Cognitive Skills and Labor Market Returns to Field of Study among Higher Education Graduates

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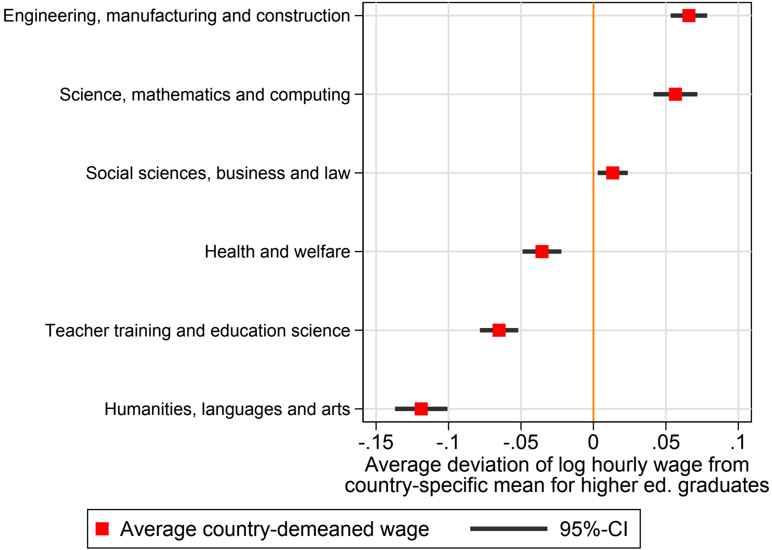
Fields of study and wage returns

- Large literature on relationship between education and labor market attainment (wages, occupational status, ...)
- Strong focus on *level* of education
- In recent years, increasing attention to fields of study, especially in higher education
- Several studies find that labor market attainment varies by field of study/college major (e.g., Reimer et al. 2008)
- In the US, wage gap between highest and lowest earning college majors about as large as the college/high school gap (Altonji et al. 2012)
  - Similar results for other countries (e.g., Norway; Kirkeboen et al. 2016)

Wage differences: PIAAC



Why do some fields pay more than others?

- Why do we see these large wage differences?

- Many studies argue that *skills* play a major role
- Some programs provide students with more skills (acquisition) or selection of individuals with higher competencies into higher-paying fields (selection)
  - Reimer et al. (2008) suggest that educational expansion has amplified selectivity through inflow of weaker students into 'soft' fields

- Most studies of between-field wage differences have no direct measure of skills
  - The few exceptions mostly focus on the US

Our study

1. Use PIAAC's rich measures of cognitive skills and on-the-job skill use to better understand the contribution of skills to between-field differentials in wages
2. Do so for a diverse set of advanced economies to reduce the impact of national idiosyncrasies (which may affect previous single-country studies)

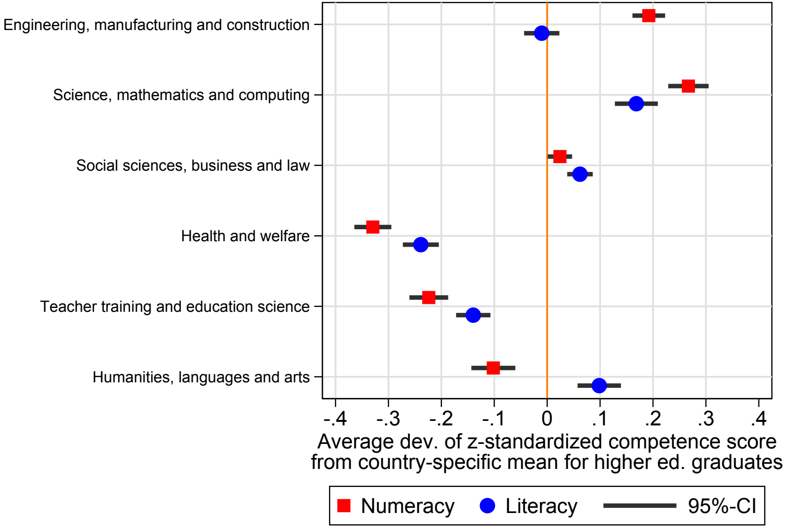
- Goal is not to identify the causal effect of field of study, but to assess the contribution of different factors to wage differentials
- Investigate how the importance of these factors differs across fields
  - For hard sciences, skills might be a crucial mechanism
  - For medicine and law, occupational closure/rent-seeking might be more important (cf. Ketel et al., 2016)

