Job Complexity and Lifelong Learning

THEMATIC REPORT
SEPTEMBER 2015

Ljubica Nedelkoska
Center for International Development at Harvard University
USA
Zeppelin University
Germany

Alexander Patt
Leuphana University
Germany

LLLight´in´Europe

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

IMPRESSUM

Coordinated by
Zeppelin University
Am Seemoserhorn 20
88045 Friedrichshafen
Germany

Authors:
Dr Ljubica Nedelkoska
Alexander Patt

Graphics, Design and Layout:
Maren Sykora

Multimedia and Website:
Urs Boesswetter, Spooo Design

Video Production:
Sascha Kuriyama

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

JOB COMPLEXITY AND LIFELONG LEARNING

About the authors

Ljubica Nedelkoska

Dr Ljubica Nedelkoska is a Growth Lab Research Fellow at the Center for International Development at Harvard University and a post-doctoral researcher at Zeppelin University. She holds a PhD in Economics of Innovation from the Friedrich-Schiller-University in Jena, Germany and a Master's Degree in Public Administration from the Appalachian State University, North Carolina. In the past, Ljubica worked as a post-doctoral researcher and a coordinator of the Economics of Innovation Research Group in Jena. Ljubica's research focuses on the areas of regional structural change, transferability of skills across jobs and occupations, learning on the job and capital-labor relations. She has also been contributing to several projects at the intersection of research and policy in the Netherlands, Sweden, Norway, Germany and Albania.

Alexander Patt

Alexander Patt is a researcher at the Leuphana University. He obtained an MSc in Economics degree from the University of Exeter and an MSc in Finance & Economics (Research) degree from the London School of Economics and Political Science. His research efforts focus on investigating the links between wages, career choice and lifelong learning.

Please cite this publication as follows: Nedelkoska, L., Patt, A. (2015): Job Complexity and Lifelong Learning. Thematic Report, proceedings of LLLight'in'Europe research project. Retrievable at: www.lllightineurope.com/publications

Job Complexity and Lifelong Learning

Ljubica Nedelkoska*and Alexander Patt†

September 13, 2015

*Zeppelin University and the Center for International Development at Harvard University. ljubica_nedelkoska@hks.harvard.edu

†Leuphana University. patt@leuphana.de

Contents

List of Figures

List of Tables

Executive Summary

Several ongoing processes in Europe guarantee that most Europeans will have no choice but to keep on upgrading and adapting their skills and knowledge in order to remain employable and productive at their jobs. First, life expectancy in Europe is high and rising, putting pressure on all economies to redesign their pension systems and extend working life. Second, the EU expansion and the migration pressure between EU and non-EU countries guarantee that the competition for jobs within EU will remain fierce. Third, as a result of the proliferation of computers, growing complexity of production and the globalization of the division of labor, the jobs in Europe are on average becoming more cognitively demanding. For the above reasons the relationship between lifelong learning and job complexity is particularly relevant in the European context.

Drawing on a large literature from psychology and economics, this thematic report discusses the relationship between job complexity and learning in adulthood. We start by discussing the biological, psychological, and economic rationale behind the timing of the investments in skills. The biological and psychological perspective of learning implies that investments which enhance our fluid intelligence (the learning-to-learn ability) should have the highest lifelong economic returns. If fluid intelligence defines the scope for accumulation of crystallized intelligence, the first order investment should be the one in fluid intelligence. Since fluid intelligence is mainly formed in childhood, skill investments in childhood appear critical. More recent economic models incorporate some of these findings and conclude that early interventions in skill formation are much more meaningful than interventions in adolescence and adulthood from an economic perspective.

However, this does not mean that learning during adulthood in unimportant. As a matter of fact, we gain a great amount of knowledge while working. To illuminate the micro-foundations of the process of learning at the job, this thematic report reviews the literature on individual and organizational learning curves. This literature shows that learning plays more significant role in more complex jobs. Learning curves are longer in occupations that are more complex and in more complex production processes. Such occupations and processes have wider scope for productivity improvements. The large scope for learning in complex jobs also means that more capable learners will progress faster, and if rewarded accordingly, earn higher wages. Higher wage inequality could result from such process.

In the context of learning curves, we also discuss the transferability of learning across tasks. The similarity between tasks, of course, facilitates transferability, but so does fluid intelligence, as well as our approach to learning (e.g., testing, re-studying and receiving feedback).

Over a career path, employees tend to move from simple to complex jobs. One reason for this pattern is that complex jobs can only be performed efficiently after sufficient time spent on learning-by-doing in simple jobs. Individuals of higher ability and individuals with certain personality characteristics (e.g., self-esteem, self-confidence and self-efficacy) also tend to choose more complex jobs. In turn, those working in more complex jobs have higher levels of job satisfaction.

Future research should further integrate psychological insights about learning

and transferability of learning into economic models.

1 Introduction

At the onset of this millennium the European Commission announced the establishment of a European Era of Lifelong Learning (Commission, 2001). It's aim, the communication from the Commission said is "[...] to empower citizens to move freely between learning settings, jobs, regions and countries, making the most of their knowledge and competences, and to meet the goals and ambitions of the European Union and the candidate countries to be more prosperous, inclusive, tolerant and democratic" (p. 3). In 2007 the Commission published the action plan on adult learning (Commission, 2007), and as of today this Era is still being developed. The purpose of this report is to discuss the relation between job complexity and lifelong learning. These two concepts, one characterizing individual behavior and the other job content go hand in hand. While lifelong learning is deeply engraved in human nature, a number of ongoing demographic, economic and social processes will ensure that the demand for adult learning remains high. First, the aging in developed countries will increase the retirement age without diminishing pressure on productivity (Vogel et al., 2013). Second, migration stemming from the EU expansion, but also from the non-EU countries is intensifying the competition for jobs within the EU (Sinn, 2004), and education has so far proven to be a strong shield against unemployment and poverty (Mincer, 1991, 1974). Finally, Europe is experiencing growth of the high-pay, high-education jobs which is partially driven by complementarity between new technologies and skills, and partially by the international division of labor (Goos et al., 2009).

Lifelong learning has been studied in various disciplines: psychology, education science, sociology and even neuroscience. Among these, this thematic report borrows significantly from cognitive psychology, because the relationship between learning and job complexity has been most intensively researched in this discipline. The literature on this topics in the field of economics is also discussed. This literature makes an important contribution by explaining the economic rationale behind the learning and occupational choices individuals make. In the field of psychology we start by discussing the perspectives of the life-span psychology (Baltes, 1987, 1993, 1997; Baltes et al., 2006, 1984; Lindenberger, 2001), and in the field of economics, the literature on learning-by-doing (Arrow, 1962; Jovanovic and Nyarko, 1994, 1995; Nedelkoska et al., 2014). It is beyond the scope of this report to discuss the educational and sociological aspects such as the types of adult education, the teaching approaches and their effectiveness, or the meaning of lifelong learning for societies and regions to name a few.

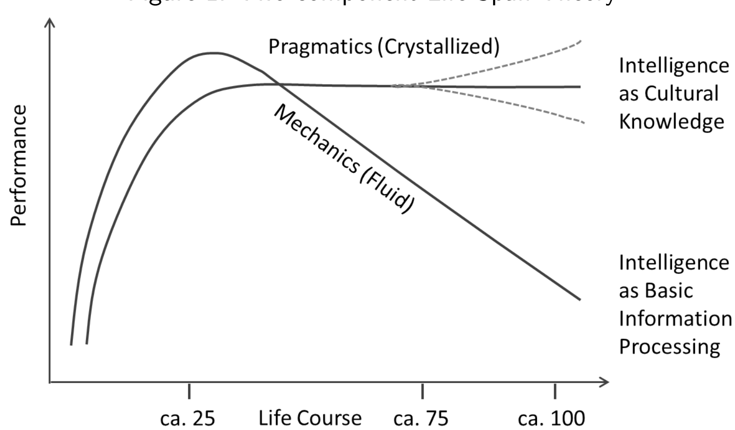
In what follows we will first introduce the foundations of lifelong learning in psychology and economics. We will then discuss the concept of job complexity and its measurement, followed by a review of the major contributions in the literature on learning curves. Next, we review the literature on the role of ability and in the choice of jobs with different level of complexity. We then discuss the relation between job complexity and job satisfaction. We finally conclude the findings and discuss key areas for future research.

2 Lifelong Learning and Job Complexity

Life-span psychologists argue for a two-component model of adult intellectual development. The first component is referred to as the mechanics of cognition and the second as the pragmatics of cognition. Psychologists argue that factors determining the level of performance within these two components are different: biological-genetic for the mechanics, and environmental-cultural for the pragmatics (Baltes et al., 2006).

