Cognitive skills, tasks and job mobility

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Abstract

The authors investigate on the basis of primary and secondary data the relationship between individual cognitive skills and the complexity of the particular work those individuals perform. Additionally, the relationship between skills and mobility between more or less complex jobs in an highly homogenous industrial environment is analyzed. The primary data consists of a survey conducted in 2011 of anonymously tested 305 participants in selected factories of four different companies. The survey consists of a newly developed dynamic problem solving test and a standard general intelligence test. Skill measurement is supplemented by information about tasks and personal background. Results are compared to larger scale secondary data sources. Special focus is placed on different employment groups within a company: assemblers, craftsmen, technicians and engineers.

Using this data, we can show that non-routine content of individual work is strongly related to cognitive skills. Also, higher cognitive skill levels predict upward occupational mobility. Finally, we demonstrate that the established "task-based approach" helps to explain why the occupational mobility between some occupational groups is lower than between others. These findings can be useful for the discovery of opportunities for occupational upward mobility in a homogenous environment.

1.1. Context to this Study

Major secular changes such as globalization and technological change have affected various characteristics of the German labour market: rising wage inequality (Dustmann et al., 2009) and occupational polarization (e.g. Goos, 2009). Those changes are driven by - among other things - shifts in the content of jobs to more non-routine and fewer routine tasks, as shown by Autor et al. (2003) for the USA. Spitz-Oener (2006) and Antonczyk et al. (2009) (and others) have implemented the so-called "task-based approach" for Germany. They have shown that non-routine analytic tasks have increased while routine manual tasks decreased in the time period from 1979 to 2006. The growth of such non-routine (or complex) tasks has led to an increase in the demand for skilled workers. However, the increase in the supply of skilled workers has slowed as the educational expansion of the 1960s and 1970s has diminished. There is no reason to believe the demand for skilled workers will reverse, but cohorts entering the labour market in the future will shrink due to demographic change. This could exacerbate the observed labour market trends of recent decades and raises the question of whether the middle-aged who are currently employed can be trained to handle more demanding work. Autor and Dorn (2009) show on an aggregated level that older and / or less-educated workers move to routine jobs while young highly educated workers reallocate to non-routine jobs.

The aim of the study is to analyse opportunities to move individuals who are in the labour market und who already have left the formal schooling system to more non-routine, complex and usually better paid jobs. Several studies have analysed to which extent individuals change their occupation: Kambourov and Manovskii (2008) show that the average level of occupational mobility in the United States is around 13% at the one-digit level or 15% at the two-digit level (which has increased over time).[1] Isaoglu (2010) points out that measurement error in occupational coding may exaggerate (true) occupational mobility. Longhi and Brynin (2010) examine occupational mobility in Britain and in Germany. They find in general an occupational mobility of 12% per year in Germany at the two-digit level (for individuals without employment breaks) but this number is far lower (ca. 3.2% - 3.4%) if only occupational code changes are counted which are accompanied by a change of the employer. Fitzenberger and Spitz (2004) analyse occupational mobility and the consequences between the actual job and the vocation learnt.

Many studies investigate occupational mobility across the whole labour market. Geel and Backes-Gellner (2011) have identified different clusters of occupations which are characterized by similar portfolios of required skills (such as maths, technical or foreign languages). They show that the probability to change occupation to another job with similar skill requirement is higher the more specific the skill requirements in an occupation are. This suggests that a focus on a narrow environment, such as a few companies, may bring insights which may be hidden in representative samples.

One important question concerns the role of cognitive skills in facilitating moves to more complex jobs. Anger and Heineck (2010) show that there are positive returns to cognitive skills (fluid intelligence) in regard to earnings for men but not for women in Germany. Pryor and Schaffer (2000) have used the US National Adult Literacy Survey to show that individuals who experience downward occupational mobility have lower cognitive skills than others with the same educational degrees. To our best knowledge, no studies have examined whether cognitive skills are a predictor for occupational change in Germany, which labour market is quite different to those of the Anglo-Saxon countries, the most frequent focus of interest.

The analysis of primary data in an industrial environment has several advantages. First, there is less heterogeneity because occupations are more comparable within an industrial environment than in the whole economy. Second, occupational coding is prone to measurement error. In our survey almost all individuals are subject to a collective wage agreement which remunerates tasks and do not depend on the educational attainment or the professional qualification of an individual. Therefore, the job contents are clearly defined and verifiable.

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[1] The ISCO classification is ordered in a four-tiered hierarchy resulting in a four digit code for the finest differentiation. There are ten occupational groups represented by the first digit and thirty occupational groups represented by the second digit and so on.

1.2. Organization of this paper

The aims of this study are to analyse to what extent individuals switch occupations, and to what degree a certain type of skill is an enabling factor of such switches. We limit our observation to 5 categories of occupations in an industrial environment, which can be hierarchically ordered according to the average wages and the average skill level of the employed. This allows us to define risers, people who move to more complex and better paid jobs, and fallers who switch to less demanding jobs. We then investigate whether different kinds of cognitive skill levels explain the direction of occupational mobility. Furthermore, we analyse how the task content of jobs explains whether occupational mobility takes place. Ultimately we want to show the relationships between tasks, skills, upskilling and upward job mobility - a subject of further investigations. Special consideration is being placed on a new psychometric tool yielding data on the cognitive skill of dynamic problem solving as distinct from general intelligence, which so far has not been available. Dynamic Problem Solving skill assessments for adults has been long on the wishlist of the skills research community. Ours is the first time that a DPS assessment has been conducted in an industrial/professional environment.

For this, in chapter 2 we first discuss our data samples and survey design. Chapter 3 examines the skill differences between occupational groups. Chapter 4 examines the tasks differences between occupational groups. Chapter 5 examines the extent of occupational mobility. In Chapter 6 we will then combine all these aspects to see which and how skill levels are related to occupational mobility.

2. Data Description and Survey Design

The analyses are based on primary and secondary data. The primary data were gathered in a survey and psychometric data collection with 305 individuals in five separate factories in four different companies in the manufacturing sector.[2] One of this company is a large German industrial firm with more than 100.000 employees. The other three companies are small scale enterprises with comparable job contents. This primary data collection allows the observation of individuals working in different occupations, both within and across the factories. The structure of the survey is in three parts. First, a background questionnaire (ca. 15 minutes) collects personal information and biographical data, job tasks and attitudes about further education. Second, a new dynamic problem solving test (45 min), is followed, third, by a short culturally fair intelligence test (20 min). The background to these cognitive tests is described in the appendix.

In two factories, the participants to the tests were invited by letters to their private homes to attend designated testing sessions. From a randomized sample of factory workers comprising around 20% of the work force, around half were invited, of which 17% participated voluntarily. The participants arrived at the testing stations anonymously, so that it could not be known who participated. It was stressed during the invitation and during the tests, that none of the test results were traceable to the individual and could therefore not be made

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[2] A further survey funded by the European Commission DG Research&Innovation will take place in 2012 and 2013 with ca. 3,000 participants.

available to management as a performance indicator. The testing design and additional cross-checks minimize the chances of a selection bias among the participants. In the other and smaller companies participants were selected randomly and spontaneously from the shop floors on the day of the test.

