The Skill-Specific Impact of Past and Projected Occupational Decline

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Motivation

How do current and future technological innovations impact the labor market?

- Skill-biased TC (e.g. Katz and Murphy, 1992; Acemoglu and Autor, 2011)
- Job polarization (Autor et al., 2003; Goos and Manning, 2017; Goos et al., 2014)
"Computers have substituted for middle-skill routine tasks and complemented high- and low-skilled labor, a phenomenon referred to as job polarization."
Motivation

- Little direct evidence on the impact of technology on the demand for specific worker traits or abilities.
  - Returns to cognitive and social skills (Lindqvist and Vestman, 2011; Edin et al.; 2017, Deming, 2017)
  - Sorting on skills across firms and occupations (Hakansson et al, 2015; Fredriksson et al, 2018; Hensvik and Skans, 2016)

- Future technological advances (AI) may affect a much broader set of tasks and different types of workers (Mitchell and Brynjolfsson, 2017).

Key policy question:
- Which specific skills will be most valuable in the future?
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**Key policy question:**
- Which specific skills will be most valuable in the future?
This paper

- Describes recent changes in occupation-level employment by initial wage and skill rank. [Figure]
- Associates occupational decline to occupational skills in multiple cog. and non-cog. dimensions.
- Use existing projections about employment change to assess if the association between occupational decline and worker skill-types will change in the future.
Outline of talk

1. Measurement of occupation-level skills
3. Occupation-level analysis
   3.1 Wages (Job polarization)
   3.2 Overall skills
   3.3 Specific skills
4. Establishment-level empl. growth
5. Projections
6. Conclusions
7. Future work
I: Measurement of occupation-level skills

- Skills: From enlistment data containing 4 cognitive ability measures and 4 non-cognitive traits.
- Standardized within draft cohort
- Focus on skills of male employees with $\leq 3$ yrs. tenure.
I: Measurement of occupation-level skills

▶ Cognitive skills:
- Verbal comprehension
- Technical understanding
- Spatial ability
- Inductive skills (reasoning)
I: Measurement of occupation-level skills

- Cognitive skills:
  - Verbal comprehension
  - Technical understanding
  - Spatial ability
  - Inductive skills (reasoning)

- Non-cognitive traits:
  - Social Maturity: Extroversion, responsibility, independence
  - Emotional stability: Tolerance to stress
  - Intensity: Activation without external pressure
  - Psychological energy: Perseverance and the ability to focus
II: Results from Fredriksson, Hensvik & Skans, 2018
## Market value of skills

<table>
<thead>
<tr>
<th></th>
<th>Dep. var: ln(wage)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cognitive skills:</strong></td>
<td></td>
</tr>
<tr>
<td>Inductive skill</td>
<td>0.0373*** 0.0216***</td>
</tr>
<tr>
<td></td>
<td>(0.0008) (0.0007)</td>
</tr>
<tr>
<td>Verbal skill</td>
<td>0.0253*** 0.0031***</td>
</tr>
<tr>
<td></td>
<td>(0.0007) (0.0007)</td>
</tr>
<tr>
<td>Spatial skill</td>
<td>0.0095*** 0.0028***</td>
</tr>
<tr>
<td></td>
<td>(0.0006) (0.0006)</td>
</tr>
<tr>
<td>Technical skill</td>
<td>0.0350*** 0.0209***</td>
</tr>
<tr>
<td></td>
<td>(0.0007) (0.0006)</td>
</tr>
<tr>
<td><strong>Non-cognitive traits:</strong></td>
<td></td>
</tr>
<tr>
<td>Social maturity</td>
<td>0.0308*** 0.0242***</td>
</tr>
<tr>
<td></td>
<td>(0.0007) (0.0007)</td>
</tr>
<tr>
<td>Intensity</td>
<td>0.0046*** 0.0049***</td>
</tr>
<tr>
<td></td>
<td>(0.0006) (0.0006)</td>
</tr>
<tr>
<td>Psychological energy</td>
<td>0.0277*** 0.0182***</td>
</tr>
<tr>
<td></td>
<td>(0.0007) (0.0006)</td>
</tr>
<tr>
<td>Emotional stability</td>
<td>0.0260*** 0.0205***</td>
</tr>
<tr>
<td></td>
<td>(0.0007) (0.0006)</td>
</tr>
<tr>
<td>Observations</td>
<td>343,440 343,440</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.3185 0.3862</td>
</tr>
<tr>
<td>Year FE:s</td>
<td>Yes Yes</td>
</tr>
<tr>
<td>Educational attainment FE:s</td>
<td>No Yes</td>
</tr>
</tbody>
</table>
How sorted are skills and traits across occupations/jobs?

- **Verbal comprehension.**
  Storage workers (LTS), Librarians (MTS), Medical Doctors (HTS).

- **Technical understanding.**
  Wood and Paper Processors (LTS), Photographers (MTS), Architects and Engineers (HTS).

- **Spatial ability.**
  Furniture Carpenters (LTS), Photographers (MTS), University Research/Teaching (HTS).

