Persons

Income growth is related to complexity

POLICY BRIEF
SEPTEMBER 2015

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LifeLong | Learning | Innovation | Growth & Human Capital | Tracks in Europe

Outcomes of skills

Persons

IMPRESSUM

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This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no 290683.

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INCOME GROWTH IS RELATED TO COMPLEXITY

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Please cite this publication as follows: Patt. A. (2015): Income growth is related to complexity. Policy Brief, proceedings of LLLight'in'Europe research project.
Retrievable at: www.lllightineurope.com/publications

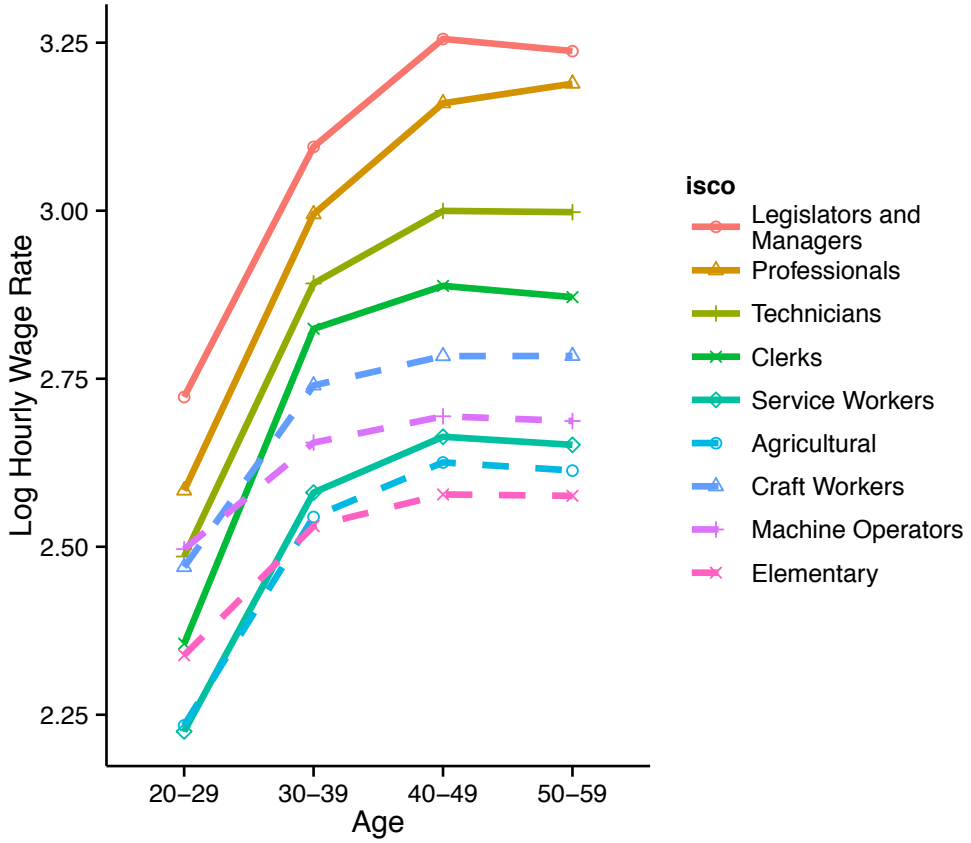
Introduction

That wages grow over lifetime is a well-known economic fact. Ever since the seminal work of Jacob Mincer (1974) lifetime earnings growth has been attributed to the investment in human capital, which was thought to take place primarily in the form of education and on-the-job training. The data show that, taking into account compositional differences of the workforce, average wage rate grows by 23% in the first 10 years since employment, 15% in the subsequent 10 years, 10% after that and finally halts with virtually no growth before retirement typically starts.

While wages in all occupations follow this general pattern, there is considerable unevenness in the magnitude of growth (fig. 1). Wages increase most in occupations that require considerable skill, such as managers and professionals, and least in low skilled occupations like craft and elementary workers. Traditionally the existence of wage curves was attributed to declining training (Ben-Porath 1967). In order to explain such differences across occupations, three explanations can be put forth. First, training in some of them may be much more prevalent. Second, higher wage growth may be a return on considerable education investment necessary to undertake more demanding occupations. Lastly, workers in some occupations may be faster learners.

