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ABSTRACT

Numeracy and Unemployment Duration*

Governments are showing an increasing interest in quantitative models that give insights into the determinants of unemployment duration. Yet, these models oftentimes do not explicitly take into account that unemployment prospects are influenced by personality characteristics that are not being fully captured by variables in administrative data. Using German survey data linked with administrative data, we show that numeracy skills are strongly related to unemployment duration, while at the same time we confirm well-established patterns documented in the literature. Low numeracy is strongly related to a longer unemployment duration of workers below median age (33) in our sample, even after including a rich set of controls. We find that unrealistic reservation wages are 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 older workers 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. Another tentative explanation, which is supported by the data, is that younger people have fewer signals to send such that their cognitive abilities may have a higher relative signalling value.

JEL Classification: D04, D61, J64, J68

Keywords: unemployment duration, cognitive and noncognitive skills, numeracy

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1 Introduction

For a long time, labour economists and other social scientists have shown an interest in understanding differences in unemployment duration between individuals, across regions and over time. Consensus has been growing that certain institutional settings and policies are influential, such as the structure of benefit schemes (Lalive, 2007), or support by work coaches (Schiprowski, 2017; Van Landeghem et al., 2017). A recent extensive meta-analysis on the effectiveness of Active Labour Market Policies (ALMPs) is provided in Card et al. (2017). It is also well-known that socioeconomic characteristics such as age, education and employment history are important determinants for one's employment status (Ichino et al., 2008). Despite this body of knowledge, it remains an open question what other individual characteristics are predictive of unemployment duration. Identifying such individual factors would help to target and personalize ALMPs.

Our paper aims to fill this knowledge gap by analyzing the relationship between unemployment duration and cognitive skills, and in particular numeracy. We use administrative data from the Institute for Employment Research (IAB) of the German Federal Employment Agency on individuals who enter unemployment between June 2007 and May 2008, and link these data to survey data administered by the Institute of Labor Economics (IZA). We document that numeracy is associated with unemployment duration. This relationship is strong for job seekers in the younger age cohort (younger than 33 years of age in our data). The richness of the data allows us to explore several channels through which this relationship manifests such as job search strategies, wage expectations, locking-in effect of training programmes, signalling, and selection effects.

Evidence on the relationship between cognitive skills and unemployment duration is rare. In fact, we are only aware of one study that assesses the role of cognition: Arendt et al. (2008) find in their Danish data of 1533 transitions from unemployment to employment that higher literacy (including mathematical literacy) is associated with higher job finding rates. While this study is the closest to our work, their data do not allow them to turn to a detailed analysis of heterogeneity and to control for noncognitive skills. The scarcity of studies in this area is somewhat surprising, given that numerous papers and policy reports have investigated the relationship between skills and other facets of labour market success. A first strand of literature studies the relationship between skills of the adult population and their labour earnings (e.g. Chiswick et al., 2003; Green and Riddell, 2001; Lee and Miller, 2000; McIntosh and Vignoles, 2001; Sum, 1999). Another strand of literature has focused on pre-market skills, i.e. the set of skills of youngsters or school-leavers, on their labour market outcomes (e.g.

Caspi et al., 1998; Kelly et al., 2012; Lamb, 1997; Lam et al., 2010; Lundtrae et al., 2010; Machin et al., 2001; Marks and Fleming, 1998). The upshot of this literature is that noncognitive and cognitive skills accumulated in childhood and adolescence boost labour market success later in life (Almlund et al., 2011). While earlier studies have typically focused on cognitive skills (Hanushek and Woessmann, 2008), and in particular educational achievement, a growing amount of survey and administrative data has allowed researchers during the last decade to assess the role of attitudes, personality traits and noncognitive skills on labour market success (see Kautz et al., 2014 and references therein). Various survey measures of people's personality and noncognitive skills seem to be correlated with labour market related behaviour and outcomes, such as job performance (Barrick and Mount, 1991), wages (Osborne Groves, 2005; Cobb-Clark and Tan, 2011), sorting into occupations and jobs (Bonin et al., 2007, selection into ALMPs such as training programmes (Caliendo et al., 2017), as well as job search behaviour (Caliendo et al., 2015). These measures are also weakly correlated with the probability of transition from unemployment into work (Wanberg et al., 2002).

Our results are important, not just to target jobseekers at risk for developing a poor labour market history, but also to finetune and design the actual content of these programmes. Indeed, our results help us to obtain further insights into which characteristics might need special attention to improve labour market success.

The paper proceeds as follows. Section 2 outlines the linked administrative and survey data used in this paper, and offers descriptives that might be useful to interpret the empirical results. Section 3.1 discusses the main empirical strategy and empirical results and Section 3.2 explores potential mechanisms that can explain the latter results. Finally, Section 4 concludes the paper.

2 Data and Descriptives

We rely on data from the IZA/IAB Linked Evaluation Dataset (administrative data v3). This consists of the scientific use file (SUF) of the IZA Evaluation Data Set Survey, which is provided by the International Data Service Center (IDSC) of the IZA and a SUF of administrative data that are provided by the IAB.[1] The survey data was collected by IZA and consists of survey information on individuals who entered unemployment between June 2007 and May 2008 in Germany (see Arni et al., 2014). The survey is a panel with three repeated measurements for each of the 12 monthly entry cohorts. Each cohort was interviewed one month, 12 months and 30 months after entry into unemployment

[1] For those survey respondents who gave their consent (90% of individuals), we merge the survey data with administrative data from the IAB. This means that we can link first round responses to labour market performance even if subjects quit the panel prematurely.

in a telephone survey. The survey data contain information on search behaviour as well as measures of personality, preferences, attitudes and beliefs. For three entry cohorts (cohorts entering unemployment in June, October and February), an additional interim wave was fielded six months after entry into unemployment. These three entry cohorts were not only interviewed more frequently than the other cohorts, but their survey was also more extensive as each round included a cognition module.[2] We therefore refer to this sub-sample as the cognition sample. This cognitive module contains a short and medium-term memory test, a word fluency test, a test for orientation in time, as well as questions on numeracy. The numeracy questions 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?