The *mechanics of cognition* start developing already during the embyogenesis, and are greatly constrained by the biological and neuro-physiological brain conditions. This cognitive development is largely genetically predisposed (Elman, 1998; Wellman, 2003) and reflects the organizational properties of the central nervous system (Singer, 2003). It is believed that they are in charge of the speed, accuracy, and coordination of elementary processing operations (Baltes et al., 2006). Cognitive mechanics peak in late 20s - early 30s, and monotonically decline afterward (see Figure 1). The concept of cognitive mechanics corresponds to Cattell's concept of fluid intelligence (Gf) (Cattell, 1971), and Ackerman's process of the Process, Personality, Interests, Knowledge Model (PPIK) (Ackerman, 1996).

Figure 1: Two-component Life-Span Theory



Source: Baltes et al. (2006)

The second component, *pragmatics of cognition*, is developed through interaction with the environment we encounter along the life-span. It is the knowledge we accumulate through this interaction and it is culture-specific. Reading and writing, educational and professional qualifications, occupation and industry-specific knowledge are examples of such development. In Cattell's theory of abilities, it corresponds with the concept of crystallized intelligence (Gc) and in Ackerman's

PPIK theory, to the concept of knowledge. In theory, the pragmatics of cognition are expected to first grow and then stabilize along the individual life cycle (Figure 1). The two component model has a strong empirical support. Schaie and Willis (1993), for instance, extensively tested the age-performance curves of adults and show that the domains of cognitive mechanics (verbal memory, reasoning, spatial orientation and perceptual speed) all decline significantly and almost monotonically after the age of 35 while the domains of cognitive pragmatics grow until the age of 35, then stabilize until the age 65-70, and only then start declining.

Our educational cycle relates to this development. We typically spend most of our childhood and adolescence in education, and our adulthood in materializing education through work. If fluid intelligence is an ability to learn, investing in education earlier in our life, during which period we can contribute to the development of fluid intelligence through education, will maximize the crystallized knowledge which we acquire later. From an economic perspective, early investments in human capital, when investment cost is relatively low, are rewarded by higher subsequent economic returns to human capital in terms of earnings. This explains the timing of education in economic models (Mincer, 1974; Ben-Porath, 1967). Combining insights from psychology, education and neuroscience, Cunha and Heckman (2007) develop a model of skill formation in early childhood which is much richer than the traditional models of human capital accumulation. In their model, the current level of skill depends on the past level of skill, the current expenditures in form of skill investment and the parental characteristics. Cunha and Heckman (2007) emphasize that remedial skill investments in early childhood have much higher returns than remedial investments in adolescence. This is driven by the nature of skill formation in our life-span. Many skills are best developed until certain age: language until the age of 12 and fluid intelligence until the age of 10. Hence, much of their policy insights urge for early interventions in skill formation.

The concept of lifelong learning however suggests that learning doesn't stop in adulthood. On the contrary, we learn a great amount by performing a particular job. Not all jobs however have the same scope for learning. Studies of job and occupational mobility show that typically individuals start their careers with simple jobs and then move to more complex ones either through promotions within firms, or by changing employers (Sicherman and Galor, 1990; Osterman, 1984). The examples are numerous: nurse to nurse practitioner, cook to chef, player to coach, officer to general, middle level manager to CEO to name a few.

Three types of learning have been identified to explain individual job dynamics: (a) learning about one's ability, (b) learning about the individual-job match and (c) learning-on-the-job or also referred to as firm-specific human capital in the earlier human capital literature. In the first approach, firms do not know the ability of their workers at the point of employment, but they learn about it by observing their productivity at the job. Higher ability workers then have higher probability of reaching a promotion (Prendergast, 1999; Gibbs, 1995; Farber and Gibbons, 1996). Similar to the assumptions in the first type of economic models, in the second type of economic models of learning, the individual-job match is not known when a new employee joins the firm. Over time, both the employee and the firm learn about their match. Good matches are then less likely to separate from the firm than bad matches (Jovanovic, 1979).

More interesting than the first two models, are models of promotion resulting from learning-on-the-job. Individuals can do little about their largely genetically predisposed ability at the time they start working, and match quality can only be improved by moving to another job. However, individuals can decide how much to learn on the job and these decisions will determine they chances to stay in the firm, as well as their chances of promotion within the firm. Jovanovic and Nyarko (1997) propose an economic model which explains promotions through a process of learning by doing. If mistakes in simpler jobs are less costly in terms of productivity than mistakes in more complex ones, individuals who try to maximize lifelong earnings will decide to first master simple jobs and only then move to complex ones. In line with this argument, more recently, a number of empirical studies have shown that, on the job, employees accumulate valuable human capital, which is task (Gibbons and Waldman, 2004; Gathmann and Schoenberg, 2010), industry (Neal, 1995; Parent, 2000) and occupation-specific (Kambourov and Manovskii, 2009). Gathmann and Schoenberg (2010) for instance find that task-specific human capital accounts for up to 52% of the overall wage growth in individual careers. They also find that this share is higher for highly skilled workers and lower for lower skilled ones. In line with these findings, Nedelkoska et al. (2014) find that in complex jobs employees accumulate twice the skills that are accumulated by employees in non-complex jobs.

3 Job Complexity: Definition and Measurement

The definitions of job complexity vary across disciplines. In psychology, according to Schroder et al. (1967), complexity increases as the information load, the information diversity, and the rate at which information changes, i.e., the degree of uncertainty increase. Similar conceptual understanding of job complexity (here referred to as task complexity) was put forward by Wood (1986). According to Wood (1986), each task contains three essential components. *Products* are measurable outcomes of acts. *Acts* are the behavioral patterns which are directed towards the purpose of creating the product. *Information cues* are needed to apply the right act for the desired product. Task complexity stems from component complexity, coordinative complexity and dynamic complexity. *Component complexity* is a positive function of the number of distinct acts and the number of distinct information cues. *Coordinative complexity* refers to the demands imposed by the timing, frequency, intensity and location requirements in the relationships between task inputs and task products. Finally, *dynamic complexity* refers to the frequency with which one needs to update the beliefs about the cause-effect relations between the task inputs and products.

Coming from vocational science, Hunter et al. (1990) relate job complexity to the information-processing demands of jobs. In the field of economics, Jovanovic and Nyarko (1995) think of job complexity as the number of decisions the worker needs to make when performing a task. According to March and Simon (1958) complex tasks are characterized by unknown or uncertain alternatives, by inexact or unknown means-ends connections, and by the number of subtasks they entail.

In management and organizational theory Campbell and Gingrich (1986) defined complexity in terms of interrelated and conflicting elements, emphasizing that a complex task places high cognitive demands on the individual. Summarizing several past studies, Steinmann (1976) explains that task complexity can be varied by changing the number of information sources (i.e., cues), the cue inter-correlations, reliability and functional forms, the task predictability, as well as the organizational principle underlying the integration of the information. More complex tasks entail larger amount of information about the task, lower internal consistency of this information, and higher variability and diversity of the information itself. Nedelkoska et al. (2014) define job complexity in terms of the frequency at which workers are exposed to novel problems at the job. Hence, most disciplines agree that what makes a job complex are the high requirements for information processing, independent of whether these stem from the number of tasks that need to be considered, the task uncertainty, the input reliability, or the pace at which new problems arrive. Most would probably agree that a consequence of this is that complex jobs impose high cognitive strains on workers.

3.1 Objective and Subjective Measures of Job Complexity

In terms of operationalization, the literature distinguishes between objective and subjective measures of job complexity. This distinction is somewhat misleading as both types of measures depend on someone's judgment about the content of jobs. However, in the case of objective measures the judgment is given by occupational experts, while in the case of the subjective ones, workers self-assess the complexity of own jobs. Gerhart (1988) for instance explains that the objective measures of job complexity gather information regarding the personnel requirements of jobs from outside observers such as occupational analysts, whereas the subjective measures gather information about the type of work activities involved in a particular job from the incumbent.

The earliest objective measures of job complexity were probably developed as part of the occupational codes in the Dictionary of Occupational Titles (DOT) of the United States in the 1960s. The creators of DOT argued that every job requires workers to function in relation to data, people, and things. In the occupational classification, three digits in each occupational code were dedicated to describing the relation which workers have with data (the 4th digit), people (the 5th digit) and things (the 6th digit). Within these digits, smaller numbers corresponded with higher task complexity as illustrated in Table 1. This information or parts of it has since then been used by researchers to compose measures of job complexity (e.g., Hunter (1983, 1986); Gerhart (1988); Gottfredson (1986); Roos and Treiman (1980)). In 1998 O*NET replaced the DOT. The occupational titles in O*NET as well as their ratings are fundamentally different from those in the DOT. O*NET's occupational classification and ratings are based on the so-called "Content Model" (for ONET Development for USDOL (2015)). Of interest for measures of job complexity, O*NET now rates each occupation based on the work performed, skills, education, training, and credentials. While the job titles, the work tasks, the training and the education relevant for the job are all defined based on responses from job

Table 1: Task Complexity when working with Data, People and Things

Data		People		Things	
0	Synthesizing	0	Mentoring	0	Setting Up
1	Coordinating	1	Negotiating	1	Precision Working
2	Analyzing	2	Instructing	2	Operating-Controlling
3	Compiling	3	Supervising	3	Driving-Operating
4	Computing	4	Diverting	4	Manipulating
5	Copying	5	Persuading	5	Tending
6	Comparing	6	Speaking-Signaling	6	Feeding-Offbearing
		7	Serving	7	Handling
		8	Taking instructions-Helping		

Source: Dictionary of Occupational Titles (1991).

incumbents, job skills and abilities are rated by trained job analysts. The latter should address potential biases in reporting of own skills and abilities either because job incumbents are not aware of the complete distribution of possible skills and abilities or because they intentionally try to overstate them.

