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Skill Mismatch and Skill Transferability: Review of Concepts and Measurements

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Skill Mismatch and Skill Transferability: Review of Concepts and Measurements[1]

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Abstract

The notion of skills plays an increasingly important role in a variety of research fields. Since the foundational work on human capital theory, economists have approached skills through the lens of education, training and work experience, whereas early work in evolutionary economics and management stressed the analogy between skills of individuals and the organizational routines of firms. We survey how the concept of skills has evolved into notions such as skills mismatch, skill transferability and skill distance or skill relatedness in labor economics, management, and evolutionary approaches to economics and economic geography. We find that these disciplines converged in embracing increasingly sophisticated approaches to measuring skills. Economists have expanded their approach from quantifying skills in terms of years of education to measuring them more directly, using skill tests, self-reported skills and job tasks, or skills and job tasks reported by occupational experts. Others have turned to administrative and other large-scale data sets to infer skill similarities and complementarities from the careers of sometimes millions of workers. Finally, a growing literature on team human capital and skill complementarities has started thinking of skills as features of collectives, instead of only of individuals. At the same time, scholars in corporate strategy have studied the micro-determinants of team formation. Combined, the developments in both strands of research may pave the way to an understanding of how individual-level skills connect to firm-level routines.

Keywords

Human capital, skills and tasks, skill relatedness, skill mismatch, skill transferability

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Introduction

The aim of this chapter is to review the concepts and the measurement of skills, and in particular, skill mismatch and skill transferability. We compare how three research areas that make extensive use of these concepts, namely evolutionary economics, management and labor economics, use and operationalize them. What connects the views on skills in these research areas is their relevance with regard to innovation. Skills are essential for innovation, but innovation is one of the main causes of skill mismatch in the economy. In the review of the concept of skills 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. In the review of the measurement of skills, skill mismatch and skill transferability, we describe an exciting recent development in both 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.

We think of skills as the part of human capital that can be acquired through education, training and practice. Skills allow us to perform specific job tasks. Indirectly, by performing tasks, skills enter the process of production. Skill mismatch occurs when the skills of individuals are different from the skills required at their jobs. Skill transferability is the human capital feature that permits us to use the same set of skills to perform tasks across different jobs, either because the same kinds of tasks occur in different jobs or because a set of skills can perform several different tasks.

The reason why we care about skill mismatch is because it is costly. Having low levels of skills or too few skills for the job can cost firms their productivity, while skill redundancies can cost workers forgone wages through lower return on their human capital. Skill mismatch has many names: skill shortage, skill redundancy, skill obsolescence, under-skilling, over-skilling, undereducation and overeducation, to name a few. It also has many causes, both transient and structural. Among the transient ones are search and matching frictions and among the structural ones are technological change and changes in the international division of labor.

Skill mismatch and skill transferability as concepts are intrinsically related, and in some cases, they can be synonyms. We say that the skill transferability between two jobs (firms, occupations or industries) is high if these employ similar sets of skills. If we do not care about the direction of skill mismatch, we can use the two terms interchangeably. Skill mismatch emphasizes the asymmetry in the transferability of skills. In a relation to a job, our skills can be too high (i.e., we can be over-skilled), too low (i.e., we can be under-skilled), or too different (i.e., our skills are unrelated to that job).

In the rest of this chapter we first review the literature on the concepts of skills, skill mismatch and skill transferability. We then focus on the measurement of skill mismatch and skill transferability across disciplines. We conclude by emphasizing the progression in economic thought with regard to these concepts and their measurement and the areas where we see scope for cross-fertilization between research fields.

The concept of skills in labor economics, evolutionary economics and management

Several different 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 the one of human capital. One can think of human capital as the stock of skills of a labor force (Goldin 2016). More specifically, human capital includes the knowledge, skills and abilities that people have and which firms can employ in the production of goods and services. It suggests that through investments in health, education and training, we can become more productive, and as a result, increase the returns to our skills (Schultz 1961; Becker 1962; Becker 2009). The relationship between earnings and human capital can be modeled as in Griliches (1977):

$$Y = p_h H e^u$$

Where Y is income, earnings or wages, p_h is the price of unit of human capital H and u is a random disturbance term. The human capital production function, at the individual level (i), translates inputs such as schooling time, on-the-job training and others into a measure of the quality of labor. These inputs are assumed to enter the function multiplicatively, which is why we exponentiate the terms on the right-hand side of the equation:

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

Substituting H in the first equation with the second one and taking logs in the first one, we obtain the standard Mincer (1974) earnings equation:

$$lnY_i = \alpha + \rho S_i + \beta_1 x_i + \beta_2 x^2 + u_i + v_i,$$

where ρ is the rate of return to schooling and β is the return to work experience. The best empirically fitting model is the one where learning on the job increases with each year spent on the labor market, but at a decreasing rate. This explains the use of a squared term of experience in the equation.

