (2014) are declining. This relationship is monotonically negative and of increasing magnitude.\textsuperscript{19} The result is important because it suggests a tight link between routine-task replacing technology and occupational decline.

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\textsuperscript{18} Fig. A.1 shows that many of the declining occupations are found in manufacturing and among machine operators while growing occupations are instead drawn from a more mixed set of groups.

\textsuperscript{19} The web appendix provides point estimates and further analyses of wage ranks and routine intensity.
Fig. 3. Growth by skill-to-wage rank ratio.

Note: The 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. The x-axis ranks occupations according to mean wages but separates occupations according to whether or not the skill rank is higher than the wage rank. All lines represent predictions from regression equations on the following form: \( \text{Employment Growth}_{\text{occupation}} = a + b \times \text{Rank}_{\text{occupation}} + c \times (\text{Rank}_{\text{occupation}})^2 \), where rank is defined as the x-axis of the respective panel.

4.2. Main results on employment growth and skill levels

Turning to our first main result, we start by analyzing 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 described in the data section. The results presented in Fig. 2c show that the relationship between skill ranks and employment growth is positive throughout the distribution. This result stands in clear contrast to the well-known U-shaped relationship between wage ranks and employment growth presented Fig. 2a. As we discuss below, this dichotomy with a U-shaped relationship between wages and employment growth but a monotonically positive relationship between skills and employment growth is very robust.

Jointly, our results imply that the skill-levels and wage-levels have opposing relationships to employment growth at the bottom of the distributions. To align the two results it is instructive to split the sample according to the relationship between skills and wages. We thus define an indicator variable \( I = \text{skill}^{\text{rank}} > \text{wage}^{\text{rank}} \) which takes the value of one for occupations that are higher up in the skill distribution than in the wage distribution – i.e. where the (ranked) skills were higher than the (ranked) wages in our start year (below/to the right of the 45° line through Fig. 1b as discussed above). This variable allows us to separately study occupations with comparatively high vs. low skills at different parts of the wage distribution. In Fig. 3 we show the association between wage ranks and employment growth (polarization) after splitting the data by this indicator. Comparing across the fitted lines at any given wage level gives the differences in employment growth between occupations with similar wages (in 2001) but with comparatively high vs. low levels of skills. It is evident that employment has consistently grown more in occupations where the workers were comparatively more skilled at each given wage level. This is particularly true in the mid-to-low part of the wage distribution. For each of these lines, the polarizing pattern remains. The fitted quadratic line is below zero (hence, declining occupations) for a long range of low skill-to-wage occupations but above zero (growing occupations) in the full range for high skill-to-wage occupations.

The results thus imply that employment has systematically grown more in low- to mid-wage jobs where workers had more skills than in other jobs with similar wages. Table 3 illustrates the same pattern in a regression framework showing that there is a statistically significant difference in employment growth depending on the relative skill intensity at the lower part of the distribution.

Overall, these results thus imply that the routine intensive mid-wage jobs that have declined (most likely because of technology according to the existing literature) paid relatively high wages to compensate for other characteristics than those captured by our vector of skills in the cognitive and non-cognitive domains, whereas the growing low-wage jobs instead employ workers with a disproportional abundance of these skills. Examples of mid-wage, but low-skilled, occupations include builders, miners and metal/machinery workers, and office clerks. Examples of growing low-paid occupations with higher overall skills are personal care workers and customer service clerks (see Appendix Fig. A.1 and also Tables 1 and 2). The transformation of labor demand from (relatively) high-paying jobs with a low need for our measured cognitive and non-cognitive 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 because of firm pay practices or because of firm-specific manual skills.

4.2.1. Robustness checks and variations

Basic robustness: We have verified that the findings regarding a polarizing relationship between wage-ranks and employment growth, and the results regarding a monotonically positive relationship between skill-ranks and employment growth, are robust to a number of variations in the model and the data used. More specifically, the main message is unchanged if we define a more granular set of occupations by interacting the occupation-codes with 10 industry groups, if we use a smoothed polynomial instead of imposing the quadratic functional form, if we change the definition of start and end points (instead taking an average of three years), or if we instead use unweighted data. These variations, and some additional checks, are shown in Figs. A.2 and A.3 in the appendix.

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$^{\text{rank}} > $Wage$^{\text{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.