While these questions were asked in all of the four waves, we will only make use of first-wave responses throughout the analysis, for two reasons: First, there was substantial attrition across the waves such that we only observe repeated measures for a subset of respondents. Second, for those for whom we have repeated measurements, the second cognition measure is likely confounded by the first one.[3]

In the first wave, questions 1, 2 and 3 were answered correctly by 84%, 51% and 17% of respondents, respectively. Table 1 displays the distribution of numeracy scores, which can vary from 0 to 3 or can be missing. The table offers descriptives for all three entry cohorts of the cognition sample, but also splits them out separately for those younger than 33 years of age (the younger cohort) and those being 33 years of age and older (the older cohort). Table 1 reveals 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 one or more of the numeracy questions (13.0%). 15.5% of individuals obtained the highest score.

Table 2 shows that numeracy scores are significantly correlated with educational achievement. The table displays estimates of linear probability models with the numeracy score (ranging from 0 to 3) as the dependent variable and a full set of either mutually exclusive school-aged or further (professional) education dummies as independent variables. The academic and professional education categories are constructed

[2]Only a subsample was exposed to this module for budgetary reasons.

[3]In fact, we observe in the data that scores tend to improve over time, suggesting a learning effect, or a selection effect, or an experience effect (e.g. respondents might be prepared for questions on cognition, have paper and pencil ready at the second telephone interview, or simply remember questions from the first round).

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

Summary Statistics						
	Full Sample		Age <= 32		Age > 32	
	Obs.	%	Obs.	%	Obs.	%
Numeracy Score						
0	61	1.6	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	325	17.8
Missing	512	13.0	287	14.0	332	17.7

based on survey responses to education. The estimated coefficients reported in the table provide a point estimate of the average numeracy score for each education category, as we have omitted the constant from the regression models. We estimate these models for the full cognition sample (column (1)), as well as for the two age cohorts (younger than 33 years of age and 33 years of age and older) separately (columns (2) and (3)). The estimates indicate that the relationship between numeracy and education is similar in the two subsamples of younger and older respondents. Individuals of the older cohort in lower categories of school-aged education score slightly better than their younger counterparts, which is not surprising given that education became more widely accessible over the years.[4]

Descriptive statistics for our key dependent variable, months in unemployment during the 30 months after first entering unemployment, are provided in Table 3. The first three columns display statistics for the cognition sample, the last three columns for the no-cognition sample, those nine entry cohorts that were not exposed to the cognition module. Respondents who left unemployment within one month after inflow, and would not return to unemployment afterwards, are assigned a value of zero months in unemployment. Those who were in unemployment for the entire period will have a count of 30. We provide the percentage of individuals with a particular number of months in unemployment for the full sample, as well as for those under the age of 33, and those of age 33 and above. The table also contains averages and standard deviations in months for these six categories.

Interestingly, the distribution of unemployment in the cognition sample and in the

[4]The explained variation is high: more than 86% of the variance is explained in regressions of numeracy scores on school-aged education dummies, and more than 85% in a regression of numeracy score on professional education dummies. The coefficient of determination would obviously be much lower if a constant term was included.

Table 2: Estimates for Numeracy Scores for Education Levels

	Dependent variable: Numeracy score		
	Full Sample	Age <= 32	Age > 32
	(1)	(2)	(3)
Highest Schooling Degree			
Basic/no education	1.350***	1.208***	1.563***
	(0.083)	(0.098)	(0.140)
Lowest secondary	1.476***	1.379***	1.561***
	(0.025)	(0.033)	(0.037)
Lower/middle secondary	1.716***	1.686***	1.747***
	(0.018)	(0.024)	(0.026)
Advanced technical qualification	1.943***	1.853***	2.068***
	(0.055)	(0.071)	(0.084)
A-levels / International baccalaureate'	2.186***	2.143***	2.240***
	(0.026)	(0.034)	(0.038)
Observations	3,428	1,769	1,657
R-squared	0.864	0.868	0.863
Highest Vocational Education			
Industrial training	1.663***	1.656***	1.671***
	(0.022)	(0.030)	(0.033)
Commercial/administrative certificate	1.842***	1.773***	1.904***
	(0.028)	(0.042)	(0.038)
Vocational school	1.657***	1.547***	1.749***
	(0.039)	(0.058)	(0.053)
Master technician	1.878***	1.978***	1.833***
	(0.060)	(0.100)	(0.075)
University degree	2.214***	2.134***	2.282***
	(0.041)	(0.060)	(0.056)
Other professional	1.841***	1.833***	1.851***
	(0.035)	(0.044)	(0.056)
No professional qualification	1.576***	1.617***	1.477***
	(0.039)	(0.047)	(0.069)
Observations	3,428	1,769	1,657
R-squared	0.855	0.853	0.858

OLS estimates, standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Distribution of Months Unemployed between $T+1$ and $T+30$ with T Month of Inflow

