Specific and general skills: concepts, dimensions, and measurements

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Abstract

A number of academic debates rely on the distinction between general and specific skills as being valuable to a large number or a few firms (Becker 1964|1993). However, the meaning attributed to these concepts as well as empirical measurement strategies have significantly varied in the literature. To address the resulting theoretical and empirical confusion, we propose a multidimensional approach for defining skill specificity, which encompasses four distinct concepts: accessibility and similarity of skill sets as well as the portability and replaceability of skills. The former two refer to skills acquired by an individual (i.e. skills are substantively specific), while the latter two depend on the structure of labour demand and supply, institutions, and firms' strategies (i.e. on economic factors) that are time-and place-dependent. This paper proposes and tests empirical strategies for measuring each concept. The results challenge assumptions in the literature that graduates of vocational training and high skilled blue-collar occupations have substantively specific skills. The multi-dimensional conceptualisation and empirical results provide a number of theoretical implications. We focus on three conceptual debates regarding firms' incentives to fund training, workers' demand for social insurance, and types of skills that facilitate or obstruct adjustment to technological and economic shocks.

Keywords

Skills of the labour force, general and specific skills, measuring specificity of skills, depth and breadth of skills

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Introduction

A number of academic debates rely on the distinction between general and specific skills: the former is valuable to a large number of employers, while the latter is of value only to one or a few firms (Becker, 1964|1993). Literature on human capital uses this dichotomy to explain differences in wages, the length of tenure, and a firm's willingness to invest in training (see Becker, 1964|1993; Acemoglu and Pischke, 1999; Leuven, 2005, and others). A strand in labour economics argues that lower levels of specificity in skills can explain for the faster labour market adjustments after exogenous shocks (Poletaev and Robinson, 2008; Lamo, Messina, and Wasmer, 2011). A variety of capitalism approaches rely on the distinction of specific and general skills in explaining institutional complementarities that shape the strategies of firms in liberal and coordinated market economies (Hall and Soskice, 2001; Hancke, Rhodes, and Thatcher, 2007). Finally, the Asset Theory of Social Policy Preferences argues that the specificity of skills of the labour force can have an effect on voter preferences regarding levels of social protection (Iversen and Soskice, 2001; Iversen, 2005).

Although the distinction is widely used, it is far from clear-cut since the meaning of these concepts varies significantly in the literature. For example, according to Streeck (2011) general and specific skills in different research traditions can refer to distinctions between: unskilled (general) and craft (specific) work; portable (general) and non-portable (specific) skills; high and broad (general) and low and narrow (specific) skill sets. Importantly, the different conceptualisations of the distinction between general – specific skills are seldom explicitly recognised. This leads to confusion, incompatible theoretical expectations, and the use of a wide range of proxies for the empirical measurement of specific and general skills. The most commonly used proxies include the type of initial education and training (academic education is assumed to lead to general skills and vocational to specific (Iversen 2005; Culpepper, 2007, among others), length of tenure (the longer, the more specific the skills (e.g. see Parent, 2000; Estavez-Abe, Iversen, and Soskice, 2001), wage penalties associated with switching firms, occupations, or industries (e.g. Kambourov and Manovskii, 2009; Sullivan 2010), structure of employment by occupational groups (Iversen, 2005), etc. However, as Hainmueller and Hiscox (2007) demonstrate, these proxies do not correlate very well which is not surprising given the differences in the implicit definitions of the concepts.

Accordingly, this paper aims to make three contributions: distinguish and conceptualise different facets of skill specificity, propose and test empirical strategies for measuring the concepts, and highlight implications to theoretical debates. The proposed conceptualisations build on Streeck's (2011) distinction between the substantive and economic dimensions of skill specificity. The two dimensions emphasise different sources or factors behind the specificity. On the substantive dimension, if a skill (or skill set) is a requisite for performing work in a large number of occupations/sectors, then such a skill is more general than the one that is useful only in a single occupation. The economic dimension refers to the ease of switching jobs and changing workers. It depends on labour market frictions, institutions, the structure of demand and supply in regional labour markets, etc. Accordingly, a specific skill set in a substantive sense may be general in the economic sense in a perfectly competitive labour market.