In a seminal paper Kenneth Arrow (1962) suggested that learning-by-doing may be a major source of productivity growth and talked about two of its types: learning by repetition and learning by problem solving. The latter type is arguably responsible for the bulk of lifetime productivity growth, and occupations where this type of learning is prevalent are conducive to fast improvements of skills and productivity. This policy brief discusses the role of lifelong learning in the form of learning by problem solving and job complexity in determining earnings and the kind of employment.

Figure 1: Wage profiles for different occupations



Source: Nedelkoska, Patt, and Ederer 2014.

Key observations

Lifetime wage growth is higher in more complex occupations

Wage growth statistics may be misleading without a structural approach to interpret them and adjust for unevenness in starting conditions in different occupations. For example, workers in high skilled occupations are considerably more educated on average. A calibration of a learning-by-doing model using the German social security data on entrants to the labour force shows that, keeping the level of starting skills constant, by the time of retirement employees in high complexity occupations improve skills by almost 60% more than employees in low complexity occupations (Nedelkoska, Patt, and Ederer 2014). Higher skill growth translates into greater productivity and lifetime earnings.

Workers employed in more complex occupations tend to have higher skills and productivity throughout life

High complexity occupations such as managers and professionals on average have 35–51 PIAAC literacy points more than low complexity occupations such as elementary workers and machine operators. Such large difference is comparable in magnitude to one standard deviation of the entire sample (see table 1). In other words, average managers and professionals have literacy skills measured approximately at 69th highest percentile, while elementary workers only at 31st percentile of the distribution. They also have a much higher share of university graduates and do well in the complex problem solving (CPS) assessment.

Table 1: Skills by occupation

Occupation	Literacy	Exp	Educ	CPS	Compl
Legislators and Managers	297	22,7	67%	521	0,92
Professionals	301	19,3	87%	515	0,79
Technicians	286	21,3	50%	483	0,59
Clerks	284	19,5	36%	466	0,33
Service Workers	270	20,0	27%	363	0,27
Craft Workers	268	22,9	23%	484	0,32
Machine Operators	262	23,5	14%	456	0,10
Elementary	250	20,5	10%	398	0,02
Sample Average	281	21,0	46%	492	0,48
Sample SD	41	9,6		96	0,29

Notes: Literacy is mean PIAAC literacy score. Exp is average years of work experience. Educ is share of university graduates (education levels ISCED 5 and 6). CPS is mean CPS score. Compl is job complexity index which ranks occupations according to the frequency of tasks that are related to solving novel problems. The lowest complexity occupation has value 0 and the highest complexity occupations has value 1.

Data source: PIAAC, BIBB and LLLight'in'Europe.

Skills do not remain constant throughout working life. Using IALS and PIAAC data from OECD, we estimate that on average for workers in complex occupations literacy skills increase by 8.9 points by the age of 30–34 and further increase by another 4.5 points to 12.4 points by the age of 35-39 above the starting level (table 2). In comparison the average increase in literacy skills of workers in simple occupations is modest and reaches at most 6 points for 35–39 years old workers.

Thus, the gap in literacy skills between these two groups of occupations widens from 17 points to a maximum of 23.4 points as workers accumulate experience. The gap shortens closer to the time of retirement due to natural deterioration of skills. PIAAC literacy scores however do not tell the full story of skill development, as they are an imperfect measure of actual skills and are likely to understate lifetime dynamics of skills.

Table 2: Age skills profiles by occupation groups

Age	30-34	35-39	40-44	45-49	50-54
High skilled	8.9	12.4	11.4	6.8	4.0
Low skilled	3.3	6.0	3.0	2.2	5.1
Difference	5.6	6.4	8.4	4.6	-1.1

Notes: the numbers indicate average PIAAC literacy points above the average for the respective skill group measured at age 25-29. The mean is 282 points and one standard deviation is 44 points. On average high skilled employees are 17 points above low skilled employees. The sample consists of Belgium, Denmark, Finland, Germany, Ireland, Italy, the Netherlands, Norway, Sweden, the United Kingdom and USA.