Table 3

<table>
<thead>
<tr>
<th></th>
<th>(1) All occupations</th>
<th>(2) Low wage</th>
<th>(3) High wage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outcome: Employment growth</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$</td>
<td>\text{Skill}^{\text{rank}} &gt; \text{Wage}^{\text{rank}}</td>
<td>9.33</td>
<td>18.56</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.031</td>
<td>0.111</td>
<td>0.017</td>
</tr>
</tbody>
</table>

In the web appendix we show auxiliary results suggesting that these “high-pay, low-skills” occupations are more likely to be found in “high rent” establishments, i.e. establishments that pay higher wages to identical workers as identified from the AKM framework of Abowd and Margolis (1999).

In the web appendix we show relationships to wage growth (“wage polarization”) where the results are less clear, both in our setting and in the literature in general.
Grades instead of skills: An important limitation of our used skills data is that they are only available for men. In addition, it may be argued that their content is determined by “military-specific” needs and therefore not equally relevant for all types of jobs. As a robustness check, Figs. 4a and 4b therefore explore high school GPA as an alternative measure of overall skills. These grades have the advantage of being available for both men and women, but at the disadvantage of mostly being related to cognitive skills; see Kramarz et al. (2021). In addition, these grades have a mechanical relationship to educational opportunities through admissions systems. Reassuringly, however, the association between skill ranks and grade ranks across occupations is very strong (Fig. 4a). Furthermore, the association between “grade intensity” and employment growth of occupations is clearly monotonically possible (Fig. 4b). In Fig. 4c, we instead use average years of education (imputed from the level of education) and the results are very similar to those relying on grades.

Jobs instead of occupations: The main analysis discussed above is performed at the occupational level, as is most of the literature, but the immediate consequences of structural change are felt by workers who lose their jobs, regardless of the 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 conducted 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 (i.e. using job-level employment growth as the outcome). The results shown in Fig. A.4 in the appendix reaffirm the picture that employment growth has a much more positive relationship to skills than to wages in the lower part of the distribution.

4.3. Employment growth and comparative skill advantages

The results presented above focus on overall skills. But our data allow us to examine the granularity underlying the aggregate score. Do workers in growing vs. shrinking occupations have comparative advantages in different types of skills? This question is analyzed in Table 4. The table first shows the linear coefficient related to the above discussion on overall skills (Column 1). Then, we redo this analysis controlling for the wage rank with a quadratic term (Column 2), and the association is, in fact, marginally stronger when estimated conditional on wages. This result reflects the pattern discussed above wherein employment growth has the most in occupations where workers are endowed with more skills, conditional on their wages.

We then turn to the eight specific skill measures. Column (3) shows the univariate regression results where each specific skill explains employment growth. The results show an unconditional skill bias in each of the 8 dimensions. As shown in Appendix Fig. A.5, all these associations are monotone if allowing for a quadratic functional form. These results are yet another reflection of the overall skill bias in the occupational employment growth. But the more profound question is if occupational employment growth has favored workers with comparative advantages in some dimensions. As a first step towards isolating the role of comparative advantages, Column (4) repeats the analysis conditional on wage rank and the positive estimates remain with only marginal changes.

To separate out the comparative skill advantages, i.e. the independent role of each skill conditional on the others, we present estimates from regressions where occupational employment growth is explained by the full vector of eight separate skill variables, each element capturing one type of specific skill. The results are presented without control-

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): the y-axis ranks occupations according to the average skills of tenured males in 2001 while the x-axis ranks occupations according to the average grades of employees in 2001. Panels (b) and (c): the y-axis displays the percent change in employment between 2001 and 2013 by occupation according to Statistics Sweden’s official calculations. Panel (b) x-axis ranks occupations according to the mean overall skill intensity of male tenured employees in 2001. Panel (c): the x-axis ranks occupations according to the average number of completed years of schooling among male tenured employees in 2001.

