# Numeracy and Unemployment Duration

Thomas Dohmen and Bert Van Landeghem

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**Abstract**

Governments are increasingly investing in quantitative profiling models, which aim to rank benefit claimants with respect to their risk of becoming long-term unemployed and which can help to allocate a shrinking budget in a better-informed way. Also in the academic literature, characteristics and policies that affect unemployment duration have been studied extensively. Models often contain standard socioeconomic variables such as age, gender and level of education, as well as measures for employment history and local labour market conditions. These models however do not take into account that unemployment prospects can be influenced by personality characteristics that are not being fully proxied with variables in administrative data. Using rich German survey data linked with administrative data, we confirm well-established patterns in the literature, but we also find that numeracy skills are strongly related to unemployment duration. In particular, for the younger cohort, low numeracy is strongly related to a longer unemployment duration, even after including a rich set of controls. We find that unrealistic reservation wages are probably not the main driver, nor do results seem to be driven by locking-in effects caused by programme participation. On the other hand, the absence of a relationship between numeracy and unemployment duration for the older cohort might well be driven by a locking-in effect for those with high numeracy, as they tend to commit more often to intensive training programmes.

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b.vanlandeghem@sheffield.ac.uk

# 1 Introduction

For a long time, labour economists and other social scientists have shown an interest in modelling differences in unemployment duration between individuals. It is well-known that socioeconomic characteristics such as age, education and employment history are important determinants for one's employment status (Ichino et al., 2008). Moreover, consensus has been growing that certain institutional settings and policies are also influential such as the structure of benefit schemes (Lalive, 2007), or support by work coaches (Schiprowski, 2017; Van Landeghem et al., 2017).

The constantly growing amount of survey and administrative data has allowed researchers to focus on other less standard determinants such as attitudes, personality traits and noncognitive skills. While many modern survey measures of people's personality and noncognitive skills seem to have an impact on labour market related behaviour such as selection into Active Labour Market Policies (ALMPs), job search behaviour and the setting of reservation wages, the relation with actually making the transition from unemployment into work is weaker (Caliendo et al. 2014, 2017). In this paper, we will however focus on the predictive power of cognitive skills, more in particular numeracy, on finding a job for a representative sample of individuals who register as unemployed and who are looking for work, and we will also explore how they relate to job market related characteristics such as wage expectations, job search activities and programme participation. Basic numeracy skills are relatively straightforward to measure in surveys and might well be good proxies for people's general problem solving skills required to some extent in almost every type of job.

There are many papers and policy reports that have looked at the relationship between skills (including numeracy) of youngsters or school-leavers on their labour market outcomes (Caspi et al., 1998; Kelly et al., 2011; Lamb, 1997; Lam et al., 2009; Lundtrae et al., 2010; Machin et al., 2001; Marks and Fleming, 1998). A second group of studies take a snapshot of (a segment of) the adult population in time (e.g. Chiswick et al., 2002; Green and Ridell, 2001; Lee and Miller, 2000; McIntosh and Vignoles, 2001; Sum, 1999). Also this second strand of literature is fundamentally different from our work, which is looking at the job finding rate of people who register as unemployed. Indeed, the latter are the individuals ALMPs are targeting and moreover, household economics teaches us that people within a household share tasks and will specialize (see e.g. Becker, 1974), which makes it rational for some people to stay out of the labour force. Closest to our work is probably the work of Arendt et al. (2008), who observe in their Danish data 1533 switches from unemployment to employment and conclude that those with high measures of literacy have a higher chance to find work. Our larger sample size allows however to look at heterogeneity across age cohorts and the richness of the data allows us to explore several channels through which the relationship could be established.

## 2 Data and Descriptives

We use the scientific use file of the IZA Evaluation Data Set collected by the Institute for the Study of Labour (IZA). The data contain samples of 12 monthly cohorts of individuals who registered themselves as unemployed between June 2007 and May 2008. The survey is a panel with 3 repeated measurements for 9 out of the 12 cohorts and 4 for the remaining 3 (called the interim sample). Unfortunately, for budgetary reasons and out of fear to boost attrition, the cognition module was only asked to the interim sample (cohorts entering unemployment in June, October and February). For those who gave their consent (90% of individuals), survey data could be merged with administrative data from the German employment office (IAB). This means that we can link first round responses to labour market performance even if subjects quit the panel prematurely.[1]

The cognitive module contains a short and medium-term memory test, a word fluency test and a test for orientation in time. The numeracy questions, which are key in our analysis, are as follows:

*Question 1* All goods cost half price at a sale in a department store. Before the sale, a washing machine cost 300 Euro. How much does it cost during the sale?