Data source: PIAAC and IALS.

Learning is behind higher skills

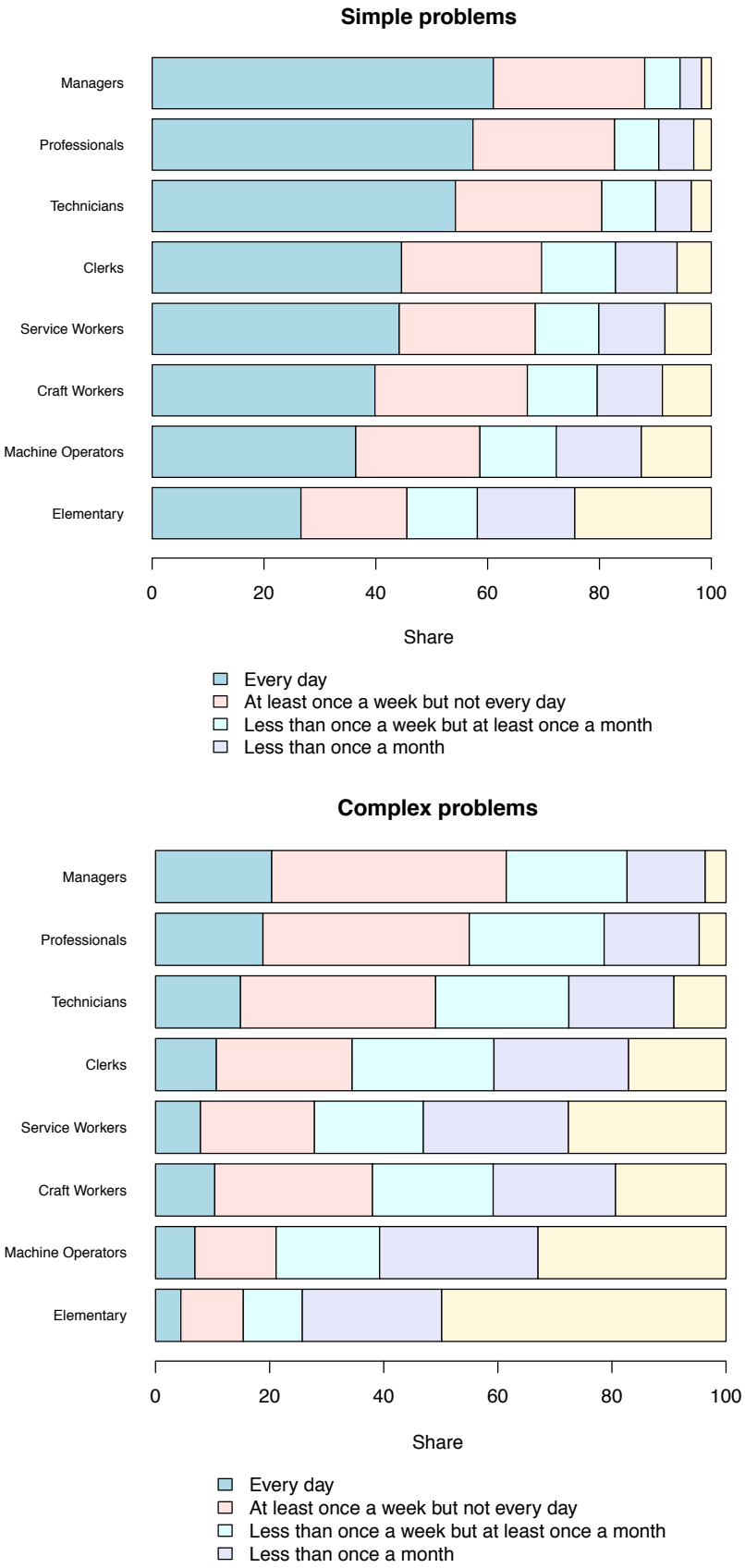
The second important feature in which occupations differ is their content as defined by task-based measures. More complex occupations such as managers and professionals engage considerably more often in problem solving activities when it comes to both simple and complex problems (fig. 2). For instance, more than 60% of managers engage in solving simple problems on a daily basis, compared to less than 25% of elementary workers. Tasks-based measures of job content predict literacy, numeracy and problem solving scores in the PIAAC assessment conditional on education, work experience and basic controls both between and within occupations. Regressions using measures such as learning at work suggest that workers who do not engage in learning at all are 15-32 literacy points below workers that engage in it every day (fig. 3). At the same time there is no substantial difference in scores between workers who engage in learning activities to a high and to some extent.