In psychology, subjective measures of job complexity are called Incumbent Perceptions of Job Complexity (Gerhart (1988); Sims et al. (1976)). As their name suggests, job complexity here is derived from survey responses of job incumbents. For instance, Stone and Gueutal (1985) used a common space analysis method to reduce the dimensionality of self-reported job characteristics from the Job Diagnostic Survey and other surveys. The first dimension which they identified in the data they associated with job complexity. More recently, job complexity measure using self-reported data on job characteristics was proposed by Nedelkoska et al. (2014) using the German BIBB/IAB and BIBB/BAuA Employment Surveys of 2006 and 2012 (Rohrbach-Schmidt and Hall (2013)). The two BIBB/IAB and BIBB/BAuA Surveys consistently ask seven questions that are arguably related to the level of job complexity. 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 recognize 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?

The authors then apply principal component analysis on these seven variables for each survey wave (2006 and 2012). In both waves, the authors find that the variables

Table 2: Subjective Measure of Job Complexity

	2006	2012
information	.570	.571
newproblems	.645	.619
difficultdecisionsalone	.598	.597
knowledgegaps	.546	.490
newtasksthink	.595	.585
processimprove newideas	.578	.549
multitask	.520	.511

Source: Nedelkoska et al. (2014) using data from the German BIBB/IAB and BIBB/BAuA Employment Surveys of 2006 and 2012.

load on one single factor with eigenvalue larger than one, which they refer to as problem-solving or job complexity factor. Table 2 shows the job complexity factor loadings. Evidently, the loadings are relatively high and very similar in both waves. This is reassuring as it speaks for the stability of the measure. As a consequence, the job complexity factor has very similar distributions in 2006 and 2012 (Figure 2).

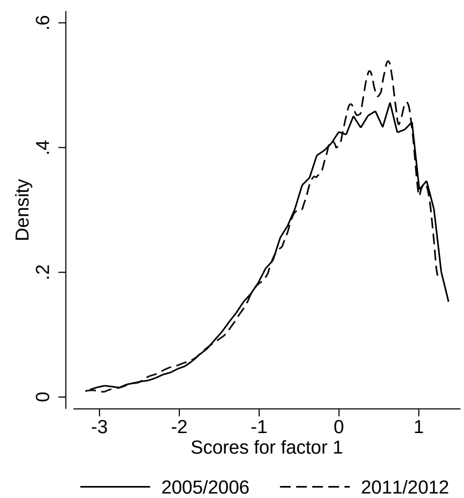
Which measures should we use, the subjective or the objective ones? One could argue that measuring job complexity using employees perceptions of information intensity can be somewhat misleading for at least two reasons. First, employees do not know the full distribution of jobs in the economy and compare their tasks with a limited set of jobs which they are familiar with. Second, perceived job complexity is relative to individual ability. However, in most research cases the measurement options will probably be limited by the availability of subjective and objective information on jobs and occupations. While the North American occupational classifications have a long history of incorporating information on job characteristics from experts and occupational analysts, most countries do not gather such information. The International Standard Classification of Occupations (ISCO) which is widely used by European countries, for instance, contains information about the level of skill and specialization of occupations. While the level of skill is highly related to job complexity, ISCO is not based on objective measures of job complexity. Early research also investigated the construct validity of perception-based measures of job characteristics. Gerhart (1988) finds significant convergence between perception-based measures of complexity and DOT-complexity.

4 Learning Curves

The earliest scientific documentation of individual learning curves probably dates back to the end of the 19th century[1] when Bryan and Harter (1897, 1899) documented the learning curves of adults learning the telegraphic language and when Thorndike (1898) designed experiments based on which he documented the learning curves of cats, dogs and chicks. To the best of our knowledge, the work of Bryan and

[1]There exists earlier literature on practice curves as mentioned in Bryan and Harter (1897).

Figure 2: Distributions of the Job Complexity Factors



Source: Nedelkoska et al. (2014)

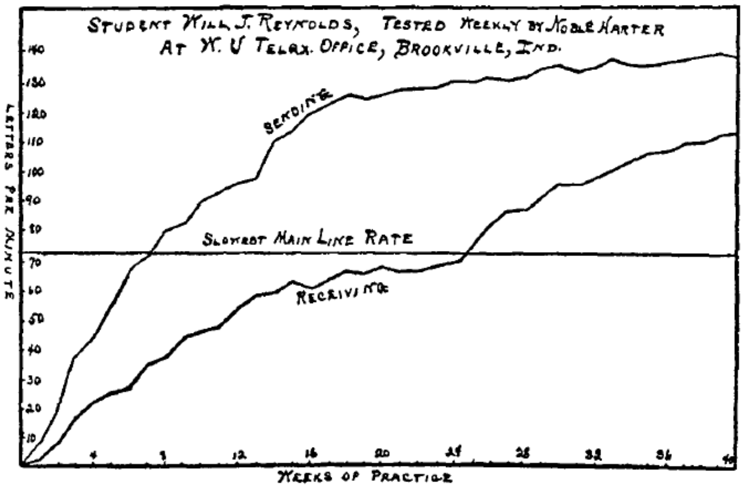
Harter is the earliest work which simultaneously: (a) analyzes the learning curves of adults, (b) discusses the role of task complexity in learning patterns.

4.1 Individual and Organizational Learning Curves

Individual learning curves show the output of a certain task as a function of time or as a function of the number of attempts. The output is sometimes measured as a success rate and sometimes as a failure rate. In Bryan and Harter's case the outcome variable is the number of letters per minute, which is a success rate measure. The typical learning curve for a simple task when the outcome variable is the success rate would take a concave form, meaning that learning is a positive function of time (number of attempts), but over time learning increases at a decreasing rate. In Figure 3 this is the upper learning curve of the signal senders.

However, the learning curve of the receivers, the authors noticed, does not take the expected concave form. The curve is first concave, but has a convex part in the 24th week of practice. Moreover, between week 24 and week 40 (the last week of observation) the curve does not reach a plateau, meaning that learning has not been exhausted. To explain the general difference in the learning rates of the two curves the authors admit that the task of the sender is much simpler than the task of the receiver. The shape of the curve however requires more explanation. In their later work Bryan and Harter (1899), the authors argue that the shape of the receivers' curves can be explained by an underlying hierarchy of psycho-physical habits. These habits in the case of the telegraphic language are: (a) the habit of learning letters, (b) the habit of learning words and (c) the habit of learning sentences. The earlier

Figure 3: Bryan and Harter's Learning Curves of the Telegraphic Language



Source: Bryan and Harter (1897)

habits stand lower and the later higher in the hierarchy. This means that higher level habits must be learned simultaneously or after the learning of lower level habits, but not before. From the beginning, the trainees learn both letters and words, but the latter they learn at a slower pace. When they add sentence-building to the learning, they probably learn this at an even slower pace. Hence, the learning of different hierarchical habits can be simultaneous, but it does not happen at the same pace. One can think of the receivers' curve as a combined curve of the letter habit, the word habit and the sentence habit. The plateau we observe in the middle of the curve indicates that lower-order habits (letters and words) are approaching the maximum proficiency. The inflection point at which the curvature changes to convex is a point at which the acquisition of the higher-order set of language habits - sentence building - becomes visible in the output. Learning of sentences is more difficult to deplete than the learning of letters and words, which could explain why we may not see a second plateau approach soon after the inflection point.

In 1936 Theodore P. Wright published an article in which he documented the aggregate learning curve of airplane production. He showed that that unit labor costs in airframe production declined with cumulative output. This is perhaps the earliest published documentation of an organizational learning curve. The robustness of this pattern was later confirmed by Alchian (1963). Arrow (1962) modeled economic growth as a function of learning-by-doing which is a by-product of firm-level production and not active investment. Since then numerous products have been subjects of studies of organizational learning curves (see Argote and Epple (1990) for a literature review).

4.2 Modeling the Learning Curve and Deriving Implications

Following Eyring et al. (1993) the rate of learning of an individual i in time t can be noted as:

$$\frac{d\xi_i}{dt} = [\lambda_i - \xi_i(t)]\,\gamma_i \tag{1}$$

where $\xi_i(t)$ is the individual's performance at time t, λ_i is the maximum possible learning or the asymptote of ξ_i, and γ_i is the speed of learning. This formula suggests that learning is proportional to the amount left to be learned $\lambda_i - \xi_i(t)$. Moreover, the higher the individual speed of learning γ_i, the higher the rate of change in the task performance. Solving equation 1 gives the learning curve:

$$\xi_i(t) = \lambda_i - [\lambda_i - \xi_i(t-1)]\,e^{\gamma_i^t} \tag{2}$$

Equation 2 suggests that for higher values of λ_i, the learning curve will take longer to reach a plateau. Fast learners will reach the learning plateau faster than slow learners.