Within each dimension, we provide two conceptualisations of skill specificity (see Table 1). Within the economic dimension, we distinguish between portability and the replaceability of skills: the former refers to the ease of changing employers, while the latter encompasses the ease of switching employees as viewed by employers. Within the substantive dimension, specificity is conceptualised through similarity and the accessibility of skills. Similarity refers to a situation when there is a large cluster of occupations that rely on similar skill sets. If this is the case, workers in these clusters have substantively general skills as they can change jobs with relative ease.

Accessibility of skills refers to how easily an individual may match a particular skill set. This idea is heavily rooted in the idea of depth of skill (i.e. the necessary proficiency level).

Table 1. Specific and general skills: dimensions and conceptualisations.

Dimension	Source of specificity	Conceptualisations
Substantive	Skill – sets acquired in education, training or through learning-by-doing.	Similarity – the number of other occupations that rely on similar combinations of skill – sets
		Accessibility – depth (level of mastery) and breadth (number) of skills used to perform tasks in occupation
Economic	Labour market frictions and institutions, firms' strategies, structure of supply and demand of regional labour markets	Portability of skills – ease of changing employers
		Replaceability of skills – ease of changing employees

Source: own elaboration

To aid in the empirical measurement of these four concepts, we assess the strategies found in the literature as well as propose and implement our own approaches. In the economic dimension we empirically measure portability and replaceability by using the European Social Survey carried out in 2010. It includes questions on portability ("How difficult or easy would it be for you to get a similar or better job with another employer if you had to leave your current job?") and replicability "How difficult or easy would it be for your employer to replace you if you left?"), that are not found in more recent waves of the survey. The empirical analysis covers all countries included in the ESS 2010 survey (i.e. 27 European countries and Israel).

On the substantive dimension, we empirically measure similarity and accessibility by using a novel approach based on the O*NET database. The O*NET database is used for the analysis as it provides an extensive overview of skills that are used in over 1,000 occupations, as well as indicates how frequently these skills are used and what the necessary level of proficiency is for each occupation. Hence, this provides the information necessary to estimate, in a broad sense, the breadth (i.e. amount of different skills) and depth (i.e. the necessary level of proficiency) of skills needed for each occupation. Differences in skill sets used provide the basis for estimating the similarity and accessibility of occupations.

Lastly, the multi-dimensional conceptualisation and empirical results provide a number of theoretical insights for three academic debates. First is related to the types of workers, who are more likely to demand more generous social insurance (Iversen and Soskice, 2001; Iversen, 2005). Second is about the types of skills that facilitate adjustment to technological and economic shocks (Lamo, Messina, and Wasmer, 2011; Mason et. al. 2018). Third is related to the conditions under which firms are willing to invest in the training of employees. The results indicate that the proposed conceptualisations provide a well needed clarification for the established academic literature on skills, which at times might seem contradictory.

The rest of the paper is structured along the two dimensions of skill specificity. We start with the substantive and then move to the economic dimension. Each section discusses conceptualisations, methods, and results of empirical measurements, as well as implications for theoretical debates. The last section concludes and outlines implications for further analysis.

Substantively specific skills

Substantive conceptualisation is based on the premise that the level of specificity depends on the types of skills acquired in education and training or gained as part of learning-by-doing. If a skill set is a requisite for performing work in a large number of occupations/sectors, then it is more general than the one that is useful only in a single occupation and/or sector. In this regard, the literature offers two approaches to conceptualisations of why and how some skills are substantively specific or general. First, we present and discuss the relative merits of the two approaches. Second, we propose a method for measuring substantive skill specificity of occupations in terms of similarity of skill sets used as well as the breadth and depth of skills. We conclude the section by discussing the implications of conceptualisations and measurements of substantive skill specificity.