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23 See Black and Spitz-Oener (2006) and Cor (2021) for studies of technology, tasks and gender.
24 In the web appendix we show that the sorting-patterns across occupations based on grades are very similar for men and women.
ling for wages in Column (5) and with a wage control in Column (6). The estimates point in a very similar direction in the two models, although there are some differences in magnitudes and precision. Since our objective is to isolate the role of comparative skill advantages in different dimensions, we focus our interpretation on the model in Column (6) which allows wages to remove the impact of other unobserved attributes. The adjusted $R^2$ grows from 0.18 (Column 2) to 0.29 (Column 6) when including the specific skills instead of the joint skill score alongside the wage. This illustrates that occupational decline has a statistical association to the specific skill use in the occupations (adjusted R2 moves from 0.06 to 0.12 when adding specific skills in models without controls for wages). The table orders the skill from top to bottom according to the size of the point estimates in Column (6), ranging from the most positive to the most negative estimate. As is evident, the conditional associations are indeed very different for different scores, and these also vary within the groups of cognitive abilities (indexed by A) and non-cognitive traits (T) that have been emphasized in the previous literature. The results show that the social maturity trait as well as the verbal and technical abilities have strong positive associations with employment growth, whereas the psychological energy (i.e. perseverance and ability to focus) trait and the inductive (i.e. pattern recognition) cognitive ability have negative associations with employment growth conditional on the other skills.

As for the results discussed in the previous subsection, we use the appendix (see Fig. A.6) to show that the associations between comparative skill advantages and employment growth are robust to a number of variations in the estimated model.25

In the two final columns of Table 4, we use the routine-task intensity as the outcome (instead of employment growth) in regression models that otherwise mirror the models used in Column (5) and Column (6). These results thus describe the association between routine-task intensity at the occupational level and the skill intensities (in eight dimensions) of workers employed in the occupation with and without controls for wages. The results show that the same skills that were positively related to employment growth (although not significant for verbal skills) also appear relatively scarce in routine-intensive occupations, and vice versa. Thus, jobs with low routine intensity, that we know to have remained resilient against previous waves of automation, also employed workers with comparative skill advantages in terms of social maturity and technical abilities. In contrast, workers in declining routine intensive jobs instead tend to rely more on inductive abilities.

### 4.4. Employment projections and assessed resilience to automation

Finally, we turn to the projected future. As noted above, a large part of the concerns regarding the future of labor rests on the fear that tech-

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25 In the web appendix we further show that verbal skills are more important as a predictor in high-wage occupations, whereas social maturity and technical abilities matter more in low-wage occupations.
Table 5
Correlations between past/projected growth and other technology-based resilience measures.

<table>
<thead>
<tr>
<th>Panel A: Past and projected growth</th>
<th>Past growth</th>
<th>Projected growth (BLS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past growth</td>
<td></td>
<td>0.341 (0.001)</td>
</tr>
<tr>
<td>Projected growth (BLS)</td>
<td>0.341</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Panel B: Other technology-based resilience measures</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frey &amp; Osborne</td>
<td>0.219</td>
<td>(0.027) 0.467 (0.000)</td>
</tr>
<tr>
<td>Webb Software</td>
<td>0.105</td>
<td>(0.284) 0.347 (0.001)</td>
</tr>
<tr>
<td>Webb Robot</td>
<td>0.091</td>
<td>(0.353) 0.310 (0.003)</td>
</tr>
<tr>
<td>Webb AI</td>
<td>0.062</td>
<td>(0.523) 0.153 (0.149)</td>
</tr>
</tbody>
</table>

Note: Panel (a) shows the correlation between ranked percent change in employment between 2001 and 2013 and ranked future employment growth as projected by the US Bureau of Labor Statistics transposed into Swedish occupational codes by the authors. Panel (b) shows the correlations between past and projected growth and (i) the ranked resilience as projected by Frey and Osborne (2017) transposed into Swedish occupational codes by Heyman et al. (2016), (ii) ranked resilience to Software, Robot and AI technology as projected by Webb (2019). Each observation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Reported in parenthesis is the significance level of each correlation coefficient.

Table 6
Projections and overall skills.

<table>
<thead>
<tr>
<th>Panel A: Past and projected growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skill rank</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R-squared</td>
</tr>
<tr>
<td>Controls for wage rank</td>
</tr>
<tr>
<td>Panel B: Other technology-based resilience measures</td>
</tr>
<tr>
<td>F&amp;O</td>
</tr>
<tr>
<td>Skill rank</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R-squared</td>
</tr>
<tr>
<td>Controls for wage rank</td>
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<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Note: The dependent variables are defined as follows: Panel A, Column (1) and (2) Past growth: change in actual growth expressed as percent between 2001 and 2013 by occupation according to Statistics Sweden’s official calculations. Columns (3) and (4) Projected BLS: ranked change as projected by the US Bureau of Labor statistics transposed into Swedish occupational codes by the authors. Panel B: Columns (1) and (2) Projected Frey and Osborne: ranked resilience as projected by Frey and Osborne (2017) transposed into Swedish occupational codes by Heyman et al. (2016). Columns (3) and (4) Projected Webb: ranked resilience as projected by Webb (2019) transposed into Swedish occupational codes by the authors. Each observation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). The 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. The table shows the estimates with and without controls for the initial wage rank with squares. Wage rank ranks occupations according to mean wages in 2001.