Jovanovic and Nyarko (1995) propose a different way of modeling the learning curve. They rightfully argue that the learning curve in equation 2 only informs about the first moments of the learning distribution at each moment t, although the variability in learning and productivity as a function of time are also of scientific interest. Moreover, the approach taken by Jovanovic and Nyarko (1995) allows us to think about individual and organizational learning curves in a unified way. The underlying mechanisms of both individual and organizational learning curves have some things in common, they argue. Each time there is a productivity improvement in the production function of a product as a function of experience, "someone - the manager, the worker, the engineer, the head of purchasing - makes better decisions" (p. 248). Hence, they claim, productivity improvements can be modeled as outcomes of an optimization process where better decisions are being made as experience accumulates. This is why the authors decide to model the learning curve using a decision-theoretic framework or a model of Bayesian updating.

Jovanovic and Nyarko (1995) design a production function with input parameters for which a best decision exists, but *apriori* it is unknown which decision is the best one. In the real world such parameters can be for instance, the amount of certain ingredient which needs to be added in the production process, choosing a type of employee for the job, or deciding on the division of work among employees. Prior to each production round, the decision-maker chooses a parameter value (makes a decision) without knowing what is the best possible value. The outcome of each production round reveals something about the performance of her decision. In the next round, the decision-maker updates her beliefs about the best decision. The authors differentiate between simple and complex tasks. The complexity of the production function varies in the number of unknown parameters which the decision-maker needs to guess (make a decision about). The authors derive the following two equations for a simple task or single decision task, and a complex task, or a task involving multiple decisions:

$$E_\tau(q_\tau) = A(1 - x_\tau - \sigma_w^2) \quad (3)$$

$$E_\tau(q_\tau) = A(1 - x_\tau - \sigma_w^2)^N \quad (4)$$

where q_τ is to production efficiency [2] and $E_\tau(q_\tau)$ is its expectation after τ production rounds; A is the maximum attainable q.[3] $x_\tau$is the posterior variance over the mean of the best (ideal) decision given information from the first τ production rounds and σ_w^2 is the variance of the noise w. The noise, w, is normally distributed random variable with mean zero and variance σ_w^2. N is the number of tasks for which the decision-makers need to make decisions and indicates the level of task complexity.

The learning curves as defined by Jovanovic and Nyarko (1995) have a number of interesting properties. First, the learning curve must be concave when the number of tasks is one. Second, the learning curve can have a convex part (like in Bryan and Harter (1897, 1899)) and this part is more likely to appear if N is higher. The convex part either appears in the beginning of the curve or not at all. However, a learning curve with a convex part later in time can occur if the job consists of simple and a complex task such that the simple task enters the efficiency equation additively and the complex ones in multiplicative fashion:

$$q = \underbrace{A_1\left[(y_1 - z_1)^2\right]}_{q^{simple}} + \underbrace{A_2 \prod_{j=2}^{N} \left[1 - (y_j - z_j)^2\right]}_{q^{complex}} \quad (5)$$

where y is the parameter we do not know and z is our best guess (optimal decision given the information at hand) of y. If the beliefs and signals are identically and independently distributed as in 2, q^{simple}will be concave in τ and for sufficiently large N, $q^{complex}$ will be S-shaped. We can then rewrite 5 as:

$$E_\tau(q_\tau) = A_1(1 - x_\tau - \sigma_w^2) + A_2(1 - x_\tau - \sigma_w^2)^{N-1} \quad (6)$$

It is remarkable that about a century after the publishing of Bryan and Harter's work, Jovanovic and Nyarko establish very precise scenarios under which a learning curve with a concave and convex component can occur. Both studies use a similar intuition to explain the shape of such learning curve: it must be a result of a combination of tasks, among which some are of lower and some of higher complexity. In the case of Bryan and Harter, simpler jobs are composed of lower-order habits and in the case of Jovanovic and Nyarko, simpler jobs involve single decisions.

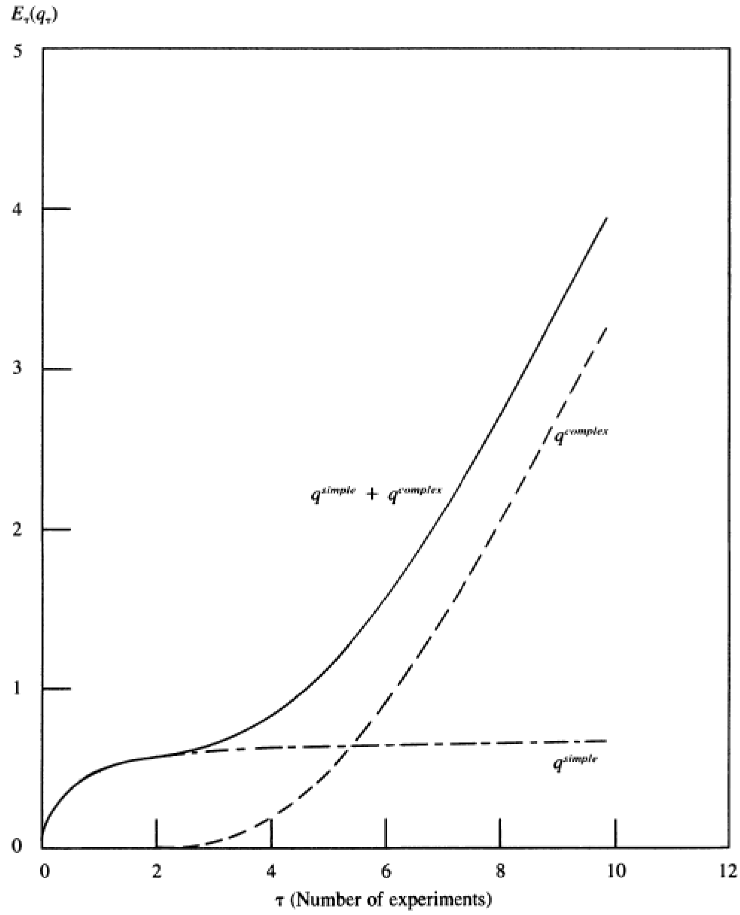
Figure 4 demonstrates the learning curves in equations 3 (q^{simple}), 4 ($q^{complex}$) and 6 ($q^{simple} + q^{complex}$).[4]

[2] q_τ is comparable to $\xi_i(t)$ in equations 1 and 2 only that q is more generally defined for either individuals or organizations and is here expressed in terms of production rounds τ and not time t.

[3] A is comparable to λ_i in equations 1 and 2.

[4] The following assumptions and settings hold: the prior beliefs about the means of the unknown parameters $(\theta_1, ..., \theta_N)$ are identical and mutually independent, with variance $\sigma_\theta^2 = 0.6$. The noise

Figure 4: Learning curve of a simple, complex, and combined task



Source: Jovanovic and Nyarko (1995)

Moreover, the authors show that the variance of efficiencies among the decision-makers can increase by a lot for intermediate values of τ[5] only as a function of the signal variance. Some decision-makers will be lucky to obtain better signals and some will be unlucky. This variance, or inequality increases exponentially in the number of N, i.e., in job complexity. Finally, they show that the increase of N skews the distribution of efficiencies to the right.

Another result in the model of Jovanovic and Nyarko (1995) is that cumulative productivity growth is higher in more complex jobs. At the individual level, Nedelkoska et al. (2014) find that cumulative productivity growth as measured by the individual wage growth is higher in more complex jobs (Figure 5). Within the first 10 years at the job, the average real hourly wage of a machine operator grows by about 12%, while in the case of professionals, it grows by over 50% and in the case of legislators and managers by something less than 50%.

