

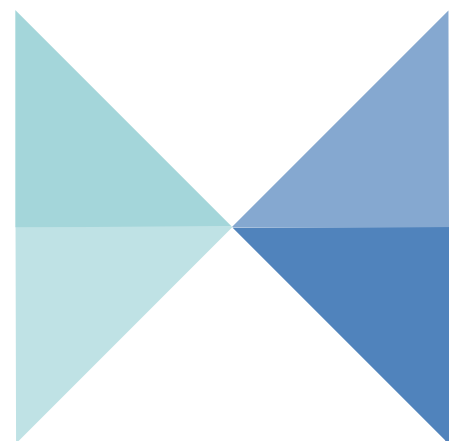


Job Complexity and Lifelong Learning

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JOB COMPLEXITY AND LIFELONG LEARNING

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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 is 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 (European Commission, 2001). Its 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 (European 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 and Boersch-Supan, 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; Mincer, 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, Manning and Salomons, 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 relevant economic literature regarding the topic 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; Baltes, 1993; Baltes, 1997; Baltes, Lindenberger and Staudinger, 2006; Baltes, Dittmann-Kohli and Dixon, 1984; Lindenberger, 2001), and in the field of economics, the literature on learning-by-doing (Arrow, 1962; Jovanovic et al., 1994; Jovanovic and Nyarko, 1995; Nedelkoska, Patt and Ederer, 2014). Although relevant, it is beyond the scope of this report to discuss the educational and sociological aspects of the relationship between job complexity and lifelong learning such as the types of adult education, the teaching approaches and their effectiveness, or the meaning of lifelong learning for societies and regions.

In what follows we will first introduce the foundations of lifelong learning in psychology and economics.

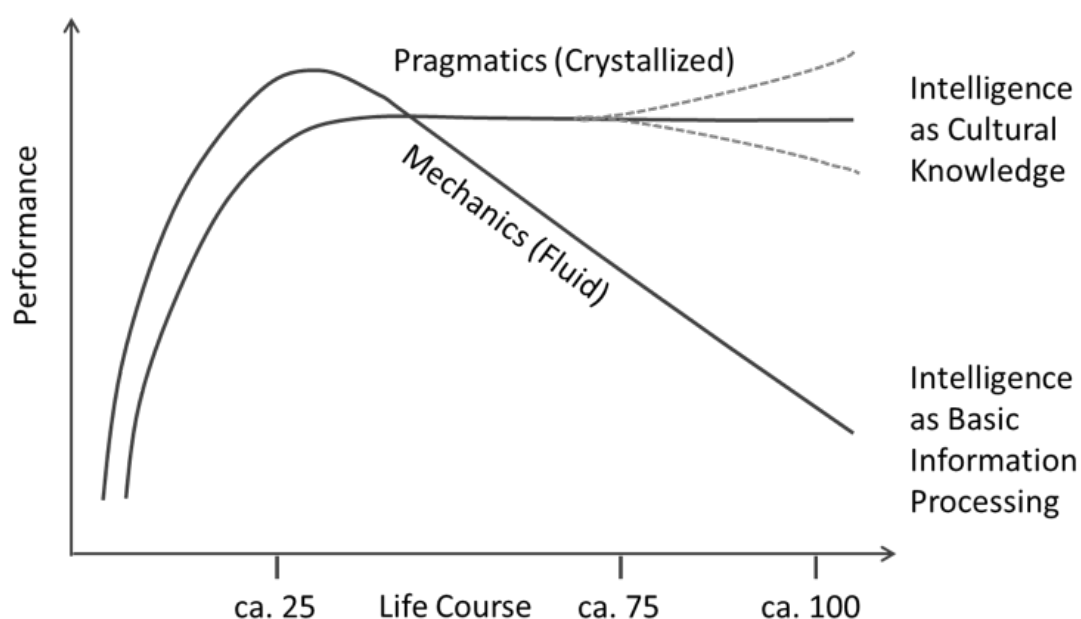
We will then discuss the concept of job complexity and its measurement, followed by a review of the major contributions in the literature on learning curves. Next, we will review the literature on the role of ability and in the choice of jobs with different level of complexity. We will then discuss the relationship between job complexity and job satisfaction. We will 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 embryogenesis, 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 et al. (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.