This evidence suggests that learning by doing may be an important driver of lifetime skill improvement. Jobs that provide opportunities to engage in problem solving and deal with novel situations allow workers to considerably improve their skills.

Job complexity predicts complex problem solving skills

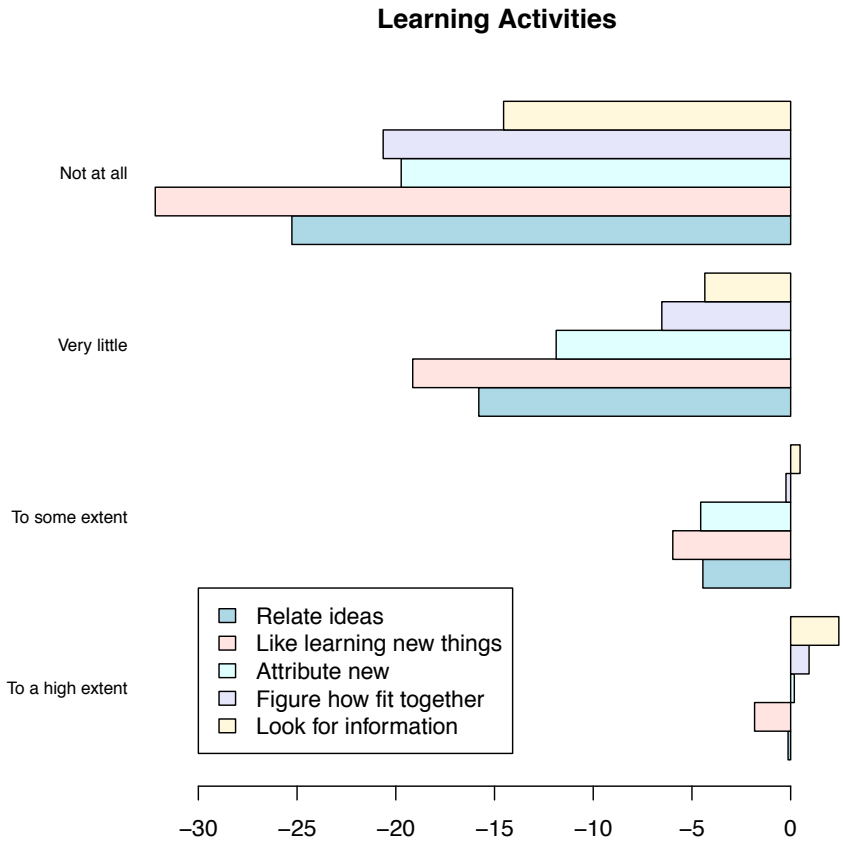
The data on complex problem solving (CPS) skills show that workers in complex occupations are better problem solvers. Keeping age and education constant and controlling for basic demographic factors, we find that individuals employed in complex jobs score by 60-80 points more on average in the CPS assessment compared to their peers employed in simple jobs (fig 4). Such differences are large compared to the population and are not affected by adjusting for differences in performance in the assessment across major occupation groups. In complex jobs the frequency with which workers deal with novel problems is much higher, therefore they provide better opportunities to improve or maintain one's problem solving skills at a high level.

Figure 2: Extent of problem solving across occupations.



Data source: PIAAC.