Nedelkoska et al. (2014) and Yamaguchi (2012) take a different approach to estimating learning curves. Based on the assumption that hourly wages correspond to the marginal productivity of individual workers, these authors derive the learning curves by calibrating empirical observations of individual-level wage growth. In Nedelkoska et al. (2014), the hourly wage is defined by two components: the price of a task, which is a linear positive function of job complexity, $p(x)$, and the task productivity for given complexity level x and skill level z, $q(x,z)$.

$$W(t,x) = p(x)q(x,z(t)) \tag{7}$$

where, price increases with complexity, productivity decreases with complexity, and productivity increases with skill. The instantaneous growth rate of skills is a linear function of the gap between the level of job complexity and the current skill level:

$$\frac{\dot{z}}{z} = \alpha(\eta x - z) + \beta \tag{8}$$

where α is the rate of learning assumed to be larger than 0, η is a scale parameter also assumed to be larger than 0, and β is a shift parameter which ensures that the left-hand side of the equation has a non-negative part. Equation 8 suggests that the growth of skills is higher in positions with higher scope for learning (positions with large gaps between skills and job complexity). By solving equation 8 with respect to t, we obtain:

$$\frac{\dot{z}}{z}(t) = \alpha\left[z^* - z(t)\right] \tag{9}$$

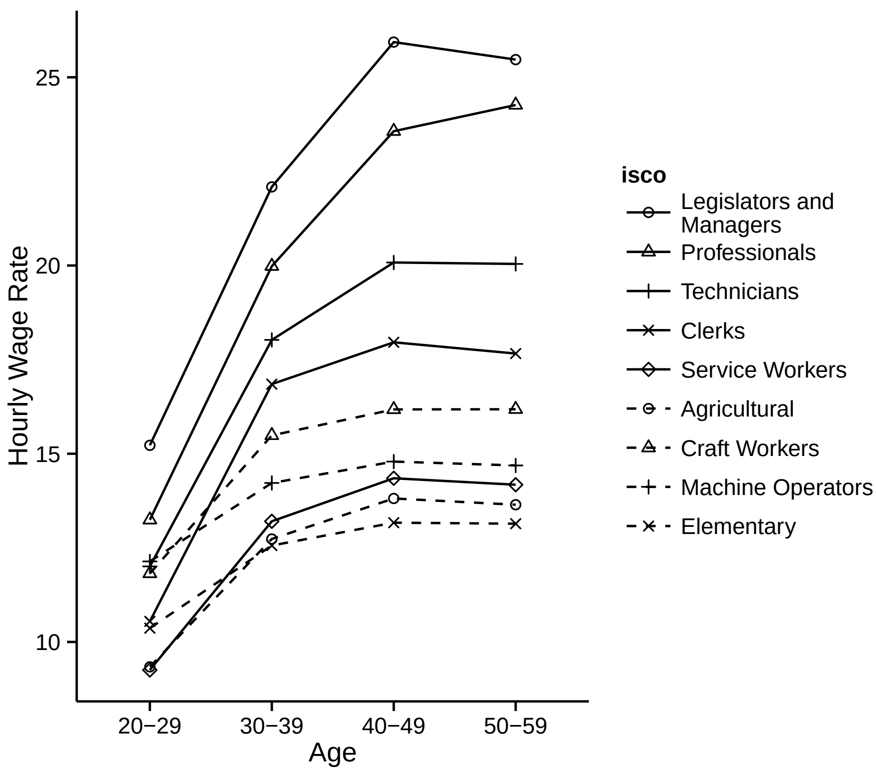
A key message of equation 9 is that z grows at a rate proportional to the distance to the asymptotic value of z. Based on the expected behavior of skill growth, the authors then derive the implications for the relationship between wage growth, skills

---

of the signals $w_1, ..., w_N$ are identically and independently distributed with $\sigma_w^2 = 0.3$; $N = 50$, $A_1 = 1$, $A_2 = 10^8$.

[5]For $\tau = 0$ or $\tau = \infty$the signal is first absent and then perfect, and hence the variability of q will be low.

Figure 5: Wage growth profiles for jobs with different complexity



Source: Nedelkoska et al. (2014)

and job complexity. Wages are expected to grow most for positions where the initial skill is low, but job complexity is high. Low skill - low complexity positions will incur little growth, and so would high complexity - high skill positions. The authors find that, when tenure is low, wage growth is positively related to job complexity and negatively related to initial skill level, just as it was predicted by the model.

4.3 Learning to Learn

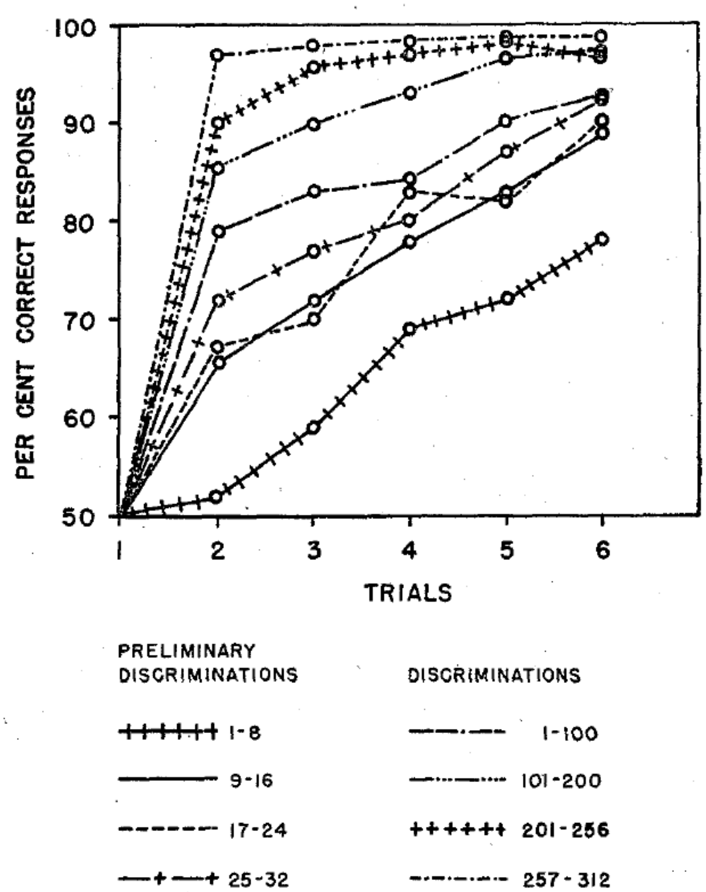
Is the knowledge learned by practicing one task transferable to other tasks and if yes, what facilitates such transferability? Harlow (1949) argued that mammals are capable of attaining higher order learning - a learning how to learn efficiently. He describes this as a process in which animals and humans transition from learning by trial and error to learning by hypothesis testing. He refers to this process as the formation of learning sets. Harlow conducted experiments with monkeys in which he introduced a new task once the monkeys absolved an earlier task, but retained the principles based on which the tasks were built. Figure 6 illustrates his main findings. The lower four curves show the learning of the first 32 tasks, which were grouped into sets of eight. The learning curve of the first 8 tasks is S-shaped. Harlow explains this shape as resulting from a trial and error approach. This is interesting in the light of the work by Jovanivic and Nyarko discussed earlier in this section, where S-shaped curves are the result of learning complex tasks. Although the tasks which Harlow designed for the monkeys were not complex, what they had in common with complex tasks at the beginning of the problem-solving is that mistakes were common because the task principles were unknown. Next, the learning curves of problems 8-32 start with a convex part and reach higher success rates. The eighth learning curve, corresponding to tasks 257 to 312 (the last set of tasks) almost reaches the asymptotic learning point (100% success rate) after the second trial. In Harlow's interpretation, the monkeys formed learning sets or methods in the first groups of tasks which later helped them solve similar problems more efficiently. Harlow's findings were later replicated for humans by Ellis (1958, 1965).

That intelligence plays a role in the transferability of learning has been argued since the work of Charles Spearman, Godfrey Thomson, and Edward L. Thorndike. Deary et al. (2008) for instance cite a statement given by Spearman in 1931 at the International Examinations Inquiry Meeting in 1931:

> **"And** so the discovery has been made that G is dominant in such operations as reasoning, or learning Latin; whereas it plays a very small part indeed in such operation as distinguishing one tone from another... G tends to dominate according as the performance involves the perceiving of relations, or as it requires that relations seen in one situation should be transferred to another. . . ." (p.11).

Proving this has been much harder. Several decades later, the work of Ackerman (1988) decisively concluded that intelligence represents an ability to learn by showing that higher ability individuals learn faster than low ability ones, and that the relation between ability and learning is enhanced in more complex tasks. Besides intelligence,

Figure 6: Learning Curves of Successive Tasks with Transferable Knowledge



Source: Harlow (1949)

learning by repetition and learning by testing has been found to improve the transfer of learning, with testing having a stronger positive effect than re-learning only (Butler, 2010; Carpenter, 2012; Carpenter and Kelly, 2012). Carpenter and Kelly (2012) showed that individual learning of complex tasks (in their case spatial orientation) benefited more from testing of individuals' learning than from re-learning only. They find similar results for testing and feedback vs. re-learning, while the differences between testing and testing and feedback were insignificant. Finally, they find that testing enhanced the transferability of learning more than re-studying, although they admit that this might be due to the similarity of testing as a treatment to the final test which the participants were taking.

