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Tina Dulam[1] and Kees Hoogland[2]

[1] HU University of Applied Sciences & Utrecht University, Utrecht, The Netherlands; tina.dulam@hu.nl

[2]HU University of Applied Sciences Utrecht, Utrecht, The Netherlands; kees.hoogland@hu.nl

We assess the incidence of numeracy skills mismatch in five countries: Belgium, Chile, Italy, Netherlands, and the United States of America. To do this, we make use of a new approach (Brun-Schamme & Rey, 2021), namely by identifying someone as being mismatched if the score for numeracy skills is outside the interval [median – SD , median + SD]. *We make use of the PIAAC dataset, collected by the OECD, a survey that measures adults' proficiency in numeracy among other type of skills. We find that 14% of the workers are over-skilled, whereas 16% are under-skilled. Being over-skilled is more likely for men, younger age-groups, having a high level of education, using numeracy skills often at work, and having studied science, mathematics, and engineering.*

Keywords: Numeracy, skills mismatch, over-skilled, under-skilled, occupations.

Introduction

The world has seen major developments in technological progress, human capital formation, and labour demand. Numeracy has increasingly become one of the crucial basic skills for adults to cope with the digitalised and technologized 21st-century society. Having an adequate numeracy level determines the success of individuals' participation in their roles as citizens and professionals. Hence there is a need to measure the numeracy proficiency and whether there is a good match between the possessed skills and required skills in numeracy.

Skills mismatch, defined as possessing qualifications or skills that does not adequately meet the qualifications or skills necessary for the doing one's job, has negative effects at all levels of the economy: at individual (micro) level, skills mismatch is leads to lower job satisfaction and wages. At company (meso) level mismatch leads to a higher staff turnover, and inefficiencies. At country (macro) level, to unemployment, lower productivity[1] and lower economic growth mainly due to wasting human capital (OECD, 2013). The aim of this study is to inform national policymakers on lifelong learning especially regarding numeracy and the mismatch of skills.

The Programme for International Assessment of Adult Competencies (PIAAC), a major survey conducted by the OECD in over 40 countries, provides the opportunity to measure skills proficiency (in literacy, numeracy, and problem solving in a technological rich environment) and the degree to which people are well-matched in a harmonized way. This paper focusses on numeracy skills, because 1) these skills are the most comparable throughout different countries (Perry et al., 2016) and 2) these skills have a mathematical foundation.

[1] Being under-skilled can lead to lower productivity because the worker is performing below the required skills.

The OECD (2013) defines numeracy skills as "the ability to access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life." To this end, numeracy involves "managing a situation or solving a problem in a real context, by responding to mathematical content/information/ideas represented in multiple ways."

Theoretical background

Human capital is formed by the skills and education an individual gains over time (Wiederhold & Ackermann-Piek, 2014). Human capital positively affects an individual's success, and productivity. To put skills to effective use, it is important that they are aligned with the required skills at work. Wiederhold and Ackermann-Piek (2014) discuss the reasons why workers may be over-skilled or under-skilled. Factors that may play a role are shifts or changes in the economy, the occupation type, the timing in the professional career (experience), discrimination in the labour market, and family responsibilities.

Pellizari and Fichen (2013) developed a theoretical framework to define and measure skills mismatch with PIAAC data. In this framework jobs are defined as production functions and skill use, which is treated as an endogenous choice of the worker, is considered as the only input. The model furthermore assumes that there are fixed costs to carry out the job and that the marginal product of used skills is locally constant and that it declines above a certain threshold (it is equal to zero). These assumptions lead two critical values in the definition of skills mismatch, namely that workers with a skill proficiency below the lower critical value are under-skilled and workers above the upper critical value are over-skilled. Furthermore, the model assumes that production technologies of firms do not change and that the skills mismatch is measured in the short run.