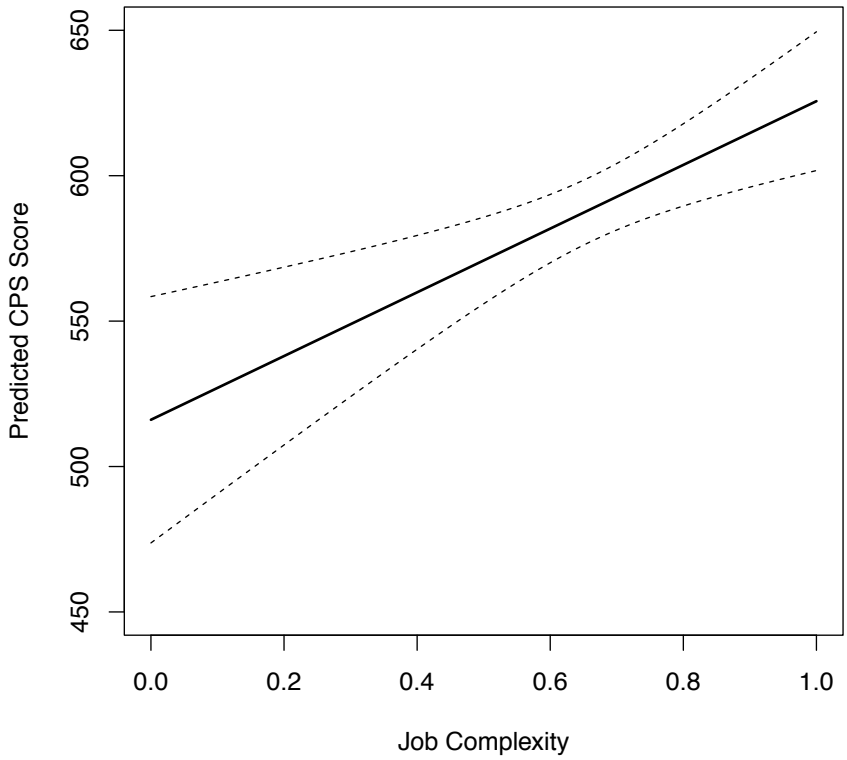
Figure 3: Effect of learning activities on literacy skills.



Notes: the numbers tell literacy points difference from the level of activity corresponding to "a very high extent". One standard deviation is 44 points.

Data source: PIAAC.

Figure 4: The relation between CPS scores and job complexity



Notes: solid line is predicted CPS score for varying job complexity (measured in percentiles with 0 being the least complex occupation and 1 most complex occupation). Dashed lines indicate confidence intervals. The scores are predicted from a regression of CPS on education, age, gender, country and job complexity. The reference person for the figure is a male with a university degree. CPS scores are measured on a scale such that 500 is the mean and 100 is one standard deviation. The construction of job complexity index is explained in the evidence and background section.

Data source: LLLight'in'Europe.

Learning is a factor of career choice

Learning matters not just for wage growth, but also for career choice. Using the Current Population Survey data from U.S. Census and BLS on individuals living at the same household during one year, we classify occupation switches into those that are "job upgrades" and "job downgrades" based on whether they are an increase or respectively a decrease over the complexity of the previous job. For the period of one year only 58% of individuals keep the same occupation (whether or not they change employers)[1]. Approximately 1/6 of all job switches are job upgrades, 1/6 are job downgrades and 2/3 are switches into a different occupation that has the same complexity. The direction of an occupational change is strongly related to the previous occupation: the lower the complexity of the previous job, the higher is the gain in complexity by taking a new job.

Older workers tend to be employed in more complex occupations. This pattern is consistent with a job transition mechanism, according to which workers gradually shift into more complex occupations as learning and skill growth enable them to do so. As evidenced by figure 5, the average complexity of jobs held by individuals aged 26 corresponds to the 46th percentile of the entire population, while the average complexity of jobs of individuals aged 41 to the 53rd percentile — an increase by 7 points. The increase in complexity cannot be attributed to changes in worker composition due to having more years of schooling, though it slightly lowers the difference. In fact, in this sample, workers aged 40-55 have fewer years of schooling on average than younger workers, while the complexity of their jobs remains high. Therefore, their acquired skills must be sufficient to compensate for having less education and promote them into more complex jobs. Of course, not all occupation switches are because of learning: some happen due to wage arbitrage, others are forced switches due to layoffs and no doubt there are many other reasons, however, the evidence suggests that the learning motive plays an important role.