Research questions

Research questions:

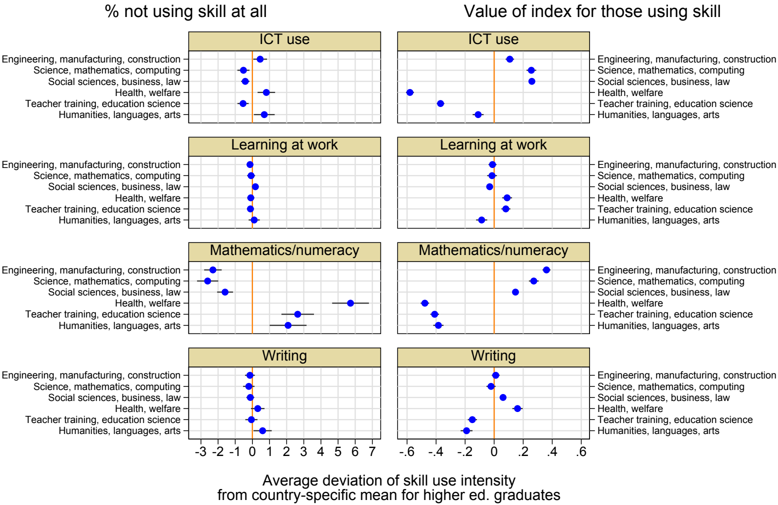
- To what extent can we explain between-field wage differences with differences in literacy/numeracy skills and on-the-job skill use?
- Are 'skill effects' equally important for all fields of study?
- To what extent do other compositional factors explain between-field wage differences?
  - Gender, parental education (social class).

Cross-field differences in literacy and numeracy



Fields ordered by average hourly wage.

On-the-job skill use (4 out of 12 dimensions)



ICT=Information and Communication Technologies. The skill use indices are provided with the PIAAC data. Each index is based on several questions about how frequer at work (For details, see pages 141ff. in OECD 2013, Skills Outlook, Paris: OECD, and pages 40ff. in OECD 2013, The Survey of Adult Skills: Reader's Companion, Paris: OECD). No index values are provided for respondents who answered 'never/none of the time' to all questions underlying a specific index. To include these cases in the anaylsis, we assigned them the minimum value of the index and included a dummy variable to identify them (the left column shows by how much the field-specific percentage of respondents with all-zero answers differs from the overall percentage for all higher-education graduates in a country. After assigning values to all-zero respondents, we rescaled the index to have a mean of zero and a standard deviation of one in our analytic sample. The right column shows the average deviation of this measure from the country mean for all higher-education graduates.

Data

- First (2011/12) and second (2014/15) round of PIAAC
  - 29 out of 33 participating countries (w/o Australia, Russia, Cyprus, Philippines)
  - Literacy and numeracy skills
  - Rich info on skill use at work (12 dimensions)
- 24,731 higher education graduates (ISCED 5-6) in six major groups of fields
  - Humanities, languages, arts
  - Teacher training and education science
  - Social sciences, business, law
  - Science, mathematics, computing
  - Engineering, manfacturing, construction
  - Health and welfare

  $\Rightarrow$ Drop three smaller groups that do not exist in all countries
- Outcome: Log hourly wage (mean values for earnings deciles; similar results when we use exact wage where available)

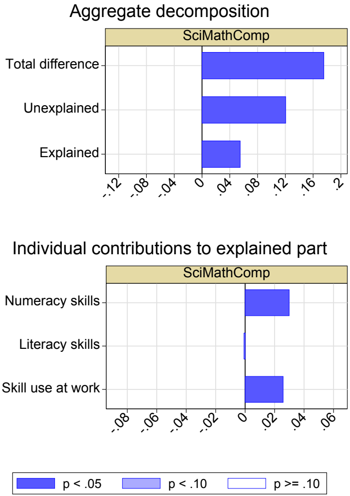
Methods

- Country-demean wages and explanatory variables (to remove country fixed effects)
- Can differences in skills, skill use, and other factors account for wage differentials among fields?
  - Oaxaca-Blinder decompositions (twofold)
  - Pairwise comparisons: Other fields vs. humanities/languages/arts
  - Reference coefficients based on pooled model for all graduates
- Two sets of covariates
  - Skills only: Cognitive skills and skill use measures
  - Skills + alternative mechanisms/controls: sex, parental education, potential experience, years of education, foreign-birth/foreign-language status.