*Question 2*: A second-hand car dealer sold a car for 6000 Euro. This is two-thirds of what the car cost when new. How much did the car cost when new?

*Question 3* Let us assume that you have 1000 Euro in savings and you receive 10% interest for it each year. How much money do you have after two years?

In the first wave, questions 1, 2 and 3 were answered correctly by 84%, 51% and 17%, respectively. Table 1 shows us the distribution of numeracy scores in the interim sample, which can vary from 0 to 3 or can be missing. The table offers descriptives for the entire interim samples, as well as for those under 33 of age and from 33 years of age onwards separately. Table 1 shows us that the distribution of scores is almost identical in both age groups. Almost nobody had a score of 0 (1.6% in the full sample) but at the same time, a substantial fraction of respondents did not answer the numeracy questions (13.0%). 15.5% of individuals obtained the highest score. While this might seem a small

[1]A more in-depth discussion of the IZA/IAB Evaluation Dataset and its content can be found in Arni et al. (2014).

percentage, one should note that it concerned a long questionnaire which was not filled out on paper but questions were asked through the phone.

Of particular interest seems the distribution of cognition scores across different levels of education, as one can very well imagine that they should be highly correlated. The survey part of the data contain rich information about academic and professional education, which are coded into sets of exhaustive and mutually exclusive dummies. As to obtain an idea on how numeracy is correlated with and distributed across education categories, Table 2 shows us linear probability models with as the dependent variable the numeracy score (ranging from 0 to 3) and with as independent variables a full set of either academic or professional education dummies. By omitting the constant from the models, the estimated coefficients give us a point estimate of the average numeracy score for each education category. Regressions are run on the full intermediate sample, as well as on subsamples for the two age cohorts (up to 32 years of age, or 33 years of age and above).

The results show that education is more or less distributed in the same way across the different samples. Individuals of the older cohort in lower categories of academic education score slightly better than their younger counterparts, which is not surprising as education became more democratic over the years. R-squareds are very high, more than 86% in regressions with academic education dummies, and more than 85% in those with professional education dummies. The R-squareds would obviously be much lower if a constant term was included.

# 3 Analysis

## 3.1 The Relationship Between Transition Into Work and Numeracy

We first explore the relationship between transition from unemployment into work on the one hand, and numeracy on the other hand, with three sets of Ordered Logit regressions. The dependent variable counts the number of months in unemployment from months 6 to 30 after initial registration, but is truncated at 6 months to reduce the number of categories. Descriptive statistics for our key dependent variable are provided in Table 3. The first set looks at the entire sample, while sets 2 and 3 are restricted to a younger and older cohort, respectively. The younger cohort includes individuals up to 32 years of age at time of registration, and the older cohort the others. Results are displayed in Tables 4 to 6.

The first column of each table contains the most parsimonious specification, only containing the main variables of interest: a dummy taking 1 if either zero or one out of three numeracy questions were answered correctly, and a dummy taking 1 if two out of three numeracy questions were answered correctly (three correct answers being the baseline). In addition, we include a dummy indicating whether the numeracy score is missing, and a dummy which indicates whether one belongs to the nine cohorts in which the numeracy questions were not asked. The next columns show results of specifications in which the set of controls is gradually extended. In a second column, a female dummy and a quadratic in age are added, in column 3 a set of vocational and academic education dummies, and in a final column available measures for personality traits, internal and external locus of control, the other cognition measures, labour market history and the local unemployment rate.