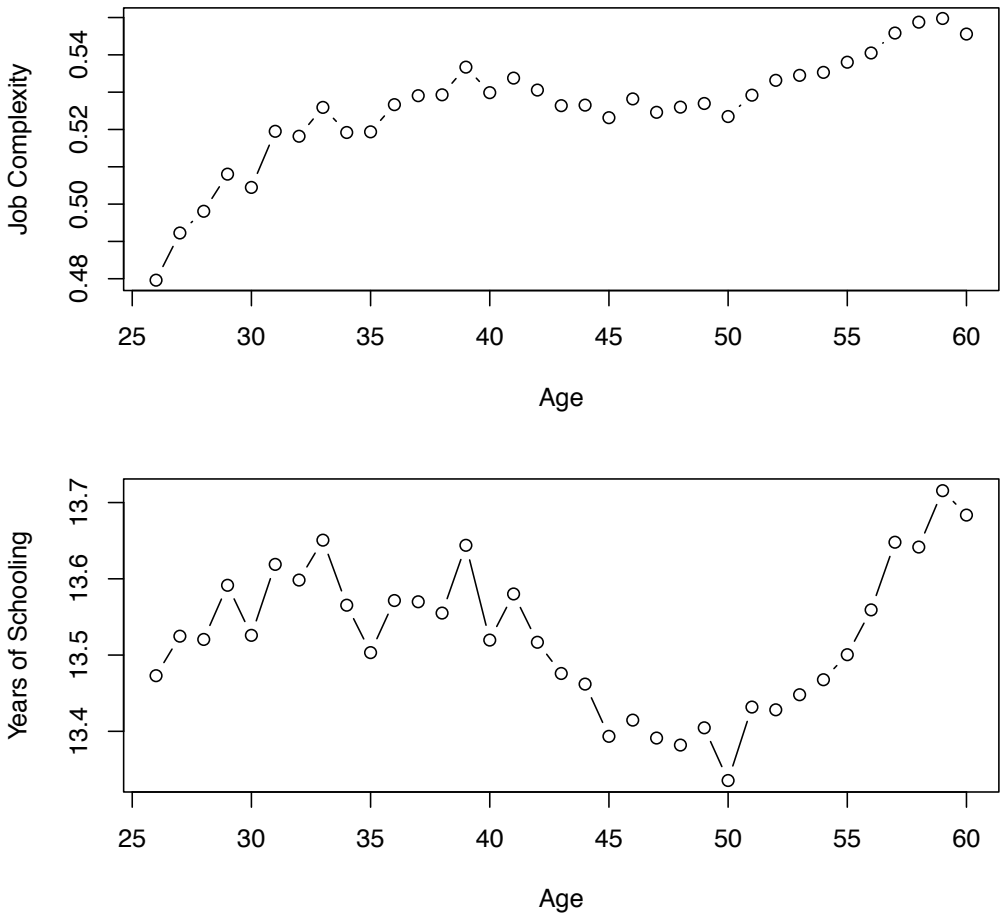
[1] March CPS data may have large recording errors that may lead to incorrectly treating data errors as occupational changes. However, high occupational mobility is a known feature of most labour markets.

Learning is a factor of migration

Among all people born in the USA as many as 30% eventually move into a different state. People are attracted by differences in economic and social factors between the state of origin and the new place. Younger individuals tend to move to locations which provide better opportunities to learn due to more complex work environments. Senior workers are more strongly attracted by positive wage differences and by lack of experienced workforce in the state of destination.

Migration is not only an outcome of variation in the learning opportunities, but also its source. A shift in the number of immigrants has profound effects on the kind of employment that native workers pursue: an inflow of low skilled workers causes native workers to move into more complex occupations where they have competitive advantage, thus increasing the scope for learning-by-doing. Using the framework of Peri and Sparber (2009), we find that a 1% change in the share of migrants living in a state results in 0.6% change in mean job complexity of native low skilled workers and 0.4% change for high skilled workers. The result is higher income levels and better future wage growth prospects.