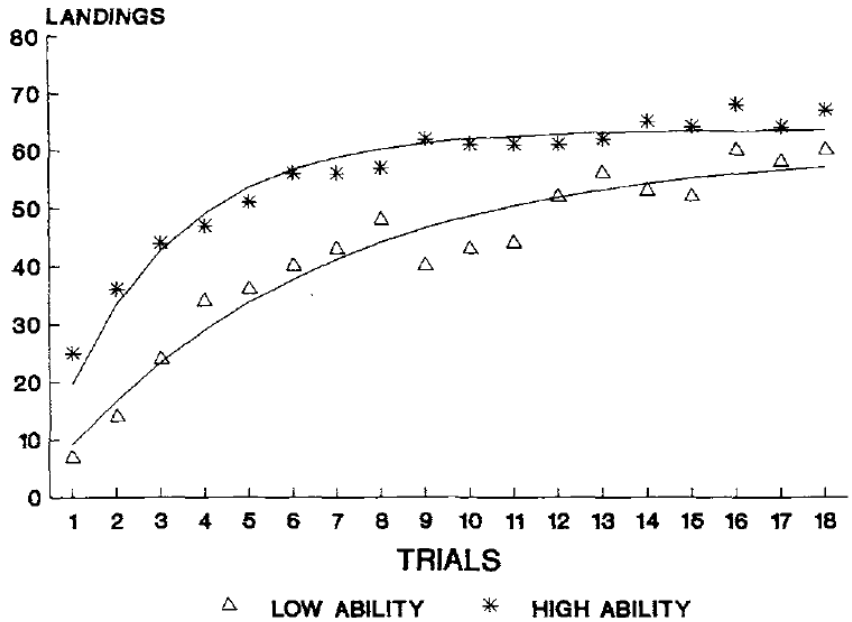
5 Matching Abilities with Job Complexity

The way people are distributed across jobs is far from random. While it is true that the structure of jobs in the economy is continuously changing and hence there is a great deal of constraints on the available jobs from which individuals can choose, it is also known that people select their professions and jobs based on characteristics such as gender (Lent et al., 1991), culture (Fouad and Byars-Winston, 2005) and risk attitudes (Bonin et al., 2007). This section will focus on ability as an important factor of job choice.

Ackerman (1987, 1988) showed that intellectual ability plays a crucial role in explaining individual-level differences in learning. Interestingly, Ackerman (1988) also concluded that for simple, consistent tasks (e.g., many of the military and industrial tasks), individual differences in job performance are only moderately correlated with general intelligence. In these tasks additional factors such as motivation may play increasingly more important role over time, once the mechanics and the logic of the tasks have been understood. The decline in the general ability-performance correlation is smaller for complex or less consistent tasks. This pattern is consistent with understanding of general intelligence as an ability to learn, and more complex tasks as having more scope for learning.

Eyring et al. (1993) tested the effect of ability, self-efficacy and task familiarity on task performance. Unlike ability, which is an objective attribute, self-efficacy is the individual's belief in own capabilities and personal efficacy in exercising control over events (Bandura, 1977, 1986). Task familiarity is the individual's declarative knowledge and procedures relevant for the performance of a given task. Such knowledge can be gained through prior experience with the same or similar tasks. To test their hypotheses the authors designed an experiment where 120 individuals played a simulation of an Air Traffic Control (ATC) task. The task had three basic components: (a) accepting planes into the airspace, (b) moving planes in a three-level hold pattern, and (c) landing planes on the appropriate runways. Performance was measured as the number of planes landed during each 5-min trial. For each individual the authors measured the ability, the self-efficacy and the task familiarity. The key findings about the relationship between ability and task performance are demonstrated in Figure 7 where the learning curves of the highest and lowest performing individuals are plotted. Better able individuals started with higher ini-

Figure 7: Ability and Task Performance



Source: Eyring et al. (1993)

tial performance and reached the asymptotic learning faster. Interestingly, similar findings hold for the relation between self-efficacy and task performance, with the difference that those with lowest self-efficacy did not reach the asymptotic performance which the high self-efficacy individuals did (not shown here). To conclude, both objective ability and perceived ability matter for task performance, but they are more important in tasks with higher scope for learning.

Wilk et al. (1995) and Wilk and Sackett (1996) hypothesize that higher ability individuals tend to choose more complex jobs. Wilk et al. (1995) use the National Longitudinal Survey of Youth (NLSY) to test this hypothesis. They find that individual-level general ability as measured by the General Aptitude Test Battery (GATB) in 1982 predicted the individual job complexity in 1987. These results are consistent with the findings on the relationship between task performance and ability. If ability is more instrumental to the performance of complex tasks, maximizing performance is better achieved by assigning more able individuals to more complex tasks. Hence, both employers and employees will strive to match better able individuals with more complex tasks.

6 Job Complexity and Job Satisfaction

Work psychologists and organizational scientists have shown great interest in understanding what drives individual satisfaction with jobs. To understand the room for policy, the main objective has been distinguishing genetically predisposed factors such as fluid intelligence from factors that firms can actually influence, such as work conditions and work content. For instance, Brief (1998), as cited in Judge et al. (2000), puts forward two models of job satisfaction: top-down, in which job satisfaction is derived from how one interprets the environment, and bottom-up, in which job satisfaction is derived from the experience of job conditions.

The top-down model leaves little room for policy intervention in adulthood if one's subjective interpretations of the work environment depend primarily on factors which are genetically predisposed or formed in childhood and early adulthood, such as personality and fluid intelligence. Early research on the topic provided support for the top-down model. For instance, Arvey et al. (1989) studied the impact of genetic and environmental factors of job satisfaction using a sample of monozygotic twins who were separated from an early age. They find that the twins held jobs that were similar in terms of their complexity level, motor skill requirements, and physical demands, suggesting that genetics play a critical role in the job choices people make. They conclude that organizations may have less influence over job satisfaction than is commonly believed, but they also comment that job enrichment efforts may raise mean levels of job satisfaction for the individuals, even if their rank ordering does not change. Using direct measurements of dispositional factors (i.e., individual-specific factors such as self-esteem which are unrelated to job content), Judge et al. (1998) and Judge et al. (2000) find that these factors have direct and indirect impact on job satisfaction.

The bottom-up model, on the other hand, suggests that employers can significantly influence the levels of job satisfaction among their employees. It has been more difficult to provide evidence for the bottom-up model. Judge et al. (2000) provided support for the bottom-up model, but admitted that the positive partial correlations between job complexity and job satisfaction may suffer from the problem of reverse causality. It might be that workers who are better satisfied with their jobs perceive their jobs to be more complex. Humphrey et al. (2007) also provide correlation-based support for a positive relationship between jobs complexity and job satisfaction, admitting as well that the results should not be mistaken for robust evidence about a causal relationship.

Several studies find that the relationship between job complexity and job satisfaction is mediated by personality and ability-driven self-selection in jobs. This means that better-able individuals and individuals with certain personality characteristics (e.g., high self-esteem, self-confidence and self-efficiency) prefer and choose more complex jobs and in return job complexity rewards them with higher job satisfaction. For instance, Wilk et al. (1995) and Wilk and Sackett (1996) who find that higher ability individuals are more likely to choose more complex jobs. Judge et al. (2000) also conclude that "the reason individuals with positive core self-evaluations perceive more challenging jobs and report higher levels of job satisfaction is that they actually have obtained more complex (and thus more challenging and intrinsically enriching) jobs."

Against this background, it becomes evident that both models, the top-down and the bottom-up are too simplistic. A key mechanism in the relationship between job complexity and job satisfaction is the match between individual skills and abilities on the one hand, and job content on the other. Individuals with low initial skills and abilities, i.e., low starting productivity and low learning rates may find themselves easily frustrated in jobs with high information processing demands. Highly able and ambitious individuals may get frustrated for the lack of challenging job content. Hence, instead of investigating the relationship between job complexity and job satisfaction, a more promising approach would be to focus on the relationship between skill-job content match, personality-job content match, and job satisfaction. For instance, Vieira (2005) and Johnson and Johnson (2000) find that overqualification at the job reduces job satisfaction and De Grip et al. (2007) find that overqualification actually causes a decline in the immediate and delayed recall abilities, cognitive flexibility and verbal fluency. Interestingly, the evidence is hardly existent when it comes to the relationship between under-skilling or underqualification and job satisfaction. It is not clear why this is the case, because underskilling and underqualification is very common too (Quintini, 2011; Nedelkoska et al., 2015). Future research should investigate both sides of skill mismatch, not only overqualification. More studies focusing on the underlying reasons for these relationships, like the one of De Grip et al. (2007) should also be encouraged.

7 Conclusions

Learning in jobs of different complexity has attracted ample attention among researchers in cognitive psychology and economics. Contributions from psychology help us understand the fundamentals of learning, while the research in economics illuminates the economic rationale for the education and career choices of adults and firms. This thematic report reviews the literature in these two fields on the relationship between job complexity and learning.

In psychology, the dominant theory of adult intelligence distinguishes between fluid and crystallized intelligence. It argues that crystallized intelligence peaks during adulthood and is retained at its peak for a few decades, while fluid intelligence, or the ability to learn starts declining in the mid thirties. These insights have important implications for the timing of the investments in skills. From such perspective, a unit investment in learning-to-learn ability should increase life-long individual productivity more than a unit investment in crystallized knowledge, because knowing how to learn helps individuals acquire crystallized knowledge faster. Hence, in a world where there is a tradeoff between learning and working, investments in skills should be made at times that maximize the development of fluid intelligence. From a traditional economic perspective, investing early in education increases life-time earnings because firms pay a wage premium for additional years of schooling.

