

Skill Mismatch and Skill Transferability: Review of Concepts and Measurements

Ljubica Nedelkoska and Frank Neffke

Papers in Evolutionary Economic Geography

19.21



Utrecht University

Human Geography and Planning

Skill Mismatch and Skill Transferability: Review of Concepts and Measurements

Ljubica Nedelkoska and Frank Neffke

Abstract

We survey the literature on skills, skill mismatch, skill transferability and related concepts in labor economics, evolutionary economics, management, and economic geography. Until recently, labor economics commonly equated skills with individuals' education and qualifications, while evolutionary economics and management focused on the tacit nature of skills and how they relate to firm-level organizational routines. Over the last two decades, the thinking about and measurement of these concepts evolved and somewhat converged in these fields. More direct measurements of skills (test-based, self-reported, skills implied by job tasks or by the nature of people's occupational changes) replaced old ones, and skill similarities, complementarities, and mismatch are now measured using big data and large-scale administrative records data. We identify existing research gaps that future research could address.

Keywords: skills, skill mismatch, skill transferability, skill relatedness

This working paper will appear as a chapter in the edited volume: "Handbook of Research Methods and Applications in Industrial Dynamics and Evolutionary Economics"

INTRODUCTION

The aim of this chapter is to review the literature on skill mismatch and skill transferability in evolutionary economics, management and labor economics. We show how the three research areas are converging in their notion of skills, from viewing them as a solely individual or as solely firm-level phenomenon, to embracing the importance of team-level human capital and workers' skill-complementarities. We describe an exciting recent development across fields, away from equalizing skills with years of education and towards acknowledging their multifaceted nature. We also discuss the areas where future research could benefit from further cross-fertilization of these research disciplines.

Skills can be thought of as the part of human capital that is not innate, but that is acquired through education, training and practice. Skills are related to job tasks - it takes skills to perform certain job tasks. However, skills are typically more general than tasks: math skills allow a person to perform a range of computational and analytical tasks, and medical skills can be applied in numerous job tasks related to our health. In that sense, skills are often *transferable*, allowing a worker to perform tasks across different jobs, either because the same kinds of tasks occur in different jobs or because a set of skills allows performing a variety of tasks. Skill *mismatch* occurs when the skill endowments of individuals differ from the skill requirements at their jobs.

Skill mismatch and skill transferability are intrinsically related. When two jobs employ similar skill portfolios, the skill transferability between them is high, and the skill mismatch is low. However, skill mismatch often emphasizes an asymmetry in the transferability of skills, stressing that skills can be too high (i.e., workers can be over-skilled), too low (i.e., workers can be under-skilled), or too different (i.e., workers possess skills that are unrelated to a prospective job).

Skill mismatch matters because it is costly. If workers lack some required skills, this reduces their productivity. In contrast, if workers have skills that they do not use at the job, they may forgo pay for those specific skills. These insights are not new but have been discussed in various literature using a variety of different terms, such as skill shortages, skill redundancies, skill obsolescence, under-skilling, over-skilling, undereducation and overeducation, to name a few. Skill mismatch can have different causes. Some of these causes are transient, such as search and matching frictions, but others, like changes in technologies or in the internal division of labor, will be structural.

In the remainder of this chapter we first review the literature on skills, skill mismatch and skill transferability. Next, we turn our attention to how skill mismatch and skill transferability have been quantified in different fields. We conclude by discussing recent progress in our understanding of skills and the areas where we see scope for cross-fertilization between disciplines.

THE CONCEPT OF SKILLS IN LABOR ECONOMICS, EVOLUTIONARY ECONOMICS AND MANAGEMENT

Several concepts in labor economics, evolutionary economics, management and organization science are closely related or synonymous to the concept of skills. In labor economics, the most widely used concept is human capital. One can think of human capital as the stock of skills in a labor force (Goldin, 2016). More

specifically, human capital consists in the quality of the labor force: the health, knowledge, skills and abilities of people that allow firms to produce goods and services. Human capital theory offers a way to rigorously assess the costs of investments in people’s health, formal education and on-the-job training against the expected increase in productivity of their labor (Schultz, 1961; Becker, 1962; Becker, 2009). This line of research has led to a formalization of how years of schooling and work experience increase our level of human capital, as well as how human capital translates into higher output, i.e., higher earnings (Griliches, 1977).¹ The model of earnings and human capital that tends to yield the best empirical fit implies that on-the-job learning increases a worker’s human capital, but at a decreasing rate. Therefore, work experience typically enters the model as a polynomial of degree two (the squared term in the standard Mincer equation).

Unlike in labor economics, in strategic management and evolutionary economics, authors are often less interested in the relation between individual skills and earnings, but in the peculiar way in which skills are acquired. A worker cannot *buy* ‘ready-to-use’ skills on the market. Instead, skills must be acquired through a process of learning that is often time-intensive and interactive. Evolutionary economists and scholars of strategic management therefore often stress the *tacit* nature of skills.

The notion of tacit knowledge was put forward by Polanyi (1958), who argues that objective knowledge, i.e., knowledge that is independent from our personal experiences and judgement and which can be fully explained in terms of precise rules, is rare. Skills are in Polanyi’s parlance guided by an awareness that is directed away from proximate actions toward the intended outcome of these actions. A professional swimmer, for example, directs her awareness from the motoric and respiratory details of swimming to the best strategy to overtake her opponent. The intricate details of this skilled action come about almost with no conscious effort to her. Following this reasoning, Nelson and Winter (1982)² argue that in truly skillful behavior, choices are automatic. Their example is one of an experienced car driver. At any moment, the driver makes choices about the direction and the speed of the car, but does so without attention to or awareness of the actual skill of driving. Another familiar example is the way people use language skills. In colloquial conversations, we express ourselves effortlessly, although each word and sentence require a

¹ Griliches (1977) models the relationship between earnings and human capital:

$$Y = p_h H e^u$$

where Y is wages, p_h is the price of unit of human capital H and u is a random disturbance term. The human capital production function, on the other hand, translates inputs such as years of schooling and of on-the-job training into an increased quality of labor. These inputs are assumed to enter the function multiplicatively, or in exponentiated form:

$$H_i = e^{S_i + x_i + x_i^2} e^{v_i}$$

If we use this expression for H , substitute it into the first equation and then take taking logs, we obtain the standard Mincer (1974) earnings equation:

$$\ln Y_i = \alpha + \rho S_i + \beta_1 x_i + \beta_2 x_i^2 + u_i + v_i,$$

where ρ is the rate of return to schooling and β is the return to work experience.

² In their book *An evolutionary theory of economic change*, Nelson and Winter (1982) describe skills as programs: skills represent a smooth sequence of behavior that functions as an effective unit (p. 74) of coordinated sequential behavior (p. 82). In this sense, skills bare some similarity to computer programs. First, computer programs like skills often function as units with a beginning and an end. Second, the basic organizational scheme is serial. Third, they are executed automatically, meaning that once mastered, execution does not require conscious efforts or decisions.

series of choices and muscular movements. These choices and movements seem automated, because our attention focuses away from the individual words to the meaning of the sentence that we are constructing or even to the argument that we are making. As we perfect the art of a skill, this knowledge becomes more and more tacit. Consequently, we often, if at all, understand the causalities on which our skills rely, which explains why it is so difficult to articulate how one achieves skillful behavior. The human capital production function conveniently masks this fact that the mastery of many skills from sports, music, and arts to science and other human endeavors, requires thousands of hours of practice and often interaction with experienced role models (Ericsson and Pool, 2016).

The tacit dimension of skills has profound implications for the way skills are acquired. The typical way to absorb tacit knowledge is through observing and trying to replicate the actions of a skilled role model. Such master-apprenticeship relations are typical for crafts occupations. For other tasks, knowledge tends to be more codified. Learning a programming language requires only a limited initial master-apprentice type of training, while most of the learning happens through reading help files, online discussions on specific problems and techniques. Starting in 2022, learning of programming languages is becoming increasingly assisted by Generative AI chatbots.