For the whole sample, there is a clear predictive pattern of numeracy on unemployment duration in the raw data, and there also seems to be a threshold: numeracy especially seems to increase unemployment if one scores 0 or 1. Table 4 shows us that in the most parsimonious regression, those with very low numeracy (0 or 1) or those with a missing numeracy score have a much higher chance of being unemployed for a longer time than those with a numeracy score of 3, with the odds ratios of 1.36 and 1,54 being significant at the 1% significance level. The dummy *Cohorts no cognition* helps us to distinguish between those who did refuse to answer the questions (Numeracy missing) and those who have not been asked the cognition questions. Obviously we could have reported results from regressions run on just the intermediate sample, but pooling the three cohorts from the intermediate sample and the other nine cohorts increases power which is useful to identify parameters for the control variables. Moreover, the coefficient on the *Cohorts no cognition* dummy can convey useful information as well, especially in the more parsimonious regressions. We know that the number of months in unemployment is not significantly different between the three cohorts in the intermediate sample on the one hand, and the nine other cohorts on the other hand. In that case, if cognition is distributed similarly across the two latter samples, and if the effect of cognition on the number of months in unemployment is the same as well, the coefficient on *Cohorts no cognition* should be a weighted average of coefficients on the numeracy dummies. The weights are the fractions of the numeracy categories in the intermediate sample, and can be inferred from Table 1. This weighted average in Table 4 Column 1 equals to $1.36 * 0.34 + 1.11 * 0.38 + 1 * 0.16 + 1.54 * 0.13 = 1.24$, which is indeed the same as the coefficient on the *Cohorts no cognition* dummy.

While the above results even become slightly more pronounced after including a female dummy and a quadratic in age, the effects reduce, however, in Column 3 after including the rich set of educational controls, and they become insignificant after the inclusion of a large set of further controls in Column 4.

As for the younger cohort, however, numeracy is highly significant in all specifications. We now even find a difference in unemployment duration between those with score 2 compared to those with score 3. In Table 5 Column 2, the odds ratios on the *Numeracy 0 or 1* and *Numeracy missing* dummies even increase to 2.1 and 2.3, respectively. While the coefficients decrease across specifications 3 and 4, numeracy retains significant predictive power. In Column 4, the *Numeracy 0 or 1* dummy has a coefficient of 1.38 which is significant at the 5% significance level.

Finally, Table 6 shows us that for the older cohort, numeracy does not seem to be associated with transition from unemployment into work.

Across the three tables, it appears that other measures of cognition (word fluency and memory measures) do not have additional predictive power in our case study. The other standard controls show us a picture which is in line with the literature, and socioeconomic variables (age, gender and education), employment history and local labour market conditions are significant predictors.

## 3.2 Exploring the Mechanisms

After having established a relationship between numeracy and duration in unemployment, which is robust to the inclusion of a rich set of controls particulary for the younger cohort, we turn to the associations between numeracy skills and job market related behaviours and characteristics in order to get an idea of the mechanisms.

Unreported regression results show that there are hardly any associations between numeracy and the number of job applications or the search channels being used. This might mean that cognitive ability does not matter when it comes to job search behaviour, but it is more plausible that these job search measures are no good proxies for the quality of job search. Indeed, sending out many applications could ceteris paribus increase the chance of getting an interview, but in other circumstances it is better to choose your applications carefully and to spend time on an application and researching the potential employer.

More interesting is however the relation between people's wage expectations and numeracy skills, as it is plausible that people with low numeracy overestimate their earnings potential. Table 7 suggests that this is not necessarily the case. Lower cognition is significantly associated with lower wage expectations, even after controlling for last wage earned. If we interact the two lower cognition category dummies with expected wage, the level effects disappear but the interaction term is significant and negative. This means that the gradient between expected wage and last wage earned is less steep for those with low or very low cognition.

Next, we might wonder whether the participation in Active Labour Market Programmes (i.e. training) is different across people with different numeracy scores. If people with low numeracy tend to participate into training programmes more frequently than those with high numeracy, the longer time spent into unemployment for the former group might be due to a locking-in effect: if people commit to training, looking for a job can become less of a priority.

Our data distinguishes between two types of training that are available to jobseekers. First, there are short-term light-touch training measures which last from two days up to 8 weeks. Second, there are more substantial long-term vocational training programmes that last from three months up to three years.

Table 8 shows us OLS regressions with as the dependent variables either the number of months in short-term light-touch training, or the number of months in long-term intensive training after inflow into unemployment. The independent variables are the same as those in Column 1 of tables 4-6.

Results reveal an interesting pattern. The upper half of the table shows that people with lower numeracy skills are more likely to take part in the light-touch measures such as training for job interviews, writing application letters etc. The second half of the table shows us that individuals with high numeracy skills are much more likely to be involved in more intensive, long-term vocational training courses, particularly the older cohort. These results might support two main points. The longer unemployment duration in the younger cohort among those with low or very low numeracy compared to those with a higher numeracy score, is unlikely to be caused by a locking-in effect. Although the former take part in light-touch measures more often than the latter, there is no difference in take-up of more intensive vocational training. Second, results might also explain why we do not find a relationship between numeracy and unemployment duration for the older cohorts. Those with high numeracy are much more likely to commit to intensive vocational training than individuals with low or very low numeracy scores, which might mean that a locking-in effect is at work for those with high numeracy rather than for those with low numeracy skills.