	Cognition sample			No-cognition sample		
	Full sample	Age <= 32	Age > 32	Full sample	Age <= 32	Age > 32
Month	%	%	%	%	%	%
0	8.43	10.80	5.85	7.83	10.12	5.65
1	5.84	7.10	4.47	6.12	7.09	5.19
2	6.19	7.20	5.11	6.20	7.09	5.35
3	5.33	5.89	4.73	5.93	7.11	4.80
4	4.87	5.79	3.88	4.99	5.42	4.58
5	5.41	5.06	5.74	4.91	5.06	4.73
6	4.14	4.38	3.88	4.66	5.26	4.08
7	4.77	4.72	4.84	4.30	4.04	4.56
8	3.88	4.23	3.51	4.16	3.84	4.47
9	5.28	4.43	6.17	4.53	4.28	4.77
10	4.11	4.23	3.99	4.50	3.97	5.01
11	5.91	4.96	6.97	6.14	5.33	6.92
12	5.58	5.06	6.17	5.72	4.79	6.59
13	3.86	3.06	4.73	3.83	3.32	4.33
14	3.48	2.92	4.10	3.52	2.83	4.15
15	3.43	2.33	4.63	3.18	2.34	3.98
16	2.69	2.09	3.30	3.10	2.76	3.44
17	2.82	2.19	3.51	2.45	2.18	2.68
18	2.34	1.99	2.71	2.07	1.85	2.30
19	1.47	1.31	1.65	1.59	1.16	2.02
20	1.50	1.56	1.44	1.42	1.14	1.68
21	1.19	0.97	1.44	1.18	0.98	1.38
22	1.17	1.07	1.28	1.12	1.11	1.14
23	1.12	1.36	0.85	0.98	1.05	0.91
24	0.86	0.88	0.85	0.97	0.87	1.07
25	0.63	0.44	0.85	0.65	0.83	0.47
26	0.71	0.88	0.48	0.59	0.40	0.77
27	0.56	0.78	0.32	0.58	0.73	0.44
28	0.41	0.44	0.37	0.61	0.71	0.51
29	0.38	0.24	0.53	0.37	0.45	0.30
30	1.65	1.65	1.65	1.81	1.89	1.72
Sample average (months)						
	9.50	8.76	10.30	9.53	8.82	10.20
Sample standard deviation (months)						
	7.30	7.46	7.04	7.34	7.53	7.09

no-cognition sample is very similar. This is partly due to the fact that the entry cohorts in the cognition sample are equally spread out over the calendar year (June, October and February). In both samples, the older cohort has a higher average count of months in unemployment than the younger cohort. For the younger cohort, the count of months in unemployment is on average 8.76 months and 8.82 months in the cognition and no-cognition sample, respectively. For the older cohort, the latter averages equal to 10.30 and 10.20, respectively.

3 Analysis

3.1 The Relationship Between Months in Unemployment and Numeracy

We first explore the relationship between the number of months in unemployment, a variable extensively documented in Table 3.1, and numeracy, and this with three sets of OLS regressions. We hereby follow the approach of Altmann et al. (2018), who document OLS estimates of the number of days in employment in a given time horizon. This straightforward approach takes into account that people can move out and subsequently back into a labour market state (unemployment). Due to anonymization procedures applied to our data, we are however restricted to a count of months rather than days. Analogous to the categorization in the descriptive tables, the first set of regressions look at the entire sample, while sets 2 and 3 are restricted to those up to 32 years of age at entry, and those of 33 years of age and above.

Results are displayed in Table 4, which contains four specifications for each of the three different samples described above. The first column of each set contains the most parsimonious specification, with only three dummy variables as explanatory variables that indicate the numeracy score. The first variable takes the value one if either zero or one out of three numeracy questions were answered correctly (and zero otherwise). The second variable, Numeracy 2, indicates that two questions are answered correctly. A third dummy variable, Numeracy missing, takes one if the numeracy score is missing, zero otherwise. Three correct answers is the reference category. Next, we also include an indicator which takes one if an individual belongs to the nine cohorts of inflow which were not asked to answer the numeracy questions, Cohorts no cognition. This allows us to run the regressions on the entire sample, rather than on the cognition sample only, which helps to preserve power for the control variables in the more extensive models. Finally, a full set of month-of-entry dummies are added, to control for heterogeneity between individuals who first enter unemployment at different times.

Table 4: Unemployment Duration and Numeracy

	Dependent variable: months in unemployment within 30 months after inflow											
	Full Sample				Age <= 32				Age > 32			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Numeracy 0 or 1	1.156***	1.301***	0.829**	0.726**	2.242***	2.328***	1.263**	1.124**	0.366	0.356	0.351	-0.164
	(0.356)	(0.354)	(0.357)	(0.366)	(0.530)	(0.536)	(0.535)	(0.548)	(0.472)	(0.470)	(0.478)	(0.413)
Numeracy 2	0.434	0.516	0.351	0.319	1.083**	1.125**	0.709	0.670	0.083	0.007	0.025	-0.430
	(0.348)	(0.345)	(0.347)	(0.350)	(0.521)	(0.526)	(0.524)	(0.531)	(0.457)	(0.454)	(0.457)	(0.393)
Numeracy missing	1.592***	1.758***	1.285***	-0.676	2.595***	2.663***	1.582**	-2.174	0.823	0.822	0.695	
	(0.440)	(0.436)	(0.436)	(1.178)	(0.641)	(0.643)	(0.637)	(1.597)	(0.593)	(0.590)	(0.592)	
Sample no cognition	1.019***	1.100***	0.796**	0.814*	1.762***	1.828***	1.069**	0.655	0.514	0.455	0.454	
	(0.323)	(0.320)	(0.323)	(0.485)	(0.489)	(0.494)	(0.491)	(0.699)	(0.421)	(0.419)	(0.424)	
1 if female		-0.412***	-0.359***	-0.359***		-0.608***	-0.129	-0.083		-0.243	-0.411**	-0.425**
		(0.120)	(0.129)	(0.132)		(0.176)	(0.188)	(0.194)		(0.163)	(0.177)	(0.180)
Age:												
26-32		-0.432**	0.025	0.039		-0.401**	0.342*	0.373**				
		(0.174)	(0.175)	(0.175)		(0.176)	(0.180)	(0.181)				
33-39		0.561***	0.962***	0.982***								
		(0.182)	(0.182)	(0.182)								
40-46		0.666***	1.044***	1.030***						0.116	0.130	0.111
		(0.173)	(0.172)	(0.174)						(0.191)	(0.191)	(0.192)
47-55		2.624***	2.914***	2.829***						2.065***	2.084***	2.035***
		(0.191)	(0.192)	(0.195)						(0.207)	(0.209)	(0.212)
Highest Schooling degree:												
Lowest secondary			-1.380***	-1.328***			-1.727***	-1.577***			-0.625	-0.633