Results

Skills only

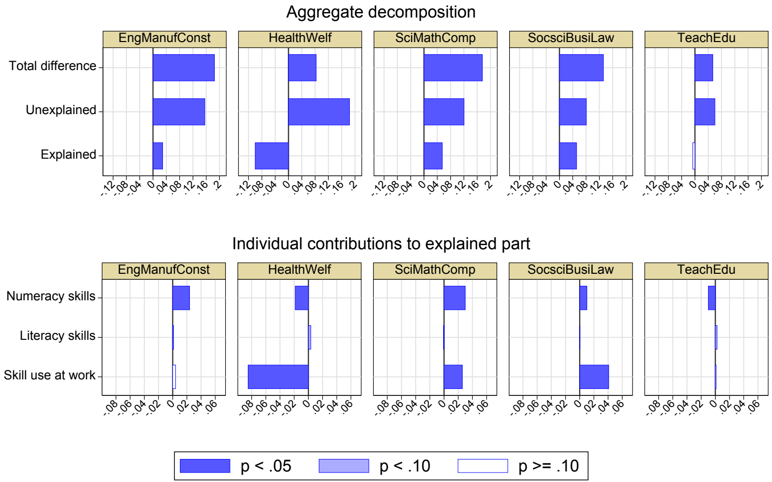
Science/mathematics/computing vs. humanities/languages/arts



- Raw wage differential of ≈ 17.5 log points
- In total, skill measures account for ≈ 5.5 log points (31% of raw gap)
- Numeracy account for ≈ 3.0 log points, literacy hardly matters
- Skill use measures account for ≈ 2.6 log points (ICT, reading, and problem-solving skills are most important)

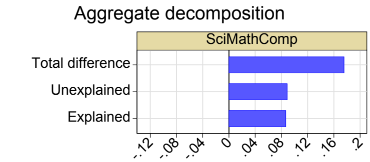
Skills only

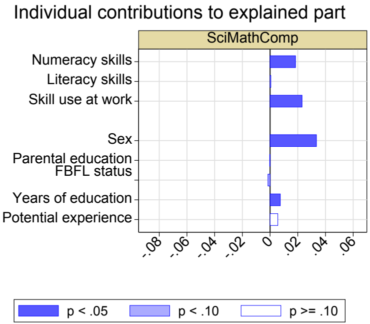
All fields vs. humanities/languages/arts



Adding further variables

Science/mathematics/computing vs. humanities/languages/arts

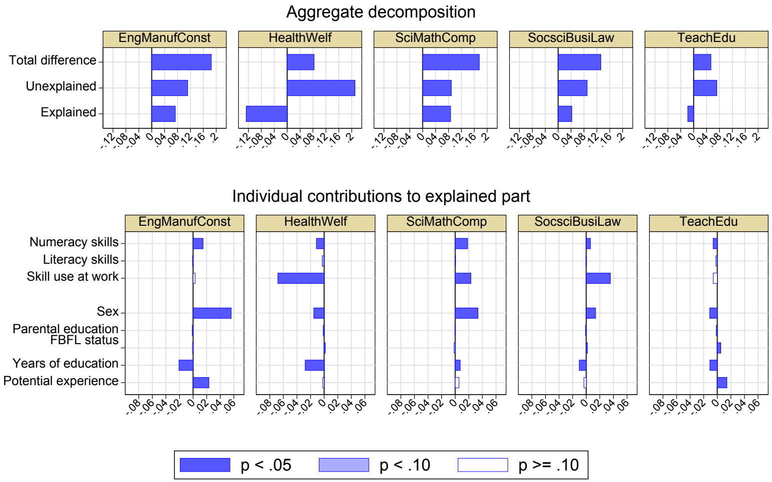




- Accounting for alternative explanations/controls raises explaine part from 5.5 to 8.6 log points (49% of total gap)
- Sex composition is the major factor (3.3 log points, 19% of total gap)
- Parental education plays no role
- Contributions of other covariates also tend to be small

Skills only

All fields vs. humanities/languages/arts



Summary & Discussion

- We find large wage differentials by fields of study for a large and heterogeneous sample of advanced economies
  - Numeracy skills partly explain the high wages of STEM graduates (engineering, math) and, to a lesser extent, the advantage of graduates from social sciences, business and law
  - On-the-job skill use partly accounts for the wage advantage of graduates from science, mathematics and computing as well as social sciences, business and law
  - Overall contribution of skills and skill use measures is modest, however, especially for non-STEM fields

Summary & Discussion

- Results suggest that other factors are important as well
  - Sex composition is a major factor even after accounting for skills and skill use
  - Unaccounted advantages of graduates from health and welfare as well as social sciences, business and law seem consistent with the notion that certain (regulated) occupations yield 'monopoly rents' (doctors, lawyers)
  - Recent quasi-experimental evidence from lottery-based admission to medical school in NL finds that early-career earnings of doctors are 20% higher than for people in second-best occupation; premium grows even larger benefits in the long run (Ketel et al. 2016)

- De-regulate access to closed occupations?