Table 1: Occupations investigated in the survey

Occupational Group	#	Share tertiary education	Share vocational qualification	Median age	25th percentile base wages	Modal base wages[3]	75th percentile base wages
All individuals	305	64 (21%)	256 (84%)	40-44	2,077€	2,077€	4,065€
Technicians	67	19 (28%)	55 (82%)	35-39	2,435€	4,908€	4,908€
Foremen	29	11 (38%)	24 (83%)	45-49	2,142€	2,142€	4,065€
Craftsmen (without foremen)	54	1 (2%)	51 (94%)	45-49	2,142€	2,142€	2,676€
Machine operators and assemblers	72	2 (3%)	65 (90%)	40-44	2,024€	2,077€	2,077€
Labourer	9	0 (0%)	7 (78%)	40-44	1,983€	2,024€	2,024€

Source: Own calculations (assumption of at least 36 months of company tenure for higher paid individuals)

The study focuses on six technically-oriented jobs which account for two-thirds of all personnel within the large industrial company, where we tested in two large factories:[4]

1. **Labourers**: unskilled jobs for which an individual needs only up to three days of training. Due to the low skill-specificity of the job content, labourers exhibit the highest average occupational mobility.
2. **Machine operators and assemblers**: unskilled jobs of low complexity, routine tasks, which require extended on-the-job experience
3. **metal and machinery craftsmen:** skilled jobs which typically require a multiyear vocational training or equivalent on-the-job experience and consist of higher complexity and fewer routine tasks.
4. **foremen:** supervisors with varying levels of training and who have shown excellent technical skills and capacity on the shop floor particularly including non-routine problem solving and management tasks.
5. **technicians**: advanced skilled jobs which require multiyear vocational training and several years of job experience which consist of yet higher complexity and fewer routine tasks
6. **engineers:** jobs that typically require a tertiary degree although equivalent qualifications can also be acquired through formal adult training and are primarily focused around non-routine, complex tasks.

Due to their hierarchy in terms of wages earned and typical average educational attainment, these six occupations form an occupational pathway along which occupational mobility can be observed as shown in Figure 1.

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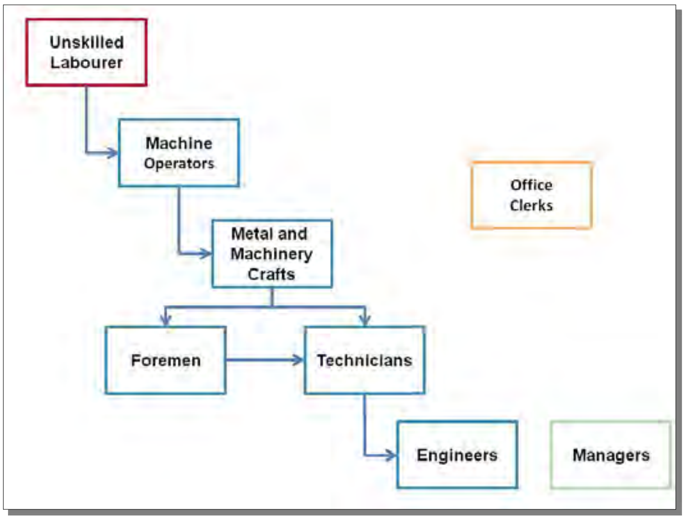
[3] Without additional payments such as premiums, holiday pay etc.

[4] The main emphasis is on the occupations 21xx, 31xx, 72xxx, 73xx, 81xx, 82xx and 93xx according to the ISCO88-classification. The personnel register contains all workers without apprentices and non-tariff workers.

Figure 1: Occupational Pathways in industrial environments



These occupations are derived from the International Labour Organisation's (ILO) International Standard Classification of Occupations (ISCO) which is a tool for organizing jobs into a clearly defined set of groups according to the tasks and duties undertaken in the job. They depend partially but not entirely on an extended qualification such as a vocational training or a tertiary education[5]. There is evidence that these occupations, especially in the observed industrial environment, do not depend solely on the educational or vocational biography of an individual. Several members of the top management in the smaller companies which we investigated for instance, did not complete tertiary degrees, but instead rose through the ranks beginning from lower secondary school, vocational training and then on-the-job experience gathering. It would therefore be better to describe these occupations by tasks rather than educational requirements. Unfortunately the ILO classification are a mixture of both. Table 2 gives the distribution of these occupations within the large of the industrial companies surveyed, across the entire company.

Table 2: Share of investigated occupations within the largest company of the survey

Occupational Group	Share in the company
Labourer	>2 %
Machine operators and assemblers	28%
Metal and machinery craftsmen	14%
Foremen	<2%
Technicians	11%
Engineering professionals	10%
Managerial Occupations	7%

The majority of the participants are subject to a collective wage agreement which remunerates tasks and individual performance and does not depend on the educational attainment or the professional qualification of an individual. The participants in the survey work in technical occupations with similar processes and products,

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[5] We used the coding instructions GESIS – Center for Survey Design and Methodology, see Geis (2009).

but differ in the complexity of the tasks they perform. The homogeneous environment and the task oriented collective agreement both help to reduce the heterogeneity in the survey. This situation in Germany to pay by tasks and not by education, but to do so within the framework of a collective bargaining agreement with industry-based unions, ensures comparability of the actual job contents across and within companies. This allows us to compensate for the short comings of the ILO classifications.

3. Skill Differences between Occupational Groups

Problem solving has long been recognized as a distinctive cognitive skill separate to general intelligence (Wirth et al., 2005). Figure 2 shows the distribution of Static Problem Solving Skills[6] for four different occupational groups[7] in Canada 2003 from the Adult Literacy and Life Skills Survey (ALL). ALL is an international survey measuring skills of the adult population which took place in 2003. We limit our analysis to Canadian data from 2003 because Canada provides the largest sample size (more than 40% of all participants in 2003 were surveyed in Canada) and we do not want to create additional heterogeneity by mixing different country data. The black lines show the median competencies for each of the first three occupational groups. The upper (lower) ends of the boxes show the upper (lower) quartile of each group while the whiskers show the most extreme value which is no more than 1.5 the respective height of the box. We calculated the share of potential risers as the fraction of individuals in each occupational group who perform better than the median individual of the immediate more complex occupation. This shows that on the basis of this single cognitive measure, many individuals could perform more demanding work.

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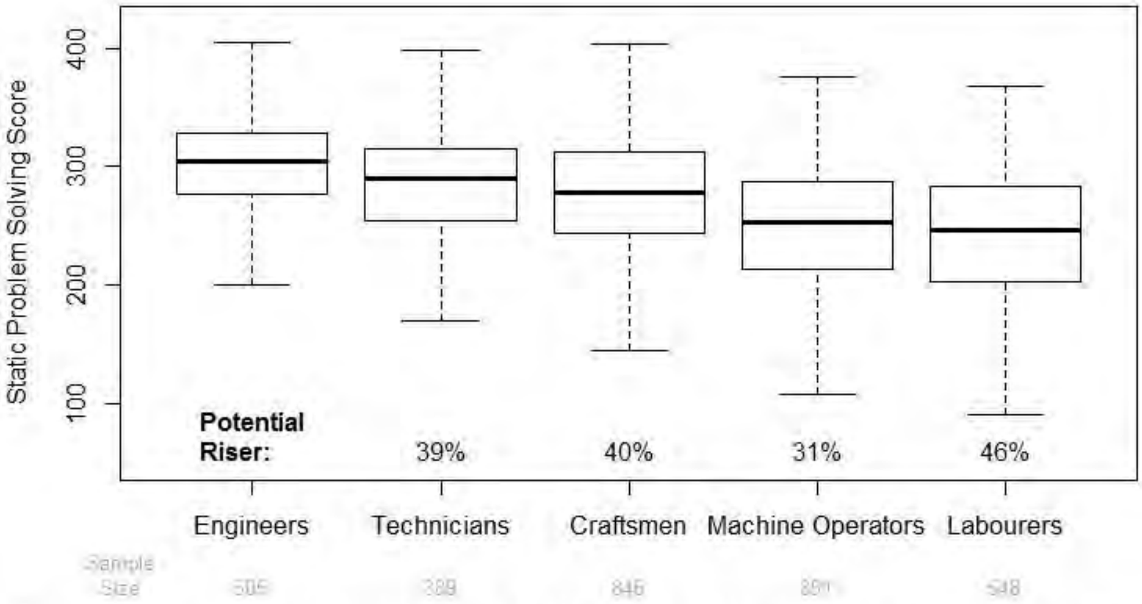
[6] Static Problem Solving is a construct which can be seen as a predecessor of Dynamic Problem Solving. It lacks interaction effects due to the paper and pencil design of the test. It has been used in PISA 2003 and in ALL.