# 4 Conclusion

For a long time, economists have been interested in which factors and labour market policies affect unemployment duration. Recently, the growing availability of big data has increased the interest of policy makers in developing profiling models which predict the duration of unemployment spells of new entrants into unemployment.

In this study, we use rich survey data linked with administrative data from people who entered unemployment in Germany. Our analyses are able to confirm findings that are well-established in the existing literature: unemployment duration is related to socioeconomic characteristics such as age and education, as well as to employment history and local labour market conditions. Our data also contain novel measures for cognitive and noncognitive skills, inspired by the Psychology literature. We do not find a clear relationship between unemployment duration for new entrants and their noncognitive skills (such as personality traits and locus of control), but cognitive skills seem to have predictive power. In particular for younger cohorts, the score on an easy-to-implement numeracy test is strongly related to unemployment duration, even after including a rich set of controls. It seems that an unrealistic reservation wage or a locking-in effect are not the primary drivers of these results. However, the absence of a relationship between numeracy and unemployment duration for the older cohort might well be caused by a locking-in effect for people with high numeracy scores, as they tend to commit to intensive training more often than those with low numeracy.

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Table 1: The Distribution of Numeracy Scores in the Interim Sample

| Score | Obs. | % | Obs. | % | Obs. | % |
|---|---|---|---|---|---|---|
| | Full Sample | | Under Age 33 | | Above age 33 | |
| 0 | 61 | 1.5 | 32 | 1.6 | 29 | 1.5 |
| 1 | 1269 | 32.2 | 682 | 33.2 | 586 | 31.2 |
| 2 | 1486 | 37.7 | 776 | 37.7 | 710 | 37.8 |
| 3 | 612 | 15.5 | 279 | 13.6 | 332 | 17.7 |
| Missing | 512 | 13.0 | 287 | 14.0 | 223 | 11.9 |

Table 4: Unemployment Duration and Numeracy: Full Sample

| VARIABLES | (1) spec1 | (2) spec2 | (3) spec3 | (4) spec4 |
|---|---|---|---|---|
| Numeracy 0 or 1 | 1.3631*** | 1.4375*** | 1.2120** | 1.1413 |
| | (0.123) | (0.131) | (0.113) | (0.110) |
| Numeracy 2 | 1.1131 | 1.1534 | 1.0598 | 1.0425 |
| | (0.098) | (0.102) | (0.095) | (0.095) |
| Numeracy missing | 1.5433*** | 1.6408*** | 1.4017*** | 0.7889 |
| | (0.173) | (0.185) | (0.161) | (0.305) |
| cohorts no cognition | 1.2395*** | 1.2703*** | 1.1327 | 1.0357 |
| | (0.094) | (0.097) | (0.088) | (0.131) |
| female | | 0.8556*** | 0.9184*** | 0.9404* |
| | | (0.026) | (0.030) | (0.032) |
| Age | | 0.9495*** | 0.9870 | 0.9792 |
| | | (0.011) | (0.012) | (0.014) |
| Age squared | | 1.0010*** | 1.0005*** | 1.0006*** |
| | | (0.000) | (0.000) | (0.000) |
| Educac_lowsec | | | 0.6814*** | 0.6944*** |
| | | | (0.074) | (0.076) |
| Educac_sec | | | 0.5781*** | 0.5822*** |
| | | | (0.062) | (0.063) |
| Educac_advancedsec | | | 0.4353*** | 0.4590*** |
| | | | (0.054) | (0.057) |
| Educac_alevel | | | 0.4917*** | 0.5155*** |
| | | | (0.055) | (0.059) |
| Educprof_certind | | | 0.6886*** | 0.6800*** |
| | | | (0.039) | (0.039) |
| Educprof_certadm | | | 0.6903*** | 0.7027*** |
| | | | (0.042) | (0.044) |
| Educprof_voctech | | | 0.6015*** | 0.6015*** |
| | | | (0.042) | (0.042) |
| Educprof_uni | | | 0.5425*** | 0.5729*** |
| | | | (0.043) | (0.046) |
| Educprof_other | | | 0.6145*** | 0.6218*** |
| | | | (0.037) | (0.039) |
| Word fluency above median | | | | 1.0160 |
| | | | | (0.069) |
| Word fluency missing | | | | 0.9996 |