Thank you!

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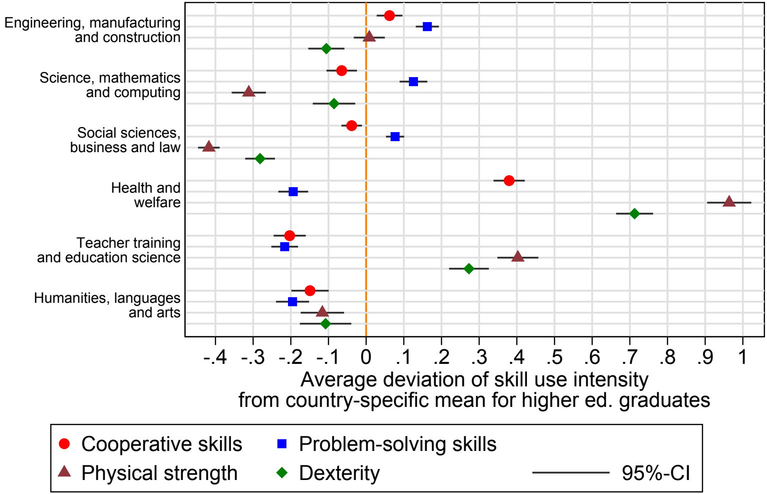
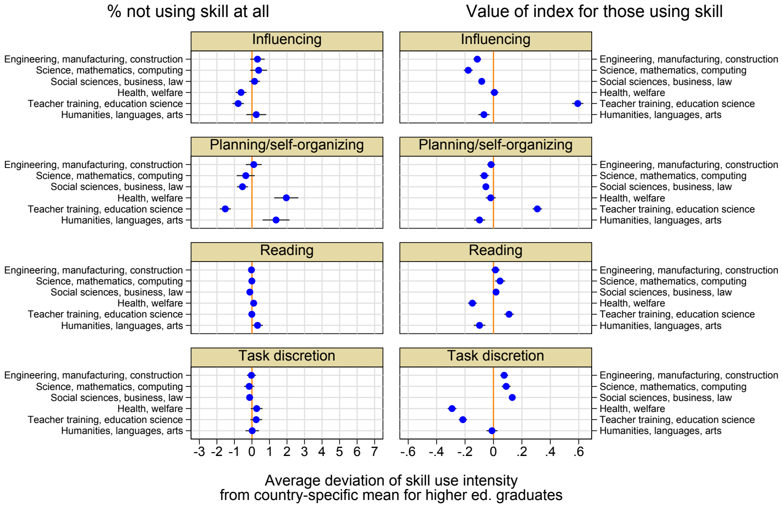
Additional slides

On-the-job skill use (single-item measures)



Each skill use measure is based on a single question about how frequently the respondent uses the respective skill. Values range from 1 (never/none of the time) to 5 (every day/all of the time). Variables are treated as continuous in the present graph (the decomposition analysis uses dummy variables)

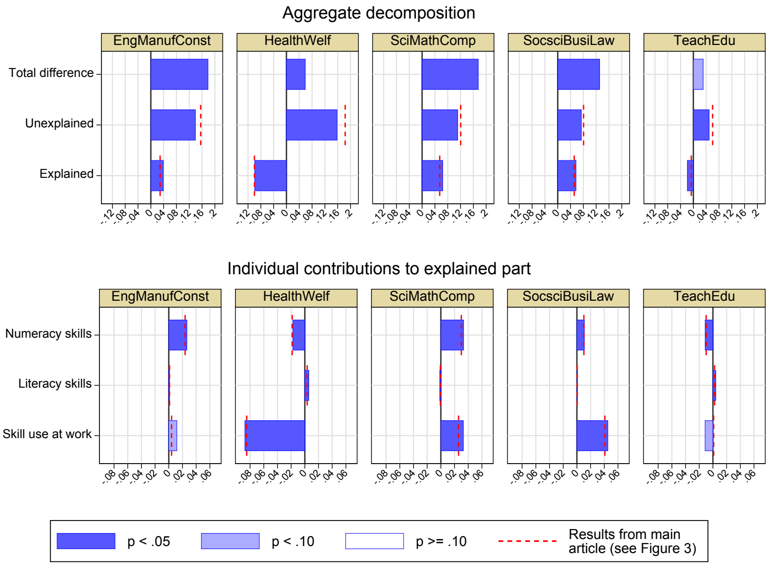
On-the-job skill use (second set of indices)