In the strategic management literature and in evolutionary economics, skills tend to be analyzed as a firm-level phenomenon. 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 are presented as firm-level skills. Organizational routines are learned, highly patterned, repetitious and partly tacit (Winter 2003). They can be ordinary or dynamic. Dynamic routines, best known in the literature as dynamic capabilities (Teece and Pisano 1994; Teece, Pisano and Shuen 1997) determine the rate of change of the ordinary ones (Winter 2003). This perspective on skills facilitates the understanding of how innovation comes about, which is of core interest in evolutionary economics, as well as how firms gain and maintain competitive advantage, which is a core interest in strategic management. Winter (2003) argues that investing in dynamic capabilities can serve as a partial hedge against the obsolescence of existing capability, and can sometimes give firms sustainable advantage over other firms, but such investments cannot always shield firms from being outcompeted by imitators or those that serendipitously manage to overcome obstacles towards higher competitiveness without making costly investments in dynamic capabilities. The concept of organizational routines as firm-level skills is closely related to the (core) competencies of Prahalad and Hamel (1990). Prahalad and Hamel (1990) define core competencies as "the collective learning in the organization, especially how to coordinate diverse production skills and integrate multiple streams of technologies" (p. 81).

Nelson and Phelps (1962) pioneered work at the intersection of labor economics and evolutionary economics. They use the concept of human capital in the fashion of labor economics, i.e., focusing on individual-level skills, but their research question is typical for evolutionary economics: how does innovation diffuse? They observe that better educated workers aid firms adopt technologies because such workers are better at understanding and using new information.

A growing number of scholars now goes beyond the dichotomy of 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 the social routines that allow teams to tap into and coordinate these skills. For instance, firms not only require workers who have the 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. Within this view, Arcidiacono, Kinsler and Price (2017) show that coworkers create spillovers by enhancing productivity of peers. Marx and Timmermans (2015, 2017) show that a significant share of job switchers in Denmark move as coworker pairs and coworker teams. These teams earn a premium at the new place over similar single movers. Neffke (2017) 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 explain large parts of the urban and large-plant premium. The above studies demonstrate that team human capital is an area where labor economics, management science and evolutionary economics converge.

A final important concept related to skills is the concept of tacit knowledge (Polanyi 1958), which has been widely used in evolutionary economics. Polanyi 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 swimmer, for example, directs her awareness from the motoric and respiratory details of swimming to the speed and direction that brings her to her goal. Many of the micro details of skilled action come about almost with no conscious effort to her. Following this reasoning, Nelson and Winter (1982)[4] argue that in a truly skillful behavior, choices are highly automatic. Their example is one of an experienced car driver. At any moment, the driver makes

[4] 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.

choices about the direction and the speed of the car, but does so without attention or awareness. Another familiar example is the way people use language skills. In colloquial conversations, we express ourselves effortlessly, although each word and sentence in fact require choices. These choices seem automated, because our attention focuses away from the individual words to the meaning of the sentence we are constructing or even the argument we are making. As we perfect the art of a skill, this knowledge becomes more and more tacit. As a consequence, the causalities on which our skills rely are often, if at all, poorly understood by us, which explains why it is so difficult to articulate how one achieves skillful behavior. Therefore, the mastery of many skills in sports, music, and arts requires thousands of hours of practice rather than simply a systematic learning effort of the principles behind a performance.

Although most economists still analyze skills as mainly acquired through a system of general education, 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 individual. 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 the majority of learning happens through reading the help files of programming languages. Although we can make these distinctions, it is important to note that even skills that at 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 solving mathematical problems requires the tacit application of theorems.