Several studies (OECD, 2013; Perry et al., 2016, McGuinness et al., 2018, Flisi et al., 2017, Allen et al., 2011) have used PIAAC data to measure skills-mismatch in various ways. This paper applies the latest approach as developed by Brun-Schammé and Rey (2021) to measure numeracy mismatch. Flisi et al. (2017) provide 20 indicators for occupational mismatch for 17 European countries, whereas Perry et al. (2016) evaluates six measures for mismatch. The preferred method by the OECD, developed by Pellizari and Fichen (2013), is the method where self-reported[2] mismatch is identified as an objective measure (whether the score for numeracy skills exceeds 95th percentile of the distribution within the same occupation or whether it is lower than the 5th percentile of the distribution). The main argument against this method is firstly, the bias raised due to overconfidence or misinterpretation, and secondly, that the mismatch is measured within one-digit occupational code leaving little room for the heterogeneity within the 1-digit occupation. Brun-Schammé and Rey's approach therefore make use of the two-digit occupation code to take some more heterogeneity into account (ending up with 40 occupational categories instead of 10). It assesses the skills mismatch for France and categorizes someone as being mismatch if the score for numeracy skills is outside the mean and one standard deviation. Using this approach, we assess the prevalence of skills mismatch

[2] By asking workers whether they can do a more demanding job or whether they need extra training to their job.

in five countries, and look for associations between mismatch and socio-demographic and job-related characteristics such as job satisfaction, wages, and skills use.

Data and methods

The PIAAC dataset is based on an international comparable survey conducted by the OECD in over 40 countries in three rounds: the first one in 2011-12, the second in 2014-15, and third in 2017. The data we use are for Belgium, Netherlands, and Italy from the first round, Chile the second, and the USA from the third round. Around 5000 non-institutionalized people per country were surveyed. To obtain representative results, the sample was chosen through a multistage clustered design. The proficiency scores in the original dataset were based on the Item Response Theory scaling methodology resulting in 10 plausible values for each type of skill proficiency in the dataset (Yamamoto et al., 2013).

We perform a quantitative analysis, by measuring the incidence of numeracy skills mismatch conforming to Brun-Schammé and Rey (2021) as follows. Firstly, we calculate the median and standard deviation of the numeracy skills score[3] for each two-digit ISCO occupation. Secondly, we qualify a worker as being over-skilled if the score for numeracy proficiency score is above the median plus one standard deviation and as being under-skilled if the numeracy proficiency score is below the median minus one standard deviation.

We furthermore perform binary logistic regression to study the association between mismatch and socio-demographic and job-related variables. Our sample size is 12,166 in total.

Table 1 below provides the statistics. We see that on average 14% of the workers are over-skilled and 16% under-skilled. A critique from Pellizari and Fichen (2013) is that having a mismatch percentage of 30% can be attributed to the normal distribution of numeracy proficiency skills score. In a normal distribution, for instance, 32% will score below or above one standard deviation from the median. Nevertheless, it can be interesting to find out which variables are associated with being over-skilled and under-skilled respectively.

Table 1: Descriptive statistics

Variable (in percent)	Total	Belgium	Chile	Italy	Netherlands	USA
Over-skilled	14.13	13.56	15.49	14.29	13.18	14.6
Under-skilled	16.37	17.35	16.43	16.66	16.24	14.76
Gender (% of women)	50.64	49.76	50.84	48.69	50.6	53.87
Education level						
Lower secondary or less	19.86	11.42	24.38	27.53	25.68	7.63

[3] Based on the 10 plausible values of the numeracy proficiency and taking the corrected standard error into account by using the Repest command (Keslair, 2020). Occupations with less than 25 observations were eliminated.

Upper secondary	42.13	41.64	44.8	49.78	40.31	34.02
Post-secondary, non-tertiary	2.16	3.87		1.29		
Tertiary – professional degree	12.32	26.29	17.77	0.25	4.34	7.25
Tertiary – bachelor degree	14.93	1.84	11.5	18.69	20.42	11.9
Tertiary – master/research degree	8.61	14.95	1.55	2.47	9.25	24.77
Area of study						
General programmes	12.23	13.1	21.4	8.35	9.31	7.48
Teacher training and education science	8.96	9.67	10.15	4.64	7.71	13.27
Humanities, languages and arts	8.76	7	11.41	16.63	3.39	8.87
Social sciences, business and law	20.23	16.62	10.48	21.54	29.47	22.22
Science, mathematics and computing	12.01	10.94	11.84	20.08	6.44	14.97
Engineering, manufacturing and construction	17.44	24.94	16.27	13.19	16.89	11.42
Agriculture and veterinary	2.3	1.95	2.13	2.32	3.34	1.23
Health and welfare	12.82	12.26	7.81	6.76	19.48	15.9
Services	5.25	3.52	8.52	6.49	3.98	4.63
Age group						
24 or less	12.77	9.99	15.61	5.44	16.77	14.12
25-34	22.78	24.11	28.29	20.66	18.63	23.04
35-44	24.93	25.65	20.79	33.71	22.81	23.42
45-54	24.97	29.06	22.05	27.63	25.08	19.85
55 plus	14.55	11.19	13.25	12.56	16.71	19.58
Occupation						
Armed forces	6.99	7.85	2	1.09	11.08	11.84
Legislators, senior officials and managers	19.46	23.21	11.86	15.22	22.44	23.69
Professionals	17.54	16.15	13.29	21.5	17.62	20.71
Technicians and associate professionals	11.73	13.48	11.5	13.64	12.78	5.62