The skill use indices are provided with the PIAAC data. Each index is based on several questions about how frequently respondents perform certain tasks at work (For details, see pages 141ff. in OECD 2013, Skills Outlook, Paris: OECD, and pages 40ff. in OECD 2013, The Survey of Adult Skills: Reader's Companion, Paris: OECD). No index values are provided for respondents who answered 'never/none of the time' to all questions underlying a specific index. To include these cases in the anaylsis, we assigned them the minimum value of the index and included a dummy variable to identify them (the left column shows by how much the field-specific percentage of respondents with all-zero answers differs from the overall percentage for all higher-education graduates in a country. After assigning values to all-zero respondents, we rescaled the index to have a mean of zero and a standard deviation of one in our analytic sample. The right column shows the average deviation of this measure from the country mean for all higher-education graduates.

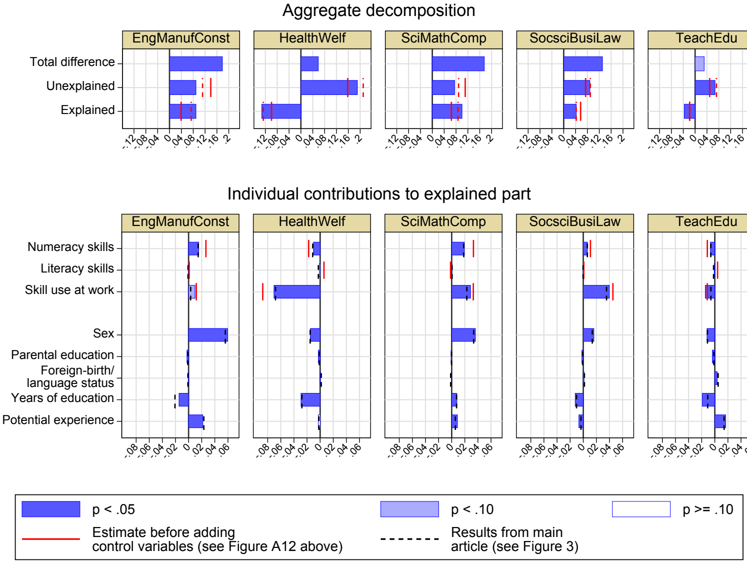
Decomposition results with exact wage (22 countries)

Decomposition with skills only



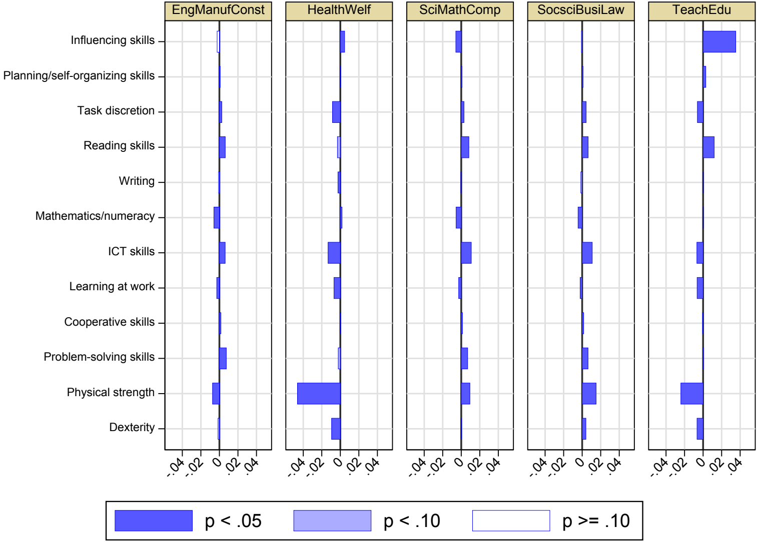
Decomposition results with exact wage (22 countries)