Conceptualisations of skills

The most widely used approach holds that, on the one hand, specific skills are obtained in vocational education and training (VET), which provides skills that are directly relevant for particular occupations and industries (Krueger and Kumar (2004), Cusack et al. (2006), Busemeyer (2009), among others). The main assumption of this approach is that graduates of VET cannot access jobs beyond the occupations for which they received training, while others cannot access the jobs that require VET qualifications. On the other hand, general skills are obtained as part of academically based education. Since it provides a broad range of competences, graduates can easily find jobs across multiple industries and occupations. Somewhat similarly, Konings and Vanormelingen (2010), Barmbry et al. (2012), and others argue that skills become increasingly specific the longer the employee stays with the same firm. Conversely, short tenures provide opportunities to acquire multiple skills as part of learning-by-doing in multiple firms, which leads to more transferable skill sets. Accordingly, skill specificity could be defined on the basis of type of acquired qualifications and length of tenure.

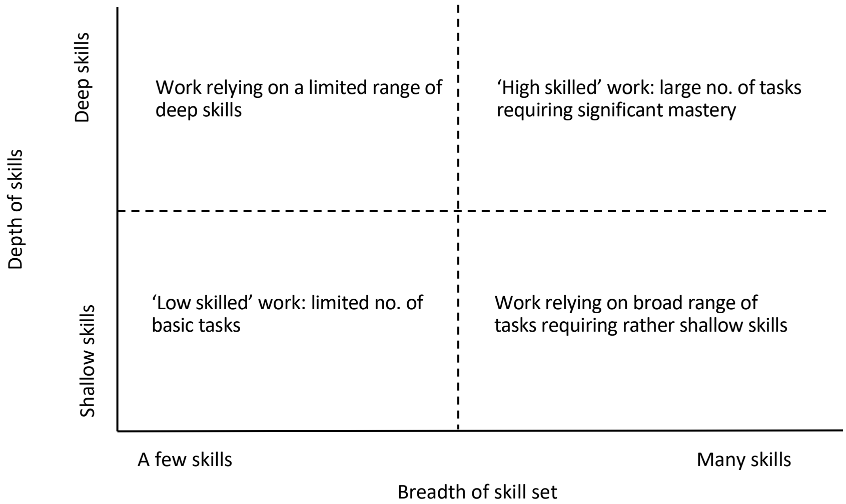
However, the argument that the type of education and length of tenure represents the source of skill specificity has a number of limitations. First, empirically, the link between the type of education and skill specificity does not always hold. On the one hand, there are significant cross-national differences in the curricula and the design of VET systems. For example, some provide skills for a narrowly conceived occupation, while others seek to develop a relatively broad range of skills (Busemeyer, 2009; Streeck, 2011). On the other hand, a large number of programmes at higher levels of academic education lead to very concrete occupations. Examples include graduates from medical, business, engineering, law, and similar programmes. Second, conceptual distinctions between different types of education are rather blurred. The argument that VET graduates have specific skills because they cannot access other occupations is problematic since the same holds true for most higher education graduates, e.g. studies in social sciences and humanities do not provide direct access to careers in engineering. Similarly, the academic education provided by primary and secondary schools typically does not provide access to jobs requiring VET or tertiary education. Third, the assumption that long firm-tenure fosters the acquisition of specific skills is also problematic. The literature (e.g. see Lazear, 2003) has systematically failed to identify any non-trivial examples of skills that could be relevant only for a single firm.

Hence, an alternative conceptualisation has been proposed by a skills weight approach (Lazear 2003). It is based on the assumption that jobs typically include multiple tasks and the successful performance of each task requires a set of skills rather than a single one (Martinaitis, 2014). Hence, each skill is general in nature, i.e. there are no firm-specific skills, but the uniqueness of the combination of skills used to perform work and the weight put on each skill make them specific. For example (cf. Lazear, 2003), a person working with tax optimisation software needs programming skills as well as a knowledge of the tax system. Though both of these skills individually are quite general (i.e. many firms rely on expertise in taxes and programming), their combination makes them specific. That is, if a person left his or her current job, it would be difficult for him/her to find another one that utilises both of these skills to the same extent. This suggests that occupations can be viewed in terms of combination of skills that require varying levels of depth. The latter refers to the level of proficiency in a particular skill. Accordingly, each occupation can be expressed through the sum of depths λ of all required skills, i.e., $\sum_{n=1}^{N} \lambda_n$.