Continued on next page

	Dependent variable: months in unemployment within 30 months after inflow											
	Full Sample				Age <= 32				Age > 32			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			(0.404)	(0.405)			(0.568)	(0.571)			(0.549)	(0.552)
Lower/middle secondary			-1.827***	-1.844***			-2.808***	-2.700***			-0.601	-0.662
			(0.398)	(0.400)			(0.558)	(0.562)			(0.545)	(0.548)
Advanced technical			-2.881***	-2.822***			-4.337***	-4.194***			-1.016	-0.983
			(0.466)	(0.468)			(0.644)	(0.648)			(0.656)	(0.659)
A-levels /			-2.317***	-2.279***			-3.841***	-3.756***			-0.382	-0.362
International baccalaureate			(0.425)	(0.427)			(0.597)	(0.601)			(0.583)	(0.585)
Highest Vocational degree:												
Industrial training			-2.007***	-2.009***			-2.326***	-2.281***			-1.238***	-1.279***
			(0.225)	(0.226)			(0.294)	(0.296)			(0.338)	(0.340)
Commercial/administrative			-1.450***	-1.387***			-1.682***	-1.581***			-0.782**	-0.783**
			(0.247)	(0.248)			(0.330)	(0.331)			(0.365)	(0.366)
Vocational school			-2.342***	-2.366***			-3.275***	-3.292***			-1.060***	-1.096***
			(0.275)	(0.275)			(0.374)	(0.374)			(0.401)	(0.402)
Master technician			-2.808***	-2.707***			-4.160***	-3.935***			-1.590***	-1.571***
			(0.337)	(0.338)			(0.525)	(0.526)			(0.454)	(0.455)
University degree			-2.412***	-2.389***			-3.451***	-3.346***			-1.422***	-1.485***
			(0.319)	(0.321)			(0.446)	(0.449)			(0.454)	(0.457)
Other professional			-2.106***	-2.113***			-2.882***	-2.840***			-1.071***	-1.123***
			(0.255)	(0.255)			(0.343)	(0.344)			(0.375)	(0.377)
Above median score in:												
Word fluency				-0.034				-0.078				-0.189
				(0.255)				(0.359)				(0.348)
Short memory				0.240				0.252				0.024

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	Dependent variable: months in unemployment within 30 months after inflow											
	Full Sample				Age <= 32				Age > 32			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
				(0.321)				(0.445)				(0.458)
Long memory				-0.237				-0.165				-0.212
				(0.297)				(0.409)				(0.426)
Time orientation				0.146				-0.356				0.379
				(0.354)				(0.484)				(0.387)
Openness				0.041				0.023				0.005
				(0.127)				(0.185)				(0.174)
Conscientiousness				-0.153				-0.395**				0.132
				(0.124)				(0.176)				(0.172)
Extroversion				0.033				0.012				0.048
				(0.129)				(0.188)				(0.176)
Neuroticism				0.123				0.067				0.209
				(0.125)				(0.180)				(0.173)
External locus				0.330***				0.542***				0.058
of control				(0.127)				(0.181)				(0.178)
local unemployment rate				0.607***				0.912***				0.355**
				(0.123)				(0.175)				(0.172)
Constant	9.027***	8.652***	12.207***	11.712***	7.356***	7.731***	12.764***	12.526***	10.529***	10.064***	11.768***	11.745***
	(0.429)	(0.438)	(0.587)	(0.692)	(0.620)	(0.629)	(0.824)	(0.985)	(0.585)	(0.592)	(0.818)	(0.781)
Observations	15,173	15,173	15,173	15,173	7,570	7,570	7,570	7,570	7,584	7,584	7,584	7,584
R-squared	0.003	0.022	0.038	0.041	0.007	0.009	0.050	0.056	0.003	0.021	0.024	0.027

Notes: OLS estimates. Dependent variable = count of months in unemployment within 30 months after inflow. Robust standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The next columns of each set show results of specifications in which the set of controls is gradually extended. In a second column, an indicator for gender as well as age-banded dummies are added, while in column 3 a set of school-aged and further (professional) education dummies are introduced. For completeness, we also show results of a fourth specification in which we include measures for other cognitive skills (word fluency, memory, and orientation in time), and additional noncognitive skills as well as the local unemployment rate. Results from this specification, however, might be harder to interpret. It is, for example, likely that these different skills are related, and are potentially bad controls. Moreover, as skills are correlated and since our skills are measured with error, a measure for one skill might be proxying another skill. Hence, we prefer the more parsimonious specifications. Throughout the analysis, we do not use any continuous or discrete regressors: by converting each variable into a set of exhaustive and mutually exclusive dummies, we are able to include a missing indicator for each measure, such that we do not lose any of the 15173 observations for which we have the labour market status post-inflow. Further descriptive information about the control variables is provided in the Appendix, Table A1 and Table A2.

For the full 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 be associated with a higher number of months in unemployment if one scores 0 or 1. The most parsimonious specification indicates that those with very low numeracy (0 or 1) or those with a missing numeracy score spend on average more time in unemployment than those with a numeracy score of 3. On average, within the thirty-months-window that we examine, these individuals spend 1.16 and 1.59 months more in unemployment, respectively. Those who answered two of the numeracy questions correctly are predicted to spend 0.43 months longer in unemployment than individuals with a perfect score, but due to the large standard error this coefficient is not significantly different from zero at conventional significance levels. The dummy Cohorts no cognition helps us to distinguish between those who did provide an answer to the questions (Numeracy missing) and those who have not been asked the cognition questions. 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 numeracy 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 cognition sample, and can be inferred from Table 1. This weighted average in Table 4 column (1) equals to $1.16 * 0.34 + 0.43 * 0.38 + 1.59 * 0.13 = 0.76$, which means that the difference with the coefficient on Cohorts no cognition amounts to less than its standard deviation. Moreover, one needs to remember that we are including month-of-entry dummies, and the months of entry are, by construction, different in the cognition and no-cognition sample which means that the latter are correlated with the Cohorts no cognition dummy. If we rerun the specification without the month-of-entry dummies and repeat the above exercise, we obtain a weighted average of 0.77 which is very similar as before. The coefficient on Cohorts no cognition, however, then equals 0.78, which means that its point estimate in this specification is nearly identical to the weighted average of the numeracy coefficients.