[7] The sample size which has been used for Figure 2 is 2,126. Occupational groups are 21xx for the engineering professionals, 31xx for technicians, 72xx and 73xx for craftsmen, 81xx and 82xx for machine operators and 93xx for labourers.

Figure 2: Static Problemsolving Skills for four different technical occupational groups in Canada



We calculated the share of potential risers as the fraction of individuals in each occupational group who perform better than the median individual of the immediate more complex occupation.

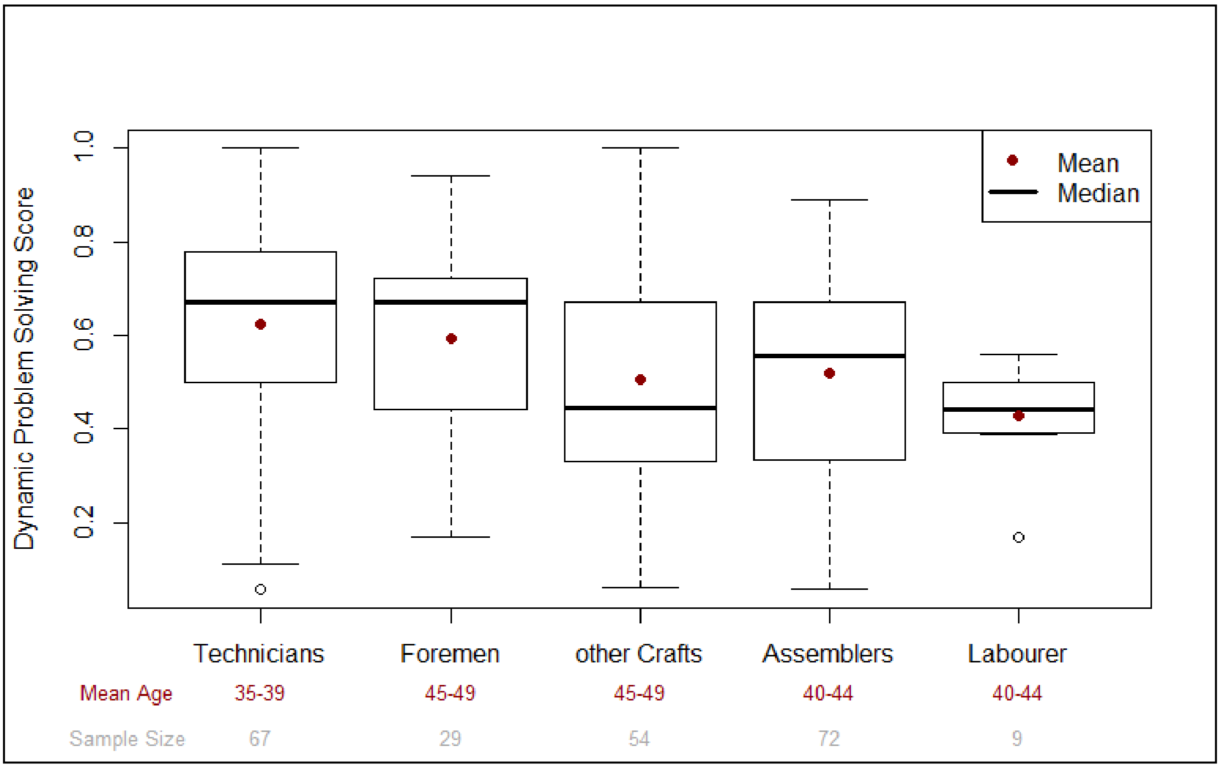
Source: Own computations based on Adult Literacy and Life Skills Survey

Figure 3 shows a similar analysis, but with the results of our new dynamic problem solving ("DPS") survey of individuals who work either as technicians, foremen, craftsmen, machine operators or assemblers, or labourer. Engineering professionals are excluded because only few individuals (n=13) work in these jobs in our survey and they perform very different kind of jobs.

The mean DPS score in the whole sample (n=302) is 0.57 and the standard deviation is 0.23 (see Appendix).

The median performance between technicians and foremen is very similar and there are no significant mean differences between both groups (p=0.53 in a two-sided Welch t-test). The DPS skills differ significantly between technicians on the one hand and craftsmen (foremen excluded, p=0.01), assemblers and machine operators (p=0.01), and labourers (p=0.001) on the other hand. Again we conclude that from the perspective from a (different) cognitive skill measurement, many people could work in more complex jobs.

Figure 3: DPS skills for different technical occupations in Germany, 2011



A second cognitive measure collected in this survey is the test of general intelligence (fluid intelligence, see Appendix).[8] Figure 4 shows that differences in general intelligence scores are more pronounced than differences in DPS scores. Technicians' and foremen's mean IQ scores differ with slight significance (p=0.03). However, there are distinct differences in IQ scores between technicians on the one hand, and craftsmen (foremen excluded, p<0.001), assemblers and machine operators (p<0.001), and labourer (p=0.003) on the other hand. A possible reason for the more pronounced differences in IQ scores in comparison with DPS scores are age-differences between occupational groups. Technicians in the sample are on average younger than other individuals, and IQ-scores are standardized by age while DPS scores are not.[9] The mean IQ score in the whole sample is 104 with a standard deviation of 17 (see Figure 12).

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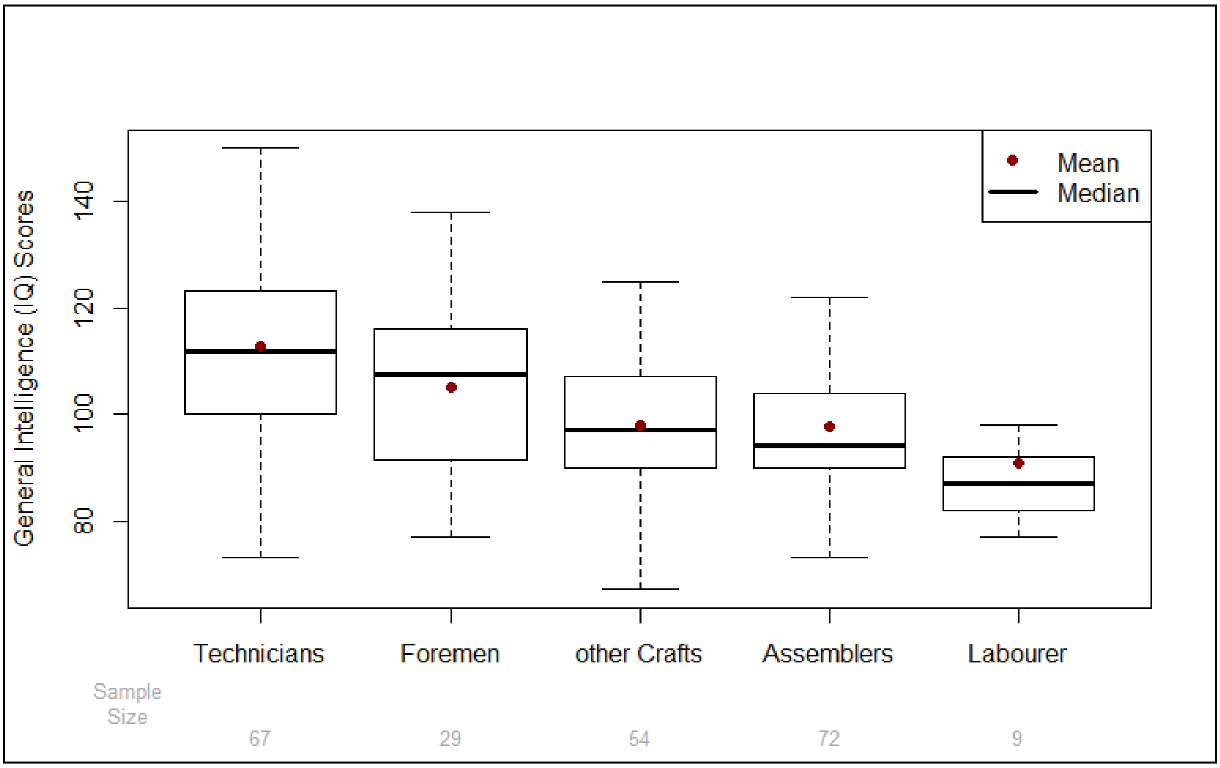
[8] For 298 individuals IQ scores are available.