The skill weights approach implies that there are two possible conceptions of skill specificity. First, occupations that rely on a unique combination of skills could be considered as relying on specific skill sets. Workers within these occupations cannot easily move to other occupations due to incompatible skill sets. Furthermore, such occupations are also inaccessible to outsiders due to the unique combination of required skills. Importantly, skill specificity in this sense refers only to difficulties in changing occupations, but remains silent about the difficulty of changing jobs within the same occupation. This is because the latter, to a large extent, depends on the level of labour market demand for particular occupations (see economic conceptualisation of skills in the next section).

Second, substantive skill specificity could also be understood in terms of the accessibility of occupations. The intuition here is that individuals can move between rather unrelated occupations by deskilling, i.e. foregoing depth and/or breadth of previously held skills. To illustrate this, Figure 1 maps skill sets along two dimensions: breadth and depth of skills. It is possible to de-skill by moving from the top to the bottom (losing depth of skill) or from the left to the right (losing breadth of skill). However, the reverse does not hold true: occupations requiring significantly deeper and/or broader skill sets are not easily accessible to others.

Figure 1. Types of substantive skills



Source: own elaboration

Measuring substantive skill specificity: which occupations rely on specific skills?

Which occupations rely on specific skills according to the two above discussed conceptualisations, i.e. similarity of skill sets and accessibility of an occupation? To answer this question, this sub-section outlines the proposed methodology for measuring substantive skill specificity.

Previous studies have proposed a variety of ways for measuring both the depth and breadth of skills. Regarding the breadth, Geel, Mure, and Backes-Gellner (2010) used the BIBB/IAB Qualification Survey[i] to estimate which skills employees in different occupations use in carrying out their work and which provided skills' profiles for occupations. Leping (2009) used online job portals to estimate which skills are considered essential across job ads for a range of occupations. Ingram and Neuman (2006) estimated the breadth of skills by analysing the key characteristics of occupations as described in the Dictionary of Occupational Titles (DOT). Reiter-Palmon et al (2006) proposed using the O*NET database, which is an evolution of the DOT, and an expert opinion to estimate skills. The O*NET database was developed by the US Department of Labour and it describes around 1,000 occupations. They used the O*NET database to find which general skills are only used for specific tasks. In this way, they managed to find what skills are, as they call them, occupationally specific, and how many of those skills employees from each occupation have to know. Regarding depth of skill, it is predominantly measured through proxies, such as education level (e.g. see Murray and Steedman (1998), McKnight (1999)) or tenure and wage differentials (Elias and McKnight, 2001). However, these proxies do not provide sufficiently fine-grained insights into the depth of specific skills across occupations.

Considering the pros and cons of the previous estimates of the breadth and depth of skills, as well as a want to alight closer to the Lazear (2003) idea of skill specificity, we propose an approach based on the O*NET database. This is selected because it provides very detailed information on skills, abilities, and the knowledge required for each occupation as well as estimates of the extent to which any one particular skill is important for each, and what level of proficiency it requires. The 24th version of the O*NET database is used in the analysis, which was released in August 2019. The O*NET database is used to estimate the breadth and depth of skills for each occupation through a six-step process.

First, we extracted relevant information from the O*NET database by using a web scraping algorithm. This included the estimated level of the importance and proficiency of skills. Second, we input missing values. For some occupations, data on the importance and/or level of utilisation of a particular skill was missing. Gaps in the data were filled using a MICE (Multiple Imputation by Chain Equations) algorithm. This algorithm was chosen as it is a robust approach that imputes missing data by looking at other variables that correlate to the variables with missing observations. In the majority of cases, the algorithm imputed very low values, thus implying that the data was missing, as the skills were not heavily used by occupations.

Third, we estimated the depth of each skill of each occupation by multiplying the importance of each skill with the level of necessary proficiency. This allowed accounting for a different level of utilisation of each skill in different occupations. The result of the calculations is the depth of each skill for each occupation found on the O*NET platform.