However, it is important to note that even skills that at a first glance seem to rely exclusively on codified knowledge typically have a substantial tacit component. Both Polanyi and Nelson and Winter, for instance, discuss how expert mathematicians rely on the tacit application of theorems when solving mathematical problems. In fact, when problems are complex, in the sense that the number of contingencies encountered when solving them are large, even extensive episodes of formal education in which the theoretical basis of the subject matter is studied must be complemented by equally lengthy episodes of learning-by-doing.³ This explains why high-level technological endeavors, such as designing nuclear weapons (MacKenzie and Spinardi, 1995) or spacecrafts (Collins and Pinch, 2014) are characterized by long apprenticeship-like learning periods and the tacit application of judgment. This explains why acquiring new skills is often hard outside the learning-by-doing environments that jobs offer.

Tacitness is not only a feature of individual's skills, but it also characterizes the collaborative work of groups. This is another important distinction between the notions of skills in labor economics which are almost always observed as an individual phenomenon, and that in evolutionary economics and management. For instance, Nelson and Winter's (1982) discussion of skills serves primarily as a metaphor that sets the stage for the notion of organizational routines, which they present as "firm-level skills". Accordingly, organizational routines are learned, highly patterned, repetitious and partly tacit (Winter, 2003). The concept of organizational routines as firm-level skills is furthermore closely related to the concept of (core) competencies of Prahalad and Hamel (1990), which they define as 'the collective learning

³ In several related articles (Jovanovic and Nyarko, 1994a; 1994b; 1995a; 1995b; 1997) Jovanovic and Nyarko analyze the relationships between learning-by-doing and productivity, learning-by-doing and promotions and learning-by-doing and the cost of switching technologies. Learning is modeled as a Bayesian process. On the job, much of the learning happens in relation to technology. Incremental learning results in concave learning curves (decreasing returns to learning) when the technology is simple to learn, and in learning curves with areas of exponential growth when learning happens in interaction with complex technologies.

in the organization, especially how to coordinate diverse production skills and integrate multiple streams of technologies' (p. 81).

It is not only skills that must be learned; the act of learning new skills is as well a skill that individuals and firms need to acquire. This notion lies at the heart of the concept of dynamic capabilities (Teece and Pisano, 1994; Teece et al., 1997), i.e., higher-level organizational routines that determine the rate of change of ordinary ones (Winter, 2003). Investing in dynamic capabilities can serve as a partial hedge against the obsolescence of existing capability (Winter, 2003). It can therefore give firms sustainable advantage over other firms. However, such investments cannot shield firms indefinitely from being outcompeted by imitators or competitors that serendipitously manage to increase their competitiveness without making costly investments in dynamic capabilities. Understanding the acquisition of skills at the individual and at the group level therefore is an important ingredient in understanding how innovation comes about – a topic of central interest in evolutionary economics – as well as how firms gain and maintain competitive advantage, which is a core topic in strategic management.

The link between individuals and organizations is, however, not just metaphorical. This can be seen in, for instance, the work by Nelson and Phelps (1962) at the intersection of labor economics and evolutionary economics. They use the concept of human capital in the fashion of labor economics, i.e., they focus on individual-level skills, but their research question anticipates a core concern in modern-day evolutionary economics: how does innovation diffuse? They observe that individual skills are key to what we may now call dynamic capabilities: better-educated workers help firms adopt technologies, because such workers are better at understanding and using new information.

In line with this, a growing number of scholars has started moving beyond the dichotomy between individual-level skills and firm-level routines. For instance, Kogut and Zander (1992) claim that '[organizational] capabilities are a composite of individual and social knowledge' (p. 396), by which they mean that the competencies of a firm rely on both the skills of individual workers and on the social routines that allow teams to tap into and coordinate these skills. For instance, firms not only require workers with the relevant know-how to carry out specific tasks, but they also need to be able to locate where this know-how can be found within their workforces. To be able to function, firms need to develop organizing principles that build on a shared language that helps codify how personal knowledge can be used and coordinated to achieve common goals. The interrelated nature of individual skills and firm level competences has spurred interest in what Chillemi and Gui (1997) call team human capital. Team-level human capital implies that skills of coworkers matter. At a basic level, coworkers create spillovers by enhancing productivity of peers (Arcidiacono et al., 2017). However, the mutual reliance among coworkers goes beyond simple spillovers. For instance, Marx and Timmermans (2015, 2017) show that a significant share of job switchers in Denmark move to new firms in pairs or even larger teams. In the new firm, these teams earn a premium over workers who switch jobs alone. Similarly, Neffke (2019) quantifies coworker complementarities in Swedish firms and shows that such complementarities produce premiums that are of the same magnitude as the college wage premium and that explain large parts of the urban and large-plant premium. Team human capital is therewith an area where labor economics, management science and evolutionary economics converge.

THEORIES OF SKILL MISMATCH AND THE REPERCUSSIONS OF SKILL MISMATCH

Once acquired, workers need to find jobs where they can put their skills to use. Skill mismatch occurs when the skills of individuals are different from the skills required at the job.⁴ Skills can be too high, too low or too different from a job's skill requirements. Such mismatches can be costly. From the perspective of the worker, skill mismatch can result in lower earnings, lower job satisfaction and more job mobility. From the perspective of the firm and the economy as a whole, skill mismatch results in lower productivity.

The Cost of Skill Mismatch

Hypotheses about the cost of skill mismatch are often derived from one of four different theories: assignment models (Sattinger, 1975, 1993, 2012), search and matching theory (Mortensen and Pissarides, 1999; and Rogerson et al., 2005 provide reviews of the literature), job competition theory (Thurow, 1975) and human capital theory (Becker, 1962; Becker, 2009; Schultz, 1961).

In assignment models (Tinbergen, 1951; Roy, 1951; Sattinger, 1975, 1993), workers are allocated top-down according to their skills, with the most competent worker being assigned to the most complex job and the least competent worker to the simplest job. Under this theory, educational and skill mismatches can be explained by the differences between the complexity distribution of jobs and the skill distribution of workers. At the macro level, mismatch between these two distributions leads to earnings inequality. Oversupply of certain skills will drive down the earnings of workers with these skills. As the earnings between workers with different skills diverge, earnings inequality grows. The role of a central planner is to balance the supply of skills through general education and other means, acting as an equalizer of earnings (Goldin and Katz, 2009).⁵

In search and matching theory, skill mismatch can result even if the distribution of skills and the distribution of job complexity are perfectly aligned. Here, mismatch emerges from the fact that there is imperfect information about where skills can be found and who may be demanding them. Mismatch is costly for workers and for firms, but so is search. That is why search sometimes ends before the ideal match has been identified. Search frictions, while always present, are temporary in nature and can be reduced at the macro level through more effective job matching technologies.

In job competition theory, marginal productivity is not a feature of a worker, but of a job. Firms post jobs with certain characteristics and assign wages to these jobs. Since wages are assigned to jobs and not to employees, employers pay for the required level of skill and not for the employee's actual level of skill. A direct hypothesis of this theory is that firms will not be willing to adjust the wage to the worker's actual level of skill. In other words, the returns to a year of over-skilling will be zero.

⁴ A related concept is the one of skill obsolescence (De Grip and Van Loo, 2002; Allen and De Grip, 2007 and 2012), where the focus is on the shifts away from certain types of skills as a result of technological, organizational and other changes.

⁵

In contrast to job competition theory, human capital theory posits that marginal productivity is a feature of a worker and not a job. Workers with skills in excess of what a job requires will still be more productive in this job than workers with the exact right amount of skill. Hence, there will be a positive return to each year of over-skilling and a penalty to each year of under-skilling. Moreover, these returns should be similar in magnitude to the return one gets for a year of required skills.