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| VARIABLES | spec1 | spec2 | spec3 | spec4 |
|---|---|---|---|---|
| | | | | (0.356) |
| Short memory above median | | | | 0.9184 |
| | | | | (0.073) |
| Short memory missing | | | | 0.5748 |
| | | | | (0.712) |
| Long memory above median | | | | 1.0263 |
| | | | | (0.082) |
| Long memory missing | | | | 2.2162 |
| | | | | (2.746) |
| Time orientation above median | | | | 0.9615 |
| | | | | (0.093) |
| Time orientation missing | | | | 1.3391 |
| | | | | (0.532) |
| Openness above median | | | | 1.0122 |
| | | | | (0.034) |
| Openness missing | | | | 0.8546 |
| | | | | (0.281) |
| Conscientiousness above median | | | | 0.9113*** |
| | | | | (0.031) |
| Conscientiousness missing | | | | 1.0193 |
| | | | | (0.337) |
| Extroversion above median | | | | 0.9982 |
| | | | | (0.034) |
| Extroversion missing | | | | 1.3248 |
| | | | | (0.333) |
| Neuroticism above median | | | | 0.9921 |
| | | | | (0.033) |
| Neuroticism missing | | | | 0.7166 |
| | | | | (0.264) |
| Internal locus above median | | | | 1.0921*** |
| | | | | (0.036) |
| Internal locus missing | | | | 1.4377 |
| | | | | (0.343) |
| External locus above median | | | | 1.1258*** |
| | | | | (0.038) |
| External locus missing | | | | 1.0756 |
| | | | | (0.115) |
| Local unemp. rate | | | | 1.0316*** |
| | | | | (0.009) |
| frac. recorded time unemp. (short) | | | | 0.7286*** |

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| VARIABLES | spec1 | spec2 | spec3 | spec4 |
|---|---|---|---|---|
| | | | | (0.082) |
| frac. recorded time olf (short) | | | | 0.9593 |
| | | | | (0.053) |
| frac. recorded time unemp. (long) | | | | 1.7673*** |
| | | | | (0.255) |
| frac. recorded time olf (long) | | | | 0.9520 |
| | | | | (0.081) |
| Observations | 15,173 | 15,154 | 15,003 | 14,835 |

*** p<0.01, ** p<0.05, * p<0.1

Coefficients are odds ratios

Table 5: Unemployment Duration and Numeracy: Younger Cohort

| VARIABLES | (1)<br>spec1 | (2)<br>spec2 | (3)<br>spec3 | (4)<br>spec4 |
|---|---|---|---|---|
| Numeracy 0 or 1 | 1.9449*** | 2.0641*** | 1.5377*** | 1.3779** |
| | (0.253) | (0.271) | (0.207) | (0.191) |
| Numeracy 2 | 1.4282*** | 1.4869*** | 1.2837* | 1.2232 |
| | (0.182) | (0.191) | (0.168) | (0.161) |
| Numeracy missing | 2.1976*** | 2.3094*** | 1.7790*** | 1.3276 |
| | (0.342) | (0.362) | (0.284) | (0.653) |
| Cohorts no cognition | 1.6524*** | 1.7287*** | 1.4062*** | 1.0597 |
| | (0.186) | (0.196) | (0.162) | (0.186) |
| Female | | 0.7857*** | 0.9363 | 0.9578 |
| | | (0.034) | (0.044) | (0.047) |
| Age | | 0.7239*** | 0.8620** | 0.8911 |
| | | (0.051) | (0.063) | (0.068) |
| Age squared | | 1.0064*** | 1.0035** | 1.0029* |
| | | (0.001) | (0.001) | (0.002) |
| Educac_lowsec | | | 0.6229*** | 0.6355*** |
| | | | (0.092) | (0.094) |
| Educac_sec | | | 0.4539*** | 0.4644*** |
| | | | (0.065) | (0.067) |
| Educac_advancedsec | | | 0.3005*** | 0.3121*** |
| | | | (0.049) | (0.052) |
| Educac_alevel | | | 0.3285*** | 0.3345*** |
| | | | (0.050) | (0.052) |
| Educprof_certind | | | 0.7063*** | 0.7406*** |
| | | | (0.051) | (0.057) |
| Educprof_certadm | | | 0.7141*** | 0.7579*** |
| | | | (0.057) | (0.063) |
| Educprof_voctech | | | 0.5361*** | 0.5504*** |
| | | | (0.050) | (0.052) |
| Educprof_uni | | | 0.4447*** | 0.4849*** |
| | | | (0.049) | (0.056) |
| Educprof_other | | | 0.5465*** | 0.5769*** |
| | | | (0.044) | (0.047) |
| Word fluency above median | | | | 0.9276 |
| | | | | (0.087) |
| Short memory above median | | | | 1.0559 |