In the field of economics, 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, 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 their 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 Schönberg, 2010), industry (Neal, 1995; Parent, 2000) and occupation-specific (Kambourov and Manovskii, 2009). Gathmann and Schönberg (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, Patt and Ederer. (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, Driver and Streufert (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, Schmidt and Judiesch (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, Patt and Ederer (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; Hunter, 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" (National Center for O*NET Development, 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 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.

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-Off bearing
7 Serving	7 Handling	
8 Taking instructions-Helping		

Source: Dictionary of Occupational Titles (1991)

In psychology, subjective measures of job complexity are called Incumbent Perceptions of Job Complexity (Gerhart, 1988; Sims, Szilagyi and Keller, 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, Patt and Ederer (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?

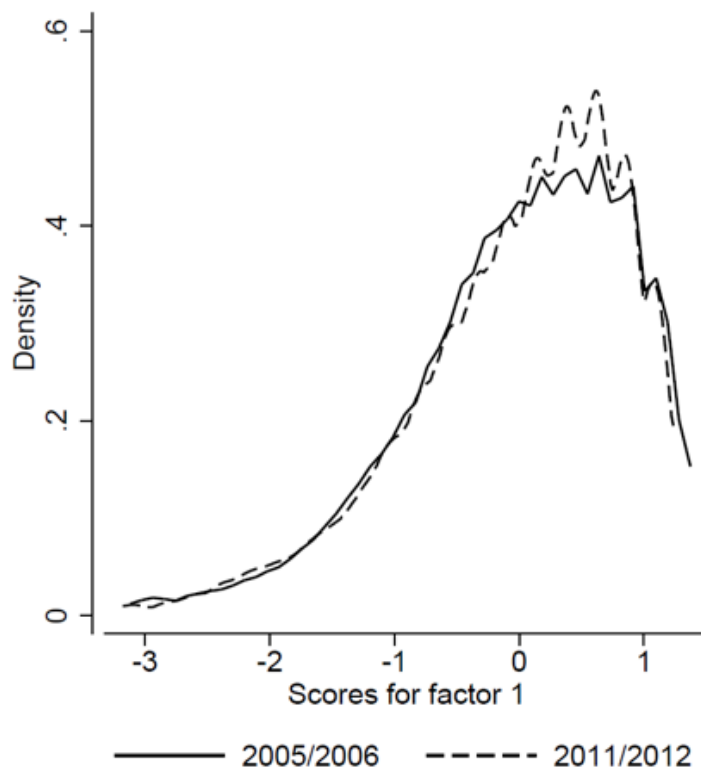
The authors then apply principal component analysis on these seven variables for each survey wave (2006 and 2012). In both waves, the authors find that the variables load on one single factor with eigenvalue larger than one, which they refer to as problem-solving or job complexity factor. Table 2 shows 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).

Table 2: Subjective Measure of Job Complexity

	2006	2012
information	0.57	0.571
New problems	0.645	0.619
difficult decisions alone	0.598	0.597
knowledge gaps	0.546	0.49
new tasks think	0.595	0.585
process improve	0.578	0.549
multitask	0.52	0.511

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

Figure 2: Distributions of the Job Complexity Factors



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

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.