However, this is far from saying that it is optimal to stop learning at certain point in adulthood. Quite on contrary, research shows that significant amount of learning happens at the job, where employees acquire valuable task, industry and occupation-specific knowledge. This knowledge is reflected in individual earnings, job security and possibilities for professional promotion.

Learning varies in tasks and jobs with different complexity. Most authors would agree that what complex tasks have in common is the information processing load they impose on individuals. Individuals, when subjected to tasks with different complexity, produce learning curves of different shapes. Simple tasks are associated with decreasing returns to practice and information, and complex tasks can result in periods of increasing returns to practice and information.

Complex tasks are associated with higher productivity and higher earnings growth because they have wider scope for learning. Over a career path, employees tend to move from simple to complex jobs. One reason for this pattern is that complex jobs can only be performed efficiently after sufficient time spent on learning-by-doing in simple jobs.

Personality and cognitive characteristics impact the choice of job content. Personality characteristics such as self-esteem, self-confidence, self-efficacy, as well as cognitive abilities have been found to positively affect the choice of more complex jobs. In turn, those working in more complex jobs have higher levels of job satisfaction. To the best of our knowledge, there is no causal evidence on the direct effect of job complexity on job satisfaction other then through self-selection.

Although the research contributions on the topic of adult learning and job complexity are many as shown in this report, there is certainly room for further research. First, there are promising areas for further fruitful combinations of psychological and economic research on learning. The traditional view in economics is that the timing of human capital investments is driven by a rational decision to maximize lifelong earnings. More recent contributions by James Heckman, Flavio Cunha and others incorporated finding from psychology, neuroscience and education to form better informed models of skill formation. These models incorporate insights about the importance of non-cognitive skills, personality traits, as well as the critical timing of skill formation in economic models. However, as of now, their main policy implications regard skill formation in childhood. Integrating the theories of formation of fluid and crystallized knowledge into economic research could give us better understanding of the optimal time for human capital investment along the life-span and not only in childhood.

Second, economics could gain from incorporating the psychologists' insights about the transferability of learning. Such study could focus on understanding the knowledge principles of occupations which make them more or less similar to other occupations. In economic models job switching has a cost and this cost is minimized by switching to jobs to which we can transfer more knowledge. However, the nature of transferability is better understood by incorporating insights from psychology.

Further area of research is the quantification of learning at the job vs. the learning through formal and informal education. Can schools teach product-specific knowledge or is this something which can only be taught at the job through learning by doing? For which products is this more or less the case? Products which production can be taught in school are easier to diffuse regionally and cross-country, improving the production prospects of lagging regions. Finally, there are areas of ample policy relevance such as predicting future job requirements, maintaining trainability and enabling requalifications in adulthood, and policies for integration of adult migrants with diverse cultural background, all of which should be prioritized on the research agenda on lifelong learning and job complexity.

References

Ackerman, P. L. (1987). Individual differences in skill learning: An integration of psychometric and information processing perspectives. *Psychological bulletin*, 102(1):3.

Ackerman, P. L. (1988). Determinants of individual differences during skill acquisition: cognitive abilities and information processing. *Journal of experimental psychology: General*, 117(3):288.

Ackerman, P. L. (1996). A theory of adult intellectual development: Process, personality, interests, and knowledge. *Intelligence*, 22(2):227–257.

Alchian, A. (1963). Reliability of progress curves in airframe production. *Econometrica: Journal of the Econometric Society*, pages 679–693.

Argote, L. and Epple, D. (1990). Learning curves in manufacturing. *Science*, 247(4945):920–924.

Arrow, K. J. (1962). The economic implications of learning by doing. *The review of economic studies*, pages 155–173.

Arvey, R. D., Bouchard, T. J., Segal, N. L., and Abraham, L. M. (1989). Job satisfaction: Environmental and genetic components. *Journal of Applied Psychology*, 74(2):187.

Baltes, M. M. (1987). Erfolgreiches altern als ausdruck von verhaltenskompetenz und umweltqualitaet. *Erbe und Umwelt. Zur Natur von Anlage und Selbstbestimmung des Menschen. Frankfurt/Main: Suhrkamp*.

Baltes, P. B. (1993). The aging mind: Potential and limits. *The gerontologist*, 33(5):580–594.

Baltes, P. B. (1997). On the incomplete architecture of human ontogeny: Selection, optimization, and compensation as foundation of developmental theory. *American psychologist*, 52(4):366.

Baltes, P. B., Dittmann-Kohli, F., and Dixon, R. A. (1984). New perspectives on the development of intelligence in adulthood: Toward a dual-process conception and a model of selective optimization with compensation. *Life-span development and behavior*, 6:33–76.

Baltes, P. B., Lindenberger, U., and Staudinger, U. M. (2006). *Life span theory in developmental psychology*. Wiley Online Library.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review*, 84(2):191.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Prentice-Hall, Inc.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *The Journal of Political Economy*, pages 352–365.

Bonin, H., Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2007). Cross-sectional earnings risk and occupational sorting: The role of risk attitudes. *Labour Economics*, 14(6):926–937.

Bryan, W. L. and Harter, N. (1897). Studies in the physiology and psychology of the telegraphic language. *Psychological Review*, 4(1):27.

Bryan, W. L. and Harter, N. (1899). Studies on the telegraphic language: The acquisition of a hierarchy of habits. *Psychological Review*, 6(4):345.

Butler, A. C. (2010). Repeated testing produces superior transfer of learning relative to repeated studying. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 36(5):1118.

Campbell, D. J. and Gingrich, K. F. (1986). The interactive effects of task complexity and participation on task performance: A field experiment. *Organizational Behavior and Human Decision Processes*, 38(2):162–180.

Carpenter, S. K. (2012). Testing enhances the transfer of learning. *Current directions in psychological science*, 21(5):279–283.

Carpenter, S. K. and Kelly, J. W. (2012). Tests enhance retention and transfer of spatial learning. *Psychonomic bulletin and review*, 19(3):443–448.

Cattell, R. B. (1971). *Abilities: Their structure, growth, and action.* Houghton Mifflin.

Commission, E. (2001). Making a european area of lifelong learning a reality. Technical Report COM(2001) 678 final, European Union.

Commission, E. (2007). Action plan on adult learning. Technical Report COM(2007) 558 final, European Union.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. Technical report, National Bureau of Economic Research.

De Grip, A., Bosma, H., Willems, D., and Van Boxtel, M. (2007). Job-worker mismatch and cognitive decline. *Oxford Economic Papers*, page gpm023.

Deary, I. J., Lawn, M., and Bartholomew, D. J. (2008). A conversation between charles spearman, godfrey thomson, and edward l. thorndike: The international examinations inquiry meetings 1931-1938. *History of Psychology*, 11(2):122.

Ellis, H. C. (1965). *The transfer of learning.* Macmillan.

Ellis, N. R. (1958). Object-quality discrimination learning sets in mental defectives. *Journal of comparative and physiological psychology*, 51(1):79.

Elman, J. L. (1998). *Rethinking innateness: A connectionist perspective on development*, volume 10. MIT press.

Eyring, J. D., Johnson, D. S., and Francis, D. J. (1993). A cross-level units-of-analysis approach to individual differences in skill acquisition. *Journal of Applied Psychology*, 78(5):805.

Farber, H. and Gibbons, R. (1996). Commitment and wage dynamics. *The Quarterly Journal of Economics*, 111.

for ONET Development for USDOL, N. C. (2015). The onet content model.

Fouad, N. A. and Byars-Winston, A. M. (2005). Cultural context of career choice: meta-analysis of race/ethnicity differences. *The Career Development Quarterly*, 53(3):223–233.

Gathmann, C. and Schoenberg, U. (2010). How general is human capital? a task-based approach. *Journal of Labor Economics*, 28(1):1–49.

Gerhart, B. (1988). Sources of variance in incumbent perceptions of job complexity. *Journal of Applied Psychology*, 73(2):154.

Gibbons, R. and Waldman, M. (2004). Task-specific human capital. *American Economic Review*, pages 203–207.

Gibbs, M. (1995). Incentive compensation in a corporate hierarchy. *Journal of Accounting and Economics*, 19(2):247–277.

Goos, M., Manning, A., and Salomons, A. (2009). Job polarization in europe. *The American Economic Review*, pages 58–63.

Gottfredson, L. S. (1986). Occupational aptitude patterns map: Development and implications for a theory of job aptitude requirements. *Journal of Vocational Behavior*, 29(2):254–291.

Harlow, H. F. (1949). The formation of learning sets. *Psychological review*, 56(1):51.

Humphrey, S. E., Nahrgang, J. D., and Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: a meta-analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology*, 92(5):1332.

Hunter, J. (1983). Overview of validity generalization for the us employment service. In *USES Test Research Report*, volume 43. US Department of Labor Washington, DC.