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| VARIABLES | spec1 | spec2 | spec3 | spec4 |
|---|---|---|---|---|
| | | | | (0.117) |
| Long memory above median | | | | 0.9238 |
| | | | | (0.102) |
| Time orientation above median | | | | 0.8187 |
| | | | | (0.106) |
| Time orientation missing | | | | 1.0340 |
| | | | | (0.520) |
| Openness above median | | | | 1.0225 |
| | | | | (0.048) |
| Openness missing | | | | 0.6800 |
| | | | | (0.412) |
| Conscientiousness above median | | | | 0.8798*** |
| | | | | (0.041) |
| Conscientiousness missing | | | | 0.9093 |
| | | | | (0.556) |
| Extroversion above median | | | | 0.9943 |
| | | | | (0.048) |
| Extroversion missing | | | | 1.0353 |
| | | | | (0.432) |
| Neuroticism above median | | | | 0.9427 |
| | | | | (0.044) |
| Neuroticism missing | | | | 0.9790 |
| | | | | (0.736) |
| Internal locus above median | | | | 1.0999** |
| | | | | (0.050) |
| Internal locus missing | | | | 1.4649 |
| | | | | (0.573) |
| External locus above median | | | | 1.1949*** |
| | | | | (0.056) |
| External locus missing | | | | 1.2935 |
| | | | | (0.242) |
| Local unemp. rate | | | | 1.0462*** |
| | | | | (0.012) |
| frac. recorded time unemployed (short) | | | | 0.6032*** |
| | | | | (0.117) |
| frac. recorded time olf (short) | | | | 0.9118 |
| | | | | (0.067) |
| frac. recorded time unemployed (long) | | | | 3.7441*** |
| | | | | (1.345) |
| frac. recorded time olf (long) | | | | 1.3463** |

Continued on next page

| VARIABLES | spec1 | spec2 | spec3 | spec4 |
|---|---|---|---|---|
| | | | | (0.194) |
| Observations | 7,570 | 7,570 | 7,489 | 7,429 |

*** p<0.01, ** p<0.05, * p<0.1
Coefficients are odds ratios

Table 6: Unemployment Duration and Numeracy: Older Cohort

| VARIABLES | (1) spec1 | (2) spec2 | (3) spec3 | (4) spec4 |
|---|---|---|---|---|
| Numeracy 0 or 1 | 1.0507 | 1.0431 | 0.9848 | 0.9192 |
| | (0.134) | (0.134) | (0.129) | (0.105) |
| Numeracy 2 | 0.9619 | 0.9471 | 0.9184 | 0.8911 |
| | (0.120) | (0.119) | (0.116) | (0.097) |
| Numeracy missing | 1.2042 | 1.2039 | 1.0609 | |
| | (0.201) | (0.202) | (0.180) | |
| Cohorts no cognition | 0.9963 | 0.9815 | 0.9373 | |
| | (0.105) | (0.104) | (0.101) | |
| Female | | 0.9245* | 0.9350 | 0.9548 |
| | | (0.041) | (0.044) | (0.047) |
| Age | | 0.7827*** | 0.7891*** | 0.7859*** |
| | | (0.043) | (0.044) | (0.044) |
| Age squared | | 1.0032*** | 1.0031*** | 1.0031*** |
| | | (0.001) | (0.001) | (0.001) |
| Educac_lowsec | | | 0.8314 | 0.8401 |
| | | | (0.135) | (0.138) |
| Educac_sec | | | 0.8139 | 0.8097 |
| | | | (0.131) | (0.132) |
| Educac_advancedsec | | | 0.7423 | 0.7856 |
| | | | (0.140) | (0.150) |
| Educac_alevel | | | 0.8568 | 0.8936 |
| | | | (0.145) | (0.154) |
| Educprof_certind | | | 0.7088*** | 0.6992*** |
| | | | (0.069) | (0.069) |
| Educprof_certadm | | | 0.6900*** | 0.7072*** |
| | | | (0.070) | (0.073) |
| Educprof_voctech | | | 0.6997*** | 0.6935*** |
| | | | (0.078) | (0.078) |
| Educprof_uni | | | 0.5847*** | 0.6000*** |
| | | | (0.071) | (0.074) |
| Educprof_other | | | 0.6851*** | 0.6874*** |
| | | | (0.069) | (0.071) |
| Word fluency above median | | | | 1.0312 |
| | | | | (0.100) |
| Word fluency missing | | | | 0.5127 |