- **Inductive skill (reasoning).**
  Storage Workers (LTS), Librarians (MTS), Medical Doctors (HTS).
- **Social maturity**: Extroversion, responsibility & independence
  Restaurant Workers (LTS), Nurses (MTS), Medical Doctors (HTS).

- **Emotional Stability**: Tolerance to stress
  Miners (LTS), Fire Fighters/Security Guards (MTS), Pilots (HTS).

- **Intensity**: Activation without external pressure
  Miners (LTS), Forestry Workers (MTS), Police Officers (HTS).

- **Psychological Energy**: Perseverance and the ability to focus
  Dairy Producers (LTS), Placement Officers (MTS), Medical Doctors (HTS).
How sorted are skills across occupations?

Table: Relationship between own and coworker skills

<table>
<thead>
<tr>
<th></th>
<th>Dep. var: Worker’s Amount of skill $k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean of skill $k$, occupational peers</td>
<td>0.5281*** (0.0069)</td>
</tr>
<tr>
<td></td>
<td>0.6636*** (0.0080)</td>
</tr>
<tr>
<td>Mean of skill $k$, coworkers in job</td>
<td>0.4911*** (0.0064)</td>
</tr>
<tr>
<td></td>
<td>0.2934*** (0.0054)</td>
</tr>
<tr>
<td>Observations</td>
<td>15,559,712</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.1801</td>
</tr>
<tr>
<td>Year FE:s</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean of all skills</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
</tr>
</tbody>
</table>

→ Strong clustering of skills within occupations and jobs
### Sorting on skill returns

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. var: Job-specific wage return to skill $k$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amount of skill $k$</td>
<td>0.0082*** (0.0003)</td>
<td>0.0059*** (0.0008)</td>
<td>0.0059*** (0.0008)</td>
</tr>
<tr>
<td>Average amount of all skills</td>
<td></td>
<td>0.0030*** (0.0009)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>200,952</td>
<td>200,952</td>
<td>200,952</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.6968</td>
<td>0.6969</td>
<td>0.6970</td>
</tr>
<tr>
<td>Year FE:s</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Job FE:s</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean dep. var</td>
<td>0.0062</td>
<td>0.0062</td>
<td>0.0062</td>
</tr>
</tbody>
</table>

→ In jobs with a standard deviation higher endowment of skill $k$, the returns to skill $k$ are twice as large.
Summary of results

- Each of the skills have independent market value
- There is heterogeneity in skill requirements across occupations
- There is considerable sorting on specific skills
- Workers are (on average) in jobs where the returns to their specific skills are higher than average
III: Occupation-level skills and empl. growth
Data sources

- **Skill ranks (2001):** "Total" skills, and by specific ability/trait
- **Wage ranks (2001):** calculated from (i) the same sample and (ii) from official Statistics (Statistics Sweden).
- **Employment change (2001-2013):** from official statistics
- **(Projected automation risks: described more below)**
Stylized fact I: Job Polarization

Percentage changes in employment shares over 2001-2013 for jobs (3-digit) ranked by the 2001 log wage.
Robustness
Stylized fact II: Routine intensity

Percentage changes in employment shares over 2001-2013 for jobs ranked by the amount of routine tasks in Goos et. al., (2014).
New fact 1: Overall skill rank

Percentage changes in employment shares over 2001-2013 for jobs ranked by their 2001 overall skill level.
Robustness
Alternative skill measure: High school grades
Result for women

Correlation male-female grade rank = 0.93
Reconciling the wage and skill results

Growing low-wage jobs are more skill-intensive than implied by the wage rank.
Reconciling the wage and skill results

Growing low-wage jobs are more skill-intensive than implied by the wage rank.

<table>
<thead>
<tr>
<th>Skills/wage ratio &gt; 1</th>
<th>(1) All jobs</th>
<th>(2) Low wage</th>
<th>(3) High wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9.33</td>
<td>18.56**</td>
<td>8.101</td>
</tr>
<tr>
<td></td>
<td>(5.902)</td>
<td>(8.711)</td>
<td>(9.251)</td>
</tr>
</tbody>
</table>

Observations 107 54 53
R-squared 0.031 0.111 0.017
## New fact III: Specific skills

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skill rank</td>
<td>0.263**</td>
<td>0.331**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.155)</td>
<td></td>
</tr>
<tr>
<td>Social maturity (T)</td>
<td></td>
<td>1.479*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.809)</td>
<td></td>
</tr>
<tr>
<td>Verbal (A)</td>
<td></td>
<td>1.427**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.579)</td>
<td></td>
</tr>
<tr>
<td>Technical (A)</td>
<td></td>
<td>1.050**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.436)</td>
<td></td>
</tr>
<tr>
<td>Emotional stability (T)</td>
<td></td>
<td>0.599</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.718)</td>
<td></td>
</tr>
<tr>
<td>Intensity (T)</td>
<td></td>
<td>0.035</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.223)</td>
<td></td>
</tr>
<tr>
<td>Spatial (A)</td>
<td></td>
<td>-0.642</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.532)</td>
<td></td>
</tr>
<tr>
<td>Psychological energy (T)</td>
<td></td>
<td>-1.422*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.821)</td>
<td></td>
</tr>
<tr>
<td>Inductive (A)</td>
<td></td>
<td>-1.974***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.674)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>107</td>
<td>107</td>
<td>107</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.068</td>
<td>0.200</td>
<td>0.354</td>
</tr>
<tr>
<td>Flexible control for wage</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
III: Job-level skills and disappearing jobs
Establishment-level analysis: Data construction