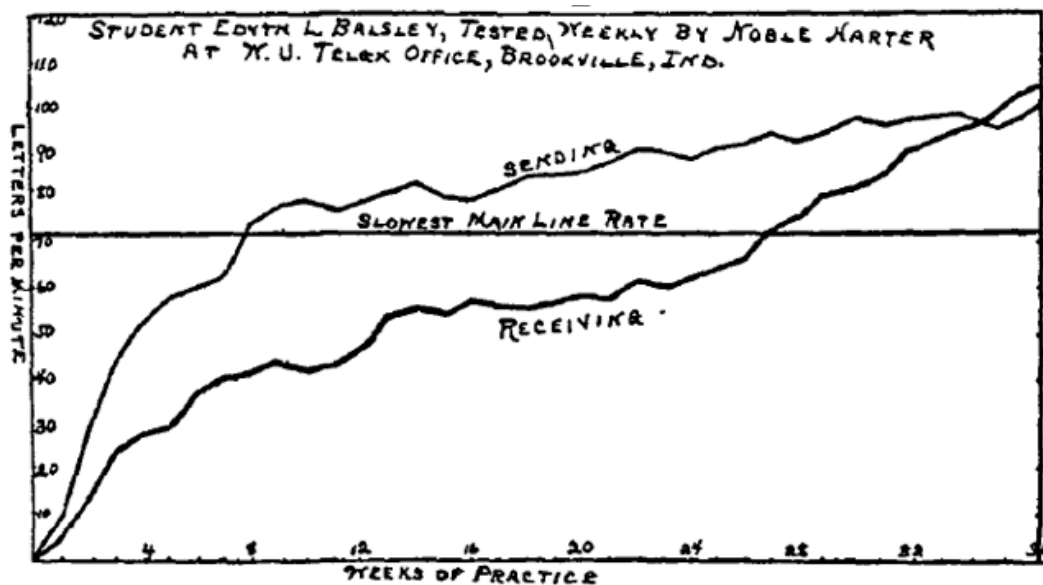
4. LEARNING CURVES

The earliest scientific documentation of individual learning curves probably dates back to the end of the 19th century¹ 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 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.

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



Source: Bryan and Harter (1897)

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.

¹ There exists earlier literature on practice curves as mentioned in [bryan1897studies].

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 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 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 Eppler, 1990 for a literature review).

4.2. Modeling the Learning Curve and Deriving Implications

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

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

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:

$$\xi_i(t) = \lambda_i - [\lambda_i - \xi_i(t-1)]e^{-r_i^t} \quad (2)$$

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 these authors 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 its 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 efficiency² and $E_\tau(q_\tau)$ is its expectation after τ production rounds; A is the maximum attainable q .³ x_τ is the posterior variance over the mean of the best (ideal) decision given information from the first τ production rounds and σ_w^2 .

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)

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 and 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:

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

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 (4), 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.

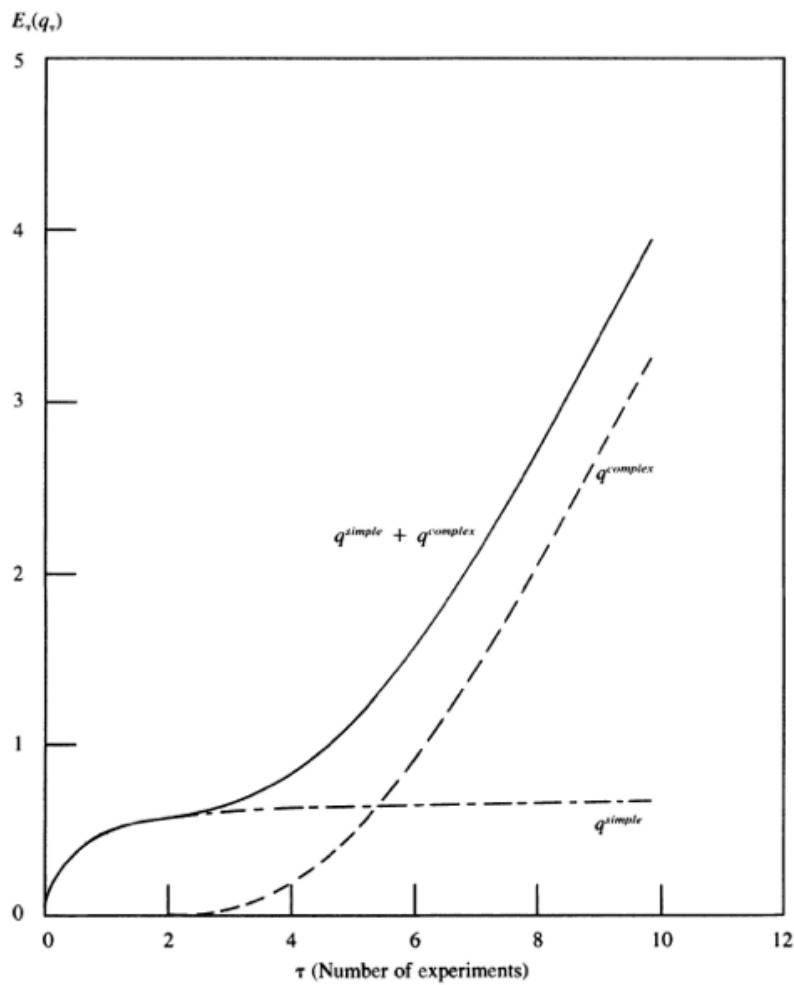
Figure 4 demonstrates the learning curves in equations (3) (q^{simple}), (4) (q^{complex}) and (6) ($q^{\text{simple}} + q^{\text{complex}}$).⁴

Moreover, the authors show that the variance of efficiencies among the decision-makers can increase by a lot for intermediate values of τ 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.