A stylized finding in the literature on educational mismatch is that overeducated workers earn somewhat more and undereducated workers earn somewhat less than workers with the right amount of education for a job (Borghans & de Grip, 2000; Hartog, 2000; Brynin and Longhi, 2009). Moreover, the return to a year of required education is higher than the return to a year in excess of this requirement. This observation rather supports the human capital theory than the job competition theory, given that the latter expects zero return to a year of excess education. Bauer (2002), for instance, tests the implications of the job competition and human capital theories on the returns to over and under-education and finds overwhelming support for human capital theory using data from Germany. He finds that the differences in the returns to overeducation, undereducation and adequate education are in fact driven by the lack of controls for unobserved worker characteristics in much of this literature. Once such unobserved heterogeneity is controlled for, the returns to a year of adequate education, a year of surplus education and a year of deficit education are about the same.

Causes of Skill Mismatch

Skill mismatch has frictional as well as structural causes. Even in the absence of skill mismatch at the macro-level, the time it takes for workers to find the right jobs, and for the employers to find the right workers ensures that a certain degree of mismatch will be present in an economy at all times (Mortensen and Pissarides, 1994; Petrongolo and Pissarides, 2001). Labor market frictions, such as geographic mismatch between the supply of and demand for skills, result in search costs associated with finding the right job given a worker's qualifications. Different from frictional causes, structural causes create a misalignment between the aggregate distribution of workers' skills and the aggregate distribution of job requirements in an economy (Restrepo, 2015). Such misalignment can stem from the supply side of skills – the provision of education, demographic characteristics, or from the demand-side – skill-biased technological change, or the outsourcing of certain industries.

On the supply side of skills, most literature has focused on institutions of general education. For instance, the debate about educational mismatch became prominent in the 1970s when Freeman (1975, 1976), among others, argued that there was an oversupply of college graduates on the U.S. labor market, and that this was likely to persist in the future. The oversupply would explain the significant decline in the college premium over high school education in this period.

Although the notion of an over-skilled workforce was soon after disputed (Smith and Welch 1978), Freeman's work illustrates well how an oversupply of skills can depress the returns to skills of highly educated workers. In their comprehensive review of the relationship between the supply of education and technology-driven demand for skills, Goldin and Katz (2009) show that acquiring a college degree played a major role in the creation of opportunities for economic mobility in the United States throughout the twentieth century. However, the actual return to a college degree has varied as a function of the supply

of college educated workers. The college premium⁶ tends to be high in periods when the supply of college degrees is low and low when the supply of college degrees is high. In other words, in periods of skill shortage, college graduates have earned extraordinarily high wages. The opposite occurred in periods when college graduates were in high supply.

On the demand side, the most important forces impacting the demand for skills over long periods of time are innovation and technological change. In one of the earliest studies on this topic, Griliches (1969) proposed that skills and capital are complements: improvements in physical capital often require a skilled workforce. Fast-forward to more recent work in evolutionary economics, Vona and Consoli (2014) propose a life-cycle perspective on the relationship between skills and technological change. At the start of a product's or a technology's life cycle, tasks are complex, ill-structured and tacit. This complexity requires creative and skilled individuals to discover the best way of doing things. As technology matures, people learn how to structure knowledge, divide labor and gradually codify and routinize the interaction with the new technology or the production of the new product. Improvements from learning reach a maximum eventually, and after that point, marginal gains from further specialization diminish, and tasks become sufficiently standardized to be performed by unskilled, but highly specialized workers. Moreover, technological change does not only affect the demand for a specific level of skills, but also for a specific content of skills. Especially when technological change is highly disruptive, workers often find their current skills becoming obsolete, or as Freeman and Perez (1988, p. 59) put it: '... as it crystallises, the new techno-economic paradigm involves [...] a new skill profile in the labour force, affecting both the quality and quantity of labour [...]'.

With some exceptions, as in the work by Vona and Consoli (2014) and Evangelista and Savona (2003), the early recognition of the impact of technology, and in particular of General-Purpose Technology (GPT) on skill requirements did not spur significant research into the topic of skills in evolutionary economics. Instead, the relation between skills and technology became widely studied in labor economics. The traditional way of studying the impact of technology on skills centered on the hypothesis of skill-biased technological change (SBTC, as reviewed in Katz and Autor 1999). Under the SBTC hypothesis, new technologies, and in particular computer capital, tend to complement skilled labor (Mincer, 1991; Bound and Johnson, 1992; Berman et al., 1994; Autor et al., 1998). That is, technologies increase the productivity of skilled labor, but not of unskilled labor. This feature of the relation between computer capital and skills was the main explanation for the observed growth in the demand for college graduates, but it failed to explain other labor market trends, such as the growth of the demand for low skilled and high skilled labor relative to middle skilled labor (job polarization).

Starting with the seminal work by Autor, Levy and Murnane (2003), the SBTC hypothesis was modified to reflect the relationship between computers and specific *task content* of jobs, as opposed to the skill level of workers. This change in approach highlighted that technology could complement one set of tasks, while substituting for another set of tasks. The distinction between tasks and skills becomes crucial (Acemoglu and Autor, 2011; Autor and Handel, 2013; Autor, 2013). Tasks are features of jobs and skills are characteristics of workers. Workers acquire skills which give them a comparative advantage in certain tasks. However, workers can move from one set of job tasks to another, meaning that they can change

⁶ i.e., the wage premium of college graduates over high school graduates.

their specialization if the price of certain tasks (effectively the pay they would receive for performing certain tasks), changes. This distinction between tasks and skills is in stark contrast with the previous popular approach of simply distinguishing between low and high skilled labor only. Among other things, this kind of technological change, dubbed task-biased technological change (TBTC), explained the phenomenon of job polarization observed in several developed economies in the 1990s and the early 2000s (Goos and Salomons, 2009; Autor, Katz and Kearney, 2008). The task-based approach initially distinguished among routine, non-routine and interactive job tasks, and between (routine and non-routine) manual and (routine and non-routine) cognitive tasks. Computer capital, according to the TBTC hypothesis, augments non-routine and interactive tasks, but substitutes for routine manual and routine cognitive tasks.

The task-based approach analyzes technological change at the level at which technologies operate – job tasks. Technologies augment or replace job tasks, not necessarily workers' skills. This is reflected in Acemoglu and Autor (2011), who adapt Dornbusch et al.'s (1977) canonical Ricardian model of trade to determine how ICTs substitute and complement different types of workers. Their model puts forward a distinction between skills and tasks. Tasks are units of work activity that produce outputs, and skills are workers' capabilities to perform these tasks. Workers can have one of three levels of skills: low, medium or high, and tasks come in three different types: manual, routine and abstract. All skill levels can be used to perform all tasks, but they have different comparative advantages: low skilled workers have a comparative advantage in manual tasks, middle skilled workers in routine tasks and high skilled workers in abstract tasks. Analogous to how different products get assigned to different countries according to countries' comparative advantage, tasks get assigned to workers depending on the comparative advantage their skill levels afford for different tasks. Computers enter this model through their effectiveness at carrying out routine tasks. Consequently, computers compete with middle skilled workers, who traditionally specialized in such tasks. As the price of routine tasks declines, the demand for their complements, the non-routine tasks, increases, driving up the demand for low skilled and high skilled labor. The model therefore helps us understand recent employment and wage dynamics in developed countries, such as falling real wages of less skilled workers and job "polarization" (Goos and Manning, 2007; Goos et al., 2009): the fact that employment in low and high wage jobs has grown, whereas employment in medium-wage jobs has declined.