[9] The correlation between age and (non-age-standardized) general intelligence scores is in our sample slightly higher (ρ=-0.36) then the correlation between age and DPS scores (ρ=-0.3).

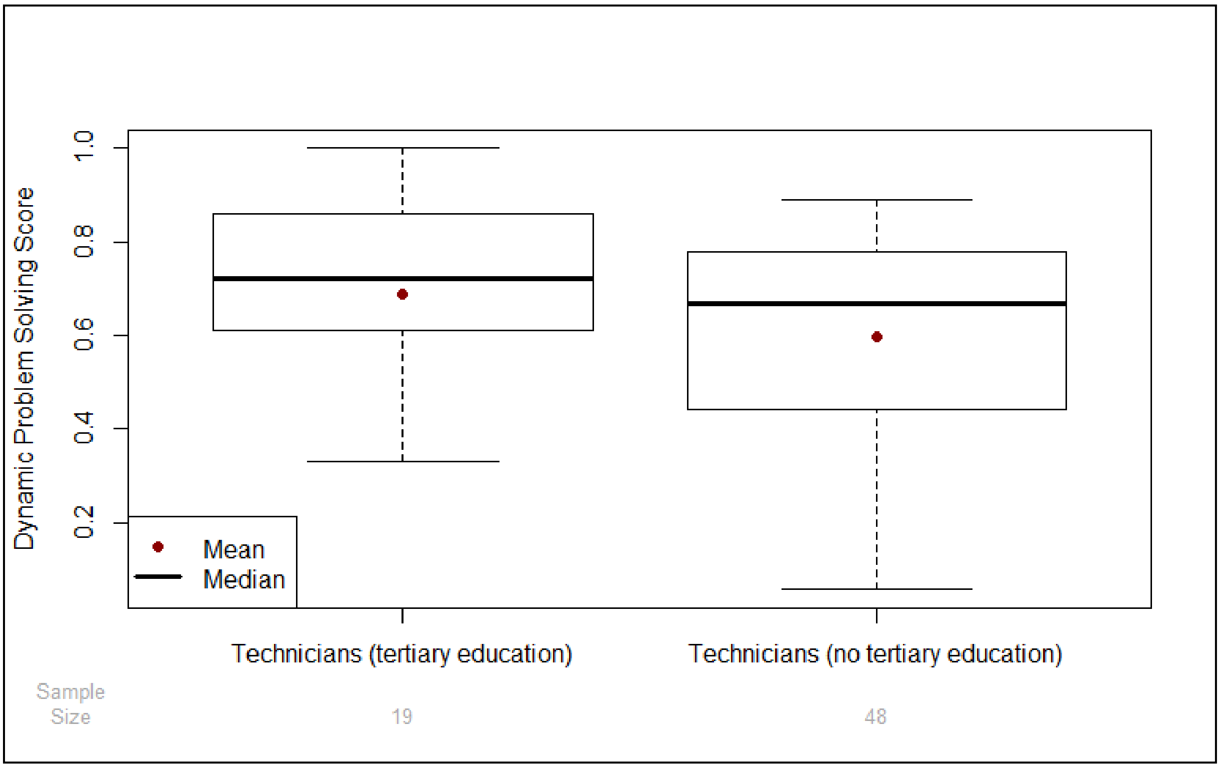
Figure 4: General Intelligence Skills for different technical occupations in Germany, 2011



Many researchers assume that general intelligence is fixed in childhood (Almlund et al., 2011). There are indications that DPS skills are malleable for a longer period (see Appendix). If this is true, less pronounced differences of DPS skills between occupational groups (in comparison with IQ skills) could be caused by later learning experiences such as learning-on-the-job. It could also of course indicate that dynamic problem solving skills are less relevant for occupation selection or occupational mobility than general intelligence. This needs to be further investigated with larger samples.

19 out of 67 technicians have a tertiary degree and provide the opportunity to compare skills differences for individuals with different educational attainment within the same occupational group. Figure 5 shows the skill distribution of both groups of technicians. There are no statistically significant differences in mean scores (p=0.14), and median-DPS scores. It seems that tertiary education endows a minimum threshold of DPS skills but fails to attract all individuals with similar potential.

Figure 5: DPS scores for technicians with or without tertiary education



4. Tasks Differences between Occupational Groups

Next, we analyse the task content of different occupational groups. We use both our own survey ("Industrial Survey"), in which we asked participants about the task performance during the daily work and the BIBB/IAB-, BIBB/BAuA-Employment Survey 2006, a (repeated) cross-sectional survey of 20,000 employed individuals who provide information about skills needed and tasks carried out (the "BIBB" study).[10] The latter survey has been widely used for different purposes. Spitz-Oener (2006) used previous waves of the survey to show that the task demand in labour market has shifted from routine tasks to non-routine tasks. Spitz-Oener defined 5 dimensions of tasks categories in her publication (see Appendix, in the following abbreviated "SO"). Antonczyk et al. (2009) suggest a different operationalization of those five dimensions of five categories (see Appendix, in the following abbreviated "AFL"). We analyse task performance very similar to both Spitz-Oener (2006) as well as Antonczyk et al. (2009) as described in the Appendix.

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[10] We used the questions about the tasks performance from the BIBB/IAB-, BIBB/BAuA-Employment Survey 2006 in our own survey.