⁴The following assumptions and settings hold: the prior beliefs about the means of the unknown parameters $(\theta_1, \dots, \theta_N)$ are identical and mutually independent, with variance $\sigma_w^2 = 0.6$. The noise of the signals w_1, \dots, w_N are identically and independently distributed with $\sigma_w^2 = 0.3$; $N = 50, A_1 = 1, A_2 = 10^8$.

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

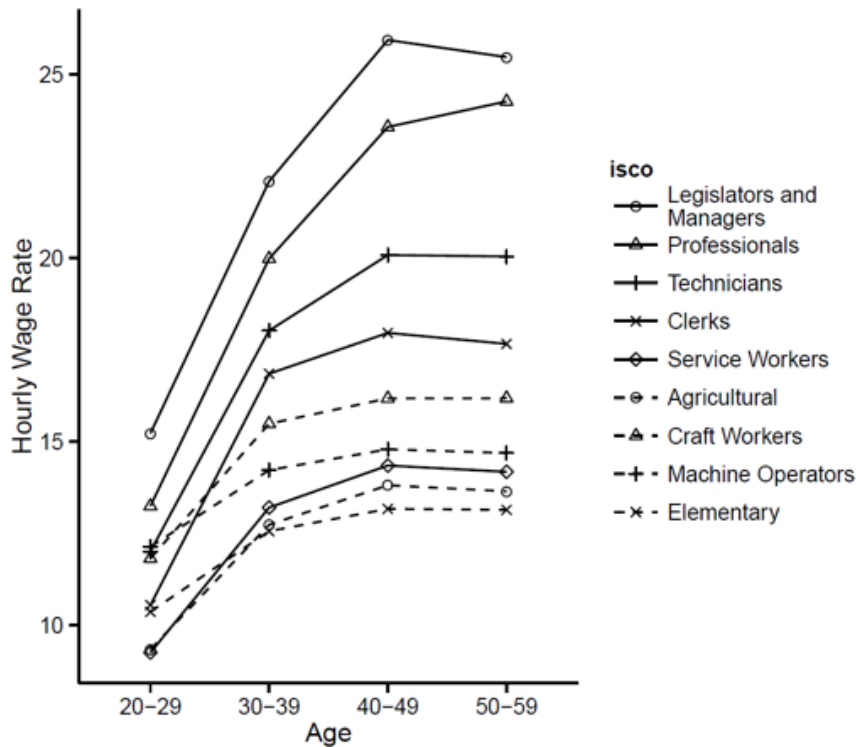
Figure 4: Learning curve of a simple, complex, and combined task



Source: Jovanovic and Nyarko (1995)

Another result in their model is that cumulative productivity growth is higher in more complex jobs. At the individual level, Nedelkoska, Patt and Ederer (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%.

Figure 5: Wage growth profiles for jobs with different complexity



Source: Nedelkoska, Patt and Ederer (2014)

Nedelkoska, Patt and Ederer (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, Patt and Ederer (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 , $q(x,z)$.

$$W(t, x) = p(x)q(x, z(t)) \quad (7)$$

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:

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

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 substituting the limiting value of $z(t)$ into equation 8 and rearranging, we obtain:

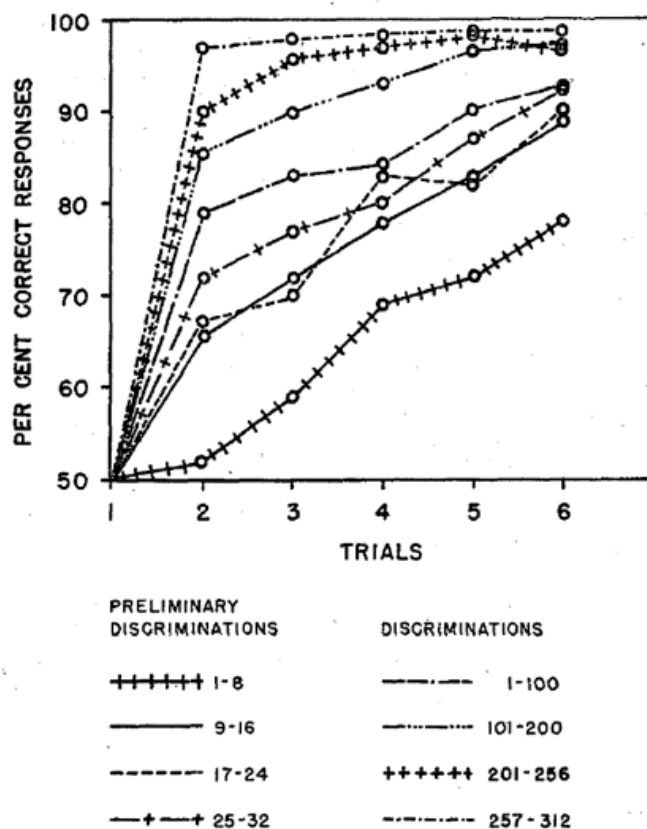
$$\frac{\dot{z}}{z}(t) = \alpha[z^* - z(t)] \quad (9)$$