Acemoglu and Autor (2011) made important assumptions in their model. These assumptions were challenged shortly after the publication of their work. As a stylized summary, under the SBTC hypothesis, computers are the major technological demand-side force; their (negative) impact is limited to routine tasks; and routine tasks are the domain where medium skill workers have comparative advantage. All these assumptions are now being questioned.

Groundbreaking recent developments in artificial intelligence (AI) and mobile robotics (MR) are changing how economists think of the impact of technologies on labor markets. In particular, Brynjolfsson and McAfee (2014) and Frey and Osborne (2017) contend that AI and MR are able to substitute for non-routine tasks, both cognitive and manual. Consequently, a long list of ubiquitous tasks until recently considered to be hard to automate – driving, legal and financial analysis, medical diagnosis, simultaneous translation, speech recognition etc. – are now deemed well within the reach of machines. Such powerful technologies

could have sweeping consequences: in the foreseeable future, close to one in two jobs in OECD countries could be either significantly reorganized or drastically downsized (Frey and Osborne, 2017; Nedelkoska and Quintini, 2018).

The proliferation of new and powerful GPTs spurred a renewed interest in the impact of technology on skills in evolutionary economics and innovation studies (Nedelkoska et al, 2018; Ciarli et al., 2021; Prytkova et al., 2024). Similarly, the green transition raised the question of mismatch between the current capabilities the demand for ‘green jobs’ and ‘green skills’ (Consoli et al., 2016; Mealy, 2018).

Another important factor in the demand for skills in an economy is trade or globalization. Complementing studies of the impact of technological change on skills, scholars have analyzed the impact of trade on job tasks. This led to the hypothesis that, currently, some of the same tasks that are at risk of automation are also at risk of being outsourced or offshored. However, the correlation between offshorable tasks and tasks at risk of automation is modest. According to Blinder (2006) and Blinder and Krueger (2013), offshorable tasks are those that do not require personal contact and that can be delivered electronically without loss in quality.

Grossman and Rossi-Hansberg (2008) formalize such thinking in a model where countries trade job tasks instead of final goods. They then analyze how the falling cost of offshoring of tradeable tasks affects the factor prices in the country of origin. They find that, when the price of a tradeable task declines, low skilled workers in the country of origin experience a positive productivity effect. This productivity boost comes from the fact that (cheaper) foreign labor is taking over part of their tasks, making them overall more productive in the remaining tasks. In this sense, offshoring has the same effect on low skilled workers as low-skill-augmenting technological change. While this is an insightful and optimistic analytical observation, it is at odds with the public perception of international outsourcing and offshoring, where the phenomenon is perceived as a process that results in net job loss in the country of origin. Subsequent work (Kohler and Wrona, 2011) is more aligned with this perception and shows that, although offshoring can result in both job destruction and job creation in the country of origin, it is easy to find conditions that would lead to net job destruction.

Empirically, the differential impact of trade across occupations has been documented in Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2017) among others. Moreover, trade can have exceptionally large net effects on employment, shifting the demand for some skills from developed to developing economies. In the U.S., for instance, Autor, Dorn and Hanson (2013) estimate that a quarter of the decline in manufacturing employment can be associated with the trade with China.

MEASURING SKILLS, SKILL MISMATCH AND SKILL TRANSFERABILITY

When measuring skills, for a long time, scholars have relied on measures of years of education or educational attainment to assess the skills acquired through general education, and of years of labor market experience⁷ to measure skills acquired through work experience. There are however a number of limitations to this approach: educational attainment is often poorly measured (Krueger and Lindahl 2001),

⁷ Job experience, firm-specific experience, occupation-specific experience and industry-specific experience have all been used to further detail the on-the-job learning of individuals.

education has different quality in different places and schools (Hanushek and Woessmann 2008; Hanushek et al. 2015), and the number of years of education tells us nothing about which skills were acquired (Ederer et al. 2015). The same holds for the measurement of work-related skills through years of work experience. In the last two decades, coinciding with an increase in the popularity of the task-based approach and the availability of direct test-scores for skills, new approaches that measure skills more directly have grown popular.

Data Sources

Traditionally, research on skills has relied on labor force surveys, cohort studies, surveys of income dynamics and the like. More recently, however, three types of data have gained in popularity. The first type describes the skills that workers apply at their jobs and the job tasks they perform. These data typically derive from relatively large surveys of workers or of occupational specialists, where skills and job tasks are self-reported or reported by observers of the occupation. Among the most widely used are the Dictionary of Occupational Titles (DOT) and its successor O*NET, for the United States.

The DOT files describe the job tasks of narrowly defined occupations in the U.S. since 1939. Over time, the DOT and, later, O*NET, added various classes of worker characteristics (skills, abilities, knowledge, interests, education, and training) and various classes of job characteristics (work activities, salaries, growth projections and other labor market information) (National Center for O*NET Development, 2019).

Whereas the DOT and O*NET are occupation-level datasets, other datasets that provide information on job tasks and skills are based on surveys of workers and are recorded at the individual level. Examples are the German BIBB/BAuA and BIBB/IAB Surveys of the Working Population on Qualification and Working Conditions in Germany (BIBB/BAuA and BIBB/IAB Surveys, Rohrbach 2009) which have been collected since 1979, and the U.K. Skills and Employment Surveys (Felstead et al., 2013) collected since 1986. More recently, various surveys have included small modules on workers' job tasks and skills, such as the OECD's PIAAC (OECD 2013), the skill tests and surveys of the Llight'in'europa project (Ederer, 2015) and the World Bank's STEP surveys (Pierre et al., 2014). These surveys have the advantage that they cover a wide range of countries, but their samples are typically smaller than those of the national skills surveys and their modules on job tasks and skills are somewhat more limited.

A second type of data are administrative data, derived from social security or tax records in countries such as Germany and Sweden. Although the administrative data lack detailed information on skills, they provide a complete picture of an economy's labor force and the full work history of employees. Moreover, these administrative data can be merged with task data at the level of occupations.

A third type of dataset offers measures of people's skills by administering direct skill tests. Examples are the International Adult Literacy Survey (IALS), the Adult Literacy and Lifeskills (ALL) Survey, and the Program for the International Assessment of Adult Competencies (PIAAC), all of which administered tests of numeracy and literacy in multiple countries. In addition to numeracy and literacy, PIAAC also tests ICT and problem-solving skills in technology-rich environments among adults. The Llight'in'europa project administered tests of complex problem-solving skills (Wüstenberg et al., 2012) for over 1100 employees in several countries.

Technological advances such as machine learning and natural language processing made it possible to measure technology, innovation, job tasks and work content at a great level of detail, by using data input from a range of sources: job advertisement data from Burning Glass Technologies, Indeed, ZipRecruiter, UpWork, data from social media networks such as LinkedIn and Facebook, patent data, as well as data from historical dictionaries of occupational titles. Such databases are becoming more widely available and are providing exciting new opportunities to study the interplay of demand and supply for skills (Anderson, 2017; Atalay et al., 2020; Miller and Hughes, 2018; Turrell et al., 2018; Nedelkoska et al, 2021; Prytkova et al., 2024; Autor et al, 2024; Javadian et al., 2024).

Measuring Skill Mismatch

Different data sources lend themselves to different ways of measuring skill mismatch. In general, there are four commonly used approaches to the measurement of skill mismatch: self-reported mismatch, job-analyses, realized matches and direct measurements of skills. The literature typically distinguishes between skill mismatch and educational mismatch, and all four approaches to their measurement have been in use.

In the self-reported approach, the level of attained and the level of appropriate and/or required education is determined by surveying workers. Workers are typically asked about the educational requirements for their job or what is the ideal, appropriate or necessary education to perform their job. Next, their attained level of education is compared to the required or the appropriate one.