Figure 5: Job complexity and age



Notes: job complexity and years of schooling are averages for the corresponding age for all employed individuals.

*Data source: IPUMS and O*NET.*

Recommendations

Investment in education is commonly thought as the primary form of investment in human capital that is available to an individual. Since it is typically undertaken early in life and is costly in terms of time and direct expenditures, learning at the job can provide another important way to increase productivity and earnings, in particular later in the career, when other options are associated with large opportunity costs. Employment in complex occupations brings many benefits: 1) greater scope for learning, 2) higher level of wages and 3) better wage growth prospects. All other things equal, choosing a more complex occupation seems to be the right decision. Yet there are certain costs that come along:

- Initial productivity drop, which is increasing in the difference between worker's starting skills and the requirements of the job;
- Psychic costs due to being overchallenged by work tasks, which result in higher likelihood of being dissatisfied with the job;
- Loss of previous job-specific human capital, though recent evidence suggests that workers who switch into more demanding occupations eventually catch up (Nedelkoska, Neffke, and Wiederhold 2015).

Given that, the optimal lifetime career strategy is to gradually transfer into more complex occupations concurrently with skill growth due to learning, so that to be constantly exposed to learning opportunities and continue to improve skills.

Evidence and background

Behind the key observations in this brief is a learning-by-doing model that relates human capital growth rates to the level of job complexity and current skill (for the exposition here we follow Nedelkoska, Patt, and Ederer (2014); see also Yamaguchi (2012) for a similar approach). Learning-by-doing presupposes the use of concepts of exposure and duration to model the learning process. By varying exposure, we change the rate at which individuals learn their trade.

For example, figure 2 tells that the majority of managers are exposed to solving complex problems on a daily basis, while most machine operators and elementary workers are never exposed to such problems. Any suitable continuous measure computed using task intensity can capture the exposure of different jobs to the relevant kind of learning. The total amount of accumulated learning is given by the duration over which exposure takes place. A suitable measure of duration is job tenure, with the caveat that workers sometimes switch occupations, thus making it necessary to consider each employment episode separately.

We suppose that wage growth of a worker is positively related to job complexity, because learning rate is higher in jobs with greater exposure, and negatively related to the skill level, because the scope of learning is lower whenever the job is already mastered and highly skilled workers have little new to discover. Let z(t) be a variable representing the stock of human capital for a worker with work tenure t (we assume no job changes). The equation that determines the growth of human capital is:

$$dz(t)/dt \,/\, z(t) = \alpha\,[\eta x - z(t)] + \beta, \qquad (1)$$

where the parameter α characterises the rate of learning, β is a shift parameter, and η is a scaling parameter for job complexity index x. We also suppose that workers receive a positive wage premium to the complexity of their job. The wage rate of a worker in job x with t years of experience is

$$W(t, x) = p(x)\, q(x, z(t)), \qquad (2)$$

where p(x) is price of output in job x and q is productivity, which adversely depends on x for constant z. In other words, there is an immediate productivity drop in more complex occupations for the same amount of skill, which however can be compensated in the long run thanks to faster learning and higher future skills as can be seen from equation (1).

In order to calibrate the model and determine the parameters α, β and η, one needs to observe the value of human capital stock of individuals employed in different occupations over time. Because productivity is strongly related to wages, in (Nedelkoska, Patt, and Ederer 2014) we use wages instead to calibrate the learning model using historic German social security data on rates of return to years of schooling, job complexity and tenure. While the exact form of functions p and q in (2) is not known, wage elasticities provide sufficient information to identify the parameters of the learning equation under certain assumptions.