Table 3: Definition of task categories

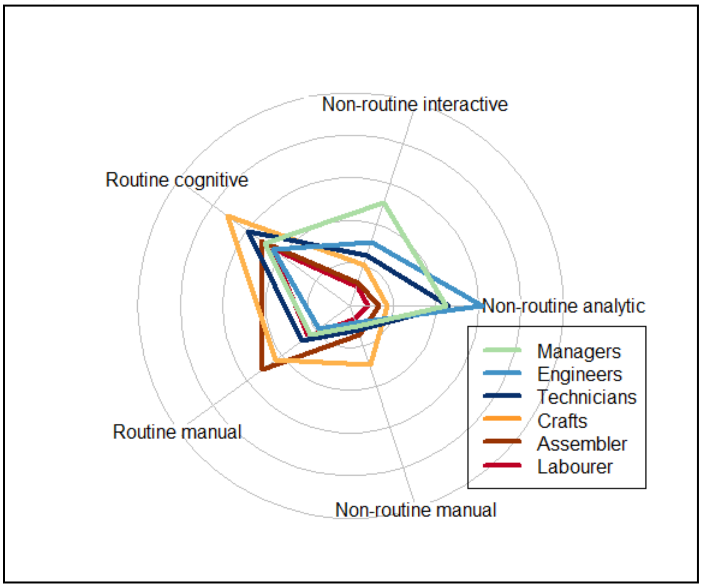
Task category	Tasks
Non-routine-analytic	developing, researching, designing, investigating, gathering and evaluating information
Non-routine-interactive	informing, advising and training, teaching, tutoring, educating and organizing, planning/preparing working processes and promoting, marketing, public relations and buying, providing, selling and to be supervisor
Routine-cognitive	measuring, inspecting, quality checks
Routine-manual	producing and fabricating goods, supervising and operating machines or conveyors
Non-routine-manual	repairing, overhauling, serving

The similarity between the BIBB study and in the Industrial Survey in terms of tasks carried out within single occupations is high dimensions for crafts, assemblers and technicians but it is somehow lower for the AFL operationalization. The correlation between the task content for technicians in both surveys is 0.97 (SO) resp. 0.73 (AFL), for craftsmen 0.99 (SO) resp. 0.84 (AFL) and for assemblers 0.98 (SO as well as AFL).

How do occupations differ from each other in terms of tasks? Figure 6 illustrates the task dimensions for different occupational groups (the data is available in Table 9 in the Appendix). The task content of the occupation in focus strengthens the idea that these occupations can be rank-ordered according to the complexity (or to be precise to the non-routineness) of tasks individuals have to perform within their work.

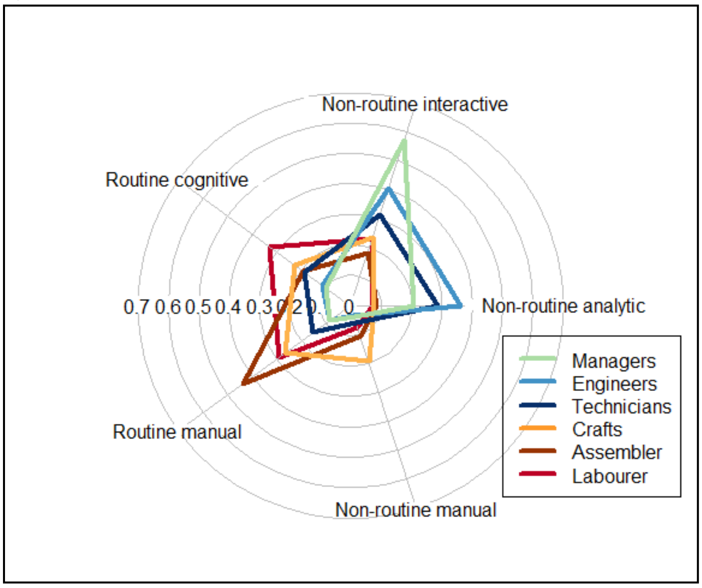
Analysing the BIBB data, we further show that (i) machine operators and craftsmen perform similar tasks (ρ =0.58 to ρ =0.91), (ii) technicians and engineers, again, perform similar tasks (ρ =0.82 to ρ =0.95), (iii) but there is no obvious picture regarding the similarities or differences in tasks content between machine operators and craftsmen on the one hand, and technicians and engineers on the other hand (see Table 4). The observed differences in tasks performance is even more pronounced in the Industrial Survey. While the correlation coefficient between engineers and technicians as well as between craftsmen and assemblers is almost identical to the one found in the BIBB survey, the correlation between technicians on the one hand and on the other hand craftsmen or assemblers turns negative.

Figure 6: Illustration of the tasks dimensions in different occupations in the Industrial survey according to the SO operationalization



Source: See Appendix and Table 9

Figure 7: Illustration of the tasks dimensions in different occupations in the "BIBB" survey according to the AFL operationalization



Source: See Appendix and Table 9

Table 4: Correlation between task portfolios of different occupations in the "BIBB" study and in the Industrial Survey, 2006.

Occupation	Index	Survey	Occupation			
			Engineers	Technicians	Craftsmen	Assemblers and Machine Operators
Engineers	SO	"BIBB" study	1	0.82	-0.01	-0.06
		Industrial Survey		0.81	-0.67	-0.65
	AFL	"BIBB" study		0.95	-0.43	-0.35
		Industrial Survey		0.95	0.45	-0.19
Technicians	SO	"BIBB" study		1	0.56	0.48
		Industrial Survey			-0.19	-0.11
	AFL	"BIBB" study			-0.31	-0.17
		Industrial Survey			0.70	0.10
Craftsmen	SO	"BIBB" study			1	0.88
		Industrial Survey				0.91
	AFL	"BIBB" study				0.73
		Industrial Survey				0.58

Technicians and engineers perform more non-routine tasks.[11] Since these occupations also exhibit higher skills, as measured by the DPS score, these skills either enable these tasks or they are a consequence of learning-on-the-job with complex tasks. The Industrial Survey allows us to examine the relationship between skill endowment and tasks performance. Table 5 shows the correlation coefficients as well as the significance of DPL scores and IQ scores on the one hand and the frequency of the five tasks in a simple bivariate linear regression. People who state that they often carry out non-routine analytic tasks or non-routine-interactive tasks show on average higher DPS skills as well as higher general intelligence in all depicted analyses using the SO operationalization. For the AFL operationalization routine cognitive tasks are often associated with lower individual cognitive skills.

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[11] We use the same classification as Spitz-Oener (2006).

Table 5: Correlation between task categories and skills

Task category	Index	Correlation between task frequency and DPS		Correlation between task frequency and IQ	
		Overall	**Technical workers**	**Overall**	**Technical workers**
Non-routine-analytic	SO	**0.16****	**0.18****	**0.17****	**0.21*****
	AFL	**0.12***	0.10	0.09	**0.18****
Non-routine-interactive	SO	**0.14***	**0.17****	**0.22*****	**0.21****
	AFL	0.06	0.05	**0.18****	**0.16***
Routine-cognitive	SO	-0.02	0.04	-0.06	-0.07
	AFL	**-0.12°**	-0.04	**-0.22****	**-0.22****
Routine-manual	SO	-0.01	-0.01	0.06	0.03
	AFL	-0.05	-0.06	-0.04	-0.07
Non-routine-manual	SO	0.02	0.04	0.01	-0.00
	AFL	-0.04	-0.03	-0.10	-0.10

Significance codes: ‘***’: p-value <0.0001: ‘**’: 0.001 < p-value < 0.01; ‘*’: 0.01 < p-value < 0.05; ‘°’: 0.05 < p-value < 0.1

5. Occupational mobility

First, we demonstrate the relevance of the occupational pathways in regard to occupational mobility in Germany with the SOEP data (GSOEP). The GSOEP is a representative annual German longitudinal household study conducted by the German Institute for Economic Research (DIW Berlin). It started in 1984 and comprises of ca. 12.000 households and more than 22.000 individuals (2009). The GSOEP is widely used by economists, sociologists or psychologists[12]. We analyse the average annual occupational mobility from 2000-2009 for those who stated that they have been active in the labour market for two consecutive years but do not make restrictions for employer changes. [13] Table 6 shows the results. The average annual occupational mobility at a two-digit level is around 15%. Labourers are an exception with an extraordinary high mobility of 25%. This is not surprising since many of these jobs do not require much job-specific knowledge. The occupational mobility is clearly exaggerated through measurement error but there is no reason to believe that there is a systematic bias.