Fourth, we grouped similar skills. One of the issues with using a skill-based approach is that some skills heavily correlate with one another (Ingram and Neuman, 2006). For example, the persuasion skill heavily correlates with negotiations skills (Pearson's correlation coefficient over 0.88). Hence, in order to prevent double counting, we used a cluster analysis to group similar skills. We used clustering analysis rather than the conventional O*NET grouping (e.g. basic skills, complex problem solving skills, etc.), as the latter is not applicable for our research. That is, the O*NET approach often bundles together skills that do not correlate with one another (e.g. O*NET classifier adds mathematics and active listening to the same skill group, basic skills).

The fifth step focused on an aggregation of the elements of each group into a single metric. After finding which skills are similar to one another and grouping them, we estimated new variables that represented each of the created groups. The new variables were created through a dimension reduction technique called principle component analysis (PCA). PCA is a statistical method that takes highly correlated variables and combines them together by creating new variables. For example, let us assume that during the previous step we found that persuasion, active listening, and active learning heavily correlate with one another. In this case, PCA would take the relationships between variables and create completely new variables called principle components (PC). The number of principle components is the same as the number of variables that were used to create them. However, the first principle component has combined information about the three variables used. For example, it could be that the first PC would explain 80% of the information found in the three variables, the second 15% and the third 5%. This means that the information that made the three variables correlate in the first place is represented in the first PC. In addition, as PCs do not correlate with one another at all, each PC represents a unique aspect of the variables contained in each group.

Six, after transforming each skill inside of a group into a principle component, their elements are summed together using information explained by each principle component as weights to create the depth of skill measure (λ) f. This can be represented through the following equation:

$$\lambda_i = \sum_{k=1}^{K} \alpha_k \omega_k \quad (1)$$

Here, λ is the depth of skills, i is the occupation, k is the principle components, α is the element of the principle component, and ω measures how much information the selected principle component has about the original skills. As part of the last step we also estimated skill profiles of occupations. More specifically, similarly to Geel, Mure, and Backes-Gellner (2010), we created a vector of numbers (skill profile) that shows how important each skill group is for each occupation found on the O*NET dataset. Each profile represents skills used by an average employee in each occupation.

The obtained skill profiles provide information for a comparison of similarities between occupations. Therefore, we estimated the Euclidian distance between occupations, whereby each skill profile was represented as a point in an N-dimensional space, where N refers to the number of skills that are used to create the skill profiles. The distance was estimated by calculating the straight-line distance between said points.

Figure 2 below provides the results of the analysis of occupations that rely on similar skill sets (full list of occupations can be found in the Appendix). Similarity means that the Euclidian distance (according to the skill profiles) between two occupations was 0.1 or less. The width of the line in Figure 2 indicates the strength of the connection (i.e. a broader width suggests higher similarity and vice versa), while the distance between nodes was selected arbitrarily in order to ease the interpretation of the results. On the one hand, the results indicate that blue-collar and lower skilled white-collar occupations (i.e. major occupational groups from 9 to 4) have very similar skill sets in general, as can be seen by the large clustering of such occupations.