In order to able to compare the BLS projections to the other projections we use, we rank occupations from lowest projected growth to highest projected growth in the analysis.

In Frey and Osborne (2017). Furthermore, more skill intensive occupations are less exposed to both Robot patents and Software patents as measured by Webb (2019). However, the estimate for AI-patents is negative, suggesting that there are more task-replacing AI-patents covering skill intensive occupations. This is related to the fact that AI-patents tend to cover tasks in high wage occupations as shown in Webb (2019). When we condition on wages, however, the results for all measures are firmly positive. This implies that jobs that are comparatively intensive in our measured skills, conditional on their wage, are less exposed to all...
forms of task-replacing patents, including AI. Thus, even though the AI patents indicate a reversed relationship to the wage, none of our results indicate that the trend we have seen in the recent past, wherein occupations that are more skill-intensive than other occupations with similar wages grow more, will be reverted in the near future.

Finally, we relate the specific skills to the projected future and to the assessed resilience to automation. Our main results, related to the BLS projections, displayed in Column (2) of Table 7, imply that occupations that employ workers with high levels of social maturity and verbal comprehension that we showed above have been growing in the past (the results repeated in Column 1) are projected to continue to grow. Meanwhile, the decline in occupations employing workers with large endowments of inductive reasoning is projected to continue. Thus, in these key dimensions, the projection suggests that occupational decline will continue to have a similar relationship to workers’ comparative advantages skills as in recent decades. The main difference is a projected 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).

The table also shows associations between specific skills and the assessed resilience to technology. Here, the results are more mixed. The results for engineering bottlenecks according to Frey and Osborne (2017) are again very similar to the BLS projections and thus, also to the past (again, in some contrast to the narrative of the original paper). This result is, however, not in line with the results derived from the patent data. In terms of the three dimensions of patents, the one consistent result is instead that these are concentrated in occupations that use workers with high technical abilities. One possible interpretation of these results is that patenting in general is more frequent in the technical domain.

5. Conclusions

In this paper, we measure the skill content of occupations by using the characteristics of tenured workers in each occupation. Our skill-vector contains four cognitive and four non-cognitive elements. We show that the skill content of occupations remains stable over time. Skills are strongly related to wages, but wages clearly vary for other reasons as well.

Our results consistently show that wages and our broad measure of cognitive and non-cognitive skills have very different relationships to employment growth: Occupation-level employment growth is monotonically skill-biased towards our composite measure summarizing all eight skill components, despite the non-linear relationship between employment growth and wages (polarization). At every wage level, occupations that employ workers with higher skills (conditional on the wage) tend to grow more. This is particularly true at the lower end of the distribution. Growing low-wage occupations rely on more skilled workers than their wage ranks would suggest, whereas the converse is true for the declining, routine intensive, mid-wage occupations. The results thus suggest that labor demand has moved away from average-paying jobs with a low need for cognitive and non-cognitive skills towards low-paying jobs with a relatively high need for such skills. This process may explain why workers in declining routine occupations in the middle of the wage distribution appear to suffer from long-term adverse effects of job loss (see e.g. Bliena et al. (2021)) as the transition into growing low-wage jobs may demand more in terms of general skills than these workers possess, despite the fact that their pre-displacement jobs were relatively well paid.

The difference in results based on skills and wages can arise 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, rent sharing practices and knowledge that is specific enough not to be captured by any of our general skill measures. Omitted aspects may, among other things, include rents from firm-specific skills acquired through on-the-job training. Our results suggest that a deeper exploration of the relative importance of unobserved earnings-related factors and their role in the decline of middle wage occupations is a key topic for future research. A tentative analysis presented in our web appendix suggests that occupations with comparatively high wages relative to the workers’ skills tend to be found in “high wage establishments” as defined by Abowd and Margolis (1999), i.e. in establishments which, in general, pay a higher wage premium to identical workers.27

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27 It is possible that the combination of relatively “high” wages and “low” skills has contributed to the decline of mid-wage occupations if these were overpaid. However, the strong association between decline and routine intensity, and the international uniformity of these patterns, suggests that it is unlikely that the pattern is driven by country-specific institutional features.
Table 7
Projections and specific skills.