Table 6: Occupational mobility between occupational pathways in Germany (annual average 2000-2009)

Occupational group next year **Occupational group previous year**	Engineers	Tech-nicians	Craftsmen	Machine operators and assemblers	Labourer	Other craftsmen or operators (3 groups)	Other (23 groups)
Engineers	84.1%	5.3%	0.3%	0.1%	0%	0.2%	9.9%
Technicians	5.5%	83%	2.1%	0.7%	0.4%	0.9%	7.3%
Craftsmen	0.3%	1.6%	89.2%	2.6%	0.9%	1.9%	3.6%
Machine operators and assemblers	0.1%	1%	3.9%	85.8%	2.6%	2.8%	3.8%
Labourer	0.3%	0.4%	2.2%	5.4%	76.0%	4.2%	11.5%

🟩 Move to a more complex occupation
🟨 Same occupation in both years
🟥 Move to a less complex occupation
⬜ Other occupations not in focus

The analysis shows specific occupational pathways. One third of all engineers who change their occupation become technicians and one third of all technicians who move become engineers. Craftsmen are not only less mobile than other occupations, they are also more likely to be a faller than a riser. Common sense would also suggest a pathway towards technicians but this is less the case: there seems to be a barrier for craftsmen moving up. So exchange is high within but not between two groups of occupations: engineers and technicians on the one hand, and craftsmen, machine operators, assemblers and labourer on the other.

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[12] For more information: GSOEP Website (http://www.diw.de/en/soep) or Wagner (2007)

[13] Some authors such as Longhi and Brynin (2010) have restricted their analysis of occupational mobility to job changes which are accompanied by employer changes to reduce the effect of measurement error. We do not limit our analysis to job changes which are associated with employer changes. The reasons are that we are more interested in occupational changes within the same company or factory because within a form career ladders and job contents are clearer to define. There are no indications that measurement error are in any way systematic. Therefore, our results will probably underestimate the true effects.

The explanation may be the two groups' different task content shown in the previous chapter. While the group of craftsmen, machine operators and assemblers (and to a lesser extent labourers) perform mainly routine or non-routine manual tasks, the engineers and technicians have to deal with non-routine tasks which require either analytic or interactive approaches, which in turn are related to both dynamic problem solving skills as well as general intelligence according to our Industrial Survey.

6. Occupational Mobility and Skills

In the previous chapters we have shown that more complex occupations show on average higher skills — as measured by general intelligence as well as dynamic problem solving. In addition, we demonstrated that occupational mobility occurs along typical pathways. Finally we showed that technicians and engineers carry out more tasks which are non-routine than craftsmen, machine operators, assemblers or labourers.

Now, we are interested whether people who move from less complex to more complex jobs, are endowed with higher skills than individuals who stay in their occupation or who move to less complex jobs. From 302 valid scores (for 3 individuals we could not obtain valid scores due to computer crashes) in DPS, 219 individuals gave sufficiently precise information about both their current and former occupation. Most of the remaining 83 individuals gave only vague information about their former occupation or said that they undertook vocational training without any information about their job. This made it impossible to classify their previous occupation.

Of these 219 individuals, 102 worked in the same 1-digit occupational group while 117 changed out of it. Of these, 66 moved to less complex jobs and 51 moved to more complex jobs. Some of these individuals do not work in technical occupations and, therefore, we exclude those who either work in non-technical 1-digit occupations or which previous occupation has been a non-technical one. This leaves us with 90 individuals who work in the same 1-digit occupational group, 55 now working in less complex jobs and 41 who moved to more complex jobs. The exclusion of individuals who either work or have worked in non-technical jobs do not drive the results, the results would have gotten more significant by leaving them in the sample. We call individuals who move from less to more complex occupations "risers" and individuals who move to less complex jobs "fallers" while we name those how stay in their occupational group "stayers".

Table 7: Occupational mobility in the Industrial Survey

		Current Occupation							
		Managers	Engineers	Technicians	Clerks etc.	Craftsmen	Assemblers	Labourer	Total
Previous occupation	Managers	2	0	0	0	0	1	0	**3**
	Engineers	0	7	3	0	4	0	0	**14**
	Technicians	3	1	29	2	2	0	0	**37**
	Clerks etc.	1	0	2	12	5	4	0	**24**
	Craftsmen	1	1	14	4	44	38	4	**106**
	Assemblers	1	0	3	3	14	8	3	**32**
	Labourer	0	0	1	0	2	0	1	**4**
	Total	**8**	**9**	**52**	**21**	**71**	**51**	**8**	**220**

🟩 Occupational Riser 🟧 Occupational Stayer 🟥 Occupational Faller ⬜ Other

Next, we compare the skills of risers, stayers and fallers. Figure 8 and Figure 9 show boxplot graphics of the skill differences between the groups. Risers have the highest, fallers the lowest skills, as would be expected. However, the simple mean differences are significant between risers and fallers in regard to general intelligence (p<0.01). They are also significant between risers and stayers for general intelligence (p=0.03) and also marginally significant between risers and fallers for DPS (p=0.10).

If high school years, tertiary degrees, age and sex are added as control variables, occupational risers have significantly higher skills in both general intelligence and in DPS. However, occupational stayers do not show skill differences in comparison with occupational fallers.[14] Table 7 shows the results of a linear regression on DPS (left column) and IQ scores (right column). Occupational fallers are the reference group for the dummy variables 'Occupational Riser' resp. 'Occupational Stayer'. DPS scores are defined on the interval [0,1] without an age standardization while general intelligence scores are standardized by 5-years age groups with a mean of 100 and a standard deviation of 15. Individuals who moved to more complex jobs possess ceteribus paribus 0.09 higher DPS scores than individuals who moved to less complex jobs (or 0.39 standard deviations; mean in the whole sample is 0.57) or 9.3 higher general intelligence scores (or 0.55 standard deviations). Considering the general intelligence measurement, risers endow also significantly higher skills than stayers (p=0.007; regression table not depicted in this paper).

Of the control variables, only age explains skill differences significantly and only for DPS. Neither years in high-school or tertiary education is a significant predictor of cognitive skills if occupational mobility is included in the estimation. This seems to call for an as-yet not established age calibration of DPS skills.

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[14] If non-technical occupations are not excluded, stayers show marginally significant DPS skills in comparison with fallers (p=0.05) and highly significant skill differences in regard to general intelligence (p=0.003).