- For each job cell (plant*2-digit occupation) in 1997 [53,015 jobs], we calculate:
  - Average wage
  - Average skills
  - Number of paid employees.
- Keep plants that are still in business in 2008 [32,336 jobs].
- Job-level empl. growth as \( G_j = \frac{N_{j,2008} - N_{j,1997}}{N_{j,1997}} \)
  - If \( N_{j,2008} = 0 \), we assume that the job disappeared. [Around 21 percent].
  \[
  G_j = \theta_p + g(s_j) + \varepsilon_j
  \]
- where \( g(s_j) \) is a second-order polynomial in total skills and \( \theta_p \) are plant fixed effects.
Predicted job-level relationships
IV: Future skill demands
This was the past- what about the future?

Two sources of predicted employment growth:

1. **Bureau of Labor Statistics (BLS):**
   - Projected growth rates (2016-2026) based on a qualitative review by economists
   - Include factors such as expectations of technological innovations, changes in business practices, reorganizations, off-shoring and cross-industry changes in demand.
Projections

Two examples:

- "Security guards: Share decreases as improvements in remote sensing and autonomous robots allow security guards to patrol larger physical areas (Productivity change)."

- "Chefs and head cooks: 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 (Demand change)."
2. Frey and Osborne (2013):
   - Subjective assessments by data scientists to identify "bottleneck-related" tasks (high resilience to automation)
   - Tasks involving complex perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks
   - The expected automation risk is a function of these task characteristics. Identified from O*NET data.
2. Frey and Osborne (2013):
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   - Tasks involving complex perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks
   - The expected automation risk is a function of these task characteristics. Identified from O*NET data.

To achieve comparability between measures, we rank the occupations according to their estimated resilience to automation.
Projected continued polarization

(a) US Labor Statistics

(b) Frey and Osborne (2013)

Note: Change is BLS predictions for employment growth from 2016 to 2018.

Projected continued skill-biased demand

(a) US Labor Statistics

(b) Frey and Osborne (2013)
Relationship between past/projected growth and overall skills

<table>
<thead>
<tr>
<th>Growth:</th>
<th>(1) Past</th>
<th>(2) Projected: BLS</th>
<th>(3) Projected: Frey &amp; Osborne</th>
</tr>
</thead>
<tbody>
<tr>
<td>Talent rank</td>
<td>0.331**</td>
<td>0.647***</td>
<td>0.788***</td>
</tr>
<tr>
<td></td>
<td>(0.155)</td>
<td>(0.180)</td>
<td>(0.182)</td>
</tr>
<tr>
<td>Observations</td>
<td>107</td>
<td>91</td>
<td>103</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.354</td>
<td>0.419</td>
<td>0.557</td>
</tr>
</tbody>
</table>

**Correlations:**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past growth</td>
<td>1</td>
<td>0.341</td>
<td>0.219</td>
</tr>
<tr>
<td>BLS</td>
<td>0.341</td>
<td>1</td>
<td>0.456</td>
</tr>
<tr>
<td>Frey &amp; Osborne</td>
<td>0.219</td>
<td>0.456</td>
<td>1</td>
</tr>
</tbody>
</table>
Specific skills: BLS
Specific skills: Frey and Osborne (2013)
Summing up

Past occupational decline has affected:
- Routine jobs in the middle of the wage distribution
- Middle-wage jobs employing low-skilled workers

Projected occupational decline will:
- Have a continued polarizing impact on the labor market
- Relationship with overall skills expected to become even stronger
In terms of specific skills:

**Past growth** in occupations employing workers endowed with:
- Social maturity
- Verbal comprehension and Technical skill (or "crystallized" cognitive skills, more malleable)

**Past decline** in occupations employing workers endowed with:
- Psychological energy
- Spatial and inductive skills (or "fluid" cognitive skills)

**In the projected future:**
- Similar patterns, but jobs using emotional stability (i.e. tolerance to stress) will decline
Future work

▶ Use PIAAC-data and/or AFQT-scores in NLSY to validate patterns.
▶ Dig deeper into mechanisms ==> what motivated the high wages in declining occupations (residual skills such as manual strength, disamenities or pure rent-seeking abilities)?
▶ How do skill mismatch vary with the business cycle?
▶ How are job amenities priced in terms of match quality?
Thank you!
Broad occupation groups:

![Graph showing changes in employment share by wage rank for different occupational groups.](image)
Correlation skill and grade ranks

Tenured males

Overall skill rank in 2001 vs. Grade rank in 2001

- ○ talentrank
- ⬇ Fitted values

Occupations weighted by the employment share in 2001