Although self-assessments can be quite informative, they suffer from a few drawbacks. For one, the measured mismatch depends on how survey question are framed (Green, McIntosh and Vignoles 1999; Leuven and Oosterbeek 2011). In this respect, Allen and van der Velden (2001) argue that it is better to ask for the appropriate than for the required level of education, because the former is more likely to reflect actual job content while the latter is more likely to reflect formal job requirements. Moreover, according to Hartog (2000), respondents may be motivated to overstate the education needed to perform their job in order to raise their status. Such overstatements could correlate with determinants of wages, such as gender and educational level, seriously biasing estimates of the impact of educational mismatch on wages. Perry et al. (2016) also advise strongly against the use of self-reported skill mismatch measures in the PIAAC data and propose that researchers use measured skills whenever available.

In the job analysis or expert assessment approach, skill and educational requirements are reported by job analysts instead of by employees. Job analysts visit work sites and compare across many jobs with similar task contents. As a result, in datasets based on expert opinions, such as the DOT and O*NET, there is no information about an individual job, but only about an average over several jobs that can be grouped into a single occupation. As a result, the level of required schooling or skills appears fixed within an occupation instead of, more realistically, occupations displaying a distribution of skills and education requirements.

Measures of skill mismatch can be obtained by merging data from expert assessments to individual-level survey data or to administrative records. Van der Velden and Van Smoorenburg (1997) compare self-reported and expert-based measures of educational requirements and conclude that the job-analyst method systematically overestimates the level of overeducation, while the self-reported approach does not.

The third approach - realized matches - uses information from occupation-specific distributions of education and/or skills. It measures required education as the mean or the mode of the distribution of realized matches. Mismatches are then measured as deviations from this mean or mode. Oftentimes, scholars following this approach choose to report these deviations in standard deviations instead of years of schooling.⁸ Guvenen et al. (2020) develop a multidimensional measure of skill mismatch by combining direct measurements of people's verbal, math and social skills as captured in the aptitude test (ASVAB) scores of the NLSY79 survey, and comparing these with the skill requirements of occupations as described by occupational experts in O*NET.

Each of these approaches has its own pros and cons and the above review reveals the variability of measures and raises questions about their comparability, sensitivity to different specifications, and validity. Therefore, a number of studies (Krahn and Lowe, 1998; Quintini, 2011; Allen et al., 2013; Perry et al., 2016) have combined direct tests of skills (e.g., PIAAC's numeracy and literacy) with self-reported skill use, or with the realized matches approach to measure skill mismatch. As illustrated in Perry et al. (2016) and Quintini (2012), even small changes in specifications and cutoffs can result in large differences in whether a person is categorized as well-matched or mismatched. Even when using only a single approach, there are a number of choices that have to be made which can result in significant differences in the measured mismatch.⁹ There are no studies that compare all major approaches. Moreover, validity is hard to assess – it is not clear what a good test of validity would look like. For instance, Van der Velden and van Smoorenburg (1997) test the validity of the self-reported and the job analysis approach by comparing the two measures to each other and by testing their predictive power with regards to wages. Perry et al. (2016) also compare the validity of PIAAC-based mismatch measures by estimating how well they predict wages.

MEASURING SKILL TRANSFERABILITY

Scholars in labor economics, management and evolutionary economic geography have all independently developed measures that capture the concept of skill transferability. While similar in nature to the concept of skill mismatch, skill transferability focuses on the skill requirements that two jobs have in common, whereas skill mismatch focuses on the differences. In management, such measures have been used as an explanation for diversification paths of firms (Farjoun, 1994; Chang, 1996; Neffke and Henning, 2013). In economic geography, they have been used to answer questions about regional diversification (Neffke et al., 2018) and regional resilience (Diodato and Weterings, 2014). In labor economics, scholars have used them to study the specificity of human capital (Poletaev and Robinson, 2008; Gathmann and Schönberg,

⁸ Hartog (2000) criticizes this choice. When mismatch is defined as a one standard deviation from the mean, the findings indicate that about 60% of all cases are well matched, while a symmetric share of cases is under and over-educated. Such result can easily be an artifact of the choice of one standard deviation as a cutoff point for classifying the mismatched.

⁹ For instance, it is not always straightforward what counts towards schooling. Duncan and Hoffman (1981) ask about formal education only, while Galasi (2008) explicitly asks about formal and vocational schooling. Other authors (Hartog and Oosterbeek, 1988; Alba-Ramirez, 1993) are not specific enough about the type of education they are referring to. Among the surveys of self-reported skills (e.g., O*NET, PIAAC's background questionnaire, BIBB/BAuA and BIBB/IAB surveys), there is also large variability in what is considered as skills.

2010). Across these three disciplines, there are three commonly used approaches to its measurement: co-occurrences, labor flows, and job tasks.

Among the earliest measures of skill transferability are those that use the similarity in occupational structure between industries to estimate the skill similarity across industries, and those that use the similarity of industry structure between firms to estimate the coherence of firms' product portfolio. Many of these studies are motivated by the resource-based view of the firm (Penrose, 1959; Wernerfelt, 1984; Peteraf, 1993; Robins and Wiersema, 1995). Farjoun (1994) for instance, takes the Euclidean distance between the occupational employment vectors of different industries to estimate if they use similar human capital inputs and uses this similarity to explain how firms diversify into new products. Teece et al. (1994), use the co-occurrence of industries within diversified corporations to estimate the relatedness of industries. This helps them demonstrate that firms' product portfolios are more coherent than previously thought.

Fueled by the availability of large administrative data, measures using labor flows between occupations or industries have also become increasingly popular. Among the earliest such measures is the one put forward by Shaw (1987). She estimates the skill distance (d) between any two occupations (i and j):

$$d^{ij} = 1 - \sum_k |P^{ik} - P^{jk}| - 2$$

where, $k \in \{J\}$ is a set of occupations; and P^{ik} (P^{jk}) are the probabilities of job change between occupation i (j) and occupations k . The skill distance between two occupations is small if P^{ik} and P^{jk} are very similar, i.e., when the employees in occupations i and j make similar choices when changing occupations. More recently, Neffke and Henning (2013) and Neffke, Otto and Weyh (2017) calculated industry skill relatedness using the labor flows across detailed industries in Sweden and Germany. They do so by comparing the observed labor flows to a random benchmark. The relatedness between two industries is higher for industry pairs with higher excess labor flows.

Finally, in labor economics a few studies have used the task content of jobs to create measures of skill transferability across occupations. Poletaev and Robinson (2008) use detailed job information from the DOT to study how similar occupations are. They first reduce the dimensionality of the data on job tasks to a few basic and, by construction, orthogonal, skills using factor analysis. Then they use the Euclidean distance between the occupational skill vectors as a measure of skill relatedness. A similar approach (though skipping the factor analysis) is adopted by Gathmann and Schönberg (2010) using the BIBB/BAuA and BIBB/IAB Surveys for Germany.

Whereas mismatch metrics depict skills as being organized completely hierarchically, i.e., from low to high, skill transferability metrics take a fully horizontal approach to skills. Hence, they ignore the inherent asymmetry in the transferability of skills. In Poletaev and Robinson (2008) and Gathmann and Schönberg (2010), for instance, the skill transferability in a career move from a nurse to a physician is the same as the skill transferability when moving from a physician to a nurse. Intuitively, however, although a nurse and a physician may have largely overlapping skill sets, they perform their tasks at different levels of skills and qualifications. Neffke et al. (2024) put forward measures of skill mismatch that combine the strengths of

the symmetric skill transferability measures and those of the educational mismatch measures. They use the BIBB/BAuA and BIBB/IAB Surveys to derive occupation-specific skill mixes and use the average years of schooling and vocational training of workers in an occupation to obtain a proxy for the complexity of the skills needed in that occupation. Combining both types of information, they measure skill transferability in terms of skill redundancies and skill shortages involved in occupational switches to reveal the asymmetry in skill transferability. They show that, when switching occupations, most people incur both, skill shortages and skill redundancies. In a sample of displaced workers, who lose their jobs during plant closures and mass layoffs, skill redundancies are associated with long-lived and large earnings losses.