Figure 8: DPS scores and Occupational Mobility

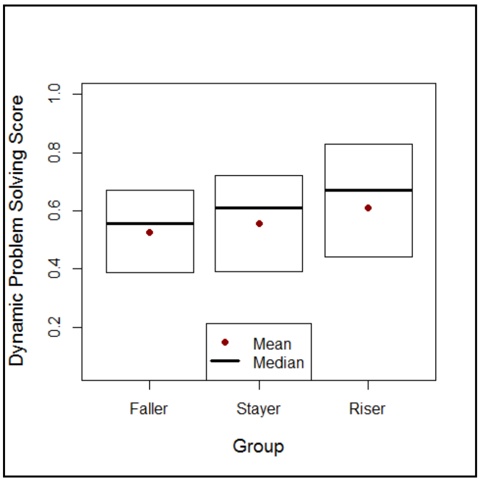


Figure 9: IQ scores and Occupational Mobility

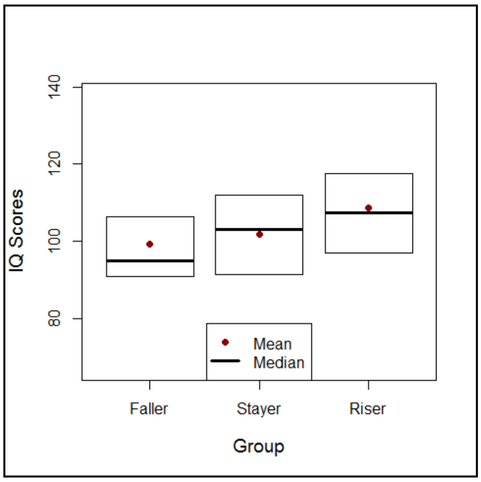


Table 8: Linear Regression on DPS / IQ

	Dependent Variable					
Independent Variables	**(1) DPS**			**(2) IQ**		
(Intercept)	0.27		(1.17)	91.8	***	(7.10)
Occupational Riser	0.09	*	(2.07)	9.3	**	(2.76)
Occupational Stayer	0.04		(0.95)	1.0		(0.35)
Occupational Faller (Reference Group)		-			-	
Years of Schooling (only High-School)	0.04	**	(2.77)	0.7		(0.54)
Tertiary Degree	0.06		(0.76)	6.3		(1.47)
Age (5-Years-Steps)	-0.03	***	(-4.11)	-0.0		(-0.01)
Sex Female	-0.08		(-1.76)	4.3		(1.16)
	R^2=0.23; n=183			R^2=0.10; n=181		

Significance codes: '***': p-value <0.0001: '**': 0.001 < p-value < 0.01; '*': 0.01 < p-value < 0.05
t-statistics in parenthesis

Conclusion

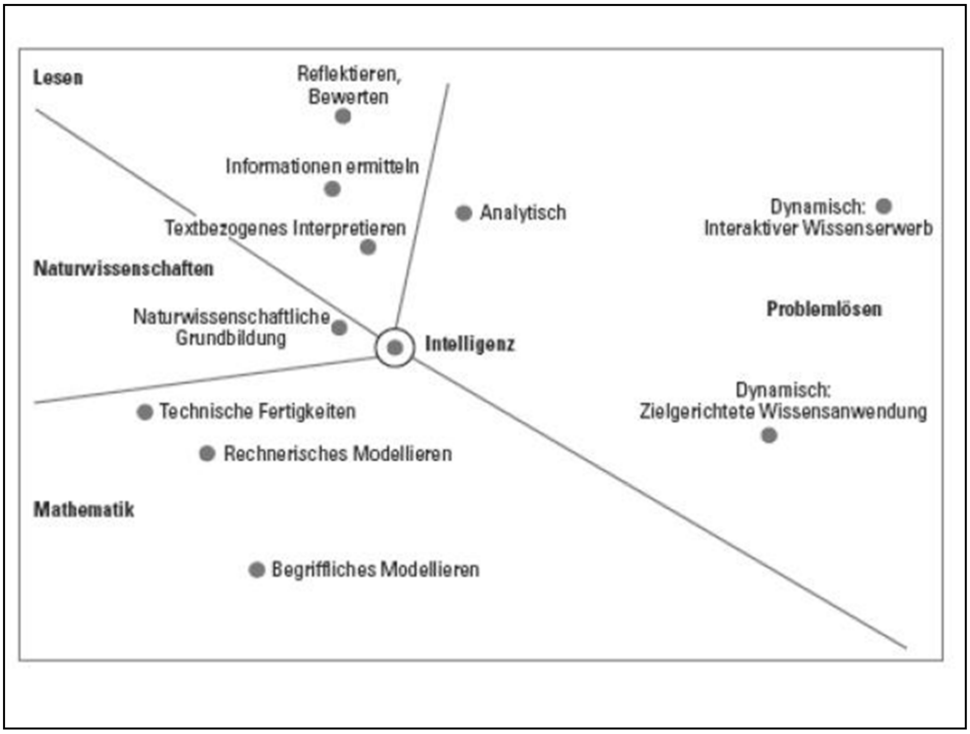
In conclusion, both secondary and primary data, including the new skill measurement Dynamic Problem Solving (DPS), show that occupational mobility – defined as movement along typical pathways that consist of occupations rank-ordered according to the complexity (non-routineness) of tasks – can be predicted by general intelligence as well as DPS. However, not all movements are equally likely and barriers appear to exist for certain occupational groups that have other explanations than those skills which we tested for.

Appendix

Dynamic Problem Solving

Dynamic Problem Solving (DPS) has been an area of major interest in experimental research over recent years (Funke und Frensch, 2007). It is based on the work of Prof. Dietrich Dörner, Universität Bamberg, in industrial psychology. DPS is defined as cognitive processing directed at transforming a given situation into a goal situation when no obvious method of solution is available (Mayer, 1992). The methodology has been revised and validated by a working team headed by Prof. Joachim Funke, Universität Heidelberg (Funke und Greiff, 2009; 2010). Previous studies have shown that DPS is sufficiently separate from general intelligence, which is to a great extent fixed in childhood (Almlund et al., 2011), and also from school marks in math or reading and writing (Abele et al., submitted; Kröner et al., 2005; Wüstenberg et al., 2012). Figure 10 depicts (in German language) the empirical correlations between different competencies and general intelligence as a radex structure: the more distant two constructs are the lesser their relationship.

Figure 10: Empirical radex structure of PISA competencies

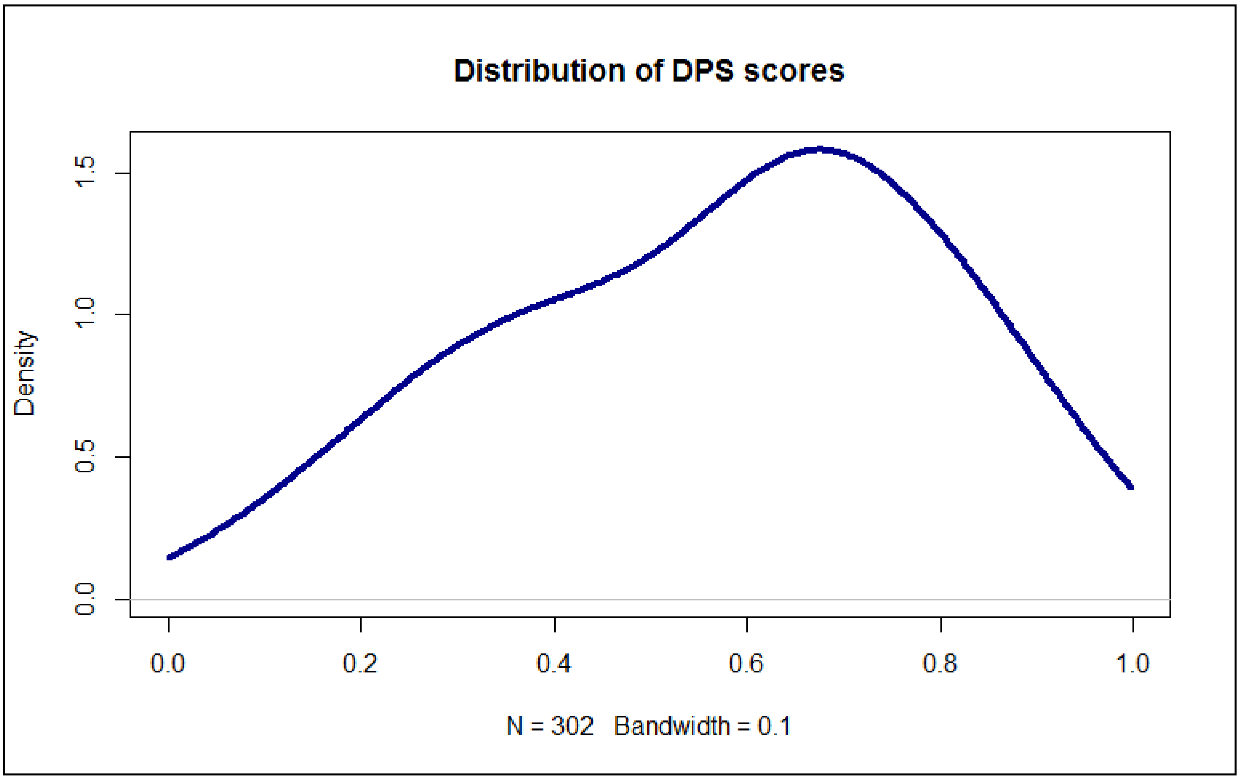


Source: Wirth et al. (2005; S. 78)

Comparatively little research has been conducted on DPS in the context of individual differences even though some efforts have been made. However, embedded in the recent development of large-scale assessments in educational settings, cross-curricular competencies such as dynamic problem solving have been discovered as valuable aspects of school achievement (OECD, 2004). In PISA 2012, for instance, a shift to computer-based assessment (CBA) will occur and, simultaneously, (dynamic) problem solving will be a major part of the PISA 2012 testing cycle (PISA Problem Solving Expert Group, 2010).