Continued on next page

| VARIABLES | spec1 | spec2 | spec3 | spec4 |
|---|---|---|---|---|
| | | | | (0.237) |
| Short memory above median | | | | 0.7822** |
| | | | | (0.089) |
| Short memory missing | | | | 5.8536 |
| | | | | (8.905) |
| Long memory above median | | | | 1.1846 |
| | | | | (0.141) |
| Long memory missing | | | | 0.2262 |
| | | | | (0.324) |
| Time orientation above median | | | | 1.1885 |
| | | | | (0.129) |
| Time orientation missing | | | | 1.8129 |
| | | | | (0.830) |
| Openness above median | | | | 0.9992 |
| | | | | (0.048) |
| Openness missing | | | | 0.9025 |
| | | | | (0.361) |
| Conscientiousness above median | | | | 0.9558 |
| | | | | (0.046) |
| Conscientiousness missing | | | | 1.1529 |
| | | | | (0.458) |
| Extroversion above median | | | | 1.0005 |
| | | | | (0.049) |
| Extroversion missing | | | | 1.3849 |
| | | | | (0.441) |
| Neuroticism above median | | | | 1.0479 |
| | | | | (0.050) |
| Neuroticism missing | | | | 0.7432 |
| | | | | (0.313) |
| Internal locus above median | | | | 1.0959* |
| | | | | (0.052) |
| Internal locus missing | | | | 1.3268 |
| | | | | (0.404) |
| External locus above median | | | | 1.0521 |
| | | | | (0.051) |
| External locus missing | | | | 0.9756 |
| | | | | (0.127) |
| Local unemp. rate | | | | 1.0218* |
| | | | | (0.013) |
| frac. recorded time unemployed (short) | | | | 0.7558** |

Continued on next page

| VARIABLES | spec1 | spec2 | spec3 | spec4 |
|---|---|---|---|---|
| | | | | (0.107) |
| frac. recorded time olf (short) | | | | 0.9527 |
| | | | | (0.086) |
| frac. recorded time unemployed (long) | | | | 1.5947*** |
| | | | | (0.255) |
| frac. recorded time olf (long) | | | | 0.9507 |
| | | | | (0.109) |
| Observations | 7,584 | 7,584 | 7,514 | 7,406 |

seEform in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Coefficients are odds ratios

Table 2: Estimates for Numeracy Scores for Educational and Professional Educational Levels

| VARIABLES | (1) Full Sample | (2) Up to age 32 | (3) Age 33 or above |
|---|---|---|---|
| Academic Education | | | |
| educac_basic | 1.3500*** | 1.2083*** | 1.5625*** |
| | (0.079) | (0.099) | (0.129) |
| educac_lowsec | 1.4760*** | 1.3793*** | 1.5611*** |
| | (0.026) | (0.037) | (0.036) |
| educac_sec | 1.7160*** | 1.6859*** | 1.7466*** |
| | (0.017) | (0.024) | (0.026) |
| educac_advancedsec | 1.9432*** | 1.8529*** | 2.0676*** |
| | (0.054) | (0.068) | (0.085) |
| educac_alevel | 2.1860*** | 2.1432*** | 2.2402*** |
| | (0.026) | (0.033) | (0.040) |
| Observations | 3,428 | 1,769 | 1,657 |
| R-squared | 0.864 | 0.868 | 0.863 |
| Professional Education | | | |
| educprof_certind | 1.6625*** | 1.6564*** | 1.6707*** |
| | (0.023) | (0.031) | (0.033) |
| educprof_certadm | 1.8415*** | 1.7729*** | 1.9037*** |
| | (0.028) | (0.039) | (0.038) |
| educprof_voctech | 1.6565*** | 1.5467*** | 1.7486*** |
| | (0.041) | (0.059) | (0.056) |
| educprof_uni | 2.2141*** | 2.1342*** | 2.2822*** |
| | (0.042) | (0.059) | (0.058) |
| educprof_other | 1.8502*** | 1.8557*** | 1.8452*** |
| | (0.030) | (0.042) | (0.041) |
| educprof_no | 1.5760*** | 1.6174*** | 1.4775*** |
| | (0.038) | (0.045) | (0.071) |
| Observations | 3,400 | 1,753 | 1,645 |
| R-squared | 0.855 | 0.853 | 0.858 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: The Distribution of the Dependent Variable used in Analyses of Table 4 to Table 6