While the coefficient on Numeracy 0 or 1 slightly increases after controlling for gender and age-banded dummies, its coefficient decreases to 0.83 after including sets of school-aged and further (professional) education dummies. This decline should not be surprising as we saw that numeracy scores are highly correlated with educational attainment (see Table 2), and these results are also reassuring that our measures are good proxies for numeracy skills. Indeed, one might expect that educational attainment has an impact on, or is at least correlated with cognitive skills. There is a further modest decline (to 0.73) in the point estimate of Numeracy 0 or 1 after including indicators for other cognitive skills as well as noncognitive skills and the local unemployment rate, which is obviously not surprising given the comments above. It is worth pointing out that the coefficient on Numeracy missing in column (4) is now negative, with a point estimate of -0.68 but far from significantly different from zero at conventional significance levels due to its huge standard error. This latter result nicely illustrates that coefficients are harder to interpret in this specification. One should remember that we are including missing indicators for all measures, and obviously non-response across items is highly though not perfectly correlated.

Remarkably, the second set of regressions displayed (Columns (5)-(8)) in Table 4 reveals that numeracy is particularly important and discriminatory for the younger cohorts, i.e. the difference in months in unemployment between groups that differ in numeracy scores is more marked for younger workers than for the full sample of workers. The first specification's point estimates for Numeracy 0 or 1 and Numeracy missing are equal to 2.24 and 2.59, which means an increase compared to their equivalent coefficients for the full sample with 93% and 63%, respectively. Moreover, the indicator for having two out of the three questions correct has now a point estimate of 1.08, an increase of more than 150% compared to the full sample estimate, and the coefficient is now also significant at the 5% significance level. While the numeracy dummies in this specification for the younger cohort are all statistically significant, it is clear that these are also economically highly significant. Indeed, the coefficients are very large given that we only look at a time window of 30 months, and that the average number of months in unemployment for the younger cohort equals 8.76 (See Table 3). Again, as for the full sample, the coefficients on numeracy dummies decline in specifications 3 and 4, and from specification 3 onwards, the dummy for Numeracy 2 is not statistically significant any more at conventional levels. But point estimates, both on Numeracy 0 or 1 and on Numeracy 2, remain substantial.

Finally, the third set of regressions (Columns (9)-(12)) in Table 4 documents results for the older cohort. Given the discrepancy between results for the full sample and the younger cohort, it is not surprising that none of the numeracy dummies in this table are statistically significant, and that point estimates are small at least compared to results from the previous two tables. For example, in the first specification, the coefficient on Numeracy 0 or 1 has a coefficient of 0.32, which amounts only to 17% of the size of the equivalent coefficient for the younger cohort. Numeracy 2 has a point estimate of only 0.08, which is about 7% of the size of its counterpart for the younger cohort.

Across the three sets of regressions, it appears that other measures of cognition (word fluency, memory and orientation in time) do not have substantial additional explanatory power in our case study. The other standard controls show us a picture which is in line with the literature, and some of the noncognitive skills (conscientiousness and locus of control) and labour market conditions (the local unemployment rate) as well as socioeconomic variables (age and education) have explanatory power.

One can obviously opt for different modelling strategies, and the descriptives in Table suggest that a Poisson model would be a good candidate. Replications of the results in Table 4 are enclosed in the appendix. These are in line with the results described above and often do even look a bit better in terms of statistical significance.

3.2 Exploring the Mechanisms

After having established a relationship between numeracy and time spent 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.

A first route to explore is the relation between individual's wage expectations and numeracy skills, as it is plausible that those with low numeracy overestimate their earnings potential. Table 5 suggests that this is arguably not the case. Lower numeracy is significantly associated with lower wage expectations, even after controlling for last wage earned.

Table 5: Expected Wage, Last Wage and Numeracy

	OLS Regression			Logit Regressions			OLS Regression		
Dependent variable:	Expected daily wage			Indicator = 1 if expected wage missing			Log(expected daily wage)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Numeracy 0 or 1	-17.379***	-12.905***	0.559	0.750***	-0.300***	0.694**	-0.210***	-0.195***	-0.032
	(2.674)	(2.422)	(4.082)	(0.073)	(0.100)	(0.118)	(0.027)	(0.027)	(0.109)
Numeracy 2	-12.971***	-9.214***	1.382	0.839*	-0.175*	0.748*	-0.135***	-0.125***	0.002
	(2.580)	(2.410)	(3.997)	(0.081)	(0.098)	(0.122)	(0.027)	(0.026)	(0.108)
Numeracy missing	-6.044*	-3.213	8.836*	0.870	-0.164	0.882	-0.057*	-0.047	0.185
	(3.300)	(3.119)	(5.092)	(0.104)	(0.123)	(0.181)	(0.033)	(0.033)	(0.117)
Sample no cognition	-11.508***	-8.461***	-2.053	0.759***	-0.283***	0.780*	-0.139***	-0.129***	-0.079
	(2.454)	(2.309)	(3.721)	(0.063)	(0.085)	(0.111)	(0.024)	(0.023)	(0.087)
Last daily wage		0.279***	0.401***		-0.001	0.999			
		(0.022)	(0.068)		(0.000)	(0.002)			
Num. 0 or 1 * last d. wage			-0.274***			1.002			
			(0.079)			(0.003)			
Num. 2 * Last d. wage			-0.196**			1.003			
			(0.077)			(0.002)			
Num. missing * Last d. wage			-0.224**			0.999			
			(0.101)			(0.003)			
Samp. no cog. * Last d. wage			-0.104			0.999			
			(0.074)			(0.002)			
Log last daily wage								0.084***	0.102***
								(0.005)	(0.023)
Num. 0 or 1 * Log Last D. Wage									-0.045
									(0.029)
Num. 2 * Log last d. wage									-0.035
									(0.029)
Num. missing * Log last d. wage									-0.064**
									(0.032)
Samp. no cog. * Log last d. wage									-0.013
									(0.024)
expected wage missing				.		.			
				(.)		(.)			
Constant	87.377***	70.976***	63.719***	1.047	0.067	1.059	4.379***	4.072***	4.001***
	(2.385)	(2.454)	(3.531)	(0.085)	(0.087)	(0.146)	(0.023)	(0.030)	(0.084)
Observations	8,277	8,114	8,114	15,173	14,723	14,723	8,364	7,861	7,861
R-squared	0.005	0.057	0.060				0.009	0.052	0.053