When the problems we need to solve are complex in the sense that the number of contingencies we encounter as we perform a job is large, even a long period of learning-by-repetition may not result in highly automated choices. In such cases, learning-on-the-job usually is required after an extensive period of studying the theoretical basis of the subject matter.[5] 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. These aspects of learning indicate the challenges to acquiring new relevant skills outside the learning-by-doing environments jobs offer.

Theories of skill mismatch and the repercussions of skill mismatch

Skill mismatch occurs when the skills of individuals are different from the skills required at the job. Skills can be too high, too low or too different from a job's skill requirements. Economists care about skill mismatch because it is costly. From the perspective of the worker, it is presumed to result in lower wages,

[5] 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.

lower job satisfaction and more job mobility. From the perspective of the firm and the economy as a whole, it results in lower productivity.

Theories deriving the cost of skill mismatch

Four different theories are often used to form hypotheses about the cost of skill mismatch: the assignment theory (Sattinger 1975; 1993; 2012), the search and matching theory (Mortensen and Pissarides 1999 and Rogerson, Shimer, and Wright 2005 provide reviews of literature), the job competition theory (Thurow 1975) and the human capital theory (Becker 1962; Becker 2009; Schultz 1961).

In the assignment theory (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 in the distributions of complex jobs and skilled workers. An important implication of the mismatch between the two distributions at a macro level is earnings inequality. Oversupply of a certain skill group will drive the relative wages of that group down. As the wages of the two groups diverge, earnings inequality grows. The role of a central planner in that case is to balance the supply of skills, e.g., through general education, acting as an equalizer of earnings (Goldin and Katz 2009).

In the search and matching theory, skill mismatch can occur as a result of imperfect information even if the distributions of worker skills and jobs are perfectly aligned (i.e., there exists a single perfect worker for each possible job). Mismatch is costly both for workers and for firms but so is search, which is why search sometimes ends before finding the ideal match. Search frictions, while always present, are temporary in nature and could be reduced at the macro level with more effective job matching technology. In the job competition theory, marginal productivity is not a feature of a worker, but a feature 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, under this theory, employers pay for the required years of education and not for the employee's actual level of education. 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, or in other words, the returns to a year of over or under-skilling will be zero. Finally, in stark contrast to the job competition theory, according to human capital theory, the marginal productivity is a feature of the worker and not the job. A worker with excess years of education will be more productive in a job than a worker with the right length of education for the job. Hence, there will be a positive return to over-skilling and a negative return to under-skilling. These returns should be equal in magnitude to the return to required level of skill.

The stylized finding in the literature on educational mismatch is that overeducated workers earn less and undereducated workers earn more than workers with the right amount of education for the job. The returns to required education are higher than the returns to attained years of education. The returns to a year of surplus education are positive and the returns to a year of deficit education are negative. Bauer (2002) tests the implications of 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. However, he also finds that much of the differences in the returns to overeducation, undereducation and adequate education are in fact returns to unobserved worker characteristics. Once he controls for unobserved heterogeneity, the returns to a year of adequate education, a year of surplus education and a year of deficit education become about the same.

Causes of skill mismatch

There are frictional and structural causes of skill mismatch. Frictions can result in search costs of finding the right job given worker's qualifications. Structural reasons may have to do with changes in the demand for skills (technological advances, trade) and changes in the supply of skills (education policy, demographic change). They refer to misalignments between the aggregate distribution of workers' skills and the aggregate distribution of job requirements in an economy.

On the supply side of skills, most literature has focused to the functioning of institutions providing general education. For instance, the debate about educational mismatch became prominent in the 1970s when Freeman (1975, 1976) among others, argued that there is an oversupply of college graduates on the labor market, and that this is likely to persist in the future. The oversupply arguably caused a significant decline in the college premium over high school education. Although these findings were soon after disputed (Smith and Welch 1978), Freeman's work illustrated 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 the acquisition of college degrees in the United States played a major role in creating opportunities for economic mobility throughout the twentieth century. And while this is the case in general, the actual premium to a college degree varied as a function of the supply of college education. The college premium[6] was high when the supply of college degrees was low and low when the supply of college degrees was high. In other words, in periods of large skill shortage, college graduates earned extraordinarily high wages and the level of earnings inequality increased. The opposite was true in periods of high supply of college graduates.