| Months Unemployed Between Months 6 and 30 Truncated at 6 | | | | | | |
|---|---|---|---|---|---|---|
| Value | Obs. | % | Obs. | % | Obs. | % |
| | Full Sample | | Under Age 33 | | Age 33 and Above | |
| 0 | 4105 | 27.0 | 2360 | 31.2 | 1742 | 23.0 |
| 1 | 721 | 4.8 | 420 | 5.5 | 301 | 4.0 |
| 2 | 776 | 5.1 | 411 | 5.4 | 365 | 4.8 |
| 3 | 666 | 4.4 | 326 | 4.3 | 339 | 4.5 |
| 4 | 808 | 5.3 | 384 | 5.1 | 422 | 5.6 |
| 5 | 716 | 4.7 | 351 | 4.6 | 365 | 4.8 |
| 6 | 7381 | 48.6 | 3318 | 43.8 | 4050 | 53.4 |

Table 7: Expected Wage, Last Wage and Cognition

| VARIABLES | (1) Spec1 | (2) Spec2 | (3) Spec3 |
|---|---|---|---|
| Numeracy 0 or 1 | -18.0482*** | -14.1762*** | 0.0183 |
| | (2.214) | (2.208) | (3.675) |
| Numeracy 2 | -12.0717*** | -9.1847*** | 3.1455 |
| | (2.141) | (2.124) | (3.442) |
| Last Daily Wage | | 0.2245*** | 0.3860*** |
| | | (0.022) | (0.039) |
| num. 0 or 1 * last D. Wage | | | -0.2706*** |
| | | | (0.059) |
| Num. 2 * Last D. Wage | | | -0.2212*** |
| | | | (0.051) |
| Constant | 86.9354*** | 73.9470*** | 64.2846*** |
| | (1.766) | (2.182) | (2.881) |
| Observations | 1,456 | 1,432 | 1,432 |
| R-squared | 0.044 | 0.109 | 0.125 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: The Relationship Between Number of Months in Training after Inflow in Unemployment and Numeracy

| VARIABLES | Full Sample | Younger Cohort | Older Cohort |
|---|---|---|---|
| | Short-Term Light-Touch Traing | | |
| Numeracy 0 or 1 | 0.1903*** | 0.2265*** | 0.1529*** |
| | (0.041) | (0.058) | (0.058) |
| Numeracy 2 | 0.1154*** | 0.0950* | 0.1406** |
| | (0.040) | (0.057) | (0.057) |
| Numeracy missing | 0.1197** | 0.0486 | 0.2206*** |
| | (0.050) | (0.069) | (0.074) |
| cohorts no cognition | 0.0940*** | 0.1003** | 0.0878* |
| | (0.035) | (0.050) | (0.048) |
| Constant | 0.2729*** | 0.2581*** | 0.2861*** |
| | (0.034) | (0.049) | (0.047) |
| | | | |
| Observations | 15,173 | 7,570 | 7,584 |
| R-squared | 0.002 | 0.003 | 0.002 |
| | Long-Term Intensive Traing | | |
| Numeracy 0 or 1 | -0.2052*** | -0.0134 | -0.3526*** |
| | (0.074) | (0.099) | (0.111) |
| Numeracy 2 | -0.1255* | 0.0213 | -0.2263** |
| | (0.073) | (0.098) | (0.108) |
| Numeracy missing | -0.0444 | 0.1151 | -0.1601 |
| | (0.091) | (0.118) | (0.141) |
| cohorts no cognition | -0.1503** | 0.0079 | -0.2742*** |
| | (0.063) | (0.086) | (0.092) |
| Constant | 0.6127*** | 0.3692*** | 0.8193*** |
| | (0.061) | (0.084) | (0.089) |
| | | | |
| Observations | 15,173 | 7,570 | 7,584 |
| R-squared | 0.001 | 0.000 | 0.002 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1