CONCLUSION AND POLICY RELEVANCE

We reviewed the literature on skills, skills mismatch and skill transferability in evolutionary economics, labor economics and management. Traditionally, labor economics has viewed skills through the lenses of education and qualifications, while evolutionary economics and management mainly focused on the tacit nature of skills and how they relate to firm-level organizational routines. Thinking and measurement of skills in all three disciplines have evolved and to some extent converged in the last two decades.

For one, the measurement of skills in labor economics, evolutionary economics and management has become more sophisticated. Many economists transitioned from measuring skills in terms of years of education to measuring them in ways that capture skills more directly, using direct tests of skills, self-reported skills and job tasks, or skills and job tasks reported by occupational experts. In all three fields scholars have more recently been using rich administrative data sets and big data to infer skill similarities and complementarities from the job switching behavior of millions of workers. Moreover, scholars have transitioned from thinking of skills as solely an individual-level phenomenon or solely as firm-level routines, to how individual skills and firm level routines blend. This is best exemplified in the growing literature that focuses on team human capital and workers skill complementarities.

The new developments in skills research are particularly promising for evolutionary economics, with its emphasis on technological change. Technologies shape the demand for skills. At the same time, skills are a prerequisite for acquiring, diffusing and using technologies. Hence, skills foster the creation and the diffusion of innovation and technologies. As technologies change, they create mismatches between the supply of and the demand for skills. The resulting skill mismatches are typically structural in nature and can therefore stall firm productivity and devalue parts of our human capital. The degree to which such mismatches can be addressed depends on many factors, among which is the level of skill transferability from one job to another, and the re-trainability of workers.

Going forward, a promising avenue for research would combine the insights of evolutionary economists into the dynamics of technological change with a better understanding of skill mismatch and its implications. For instance, one could study how the evolution of a particular industry or a particular product mix translates into changes in the skill requirements in cities and countries. These changes may differ between early and late adopters of new products, as the level of skill routinization increases over the product life cycle. At the same time, new surveys of direct skill measures such as the PIAAC Survey of Adult Skills, hold great promise for research into skills, skill mismatch and skill transferability, in particular with the growth of their country coverage. These surveys can be complemented with rapidly expanding

datasets that extract skill and task information from job advertisements and occupational directories using natural language and machine learning tools.

In light of this, we believe that the full potential of the research on skill transferability and skill mismatch is yet to be reached. At the level of occupational specializations, skill transferability can help us understand better which requalification paths from one specialization to another are feasible. New research could distinguish between transferability of skills and transferability of qualifications, where the first concept refers to the actual skills workers have, and the second to the official educational qualifications and licenses that permit entry into an occupation. In this way, we can study if formal qualifications pose obstacles to smooth transitions between occupations with transferable skills.

Stronger integration of the reviewed topics with education policy is critical for devising actionable policies that address skill mismatches. The combination of powerful automating technologies and the possibility of offshoring of tasks is making the notion of having one occupation for life, let alone a job for life a thing of the past. Current and future generations will need to be prepared to change jobs, skill sets, and geographic places of work at several points in their careers. How do we design education that allows for such flexibility? Is developing an ability to learn in early childhood (Cunha and Heckman, 2007) the only way to ensure such flexibility? What do effective life-long-learning programs look like for workers affected by automation and globalization? Countries differ starkly in their design and offerings of requalification programs. Future research could explore this variation and determine what works and what does not in requalification programs. Moreover, government agencies (such as traditional employment agencies), as well as private job matching firms have a prominent role to play in reducing search and matching frictions. Here as well, more research is needed to assess their effectiveness, and in particular when it comes to the more vulnerable and disadvantaged populations. Finally, evaluation of state programs that encourage and ease geographic mobility could shed light on their cost-effectiveness vis-à-vis programs that aim at keeping firms and jobs in places where they struggle to remain competitive.

REFERENCES

- Acemoglu, D. and Autor, D., 2011. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043-1171). Elsevier.
- Acemoglu, D. and Restrepo, P., 2017. *Robots and Jobs: Evidence from US Labor Markets* (No. w23285). National Bureau of Economic Research.
- Alba-Ramirez, A., 1993. Mismatch in the Spanish labor market: overeducation?. *Journal of Human Resources*, pp.259-278.
- Allen, J. and De Grip, A., 2012. Does skill obsolescence increase the risk of employment loss?. *Applied Economics*, 44(25), pp.3237-3245.
- Allen, J. and De Grip, A., 2007. *Skill obsolescence, lifelong learning and labor market participation*. Research Centre for Education and the Labour Market, Maastricht University, Faculty of Economics and Business Administration.
- Allen, J. and Van der Velden, R., 2001. Educational mismatches versus skill mismatches: effects on wages, job satisfaction, and on-the-job search. *Oxford economic papers*, 53(3), pp.434-452.
- Allen, J.P., Levels, M. and van der Velden, R.K.W., 2013. Skill mismatch and skill use in developed countries: Evidence from the PIAAC study.
- Anderson, K.A., 2017. Skill networks and measures of complex human capital. *Proceedings of the National Academy of Sciences*, 114(48), pp.12720-12724.
- Arcidiacono, P., Kinsler, J. and Price, J., 2017. Productivity spillovers in team production: Evidence from professional basketball. *Journal of Labor Economics*, 35(1), pp.191-225.
- Atalay, E., Phongthientham, P., Sotelo, S. and Tannenbaum, D., 2020. The evolution of work in the United States. *American Economic Journal: Applied Economics*, 12(2), pp.1-34.
- Autor, D.H., 2013. The "task approach" to labor markets: an overview. *Journal for Labour Market Research*, 46(3), pp.185-199.
- Autor, D., Chin, C., Salomons, A. and Seegmiller, B., 2024. New frontiers: The origins and content of new work, 1940–2018. *The Quarterly Journal of Economics*, 139(3), pp.1399-1465.
- Autor, D.H., Katz, L.F. and Kearney, M.S., 2008. Trends in US wage inequality: Revising the revisionists. *The Review of economics and statistics*, 90(2), pp.300-323.
- Autor, D.H., Katz, L.F. and Krueger, A.B., 1998. Computing inequality: have computers changed the labor market?. *The Quarterly journal of economics*, 113(4), pp.1169-1213.
- Autor, D. H., Dorn, D. and Hanson, G.H., 2013. The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, 103(6), pp.2121-68.

Autor, D.H. and Handel, M.J., 2013. Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, 31(S1), pp.S59-S96.

Autor, D.H., Levy, F. and Murnane, R.J., 2003. The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4), pp.1279-1333.

Bauer, T.K., 2002. Educational mismatch and wages: a panel analysis. *Economics of education review*, 21(3), pp.221-229.

Becker, G.S., 1962. Investment in human capital: A theoretical analysis. *Journal of political economy*, 70(5, Part 2), pp.9-49.

Becker, G.S., 2009. *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago press.

Berman, E., Bound, J. and Griliches, Z., 1994. Changes in the demand for skilled labor within US manufacturing: evidence from the annual survey of manufactures. *The Quarterly Journal of Economics*, 109(2), pp.367-397.

Blinder, A.S., 2006. Offshoring: the next industrial revolution?. *Foreign affairs*, pp.113-128.

Blinder, A.S. and Krueger, A.B., 2013. Alternative measures of offshorability: a survey approach. *Journal of Labor Economics*, 31(S1), pp.S97-S128.

Borghans, L. and De Grip, A., 2000. *The overeducated worker?*. Edward Elgar Publishing.

Bound, J. and Johnson, G., 1992. Changes in the structure of wages in th 1980's: An evaluation in means-tested entitlement programs. *American Economic Review*, 82, pp.371-392.