Innovation in general, and technological advancement specifically are perhaps the most important forces impacting the demand for skills over long periods of time. In one of the earliest studies on this topic, Griliches (1969) proposed that skills and capital are complements. 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 or technological 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 technology or the production of the new product. Learning and improvements reach a maximum when tasks are standardized, after which marginal gains from further specialization diminish and tasks have become sufficiently standardized to be performed by unskilled, but highly specialized workers.

Technological change does not only affect the demand of certain levels of skills, but also for certain skill content. Especially when technological change is highly disruptive, many workers may find that their present skills are becoming obsolete: "… 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…" (Freeman

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

and Perez 1988, p. 59). With some exceptions as in the work by Vona and Consoli, this early recognition of the impact of technology, and in particular of General-Purpose Technology (GPT) on skill requirements did not spur adequate research into the topic in evolutionary economics. However, the topic became widely studied by labor economists. 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, especially computer capital tend to complement skilled labor (Mincer 1991; Bound and Johnson 1992; Berman, Bound and Griliches 1994; Autor, Katz and Krueger 1998). That is, technologies increase the productivity of skilled labor, but not that of unskilled labor. Starting with the seminal work by Autor, Levy and Murnane (2003), this hypothesis was modified to reflect the relationship between computers and the more specific task content of jobs, as opposed to the skill level of workers. This task-based approach (Autor and Handel 2013; Autor 2013; Acemoglu and Autor 2011) was dubbed Task-biased Technological Change (TBTC). 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, does not only augment non-routine and interactive tasks, but also substitutes for routine manual and routine cognitive tasks. Notice moreover, that tasks are features of jobs not of workers. Workers, in turn, employ specific skills when performing these job tasks. This is a fundamental difference compared to the SBTC hypothesis: the task-based approach analyzes technological change at the level at which technologies actually 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 perform all tasks, but they have different comparative advantages: low skill workers have a comparative advantage in manual tasks, medium skill workers in routine tasks and high skill workers in abstract tasks. In an analogous way to how the production of different products gets assigned to different countries according to comparative advantage, tasks get assigned to workers depending on their comparative advantage in different tasks. Computers enter this model through their effectiveness at carrying out routine tasks. As a consequence, computers compete with medium-skilled workers, who traditionally specialize in such tasks. As the price of routine tasks declines, the demand for their complements, the non-routine tasks, increases, driving the demand for low skill and high skill labor up. The model helps us understand recent employment and wage dynamics in developed countries such as falling real wages of less skilled workers and job polarization (Goos & Manning 2007; Goos, Manning and Salomons, 2009).

Acemoglu and Autor (2011) made important assumptions in their theoretical work that were challenged shortly after the publication of their work. 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 comparative advantage of medium skill workers. All of these assumptions are now being questioned. Groundbreaking recent developments in artificial intelligence (AI) and mobile robotics (MR) are once again changing how economists think of the impact of technologies on labor markets. In particular, Brynjolfsson and McAfee (2014) and Frey and Osborne (2017) put forward the idea that the AI and MR are able to substitute for non-routine tasks, both cognitive and manual. A long list of ubiquitous tasks that were considered out of reach of machines up until recently – driving, legal and financial analysis, medical diagnosis, simultaneous translation, speech recognition etc. – are now deemed well within their reach. Such powerful technologies could have sweeping consequences: in 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 second most important factor in the demand for skills is trade or globalization. Similar to studies about the impact of technological change on skills, scholars have recently re-focused to analyzing the impact of trade on job tasks. Currently, some of the same tasks that are at risk of automation are also at risk of being outsourced internationally. However, this correlation is modest at most. 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. Based on some of these insights and the observation that today countries do not trade final goods but contribute partial value added in the making of a final product, Grossman and Rossi-Hansberg (2008) develop a theory 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. Most importantly, 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, the 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 create conditions where it results in net job destruction when economies are not at full employment. Empirically, the impact of trade on particular occupations has been documented in Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2017) among others. As a net effect, trade shifts the demand for certain skills from developed to developing economies. For the United States, 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

The economic literature has traditionally used years of education or educational attainment to measure skills acquired through general education and years of labor market experience[7] 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), a year of education has different quality in different places and schools (Hanushek and Woessmann 2008; Hanushek et al. 2015), and the number

[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.

of years of education tells us nothing about which skills were acquired (Ederer et al. 2015). Same holds for the measurement of work skills through years of work experience. In the last two decades, with the increase in the popularity of the task-based approach and the availability of direct test-scores for skills, approaches that measure skills more directly became more popular.