Decomposition with all predictors



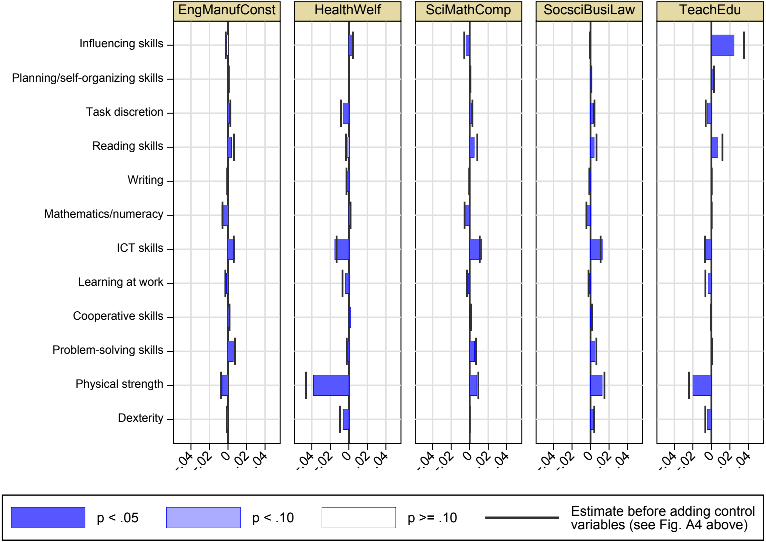
Detailed decomposition for skill use

Decomposition with skills only

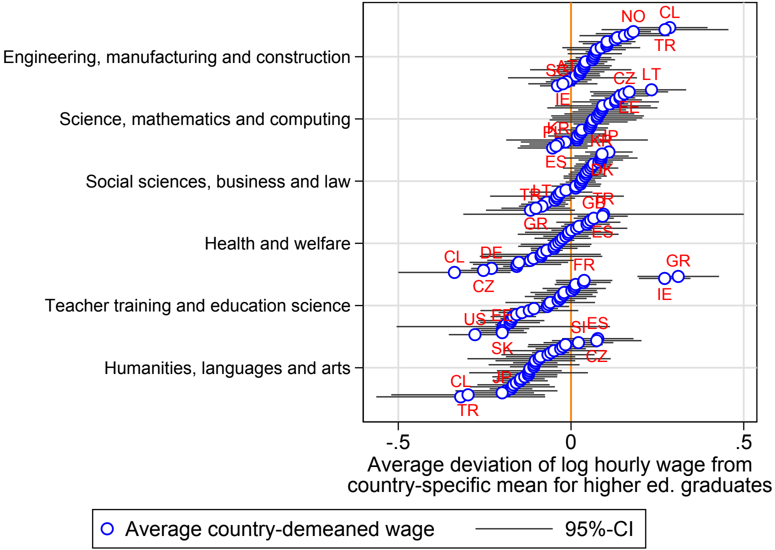


Detailed decomposition for skill use

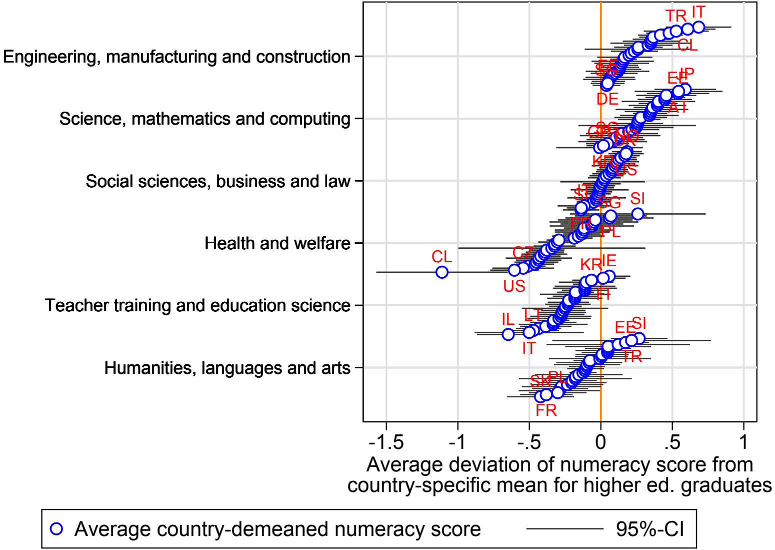
Decomposition with all predictors



Wages by country



Numeracy scores by country



Literacy scores by country