<table>
<thead>
<tr>
<th></th>
<th>Past</th>
<th>Projected growth</th>
<th>Occ. resilience</th>
<th>Occ. resilience</th>
<th>Occ. resilience</th>
<th>Occ. resilience</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BLS</td>
<td>F&amp;O</td>
<td>Webb</td>
<td>Software</td>
<td>Webb</td>
<td>Webb</td>
</tr>
<tr>
<td>Social Maturity (T)</td>
<td>1.479*</td>
<td>2.246**</td>
<td>2.121**</td>
<td>0.665</td>
<td>0.912</td>
<td>1.054</td>
</tr>
<tr>
<td></td>
<td>(0.809)</td>
<td>(1.030)</td>
<td>(0.911)</td>
<td>(0.684)</td>
<td>(0.779)</td>
<td>(0.997)</td>
</tr>
<tr>
<td>Verbal (A)</td>
<td>1.427**</td>
<td>1.754**</td>
<td>2.125*</td>
<td>-0.619</td>
<td>-2.067***</td>
<td>-0.568</td>
</tr>
<tr>
<td></td>
<td>(0.579)</td>
<td>(0.751)</td>
<td>(1.077)</td>
<td>(0.669)</td>
<td>(0.774)</td>
<td>(1.060)</td>
</tr>
<tr>
<td>Technical (A)</td>
<td>1.050**</td>
<td>0.001</td>
<td>0.674*</td>
<td>-1.187***</td>
<td>-1.095***</td>
<td>-0.836*</td>
</tr>
<tr>
<td></td>
<td>(0.436)</td>
<td>(0.547)</td>
<td>(0.405)</td>
<td>(0.363)</td>
<td>(0.416)</td>
<td>(0.456)</td>
</tr>
<tr>
<td>Emotional Stability (T)</td>
<td>0.599</td>
<td>-1.733**</td>
<td>-3.049***</td>
<td>0.338</td>
<td>0.478</td>
<td>0.391</td>
</tr>
<tr>
<td></td>
<td>(0.718)</td>
<td>(0.777)</td>
<td>(0.693)</td>
<td>(0.660)</td>
<td>(0.794)</td>
<td>(1.039)</td>
</tr>
<tr>
<td>Intensity (T)</td>
<td>0.0348</td>
<td>0.698**</td>
<td>0.966***</td>
<td>-0.230</td>
<td>-0.295</td>
<td>-0.330</td>
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<tr>
<td></td>
<td>(0.223)</td>
<td>(0.317)</td>
<td>(0.223)</td>
<td>(0.174)</td>
<td>(0.327)</td>
<td>(0.252)</td>
</tr>
<tr>
<td>Spatial (A)</td>
<td>-0.642</td>
<td>0.158</td>
<td>-0.135</td>
<td>0.428</td>
<td>0.410</td>
<td>0.489</td>
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<td></td>
<td>(0.532)</td>
<td>(0.619)</td>
<td>(0.530)</td>
<td>(0.473)</td>
<td>(0.420)</td>
<td>(0.435)</td>
</tr>
<tr>
<td>Psychological Energy (T)</td>
<td>-1.422*</td>
<td>-0.945</td>
<td>0.176</td>
<td>0.342</td>
<td>-0.192</td>
<td>-0.421</td>
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<tr>
<td></td>
<td>(0.821)</td>
<td>(1.091)</td>
<td>(1.005)</td>
<td>(0.605)</td>
<td>(0.857)</td>
<td>(0.745)</td>
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<tr>
<td>Inductive (A)</td>
<td>-1.974***</td>
<td>-1.723**</td>
<td>-2.288**</td>
<td>0.887</td>
<td>2.823***</td>
<td>0.515</td>
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<tr>
<td></td>
<td>(0.674)</td>
<td>(0.773)</td>
<td>(1.307)</td>
<td>(0.794)</td>
<td>(0.773)</td>
<td>(1.138)</td>
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<td>106</td>
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<tr>
<td>R-squared</td>
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<td>0.419</td>
<td>0.557</td>
<td>0.564</td>
<td>0.676</td>
<td>0.416</td>
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<td>Controls for wage rank</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note: The dependent variables are 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 resilience as projected by Frey and Osborne (2017) transposed into Swedish occupational codes by Heyman et al. (2016). Columns (4)-(6) Projected Webb: ranked resilience as projected by Webb (2019). Each observation is a 3-digit occupation according to the Swedish Standard of Occupations (SSYK). Regressions are weighted according to employment shares in 2001. Wage rank ranks occupations according to mean wages in 2001. Specific skills rank occupations according to the skill intensity in each dimension during 2001. The skills are ordered according to estimate size in Column (1). The different types of skills are highlighted by: T = Non-Cognitive Trait, A = Cognitive Ability. The interpretation of specific non-cognitive traits is 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.