Data sources

Traditionally, data from labor force surveys, cohort studies, surveys of income dynamics and the like have been used to study the role of skills, or more specifically, educational attainment, training and labor market experience. More recently, 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. Many of these datasets are 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 United States since 1939. Over time, the DOT and later the O*NET added various aspects of worker characteristics (skills, abilities, knowledge, interests, education, and training) and various aspects of job characteristics (work activities, salaries, growth projections and other labor market information) to the occupational descriptions (National Center for O*NET Development 2019). This enabled analysis far beyond job tasks. 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, other 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 Lllight'in'europe project (Ederer 2015) and the World Bank's STEP surveys (Pierre et al. 2014). These surveys have the added 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.

These data on tasks and skills have been used in combination with administrative data from social security records in countries such as Germany and Sweden, where researchers have merged them at the level of occupations. 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.

Another set of datasets offer measures of people's skills by administering direct skill tests. This is the case with 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 Lllight'in'europe project administered tests of complex problem-solving skills (Wüstenberg, Greiff and Funke 2012) for over 1100 employees in several countries.

Finally, a growing number of studies (Anderson 2017; Atalay 2017; Miller and Hughes 2018; Turrell et al. 2018) use data mining to measure skills in job ads data from Burning Glass Technologies, Indeed, ZipRecruiter, UpWork and others, as well as data from social media networks such as LinkedIn and Facebook.

Measuring skill mismatch

There are four commonly used approaches to the measurement of skill mismatch: self-reported mismatch, job-analysis, realized matches and direct measurements of skills. Note that the literature distinguishes between skill mismatch and educational mismatch, and in both cases, it is possible to work with all four types of approaches.

In the self-reported approach, the level of attained and the level of appropriate and/or required education is determined through surveying workers. The workers are typically asked about the educational requirements for their job, the ideal education, the appropriate education, or the necessary education to perform their job. Next, their attained level of education is compared to the required or the appropriate one. Although such self-assessments can be quite informative, they suffer from a number of drawbacks. The framing of the question, as discussed by Green, McIntosh and Vignoles (1999) and Leuven and Oosterbeek (2011), can significantly change the measurement outcome. For instance, 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 earlier is more likely to reflect actual job content while the latter is more likely to just 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 the status of the own job. Such overstatements could correlate with determinants of wages, such as gender and educational level, seriously biasing the impact of educational mismatch on wages. Perry, Wiederhold and Ackermann-Piek (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 to the measurement of mismatch, skill and educational requirements are reported by job analysts instead of by employees. Job analysts visit worker sites and compare many jobs with similar content. As a result, in datasets that use such expert opinions, such as the DOT and O*NET, there is no information about an individual job, but about an average over several jobs that can be grouped into a single occupation. As a result, it appears that the level of required schooling or skills is fixed within an occupation instead of, more realistically, occupation having a distribution of skills and/or education. To design a measure of mismatch, data from expert assessments still need to be matched 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 seen as deviations from this mean or mode. Oftentimes the scholars of this approach choose to report these deviations in standard deviations instead of years of schooling.[8]

Finally, a number of studies (Krahn and Lowe, 1998; Quintini, 2011; Allen, Levels, and van der Velden, 2013; Perry, Wiederhold and Ackermann-Piek, 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.

The above review reveals the variability of measures and raises questions about their comparability, sensitivity to different specifications, and validity. As illustrated in Perry, Wiederhold and Ackermann-Piek (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] Moreover, there are currently no studies that compare all major approaches, although as discussed above, there are some studies that compare smaller sets of approaches. Validity is even harder to test – it is not clear what a good test of validity would look like. 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, Wiederhold and Ackermann-Piek (2016) also compare the validity of PIAAC-based mismatch measures by estimating how well they predict wages. The problem with this approach however is that, at least until recently, the relationship between skill mismatch and wages was been a subject of hypothesis testing, rather than a well-established relationship that help assess a measure validity against a known outcome.