Notes: OLS estimates in columns (1)-(3) and (7)-(9), logit estimates, odds ratios reported in columns (4)-(6). Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

If we include interaction terms of numeracy dummies (and the Cohorts no cognition dummy) and 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 numeracy. Expected daily wage is missing for 45.6% of respondents, however. Therefore, a second set of columns in Table 5 shows logit regressions with the same vectors of explanatory variables as in the first set, but now the dependent variable is a dummy taking the value one if wage expectations are missing. We find that people with lower numeracy have a lower chance of not recording wage expectations. Finally, the third set of equations in Table 5 are similar to the first set apart from the wage variables being log-transformed. This means that we loose a small number of observations as for some individuals the last-earned wage has been coded to zero. The third set of equations in Table 5 allows us to draw the same conclusion as the first set.

Next, we might wonder whether the participation in ALMPs (i.e. training) is different across people with different numeracy scores. If people with low numeracy tend to participate in training programmes more frequently than those with high numeracy, the longer time spent in unemployment for the former group might be due to a locking-in effect: if people commit to training, looking for a stable 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 6 shows OLS estimates of regressions with 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 as the dependent variables. The independent variables are the same as those in column (1) of Table 4.

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 numer-

Table 6: The Relationship Between Number of Months in Training and Numeracy

	Full Sample	Age <= 32	Age > 32
	Short-Term Light-Touch Training		
Numeracy 0 or 1	0.190***	0.227***	0.153***
	(0.039)	(0.056)	(0.055)
Numeracy 2	0.115***	0.095*	0.141**
	(0.038)	(0.052)	(0.055)
Numeracy missing	0.120**	0.049	0.221***
	(0.049)	(0.063)	(0.079)
Sample no cognition	0.094***	0.100**	0.088**
	(0.031)	(0.045)	(0.044)
Constant	0.273***	0.258***	0.286***
	(0.030)	(0.044)	(0.042)
Observations	15,173	7,570	7,584
R-squared	0.002	0.003	0.002
	Long-Term Intensive Training		
	Full Sample	Younger Cohort	Older Cohort
Numeracy 0 or 1	-0.205**	-0.013	-0.353***
	(0.082)	(0.098)	(0.127)
Numeracy 2	-0.126	0.021	-0.226*
	(0.082)	(0.099)	(0.125)
Numeracy missing	-0.044	0.115	-0.160
	(0.104)	(0.127)	(0.163)
Sample no cognition	-0.150**	0.008	-0.274**
	(0.074)	(0.087)	(0.113)
Constant	0.613***	0.369***	0.819***
	(0.072)	(0.085)	(0.111)
Observations	15,173	7,570	7,584
R-squared	0.001	0.000	0.002

Notes: OLS estimates. Dependent variable = count of months in unemployment within 30 months after inflow. Standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Unemployment Duration and Numeracy: Heterogeneous Effects Across Activity Before Inflow

Dependent variable: Months in Unemployment within 30 Months after Inflow				
	(1)	(2)	(3)	(4)
	Employed	School/training	Care	Other
Numeracy 0 or 1	0.001	3.263***	4.131**	2.279*
	(0.421)	(0.841)	(1.885)	(1.347)
Numeracy 2	-0.209	1.407*	2.152	1.433
	(0.415)	(0.812)	(1.841)	(1.341)
Numeracy missing	0.890*	3.196***	4.697**	0.945
	(0.521)	(1.025)	(2.299)	(1.569)
Sample no cognition	0.227	2.210***	3.572**	2.005
	(0.385)	(0.767)	(1.778)	(1.266)
Constant	10.158***	6.267***	6.498***	9.112***
	(0.494)	(0.969)	(2.023)	(1.371)
Observations	10,357	2,938	591	1,287
R-squared	0.002	0.016	0.030	0.010

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

acy 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.[5]

Next, we explore whether it is plausible that the signalling function for the younger cohort is different than for the older cohort. Indeed, older individuals have a longer labour market history and this could imply that the numeracy skills are less important as a signalling device. To investigate this, Table **??** presents a split-sample analysis, in which we do not split the sample with respect to age at inflow, but with respect to the labour market state during the last spell preceding unemployment. The categories (based on self-reported data) that we explore are (1) non-subsidized and subsidized employment, (2) school/apprenticeship/training/internship/academic studies or similar, (3) family car, and (4) other activities.

For each of these subgroups, we run the first specification as in Table 4. There is particularly a very strong relationship between unemployment and numeracy for the subsample of school-leavers, which are almost all individuals belonging to the younger cohort. For this subgroup, those with numeracy score 0 or 1 are predicted to spend 3.23

[5]Different specifications, such as Tobit or Probit models, confirm these results.

months more in unemployment than those individuals with a perfect numeracy score. For people in family care, this coefficient even increases to 4.13. In the subsample of individuals who were in employment before inflow, on the contrary, the coefficient on the Numeracy 0 or 1 dummy equals 0.00. Such results are in line with the hypothesis that a mechanism of signalling might be at work: school leavers do hardly have any labour market history to signal, and also family carers have less signalling devices. Obviously, employers are not able to observe the numeracy scores from our survey, either, but the latter are likely to be highly correlated with grades on mathematics and other related subjects. While we have information on educational attainment, we do not observe our respondents' grades in our data. Moreover, many employers will also organize exams or let applicants sit a short test to measure their skills.