Clerks	18.12	13.59	22.38	17.1	17.81	20.66
Service workers and shop and market sales workers	0.89	0.3	2.65	0.69	0.66	
Skilled agricultural and fishery workers	.62	10.78	10.64	10.43	6.8	4
Craft and related trades workers	6.02	6.57	7.17	10.03	2.52	5.3
Plant and machine operators and assemblers	10.62	8.07	18.51	10.28	8.31	8.17
Elementary occupations						
Immigrant (born abroad)	8.65	8.15	2.61	9.74	7.9	17.47
Working part-time (< 30 h/ week)	23.05	18.83	17.53	18.34	38.67	15.04
Firmsize						
1-10 people	26.18	19.56	37.75	37.12	20.23	18.6
11-50 people	29.16	27.79	28.09	27.09	32.47	29.15
51-250 people	24.54	29.67	19.53	19.77	26.68	25.37
251-1000 people	11.53	14.53	8.68	8.3	11.93	13.85
More than 1000 people	8.58	8.45	5.95	7.71	8.68	13.03
Numeracy use at work						
All zero response	26.62	27.22	27.03	36.73	25.93	15.31
Lowest to 20%	15.85	18.02	15.65	13.3	17.43	13.03
More than 20% to 40%	13.77	14.12	13.7	13.84	13.72	13.36
More than 40% to 60%	14.75	14.98	14.76	10.73	15.58	17.36
More than 60% to 80%	14.05	12.09	14.51	12.41	13.47	19.04
More than 80%	14.98	13.56	14.35	13	13.88	21.9

Results

Figures 1-4 below are based on performing a binary logistic regression of being over-skilled on gender, age-group, education level (alternated by area of study), migrant status, occupation, working part-time or not, firm size, and numeracy use at work. The country was entered as a control variable. In the figures we see the probability of being over-skilled by each of these variables.

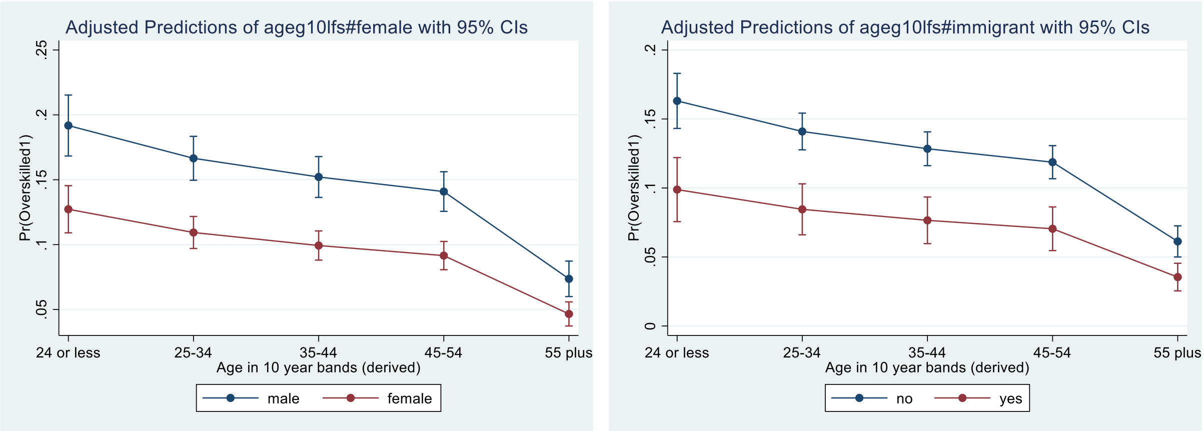

Figure 1: The probability of being over-skilled by gender, age-group, and migrant status

Men are significantly more likely to be over-skilled than women, controlling for other factors. The probability is 18 percent for men, compared to 14% for women. The probability of being over-skilled declines over years.