Our second key insight is that changes in labor demand are related to the comparative advantages of the employees even within the broader set of cognitive vs. non-cognitive skill-aggregates that have been emphasized in the existing literature on the changing worker-level returns to skills, see e.g. Edin et al. (2022). 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. Occupations that are comparatively dense in technical abilities have also grown. In contrast, we see 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.

Finally, we use labor demand projections from the BLS to assess if these indicate that patterns of the recent past are likely to change in the near future. If anything, the results point in the opposite direction. Even though the projections suggest that the growing occupations of the future will be different from those that grew in the past, our results show that the occupations that rely on more skilled (in our measured intellectual dimensions) workers is projected to continue to grow relative to other occupations. In addition, the BLS projections do not show any indications of major shifts in the relationship between specific skills and future employment growth.

One reason for the projected continued growth of skill-intensive occupations is that they are assessed to have more “engineering bottlenecks”, thus making them harder to automate. More skill-intensive jobs are also covered by fewer task-replacing robot or software patents. Although AI patents are more prevalent in skill-intensive occupations overall, this association is reversed if accounting for the wage. This last result implies that tasks-replacing AI-patents, just like other patents, engineer bottlenecks, and the overall employment decline of the recent past, are more likely to hit jobs that pay high wages for other reasons than those captured by our vector of cognitive and non-cognitive skills. Thus, our analysis of projections and assessments of technology resilience (regardless of measure) does not indicate that the trend wherein more skilled occupations grow relative to other occupations that pay similar wages is a thing of the past. An obvious caveat is that it is very difficult to know how well the future will align with these projections and assessments.28

Data availability

Data will be made available on request.

Appendix

28 A second caveat is that the patent data in all dimensions (Software, Robots and AI) in contrast to the past evolution (as well as BLS predictions, and the assessment of bottlenecks) seem to be concentrated among occupations that require much in terms of technical ability, which could indicate that there would be a change in the types of cognitive skills that are demanded in the future.
Fig. A.1. Contribution to polarization by broad occupation groups.

Note: The y-axis displays the change in employment expressed as percent 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. (a) The x-axis ranks occupations according to mean wages by tenured employees in 2001. (b) The x-axis ranks occupations according to mean skills of tenured employees in 2001. The line represents the prediction from the regression equation: \( EmploymentGrowth_{occupation} = a + b \cdot Rank_{occupation} + c \cdot (Rank_{occupation})^2 \), where rank is defined as the x-axis.
Fig. A.2. 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.
Fig. A.3. 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/third 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). The circle sizes represent weights, calculated as employment shares in the start year when applicable.
Fig. A.4. Predicted job-level employment growth by wage and skill ranks (1997–2008).

Note: We define jobs as occupations within establishments and relate initial job-level wage and skill ranks to future employment growth in surviving establishments. Details of the sample construction can be found in the web appendix. As in the main analysis, we use second-order polynomials in wage and skill ranks of the jobs and relate them to employment growth. The 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: \( \text{Employment Growth}_{j,e} = a + b \times \text{Rank}_{j,e} + c \times (\text{Rank}_{j,e})^2 \), where rank is defined as the x-axis of the respective panel.
Fig. A.5. Relationship between specific skills and employment growth.

Note: Figures show relationships between employment growth and each of the specific skills.
Fig. A.6. Specific skills-robustness checks.

Note: The figures show relationships between employment growth and specific skills when we vary the sample and variable definitions. The output comes from 5 regressions, one per specification. The 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.
Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.labeco.2023.102326

References