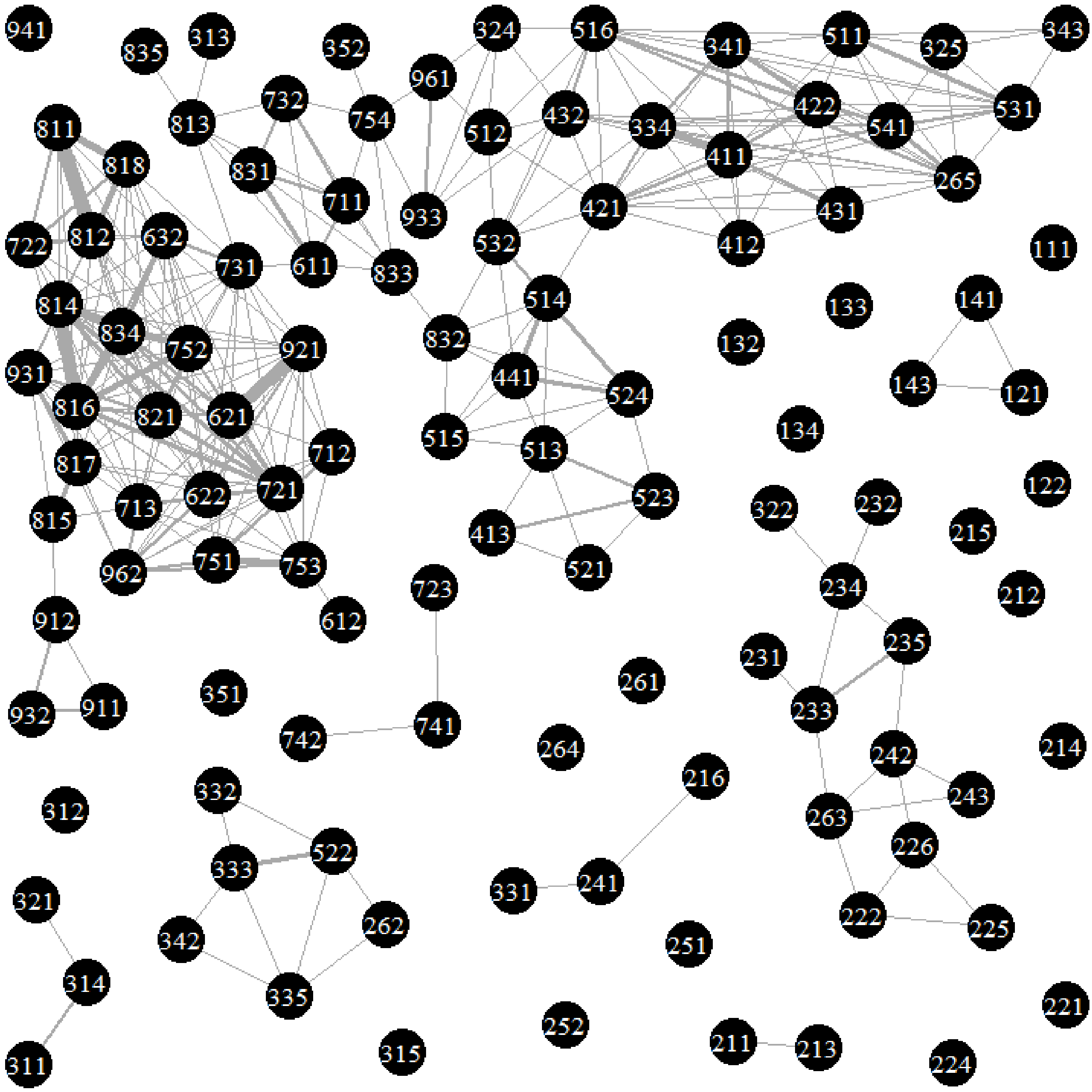
On the other hand, a majority of high skilled white-collar occupations (i.e. (1) legislators, senior officials and managers, (2) professionals, (3) technicians and associate professionals) form only small clusters or are disconnected from one another altogether. Regarding clusters, the two prominent ones are a small cluster of technicians and associate professionals and a cluster of professionals and associate professionals. The first clusters are predominantly comprised of business and administration associate professionals (332, 333, 335), but also include shop salespeople (522), other health professionals (262), and sports and fitness workers (342). Though this cluster at first glance seems odd, but it can be explained by the fact that all of these occupations heavily interact with people.

The second cluster first of all indicates that the skill set of different teaching occupations (e.g. 231 – university teachers, 232 – vocational education teachers, 233 – secondary education teachers, etc.) is quite similar, as well as the general skill set of these occupations is also closely related to other social occupations (e.g. 322 – nursing and midwifery associate professionals, 242 – administrative professionals, 263 – social and religious professionals). However, apart from these clusters, other higher skill occupations are relatively disconnected, implying that these types of jobs require skill sets that are quite unique.