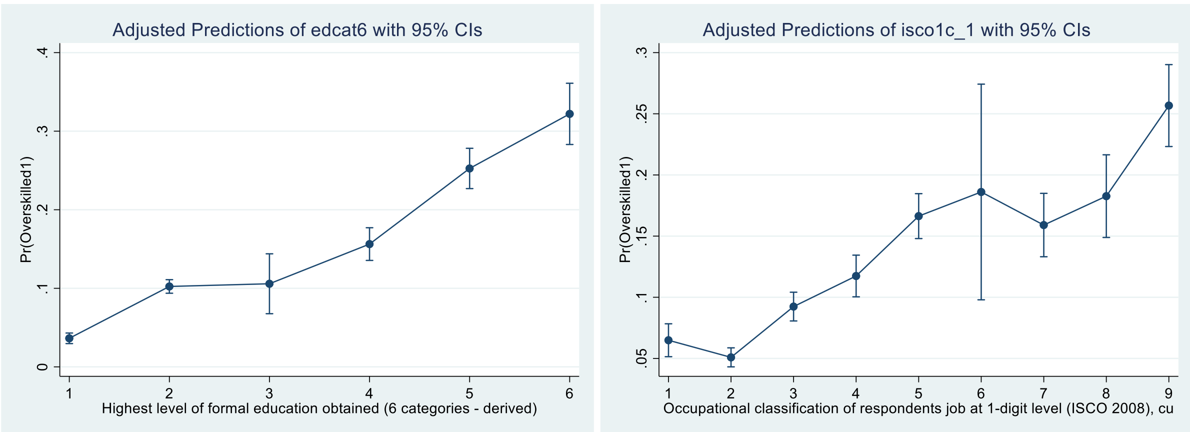

Figure 2: The probability of being over-skilled by education level[4] and occupation[5]

Being higher educated has a significant positive association with being over-skilled, controlling for other factors. People in elementary occupations are more likely to be over-skilled than people in other occupations.

[4] Legenda: 1 = Lower secondary or less (ISCED 1,2, 3C short or less), 2= Upper secondary (ISCED 3A-B, C long), 3 = Post-secondary, non-tertiary (ISCED 4A-B-C), 4 = Tertiary – professional degree (ISCED 5B), 5 = Tertiary – bachelor degree (ISCED 5A), 6= Tertiary – master/research degree (ISCED 5A/6)

[5] Legenda: 0 = Armed forces, 1 = Legislators, senior officials and managers, 2 = Professionals, 3 = Technicians and associate professionals, 4 = Clerks, 5 = Service workers and shop and market sales workers, 6 = Skilled agricultural and fishery workers, 7 = Craft and related trades workers, 8 = Plant and machine operators and assemblers, 9 = Elementary occupations

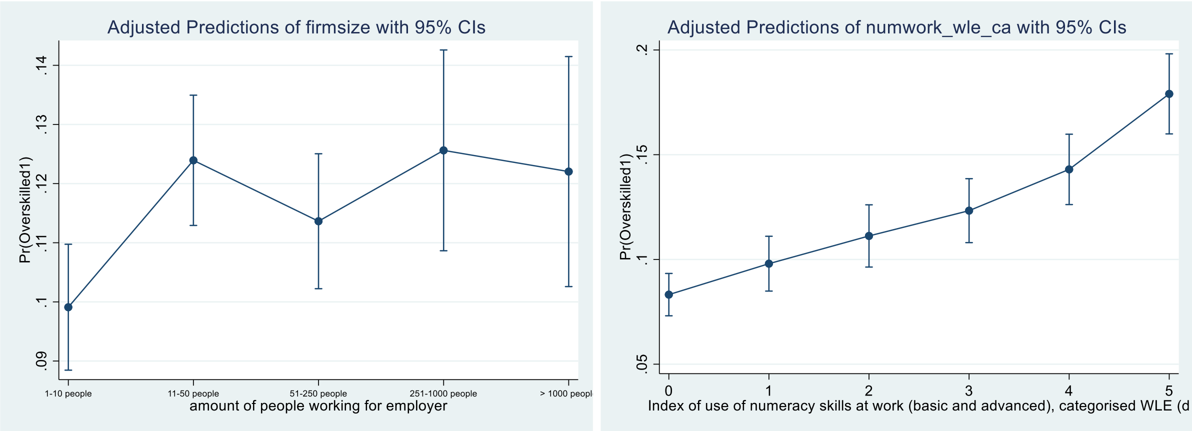

Figure 3: The probability of being over-skilled by firm-size and use of numeracy skills[6]

There is no significant difference in the probability of being over-skilled across firm of various sizes. Furthermore, we see that the likelihood of being over-skilled increases as the frequency of using numeracy skills at work increases.