Table 8: Differences in Noncognitive Skills Between the Younger and Older Cohort

Dependent Variables: Noncognitive Skills				
	Obs.	Cohort1 - Cohort 2	95% CI	P-value
External Locus	14754	-.2660	-.2987 -.2333	.000
Openness	15125	.1175	.0851 .1498	.000
Conscientiousness	15121	-.1181	-.1506 -.0856	.000
Extroversion	15079	.1836	.1515 .2157	.000
Neuroticism	15132	-.0136	-.0457 .0186	.408
Comparison with UKHLS				
Openness	15679	.1264	.0945 .1583	.000
Conscientiousness	15696	-.3451	-.3763 -.3140	.000
Extroversion	15694	.1002	.0674 .1329	.000
Neuroticism	15698	.1382	.1057 .1707	.000
Comparison with German SOEP				
External Locus of Control	13728	-.0092	-.0451 .0268	.618
Openness	13888	.1287	.0930 .1644	.000
Conscientiousness	13910	-.4995	-.5342 -.4647	.000
Extroversion	13946	.1041	.0685 .1397	.000
Neuroticism	13932	-.0692	-.1049 -.0335	.000

Notes: Variables were standardized.

Finally, the data also suggest that a selection effect might be at play: younger people are often unemployed simply because they need to find a job after leaving training or after a temporary job. Older individuals might have become unemployed for a variety of reasons and, even though they might be similar in cognitive skills, they might be different in noncognitive skills. This is suggested by the results in Table 8 which presents differences in cognitive skills between the younger and the older cohort. For comparison, the table also shows differences in noncognitive skills for younger and older people measured in two surveys which are more representative for the entire population (not just the unemployed). It concerns the United Kingdom Longitudinal Household Survey (UKHLS) and the German Socioeconomic Panel (SOEP).

The results show that younger individuals in our data have lower external locus of control, are more open to new experiences, and are more extrovert. While the younger cohort is significantly less conscientious than the older cohort, the gap is much smaller than in the general population, as do suggest our results from the UKHLS and the German SOEP.

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 labour market trajectory of new entrants into unemployment, as well as in developing evidence-based strategies to taylor the actual content of ALMPs.

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, certain noncognitive skills and local labour market conditions. Our data also contain measures for cognitive skills. Cognitive skills seem to have explanatory power. In particular for younger cohorts, the score on an easy-to-implement numeracy test is strongly related to time spent in unemployment, 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. Finally, we also show evidence which suggests that numeracy is simply more important for the younger cohort as a signalling device than for the older cohort. Also, older unemployed individuals might constitute a sample that is prevented to benefit from their cognitive skills due to having insufficient noncognitive skills. 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. Therefore we recommend to collect and/or make use of such information in research on labour market outcomes.

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A Appendix

A1 Additional Descriptives

Table A1: Distribution of Highest Educational Levels across the Samples

	Full Sample		Up to Age 32		Age 33 and Above	
	Number	%	Number	%	Number	%
	Highest Level of School-Aged Education					
Lowest Secondary	3340	22.01	1549	20.46	1785	23.54
Lower Secondary	7445	49.07	3656	48.30	3784	49/89
Advanced Secondary	812	5.35	476	6.29	336	4.43
A-Levels	3151	20.77	1653	21.84	1491	19.66
No Qualification	408	2.69	234	3.09	173	2.28
Missing	17	0.11	2	0.03	15	0.20
	Further (Professional) Education					
Industrial Certificate	4674	30.80	2304	30.44	2364	31.17
Administrative Certificate	2923	19.26	1439	19.01	1481	19.53
Vocational school	1531	10.09	713	9.42	817	10.77
Master technician	654	4.31	197	2.60	457	6.03
University	1336	8.81	584	7.71	749	9.88
Other	2108	13.89	1018	13.45	1086	14.32
No Qualification	1810	11.93	1235	16.31	574	7.57
Missing	137	0.90	80	1.06	56	0.74

Table A2: Descriptives for Additional Controls Used in Analysis

	OBS.	%
Variables Recorded in Entire Sample		
1 if female	7176	47.29
Age		
16-25	4751	31.31
26-32	2819	18.58
33-39	2373	15.64
40-46	2718	17.91
47-55	2493	16.43
Age missing	19	0.13
Openness missing	48	0.32
Conscientiousness missing	50	0.33
Extroversion missing	94	0.62
Neuroticism missing	41	0.27
Locus of control missing	419	2.76
Local unemp. rate missing	6	0.04
Variables Only Recorded in Cognition Sample		
Word fluency missing	518	13.15
Short memory missing	497	12.61
Long memory missing	500	12.69
Time orientation missing	476	12.08

Note: We created missing indicators to be included in the regressions in order to preserve observations. For many variables we created above median indicators, and for these variables only descriptives on missings are included in the table.

A2 Additional Results

In this section, we show provide estimates of count data models for our main results. Table A3 replicates the findings of Table 4, but now using a Poisson estimation. The tables show exponentiated coefficient, which can be interpreted as count rates, i.e. the factor with which a certain count needs to be multiplied if the dummy variable associated with the coefficient estimate switches from zero to one, all else equal. For example, the coefficient in Table A3 Column (1) on Numeracy 0 or 1 equals 1.132. Hence, at the sample average of 9.5, a switch from a perfect score to a numeracy score of 0 or 1 is associated with a predicted increase of unemployment duration from 9.5 months to 10.7 months. For the younger cohort, this coefficient equals 1.31 (see Column (5)), and at a sample mean of 8.8, the latter switch is associated with an increase in predicted unemployment from 8.8 months to 11.5 months. Hence, results are very similar as the linear results presented in the main table, but now statistical inference gives us often slightly better results in terms of statistical significance.