To test whether the above approach has some external validity, we checked to what extent it could correctly predict the mobility of workers between occupations. The Eurobarometer 2005 mobility and migration survey provides information on the previous and current jobs of all respondents in an ISCO-88 level two format. The 2005 mobility data was used as we could not find a more up to date and large enough data set on mobility between occupations. In total, the data on mobility covers 25 different occupations (our analysis excluded job changes within the same occupation). To compare our results to the survey, the data was converted to an ISCO-88 level occupational classification. The two data sets were compared through a three-step process.

First, we estimated to which three occupations individuals from each of the 25 different occupations moved the most frequently. Second, using our approach we estimated three occupations that are closest to each of the 25 occupations. Third, we compared how well our approach could predict occupational changes. The match between the two was 30%. In addition, by increasing the number of occupations from three to five, the match increased to 42%. This implies that the proposed approach of using skill profiles and the distance between them is quite accurate in predicting labour mobility.

Figure 2. Social network of occupations (expressed in ISCO-08 level 3) based on skill profiles



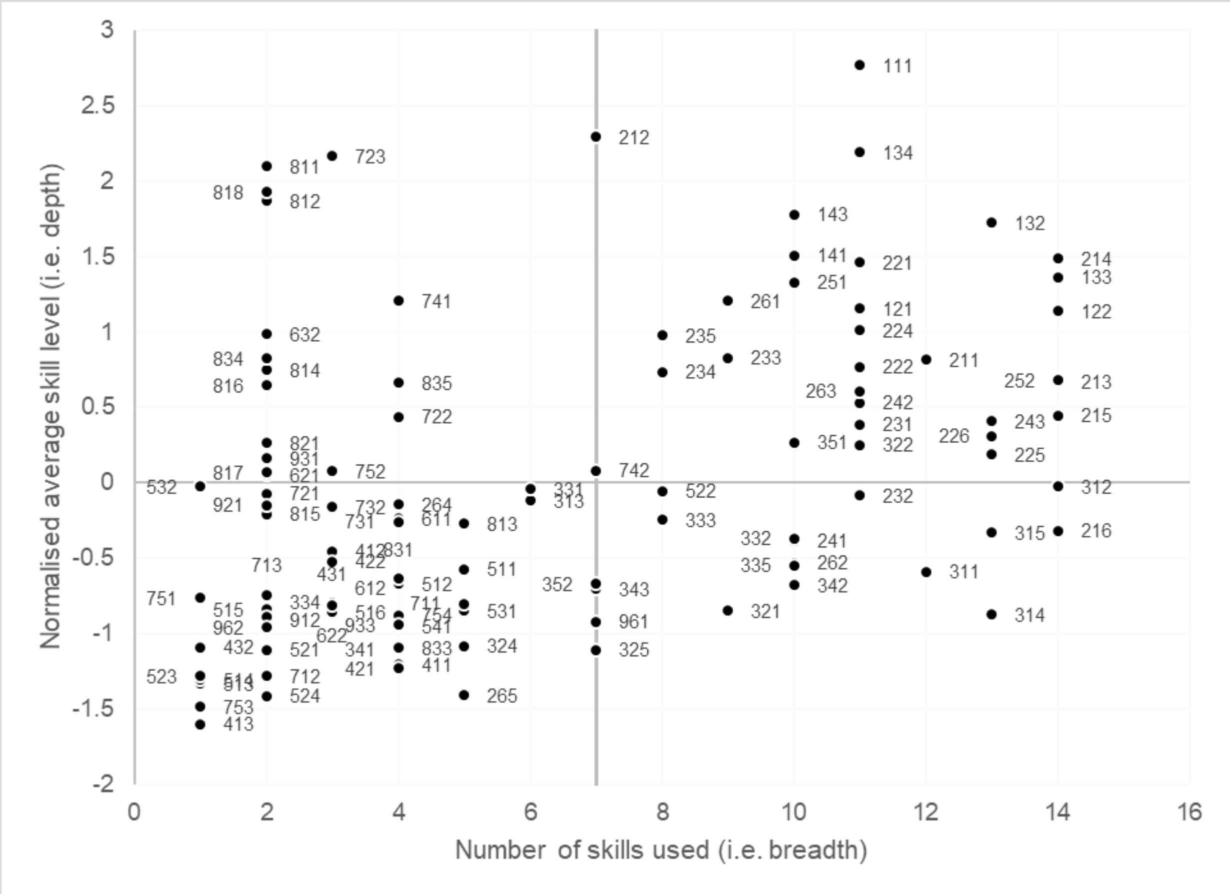
Note 1: For the data set with the distance measures that was used to create the social network, see the following link: *http://www.visionary.lt/wp-content/uploads/2019/09/Occupation-distance-matrix.csv*