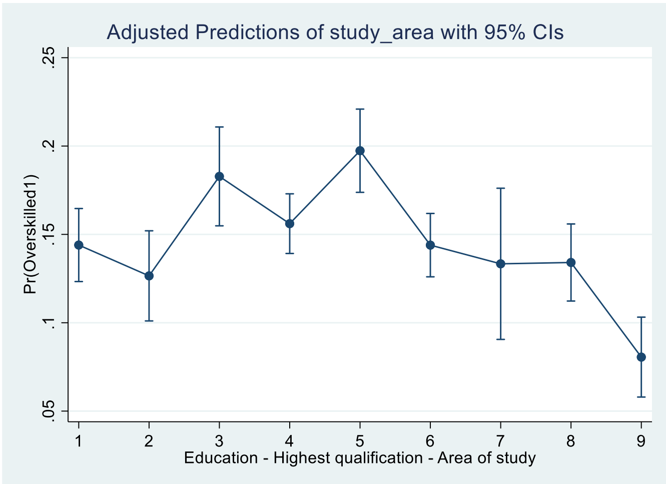

Figure 4: The probability of being over-skilled by area of study7

Being over-skilled is significantly more likely for people who studied science, mathematics and computing and significantly less likely for people who studied services.

Conclusion

Being over-skilled is more likely for men, younger age-groups, higher education, and for people who use their numeracy skills often at work. Also, people who studied science, mathematics and computing are significantly more likely to be over-skilled. Our results are largely in line with what earlier studies showed, although we used a different measure and other sample set. Further studies

[6] Legenda: 0 = All zero response, 1= Lowest to 20%., 2 = More than 20% to 40%, 3 = More than 40% to 60%, 4 = More than 60% to 80%, and 5 =More than 80%

[7] 1 = General programmes, 2 = Teacher training and education science, 3 = Humanities, languages and arts, 4 = Social sciences, business and law, 5 = Science, mathematics and computing, 6 = Engineering, manufacturing and construction, 7 = Agriculture and veterinary, 8 = Health and welfare, 9 = Services

should focus on the reasons why certain study areas are significantly associated with the probability of being over-skilled and on improving the measure for mismatch.

References

Brun-Schammé, A. and Rey, M. (2021). *A new approach to skills mismatch, OECD Productivity Working Papers, 2021-24*. OECD Publishing.

Flisi, S., Goglio, V., Meroni, E., Rodrigues, M., & Vera-Toscano, E. (2017). Measuring Occupational Mismatch: Overeducation and Overskill in Europe-Evidence from PIAAC. *Social Indicators Research, 131*(3). https://doi.org/10.1007/s11205-016-1292-7

Keslair, F. (2020). Analysing PIAAC Data with Stata. In D.B. Maehler, B. Rammstedt (Eds.), *Large-Scale Cognitive Assessment* (pp. 149-164). Springer.

McGuinness, S., Pouliakas, K., & Redmond, P. (2018). Skills mismatch: Concepts, measurement and policy approaches. *Journal of Economic Surveys*, *32*(4), 985-1015. https://doi.org/10.1111/joes.12254

OECD (2013), *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*. OECD Publishing. http://dx.doi.org/10.1787/9789264204256-en

Pellizzari, M., & Fichen, A. (2013). *A new measure of skills mismatch: Theory and evidence from the survey of adult skills (PIAAC). OECD Social, Employment and Migration Working Papers, No. 153*. OECD Publishing. https://doi.org/10.1787/5k3tpt04lcnt-en

Pellizzari, M., & Fichen, A. (2017). A new measure of skill mismatch: theory and evidence from PIAAC. *IZA Journal of Labor Economics*, *6*(1), 1-30. https://doi.org/10.1186/s40172-016-0051-y

Perry, A., Wiederhold, S., & Ackermann-Piek, D. (2014). How can skill mismatch be measured? New approaches with PIAAC. *Methods, data, analyses, 8*(2), 38. https://doi.org/10.12758/mda.2014.006

Vandeplas, A., & Thum-Thysen, A. (2019). *Skills Mismatch & Productivity in the EU*. *Discussion paper 100.* Publications Office of the European Union.

Yamamoto, K., Khorramdel, L., & Von Davier, M. (2013). *Scaling PIAAC cognitive data*. *Technical report of the survey of adult skills (PIAAC),* 408-440.