Table A3: Unemployment Duration and Numeracy: Poisson Estimates

	Dependent variable: months in unemployment within 30 months after inflow											
	Full Sample				Age <= 32				Age > 32			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Numeracy 0 or 1	1.132***	1.149***	1.093***	1.082***	1.311***	1.324***	1.170***	1.148***	1.036*	1.035	1.035	0.984
	(0.018)	(0.019)	(0.018)	(0.018)	(0.033)	(0.034)	(0.031)	(0.031)	(0.022)	(0.022)	(0.023)	(0.018)
Numeracy 2	1.050***	1.059***	1.039**	1.036**	1.150***	1.156***	1.098***	1.092***	1.008	1.001	1.003	0.959**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.029)	(0.030)	(0.028)	(0.028)	(0.021)	(0.021)	(0.021)	(0.017)
Numeracy missing	1.182***	1.203***	1.144***	0.931	1.360***	1.370***	1.209***	0.780**	1.082***	1.082***	1.069**	
	(0.023)	(0.023)	(0.022)	(0.061)	(0.040)	(0.040)	(0.036)	(0.087)	(0.029)	(0.029)	(0.029)	
Sample no cognition	1.117***	1.126***	1.090***	1.092***	1.245***	1.254***	1.147***	1.096***	1.051**	1.045**	1.045**	
	(0.017)	(0.017)	(0.017)	(0.025)	(0.030)	(0.030)	(0.028)	(0.036)	(0.021)	(0.020)	(0.021)	
1 if female		0.958***	0.960***	0.961***		0.933***	0.984*	0.988		0.976***	0.960***	0.959***
		(0.005)	(0.005)	(0.006)		(0.007)	(0.008)	(0.009)		(0.007)	(0.008)	(0.008)
Age:												
26-32		0.952***	0.998	1.000		0.955***	1.037***	1.041***				
		(0.008)	(0.008)	(0.008)		(0.008)	(0.009)	(0.009)				
33-39		1.062***	1.108***	1.111***								
		(0.009)	(0.009)	(0.009)								
40-46		1.074***	1.118***	1.116***						1.012	1.013	1.012
		(0.009)	(0.009)	(0.009)						(0.009)	(0.009)	(0.009)
47-55		1.293***	1.334***	1.322***						1.217***	1.219***	1.214***
		(0.010)	(0.011)	(0.011)						(0.011)	(0.011)	(0.011)
Highest Schooling degree:												
Lowest secondary			0.887***	0.892***			0.869***	0.884***			0.945**	0.944**
			(0.014)	(0.014)			(0.018)	(0.018)			(0.023)	(0.023)

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	Dependent variable: months in unemployment within 30 months after inflow											
	Full Sample				Age <= 32				Age > 32			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Lower/middle secondary			0.849***	0.847***			0.777***	0.787***			0.947**	0.941**
			(0.013)	(0.013)			(0.015)	(0.016)			(0.023)	(0.023)
Advanced technical qualification			0.753***	0.758***			0.642***	0.652***			0.908***	0.911***
			(0.014)	(0.015)			(0.016)	(0.017)			(0.027)	(0.027)
A-levels / International			0.806***	0.809***			0.689***	0.696***			0.967	0.969
baccalaureate			(0.013)	(0.013)			(0.015)	(0.015)			(0.025)	(0.025)
Industrial training			0.821***	0.821***			0.793***	0.796***			0.890***	0.887***
			(0.007)	(0.007)			(0.009)	(0.009)			(0.013)	(0.013)
Commercial/administrative			0.871***	0.877***			0.852***	0.861***			0.931***	0.931***
			(0.009)	(0.009)			(0.011)	(0.011)			(0.014)	(0.015)
Vocational school			0.792***	0.789***			0.702***	0.701***			0.906***	0.903***
			(0.009)	(0.009)			(0.012)	(0.012)			(0.015)	(0.015)
Master technician			0.754***	0.762***			0.624***	0.640***			0.860***	0.861***
			(0.012)	(0.012)			(0.018)	(0.019)			(0.017)	(0.017)
University degree			0.783***	0.784***			0.673***	0.681***			0.874***	0.869***
			(0.011)	(0.011)			(0.014)	(0.014)			(0.017)	(0.017)
Other professional			0.812***	0.811***			0.739***	0.741***			0.905***	0.900***
			(0.009)	(0.009)			(0.011)	(0.011)			(0.015)	(0.015)
Above median score in:												
Word fluency				0.997				0.989				0.982
				(0.012)				(0.017)				(0.015)
Short memory				1.027*				1.030				1.003
				(0.015)				(0.022)				(0.021)
Long memory				0.974*				0.981				0.979

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	Dependent variable: months in unemployment within 30 months after inflow											
	Full Sample				Age <= 32				Age > 32			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
				(0.013)				(0.019)				(0.019)
Time orientation				1.015				0.963*				1.037**
				(0.017)				(0.021)				(0.018)
Openness				1.004				1.003				1.001
				(0.006)				(0.008)				(0.008)
Conscientiousness				0.984***				0.957***				1.013*
				(0.005)				(0.008)				(0.008)
Extroversion				1.004				1.002				1.005
				(0.006)				(0.009)				(0.008)
Neuroticism				1.013**				1.007				1.021***
				(0.006)				(0.008)				(0.008)
External locus of control				1.036***				1.063***				1.006
				(0.006)				(0.009)				(0.008)
local unemployment rate				1.066***				1.110***				1.035***
				(0.006)				(0.009)				(0.008)
Constant	9.003***	8.642***	12.055***	11.430***	7.328***	7.645***	12.362***	11.990***	10.516***	10.025***	11.736***	11.701***
	(0.166)	(0.165)	(0.288)	(0.333)	(0.208)	(0.220)	(0.424)	(0.499)	(0.259)	(0.254)	(0.411)	(0.392)
Observations	15,173	15,173	15,173	15,173	7,570	7,570	7,570	7,570	7,584	7,584	7,584	7,584

Notes: Estimates of Poisson regressions. Exponentiated coefficients are displayed. Dependent variable = count of months in unemployment within 30 months after inflow. Robust standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.