Where z^* is the asymptotic level of skills for each job with complexity x . z^* is a linear increasing function of x , meaning that workers in more complex jobs can reach higher skill levels. 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 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 described this as a process in which animals and humans transition from learning by trial and error to learning by hypothesis testing. He referred 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 explained this shape as resulting from a trial and error approach. This is interesting in the light of the work by Jovanovic 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 objectively not complex, what is common with the learning of complex tasks is that the dynamics of learning are driven by a trial and error process. 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).

Figure 6: Learning Curves of Successive Tasks with Transferable Knowledge



Source: Harlow (1949)

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, Lawn and Bartholomew (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, 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 AND JOB COMPLEXITY

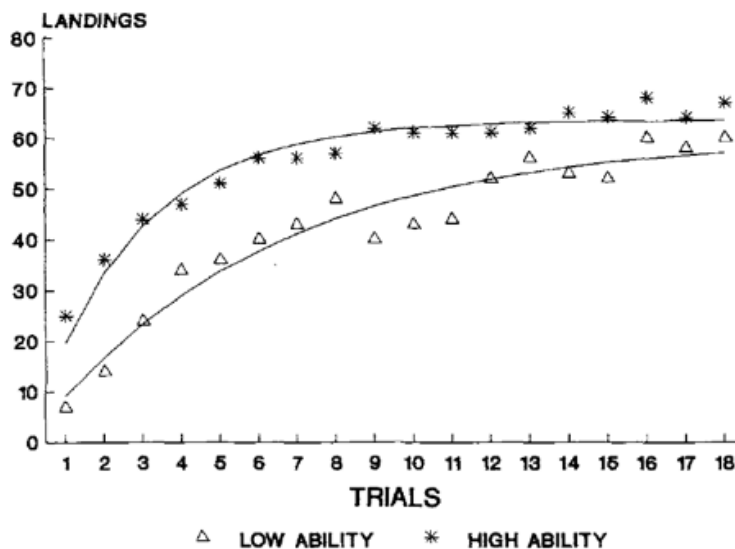
The way people are distributed across jobs is far from random. While it is true that the structure of jobs in the economy is continuously changing and hence there is a great deal of constraints on the available jobs from which individuals can choose, it is also known that people select their professions and jobs based on characteristics such as gender (Lent, Lopez and Bieschke, 1991), culture (Fouad and Byars-Winston, 2005) and risk attitudes (Bonin, Dohmen, Falk, Huffman and Sunde, 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, Johnson and Francis (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 and 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 initial 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.

Figure 7: Ability and Task Performance




Source: Eyring, Johnson and Francis (1993)

Wilk, Desmarais and Sackett (1995) and Wilk and Sackett (1996) hypothesize that higher ability individuals tend to choose more complex jobs. Wilk and Sackett (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, Bono and Locke (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, Bouchard, Segal and Abraham (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, Locke, Durham and Kluger (1998) and Judge, Bono and Locke (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, Bono and Locke (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, Nahrgang and Morgeson (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 and Sackett (1995), and Wilk, Desmarais, and Sackett (1996) find that higher ability individuals are more likely to choose more complex jobs. Judge, Bono and Locke (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, Bosma, Willems and Van Boxtel (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 on the labor market is very common too (Quintini, 2011; Nedelkoska, Neffke and Wiederhold, 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 relevant 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 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 an opportunity cost to investing in skill development, 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. From the more recent economic perspective, mainly developed by Flávio Cunha and James J. Heckman, very early childhood investments in skills have very high subsequent economic returns, while these returns to skill investments diminish very quickly even during the phase of childhood.