Brynin, M. and Longhi, S., 2009. Overqualification: Major or minor mismatch?. *Economics of Education Review*, 28(1), pp.114-121.

Brynjolfsson, E. and McAfee, A., 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Chang, S.J., 1996. An evolutionary perspective on diversification and corporate restructuring: entry, exit, and economic performance during 1981–89. *Strategic Management Journal*, 17(8), pp.587-611.

Chillemi, O. and Gui, B., 1997. Team human capital and worker mobility. *Journal of Labor Economics*, 15(4), pp.567-585.

Ciarli, T., Kenney, M., Massini, S. and Piscitello, L., 2021. Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, 50(7), p.104289.

Collins, H. and Pinch, T., 2014. *The golem at large: What you should know about technology*. Cambridge University Press.

Consoli, D., Marin, G., Marzucchi, A. and Vona, F., 2016. Do green jobs differ from non-green jobs in terms of skills and human capital?. *Research Policy*, 45(5), pp.1046-1060.

Cunha, F. and Heckman, J., 2007. The technology of skill formation. *American Economic Review*, 97(2), pp.31-47.

De Grip, A. and Van Loo, J., 2002. *The economics of skills obsolescence: a review* (pp. 1-26). Elsevier Science.

Diodato, D. and Weterings, A.B., 2014. The resilience of regional labour markets to economic shocks: Exploring the role of interactions among firms and workers. *Journal of Economic Geography*, 15(4), pp.723-742.

Dornbusch, R., Fischer, S. and Samuelson, P.A., 1977. Comparative advantage, trade, and payments in a Ricardian model with a continuum of goods. *The American Economic Review*, 67(5), pp.823-839.

Duncan, G.J. and Hoffman, S.D., 1981. The incidence and wage effects of overeducation. *Economics of education review*, 1(1), pp.75-86.

Ederer, P., Lans, T., Biemans, H.J.A. and Baggen, Y., 2015. *LLLight'in'Europe: Lifelong Learning Innovation Growth & Human Capital Tracks in Europe: Synthesis Report*. LLLightinEurope Research Consortium.

Ericsson, A. and Pool, R., 2016. *Peak: Secrets from the New Science of Expertise*. Random House.

Evangelista, R. and Savona, M., 2003. Innovation, employment and skills in services. Firm and sectoral evidence. *Structural Change and Economic Dynamics*, 14(4), pp.449-474.

Farjoun, M., 1994. Beyond industry boundaries: Human expertise, diversification and resource-related industry groups. *Organization science*, 5(2), pp.185-199.

Felstead, A., Gallie, D., Green, F. and Inanc, I., 2013. Skills and employment survey 2012: technical briefing. *London: Centre for Learning and Life Chances in Knowledge Economies and Societies, Institute of Education*.

Freeman, R.B., 1975. Overinvestment in college training?. *Journal of human resources*, pp.287-311.

Freeman R. B., 1976. *The Overeducated American*. Academic Press.

Freeman, C.P. and Perez, C., 1988. C.(1988), Structural crises of adjustment, business cycles and investment behaviour. *Technical Change and Economic Theory*. Pinter, London, pp.38-66.

Frey, C.B. and Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation?. *Technological forecasting and social change*, 114, pp.254-280.

Galasi, P., 2008. *The effect of educational mismatch on wages for 25 countries* (No. BWP-2008/8). Budapest Working Papers on the Labour Market.

Gathmann, C. and Schönberg, U., 2010. How general is human capital? A task-based approach. *Journal of Labor Economics*, 28(1), pp.1-49.

- Goldin, C.D. and Katz, L.F., 2009. *The race between education and technology*. Harvard university press.
- Goldin, C., 2016. Human capital. *Handbook of cliometrics*, pp.55-86.
- Goos, M. and Manning, A., 2007. Lousy and lovely jobs: The rising polarization of work in Britain. *The review of economics and statistics*, 89(1), pp.118-133.
- Goos, M., Manning, A. and Salomons, A., 2009. Job polarization in Europe. *American economic review*, 99(2), pp.58-63.
- Green, F., McIntosh, S. and Vignoles, A., 1999. *Overeducation and skills-clarifying the concepts* (No. dp0435). Centre for Economic Performance, LSE.
- Griliches, Z., 1969. Capital-skill complementarity. *The review of Economics and Statistics*, pp.465-468.
- Griliches, Z., 1977. Estimating the returns to schooling: Some econometric problems. *Econometrica: Journal of the Econometric Society*, pp.1-22.
- Grossman, G.M. and Rossi-Hansberg, E., 2008. Trading tasks: A simple theory of offshoring. *American Economic Review*, 98(5), pp.1978-97.
- Groot, W. and Van Den Brink, H.M., 2000. Overeducation in the labor market: a meta-analysis. *Economics of education review*, 19(2), pp.149-158.
- Guvenen, F., Kuruscu, B., Tanaka, S. and Wiczer, D., 2020. Multidimensional skill mismatch. *American Economic Journal: Macroeconomics*, 12(1), pp.210-244.
- Hanushek, E.A. and Woessmann, L., 2008. The role of cognitive skills in economic development. *Journal of economic literature*, 46(3), pp.607-68.
- Hartog, J., 2000. Over-education and earnings: where are we, where should we go?. *Economics of Education Review*, 19(2), pp.131-147.
- Hartog, J. and Oosterbeek, H., 1988. Education, allocation and earnings in the Netherlands: Overschooling?. *Economics of Education Review*, 7(2), pp.185-194.
- Hanushek, E.A., Schwerdt, G., Wiederhold, S. and Woessmann, L., 2015. Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, 73, pp.103-130.
- Javadian Sabet, A., Bana, S.H., Yu, R. and Frank, M.R., 2024. Course-Skill Atlas: A national longitudinal dataset of skills taught in US higher education curricula. *Scientific Data*, 11(1), p.1086.
- Jovanovic, B. and Nyarko, Y., 1994a. *Learning by Doing and the Choice of Technology* (No. w4739). National Bureau of Economic Research.
- Jovanovic, B. and Nyarko, Y., 1994b. *The Bayesian foundations of learning by doing*. National Bureau of Economic Research.

Jovanovic, B. and Nyarko, Y., 1995a. The transfer of human capital. *Journal of Economic Dynamics and Control*, 19(5-7), pp.1033-1064.

Jovanovic, B. and Nyarko, Y., 1995b. A Bayesian learning model fitted to a variety of empirical learning curves. *Brookings Papers on Economic Activity. Microeconomics, 1995*, pp.247-305.

Jovanovic, B. and Nyarko, Y., 1997, June. Stepping-stone mobility. In *Carnegie-Rochester Conference Series on Public Policy* (Vol. 46, pp. 289-325). North-Holland.

Katz, L. and Autor, D., 1999. Changes in the Wage Structure and Earnings Inequality. Ashenfelter, O. and D. Card (eds), *Handbook of Labor Economics.*, 3A: 1463–1555.

Kohler, W. and Wrona, J. 2011. Offshoring tasks, yet creating jobs?, University of Tübingen Working Papers in Economics and Finance, No. 12.

Krahn, H. and Lowe, G.S., 1998. *Literacy utilization in Canadian workplaces*. Canada: Statistics Canada.

Krueger, A.B. and Lindahl, M., 2001. Education for growth: why and for whom?. *Journal of economic literature*, 39(4), pp.1101-1136.

Kogut, B. and Zander, U., 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science*, 3(3), pp.383-397.

MacKenzie, D. and Spinardi, G., 1995. Tacit knowledge, weapons design, and the uninvention of nuclear weapons. *American journal of sociology*, 101(1), pp.44-99.

Marx, M. and Timmermans, B., 2015. Comobility. In *Academy of Management Proceedings* (Vol. 2015, No. 1, p. 14836). Briarcliff Manor, NY 10510: Academy of Management.