Measuring Skill Transferability

Scholars in labor economics, management and evolutionary economic geography have all independently developed measures that capture the concept of skill transferability. In management, a common use has been around questions of firm diversification (Farjoun 1994; Chang 1996; Neffke and Henning 2013). In economic geography the most common uses have been to answer questions about regional diversification (Neffke, Hartog, and Boschma 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 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 are those that use the similarity of occupational structure between industries to estimate the skill similarity across industries, and those that use the similarity of industry

[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.

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 skill-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 between 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 $j)$:

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

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, Otto and Weyh (2017) calculated industry skill relatedness using the labor flows across detailed industries in 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 skill data 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 final measure of skill relatedness. A similar approach is adopted by Gathmann and Schönberg (2010) using the BIBB/BAuA and BIBB/IAB Surveys.

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 of a job move from a nurse to a physician is the same as the skill transferability from a physician to a nurse. We know intuitively, however, that although a nurse and a physician may have largely overlapping skill sets, they perform their tasks at different levels of skills and qualifications. Nedelkoska, Neffke and Wiederhold (2015) 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 the occupation-specific skill mix 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 shortage and skill redundancy compared to their new occupation. Skill redundancies are associated with large long-term earnings losses among workers displaced from their jobs in the course of plant closures.

Conclusion and policy relevance

We review the literature on skills, skills mismatch and skill transferability in evolutionary economics, labor economics and management. In earlier work, labor economics viewed skills through the lenses of education and qualifications, while evolutionary economics and management mainly thought of skills as related to firm-level organizational routines. The approaches in all three disciplines have changed and to some extent converged in the last two decades. The current research on skills in labor economics, evolutionary economics and management has become more sophisticated in how skills are being measured. Many economists transitioned from measuring skills in terms of years of education to measuring them in ways that capture skills more directly, such as 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 started using rich administrative data sets 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 thinking of skills as a combination of the two. This is evident in the growing literature that focuses on team human capital and workers skill complementarities.

These approaches are particularly promising for evolutionary economics and its emphasis on technological change. Technologies shape the demand for skills. At the same time, skills are a prerequisite for learning, diffusing and advancing 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, especially when structural in nature, can stall firm productivity and lower the returns to human capital. The degree to which such mismatches can be addressed depends on many factors, among which the level of skill transferability from one job to another, and the re-trainability of workers.

Going forward, promising new research could arise from combining the insights of evolutionary economists into the dynamics of technological change with the cutting-edge approaches to understanding skill mismatch and its implications. One idea would be to study how the evolution of more specific industries and products, as depicted for instance in the product space of nations (Hausmann and Klinger 2007; Hidalgo et al. 2007), translates into changes in the skill composition of places and countries. These changes will be different in countries that are early adopters of new products and those that are late adopters, as the level of skill routinization increases over the product life cycle. New research could study these differences. At the same time, new surveys of direct skill measures that are becoming available hold great promise for research into skills, skill mismatch and skill transferability. Such surveys are now available only in a few countries, but the coverage is improving over time. PIAAC, which currently covers fewer than 35 economies, is the largest cross-country survey of relatively large sample size. The World

Bank's STEP surveys are the first surveys of skills administered in low and medium-income countries and currently cover around 20 countries. New research should benefit from the expansion of these databases in more countries.

The full potential of the concept of skill transferability is yet to be reached. It is the concept that, at the level of occupational specializations, can help us better understand the feasible options of requalifying from one specialization to another. New research could distinguish between transferability of skills and transferability of qualifications, where the first concept refers 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 sometimes pose obstacles to smoother transitions from one occupation to another.

Stronger integration of the here reviewed topics with education policy is critical for devising actionable policies toward addressing skill mismatches. The combination of powerful automating technologies and the possibility for offshoring of tasks is creating enormous pressure on the idea of having one occupation for life, let alone the idea of a job for life. Current and future generations will need to be prepared to change jobs, skills sets, and geographic place 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? How does an effective life-long-learning program look like for workers affected by automation and globalization? Countries differ starkly in their design and offerings of requalification programs and future research could explore this variation in order to learn what works. Moreover, agencies (such as traditional employment agencies), as well as private job search and matching programs have a prominent role to play in reducing search and matching frictions and more research is needed into their effectiveness, in particular for the more vulnerable populations. Finally, evaluation of state programs that encourage and ease worker geographic mobility could shed light on their cost-effectiveness vis-à-vis programs that subsidize firms to prevent them from outsourcing or offshoring their jobs.

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