However, this is far from saying that it is optimal to stop learning at a 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 high 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 than 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, Flávio 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, and in particular for disadvantaged children. 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, economists know little about the nature of knowledge transferability.



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.

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9. 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
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EU Contribution	€ 2,695,000
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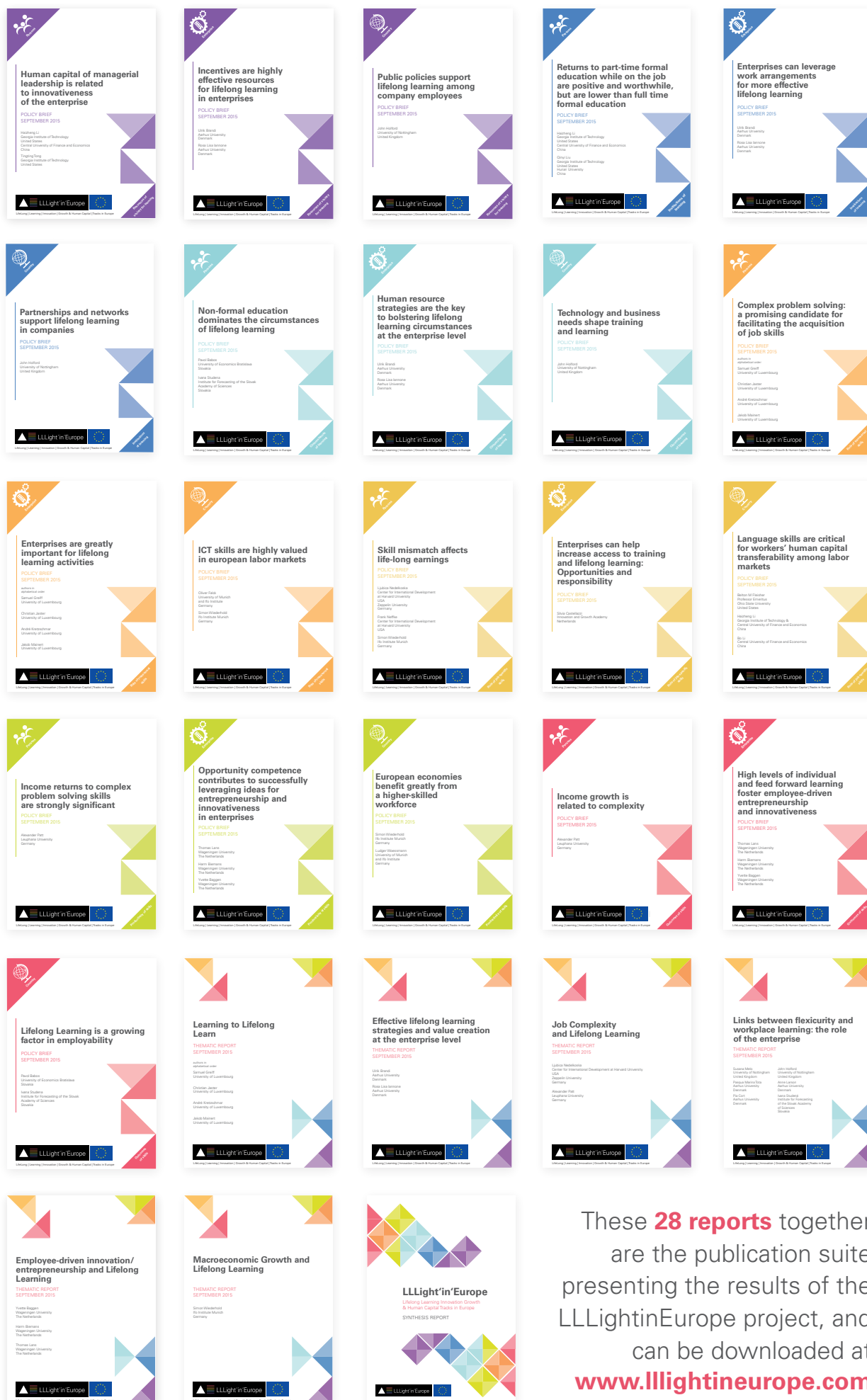


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