Marx, M. and Timmermans, B., 2017. Hiring molecules, not atoms: Comobility and wages. *Organization Science*, 28(6), pp.1115-1133.

Mealy, P., del Rio-Chanona, R.M. and Farmer, J.D., 2018. What you do at work matters: new lenses on labour. (March 18, 2018).

Miller, S. and Hughes, D., 2017. The quant crunch: How the demand for data science skills is disrupting the job market. *Burning Glass Technologies*.

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

Mincer, J., 1991. *Human capital, technology, and the wage structure: what do time series show?* (No. w3581). National Bureau of Economic Research.

Mortensen, D.T. and Pissarides, C.A., 1994. Job creation and job destruction in the theory of unemployment. *The review of economic studies*, 61(3), pp.397-415.

Mortensen, D.T. and Pissarides, C.A., 1999. New developments in models of search in the labor market. *Handbook of labor economics*, 3, pp.2567-2627.

National Center for O*NET Development. The O*NET® Content Model. *O*NET Resource Center*. Retrieved March 7, 2019, from <https://www.onetcenter.org/content.html>

Nedelkoska, L., Diodato, D. and Neffke, F., 2018. Is our human capital general enough to withstand the current wave of technological change?. *CID Research Fellow and Graduate Student Working Paper Series*. No 93.

Nedelkoska, L., Matha, S.G., McNerney, J., Assumpcao, A., Diodato, D. and Neffke, F., 2021. Eight decades of changes in occupational tasks, computerization and the gender pay gap. CID Working Papers 151a, Center for International Development at Harvard University.

Nedelkoska, L. and Quintini, G., 2018. Automation, skills use and training. *OECD Social, Employment and Migration Working Papers*. No. 202, OECD Publishing, Paris, <https://doi.org/10.1787/2e2f4eea-en>.

Neffke, F.M., 2019. The value of complementary co-workers. *Science advances*, 5(12), p.eaax3370.

Neffke, F., Hartog, M., Boschma, R. and Henning, M., 2018. Agents of structural change: the role of firms and entrepreneurs in regional diversification. *Economic Geography*, 94(1), pp.23-48.

Neffke, F. and Henning, M., 2013. Skill relatedness and firm diversification. *Strategic Management Journal*, 34(3), pp.297-316.

Neffke, F., Nedelkoska, L. and Wiederhold, S., 2024. Skill mismatch and the costs of job displacement. *Research Policy*, 53(2), p.104933.

Neffke, F.M., Otto, A. and Weyh, A., 2017. Inter-industry labor flows. *Journal of Economic Behavior & Organization*, 142, pp.275-292.

Nelson, R.R. and Phelps, E.S., 1966. Investment in humans, technological diffusion, and economic growth. *The American economic review*, 56(1/2), pp.69-75.

Nelson, R.R. and Winter, S. G., 1982. *An evolutionary theory of economic change*. Harvard University Press.

OECD, 2013. Technical report of the survey of adult skills (PIAAC).

Penrose, E., 1959. *The theory of the growth of the firm*. John Wiley & Sons, New York.

Perry, A., Wiederhold, S. and Ackermann-Piek, D., 2016. How can skill mismatch be measured? New approaches with PIAAC. *methods, data, analyses*, 8(2), p.38.

Peteraf, M.A., 1993. The cornerstones of competitive advantage: a resource-based view. *Strategic management journal*, 14(3), pp.179-191.

Petrongolo, B. and Pissarides, C.A., 2001. Looking into the black box: A survey of the matching function. *Journal of Economic literature*, 39(2), pp.390-431.

Pierre, G., Puerta, M.L.S., Valerio, A. and Rajadel, T., 2014. STEP Skills Measurement Surveys. *California: world Bank Group*.

- Polanyi, M., 1958. Personal Knowledge: Towards a Post-Critical Philosophy. *University of Chicago Press*.
- Poletaev, M. and Robinson, C., 2008. Human capital specificity: evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000. *Journal of Labor Economics*, 26(3), pp.387-420.
- Prytkova, E., Petit, F., Li, D., Chaturvedi, S. and Ciarli, T., 2024. The employment impact of emerging digital technologies.
- Hamel, G. and Prahalad, C.K., 1990. The core competence of the corporation. *Harvard business review*, 68(3), pp.79-91.
- Quintini, G., 2011. Over-qualified or under-skilled. OECD Social, Employment and Migration Working Papers, No. 121, OECD Publishing, Paris, <https://doi.org/10.1787/5kg58j9d7b6d-en>.
- Restrepo, P., 2015. Skill mismatch and structural unemployment. Massachusetts Institute of Technology Job Market Paper, 13(9), pp.66-94.
- Robins, J. and Wiersema, M.F., 1995. A resource-based approach to the multibusiness firm: Empirical analysis of portfolio interrelationships and corporate financial performance. *Strategic management journal*, 16(4), pp.277-299.
- Rogerson, R., Shimer, R. and Wright, R., 2005. Search-theoretic models of the labor market: A survey. *Journal of economic literature*, 43(4), pp.959-988.
- Rohrbach-Schmidt, D., 2009. The BIBB/IAB-and BIBB/BAuA Surveys of the Working Population on Qualification and Working Conditions in Germany: Data and methods manual. *BIBB-FDZ Daten-und Methodenbericht; 2009, 1*.
- Roy, A.D., 1951. Some thoughts on the distribution of earnings. *Oxford economic papers*, 3(2), pp.135-146.
- Sattinger, M., 1975. Comparative advantage and the distributions of earnings and abilities. *Econometrica (pre-1986)*, 43(3), p.455.
- Sattinger, M., 1993. Assignment models of the distribution of earnings. *Journal of economic literature*, 31(2), pp.831-880.
- Sattinger, M., 2012. Qualitative mismatches. *Foundations and Trends in Microeconomics*, 8(1–2), pp.1-168.
- Schultz, T.W., 1961. Investment in human capital. *The American economic review*, 51(1), pp.1-17.
- Shaw, K.L., 1987. Occupational change, employer change, and the transferability of skills. *Southern Economic Journal*, pp.702-719.
- Smith, J.P. and Welch, F., 1978. The Overeducated American? A Review Article.

Teece, D.J. and Pisano, G., 1994. The dynamic capability of firms: An introduction. *Industrial and Corporate Change*, 3(3), pp.537-556.

Teece, D.J., Rumelt, R., Dosi, G. and Winter, S., 1994. Understanding corporate coherence: Theory and evidence. *Journal of economic behavior & organization*, 23(1), pp.1-30.

Teece, D.J., Pisano, G. and Shuen, A., 1997. Dynamic capabilities and strategic management. *Strategic management journal*, 18(7), pp.509-533.

Tinbergen, J., 1951. Some remarks on the distribution of labour incomes. *International Economic Papers*, 1, pp.195-207.

Thurow, L.C., 1975. *Generating inequality*. Basic books.

Turrell, A., Speigner, B., Djumalieva, J., Copple, D. and Thurgood, J., 2018. Using job vacancies to understand the effects of labour market mismatch on UK output and productivity.

Van der Velden, R.K. and Van Smoorenburg, M.S., 1997. The measurement of overeducation and undereducation: self-report vs. job-analyst method.

Vona, F. and Consoli, D., 2014. Innovation and skill dynamics: a life-cycle approach. *Industrial and Corporate Change*, 24(6), pp.1393-1415.

Wernerfelt, B., 1984. A resource-based view of the firm. *Strategic management journal*, 5(2), pp.171-180.

Winter, S.G., 2003. Understanding dynamic capabilities. *Strategic management journal*, 24(10), pp.991-995.

Wüstenberg, Sascha, Samuel Greiff, and Joachim Funke. "Complex problem solving—More than reasoning?." *Intelligence* 40, no. 1 (2012): 1-14.