Estimation of age-skill profiles using PIAAC data

Thanks to the PIAAC data from OECD it is possible to construct age profiles of literacy, numeracy and technology problem solving skills in order to examine lifetime dynamics of these skills. Using the PIAAC data set alone presupposes that workers of different age groups are otherwise equal. This assumption is likely to be questionable, as it ignores cohort effects. To deal with this problem, we combine IALS and PIAAC data and estimate the following model. Let y be the average skill level at age s, survey year t and in country c. Then the age profile of measured skills is given by equation

$$y(s, t, c) = \mu(t) + f(s, \cdots) + \nu(c) + \delta(t - s, c), \quad (3)$$

where δ is the cohort effect and f is the age-skill profile. The model makes the following assumptions:

1. Country effect is time–invariant
2. Age profile of skills is time–invariant
3. Survey effect is constant

We use the data on literacy skills of employed individuals from Belgium, Denmark, Finland, Germany, Ireland, Italy, the Netherlands, Norway, Sweden, USA and the UK. Eastern European countries are excluded due to comparability issues caused by economic transition at the time of the IALS survey. The sample excludes individuals aged 16-24 and 60-65.

Construction of a job complexity measure

An intensity index of job complexity can be constructed using a survey of tasks performed by employees. We use the BIBB survey by the German Institute for Employment Research and the Occupational Information Network (O*NET) survey from the USA. An analysis of the BIBB data suggests using the following questions to calculate a job complexity index with roughly equal weights:

How often does it happen at your work that you. . .

- collect, investigate and document data
- have to react to unexpected problems and resolve these
- have to make difficult decisions independently and without instructions
- have to recognise and close own knowledge gaps
- are faced with new tasks which you first have to understand and become acquainted with
- have to improve processes or try out something new
- have to keep an eye on many different processes at the same time

O*NET based measure uses the information from abilities, skills and generalised work activities to perform principal component analysis and extract the components with the largest attributable variation.

Literature

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Project Identity

LLLight'in'Europe is an FP7 research project supported by the European Union, which has investigated the relevance and impact of lifelong learning and 21st century skills on innovation, productivity and employability. Against the background of increasingly complex tasks and jobs, understanding which skills impact individuals and organizations, and how such skills can be supported, has important policy implications. LLLight'in'Europe pioneered the use of an instrument to test complex problem solving skills of adults in their work environment. This allowed for the first time insights into the development of professional and learning paths of employed individuals and entrepreneurs and the role that problem solving skills play. Additionally, LLLight'in'Europe draws on a series of databases on adult competences from across the world to conduct rich analyses of skills and their impact.

These analyses were conducted in concert with different disciplines. Economists have been analyzing the impact of cognitive skills on wages and growth; sociologists have been investigating how public policies can support the development of such skills and lifelong learning; innovation researchers have been tracking the relationships between problem solving skills, lifelong learning and entrepreneurship at the organizational level;. educational scientists have investigated how successful enterprises support their workforce's competences; cognitive psychologists have researched on the development and implications of cognitive skills relevant for modern occupations and tasks; and an analysis from the perspective of business ethics has clarified the role and scope of employers' responsibility in fostering skills acquisition in their workforce. The team has carried out its research and analyses on the value of skills and lifelong learning in EU countries, USA, China, Latin America and Africa.

The result is a multi-disciplinary analysis of the process of adult learning and problem solving in its different nuances, and of the levers which can support the development of these skills for both those who are already in jobs, and for those who are (re)entering the labor market, as well as the development of effective HR strategies and public policy schemes to support them.

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EU Contribution	€ 2,695,000
EU Project #	290683
Project Duration	January 2012 – September 2015

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Persons

This policy brief is part of the publication suite of the FP7 Project LLLight'in'Europe. The publication suite consists of 21 policy briefs, 6 thematic reports and 1 synthesis report. The 21 policy briefs discuss findings and policy implications proceeding from the project's research; they are organized along three level of analyses (persons; enterprise; country) and seven topics.

01 Resources of society for learning

02 Institutions of learning

03 Circumstances of learning

04 Role of transversal skills

05 Role of job-specific skills

06 Productivity of skills

07 **Outcomes of skills**

This policy brief discusses findings related to **Outcomes of skills** at the analysis level **persons**. For further publications and multimedia material related to the project, please visit www.lllightineurope.com