Hunter, J. E. (1986). Cognitive ability, cognitive aptitudes, job knowledge, and job performance. *Journal of vocational behavior*, 29(3):340–362.

Hunter, J. E., Schmidt, F. L., and Judiesch, M. K. (1990). Individual differences in output variability as a function of job complexity. *Journal of Applied Psychology*, 75(1):28.

Johnson, G. J. and Johnson, W. R. (2000). Perceived overqualification and dimensions of job satisfaction: A longitudinal analysis. *The Journal of Psychology*, 134(5):537–555.

Jovanovic, B. (1979). Job matching and the theory of turnover. *The Journal of Political Economy*, pages 972–990.

Jovanovic, B. and Nyarko, Y. (1994). Learning by doing and the choice of technology. *NBER Working Papers*, (4739).

Jovanovic, B. and Nyarko, Y. (1995). A bayesian learning model fitted to a variety of empirical learning curves. *Brookings Papers on Economic Activity. Microeconomics*, pages 247–305.

Jovanovic, B. and Nyarko, Y. (1997). Stepping-stone mobility. In *Carnegie-Rochester Conference Series on Public Policy*, volume 46, pages 289–325. Elsevier.

Judge, T. A., Bono, J. E., and Locke, E. A. (2000). Personality and job satisfaction: the mediating role of job characteristics. *Journal of applied psychology*, 85(2):237.

Judge, T. A., Locke, E. A., Durham, C. C., and Kluger, A. N. (1998). Dispositional effects on job and life satisfaction: the role of core evaluations. *Journal of applied psychology*, 83(1):17.

Kambourov, G. and Manovskii, I. (2009). Occupational specificity of human capital. *International Economic Review*, 50(1):63–115.

Lent, R. W., Lopez, F. G., and Bieschke, K. J. (1991). Mathematics self-efficacy: Sources and relation to science-based career choice. *Journal of counseling psychology*, 38(4):424.

Lindenberger, U. (2001). Lifespan theories of cognitive development. In *International encyclopedia of the social and behavioral sciences*, pages 8848–8854. Elsevier Science.

March, J. G. and Simon, H. A. (1958). *Organizations.* Wiley.

Mincer, J. (1974). *Schooling, Experience, and Earnings. Human Behavior and Social Institutions No. 2.* ERIC.

Mincer, J. (1991). Education and unemployment. Technical report, National bureau of economic research.

Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of labor Economics*, pages 653–677.

Nedelkoska, L., Neffke, F., and Wiederhold, S. (2015). Skill mismatch and the costs of job displacement. *Paper presented at the Annual Meeting of the American Economic Association, January 2015, Boston, MA*.

Nedelkoska, L., Patt, A., and Ederer, P. (2014). Learning by problem-solving. *unpliblished manuscript*.

Osterman, P. (1984). *Internal labor markets*, volume 1. The MIT Press.

Parent, D. (2000). Industry-specific capital and the wage profile: Evidence from the national longitudinal survey of youth and the panel study of income dynamics. *Journal of Labor Economics*, 18(2):306–323.

Prendergast, C. (1999). The provision of incentives in firms. *Journal of economic literature*, pages 7–63.

Quintini, G. (2011). Over-qualified or under-skilled.

Rohrbach-Schmidt, D. and Hall, A. (2013). Bibb/baua employment survey 2012. BIBB-FDZ Daten und Methodenbericht 1/2013, BIBB-FDZ.

Roos, P. A. and Treiman, D. J. (1980). Dot scales for the 1970 census classification. *Work, jobs, and occupations: A critical review of occupational titles*, pages 336–389.

Schaie, K. W. and Willis, S. L. (1993). Age difference patterns of psychometric intelligence in adulthood: Generalizability within and across ability domains. *Psychology and Aging*, 8(1):44.

Schroder, H. M., Driver, M. J., and Streufert, S. (1967). *Human information processing*. New York: Holt, Rinehart & Winston.

Sicherman, N. and Galor, O. (1990). A theory of career mobility. *Journal of political economy*, pages 169–192.

Sims, H. P., Szilagyi, A. D., and Keller, R. T. (1976). The measurement of job characteristics. *Academy of Management journal*, 19(2):195–212.

Singer, W. (2003). The nature-nurture problem revisited. In *Understanding Human Development*, pages 437–447. Springer.

Sinn, H.-W. (2004). The new systems competition. *Perspektiven der Wirtschaftspolitik*, 5(1):23–38.

Steinmann, D. O. (1976). The effects of cognitive feedback and task complexity in multiple-cue probability learning. *Organizational Behavior and Human Performance*, 15(2):168–179.

Stone, E. F. and Gueutal, H. G. (1985). An empirical derivation of the dimensions along which characteristics of jobs are perceived. *Academy of Management Journal*, 28(2):376–396.

Thorndike, E. L. (1898). Animal intelligence: An experimental study of the associate processes in animals. *American Psychologist*, 53(10):1125.

Vieira, J. A. C. (2005). Skill mismatches and job satisfaction. *Economics letters*, 89(1):39–47.

Vogel, E., Ludwig, A., and Boersch-Supan, A. (2013). Aging and pension reform: extending the retirement age and human capital formation. Technical report, National Bureau of Economic Research.

Wellman, H. M. (2003). Enablement and constraint. In *Understanding Human Development*, pages 245–263. Springer.

Wilk, S. L., Desmarais, L. B., and Sackett, P. R. (1995). Gravitation to jobs commensurate with ability: Longitudinal and cross-sectional tests. *Journal of Applied Psychology*, 80(1):79.

Wilk, S. L. and Sackett, P. R. (1996). Longitudinal analysis of ability-job complexity fit and job change. *Personnel Psychology*, 49(4):937.

Wood, R. E. (1986). Task complexity: Definition of the construct. *Organizational behavior and human decision processes*, 37(1):60–82.

Yamaguchi, S. (2012). Tasks and heterogeneous human capital. *Journal of Labor Economics*, 30(1):1–53.

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.

Coordinator	Zeppelin University
Project Director	Peer Ederer
EU Project Officer	Monica Menapace
EU Contribution	€ 2,695,000
EU Project #	290683
Project Duration	January 2012 – September 2015

Supervisory Board

Xavier Prats Monné
Director-General, Directorate-General for Education and Culture, European Commission

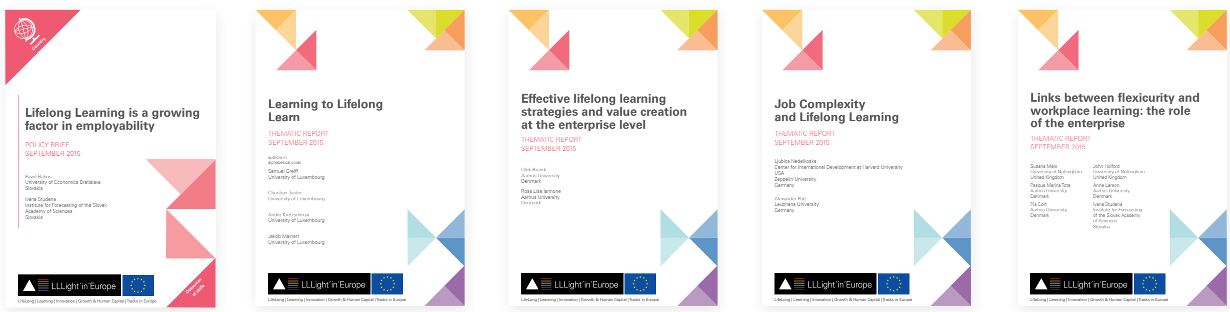
Andreas Schleicher
Director for Education and Skills, and Special Advisor on Education Policy to the Secretary-General at OECD

Iain Murray
Senior Policy Officer responsible for Policy on Learning and Skills, Educational Policy, and Regional Government and Devolution,
Trades Union Congress (TUC), United Kingdom

Oskar Heer
Director Labour Relations, Daimler AG Stuttgart

Roger van Hoesel
Chairman of the Supervisory Board at Startlife and Managing Director at Food Valley

Zeppelin University Germany Ljubica Nedelkoska	University of Nottingham United Kingdom John Holford	University of Economics Bratislava Slovakia Eva Sodomova
Department of Education (DPU), Aarhus University Denmark Ulrik Brandi	University of Luxembourg Luxembourg Samuel Greiff	China Center for Human Capital and Labour Market Research China Haizheng Li
Wageningen University Netherlands Thomas Lans	ifo Institute Germany Simon Wiederhold	Innovation & Growth Academy Netherlands Silvia Castellazzi
Leuphana University Lueneburg Germany Alexander Patt	Institute of Forecasting of the Slovak Academy of Sciences Slovakia Martina Lubyova	Ruprecht-Karls-University Heidelberg Germany consortium partner in 2012



These **28 reports** together are the publication suite presenting the results of the LLLightinEurope project, and can be downloaded at **www.lllightineurope.com**