DPS scores are defined on the interval from zero (minimum value) to one (maximum) value. Dynamic Problem Solving captures three dimensions i) rule identification, ii) rule knowledge, iii) rule application. The analyses in this paper are based on the model building dimension due to statistical and psychological reasons (including all three dimensions yields a bimodal distribution). For more information, please refer to Wüstenberg et al. (2012).

Figure 11: Distribution of DPS scores in our sample (Gaussian kernel estimator)



CFT 20-R

The CFT 20-R is a cultural fair intelligence test which captures the construct of "General Fluid Ability" according to Raymond B. Cattell. Its age-specific application range is 20-60 years and it consists of 56 items but does not contain language elements.[15]. In the Industrial Survey, the short version (ca. 14 minutes) rather than the long version (ca. 18minutes) was utilized.

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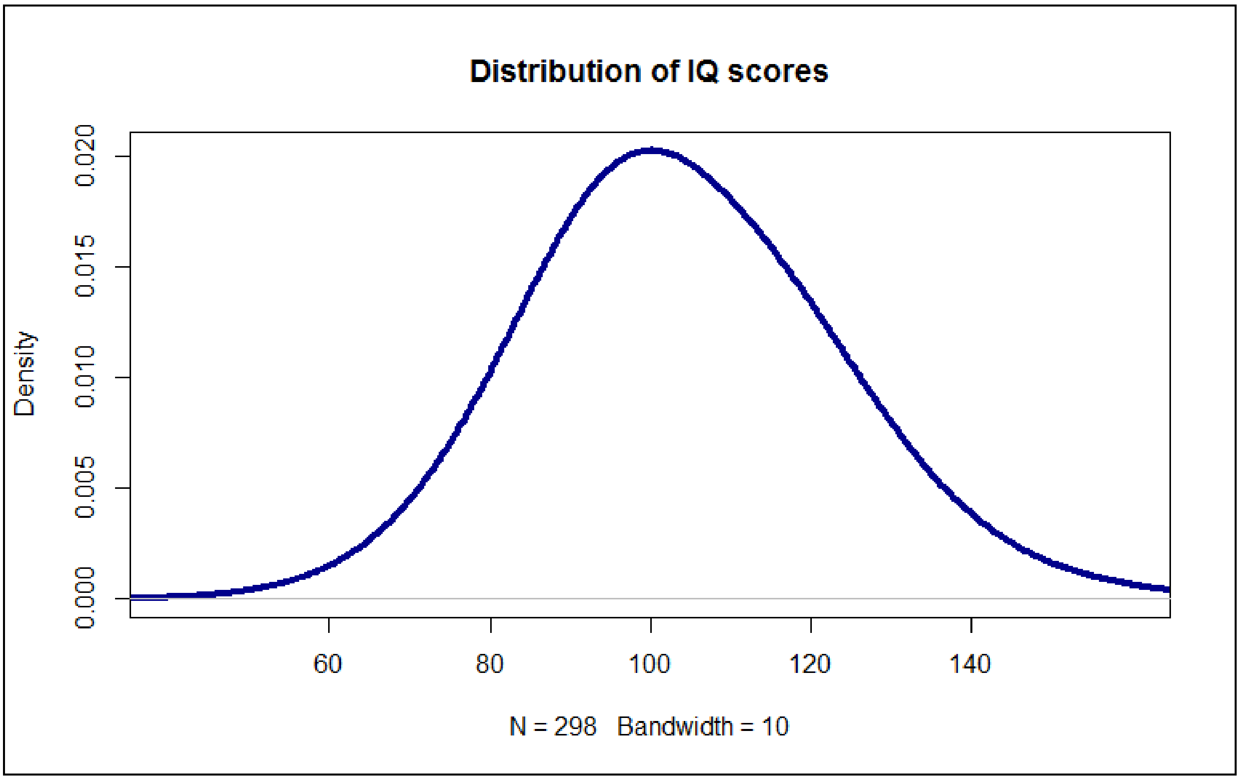
[15] A second test which measures vocabulary skills has not been used in this survey.

Figure 12: Distribution of general intelligence scores in our sample (Gaussian kernel estimator)



Task dimensions in different occupations

We analyse task dimensions very similar to Spitz-Oener (2006) and Antonczyk et al. (2009) by aggregating 13 tasks in the BIBB survey (see Table 3) to five task dimensions. As described in Antonczyk et al. (2009) we use two different operationalizations. First, we describe the task index developed by Spitz-Oener (2006), abbreviated “SO”. For each individual i task measure SO_j is defined as

$$\mathrm{SO_{ij}} = \frac{\text{number of frequently performed actitivies in category j by individual i}}{\text{total numbers of actitivies in category j}}$$

where j ∈ (non-routine-analytic, non-routine-interactive, routine-cognitive, routine-manual, non-routine-manual). Since we use only the wave 2006 of the BIBB survey our analysis is not directly comparable to Spitz-Oener (2006) who analyses the time period 1979-1999. As described in Antonczyk et al. (2009), the SO task index measures the shares of activities which an individual reports to perform among all activities in a certain category of activities j. Some individuals report several activities over all categories while others report only a few. To capture working time limitations, Antonczyk et al. (2009) suggest a different operationalization which sums up to one for each individual

$$\mathrm{AFL_{ij}} = \frac{\text{number of frequently performed actitivies in category j by individual i}}{\text{total numbers of actitivies performed by individual i over all categories}}$$

The calculation we use is slightly different to those from Antonczyk et al. (2009) who use 14 tasks (and another basic population, full-time working men aged 25-55). Due to comparability to our Industrial survey we limit ourselves to 13 questions. For the analyses we used the population weights provided in the BIBB survey.

Table 9: Tasks dimensions in different occupations (in %)

Task category	Index	Overall	Managers	Engineers	Technicians	Crafts	Assemblers and Machine Operators	Labourer
Non-routine-analytic	SO	29%	45%	62%	46%	20%	16%	08%
	AFL	18%	21%	36%	29%	8%	8%	7%
Non-routine-interactive	SO	29%	51%	31%	25%	18%	12%	10%
	AFL	45%	57%	40%	31%	24%	18%	23%
Routine-cognitive	SO	45%	5%	45%	59%	78%	75%	46%
	AFL	14%	10%	11%	19%	22%	19%	33%
Routine-manual	SO	22%	23%	19%	28%	51%	74%	25%
	AFL	14%	8%	9%	15%	27%	44%	29%
Non-routine-manual	SO	14%	10%	08%	12%	31%	17%	07%
	AFL	9%	4%	4%	6%	19%	10%	8%

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