Note 2: For the full list of ISCO-08 level three occupations see the Appendix

Source: own analysis based on O*NET

The substantive specificity of skills can also be assessed in terms of depth and number of skills required in each occupation. Number of skills used by occupations was estimated by, first, transforming the data into a standard normal form and, second, counting how many skills for each occupation have a depth of over zero. Normalised average skill level is the mean of the depths of skills that were above the zero threshold (i.e. the same skills that were used to estimate the number of skills). Figure 3 provides rather intuitive results. Highly skilled white-collar occupations require high depth and a breadth of skills, whereas the reverse holds true for a number of low skilled white- and blue-collar occupations. Most of the occupations belonging to the major group ‘Plant and machine operators and assemblers’ are characterised by high depth, but limited breadth. Limited depth, but high breadth of skill sets characterise occupations belonging to the major group ‘Technicians and associate professionals’.

Figure 3. Depth and breadth of skills used in occupations



Note: The installation skill was removed from the analysis as it is only used by a very small number of professions, which created a bias in the results

Source: own compilation based on O*NET

Which occupations rely on substantively specific skills? To facilitate comparison, Table 2 provides aggregated data for major groups of occupations. Similarly, to the more detailed data above, it suggests that high skilled white-collar occupations rely on specific skills in the sense that particular combinations of skills are not widely shared across occupations (average number of connections is small). As a result, such workers cannot easily change occupations while maintaining a full skill set. Nevertheless, high depth and breadth of skill sets allows for occupational mobility through de-skilling, i.e. losing some depth or breadth of skills. The reverse, however, is not true – jobs in these occupations are not easily accessible to ‘outsiders’ who do not have the required depth and breadth. Hence, in the face of technological or economic shocks, occupations in the North-East quadrant of Figure 3 are particularly vulnerable to skill mismatches.

Low skilled white-collar and blue-collar occupations rely on substantively general skills: there is a large number of similar occupations that share similar skill sets. However, limited depth and/or breadth of skills limit occupational mobility beyond the clusters of occupations with similar skill sets. Furthermore, the low skilled cannot easily access occupations that can be found on the North-West quadrant of Figure 3 (predominantly ‘Plant and machine operators and assemblers’) and South-East quadrant (predominantly ‘Technicians and associate professionals’).

Table 2. Summary statistics for occupational groups

Major groups of occupations	Average number of connections in the Social Network*	Average normalised depth of skills (standard deviation)	Average breath of skills (standard deviation)
1. Legislators, senior officials and managers	0.75	1.7 (0.56)	11.75 (1.67)
2. Professionals	1.92	0.55 (0.75)	10.69 (2.72)
3. Technicians and associate professionals	2.95	-0.51 (0.43)	8.63 (3.28)
4. Clerks	8.63	-0.99 (0.41)	2.71 (1.25)
5. Service workers and shop and market sales workers	7.46	-0.87 (0.45)	3 (2.12)
6. Skilled agricultural and fishery workers	10.6	-0.17 (0.75)	2.8 (0.84)
7. Craft and related trades workers	8.36	-0.18 (0.98)	3.21 (1.63)
8. Plant and machine operators and assemblers	9.86	0.53 (0.99)	2.69 (1.11)
9. Elementary occupations	6	-0.62 (0.49)	3.17 (2.04)

* Includes connections to the same and different occupational groups

Source: own compilations based on O*NET

Substantive skills specificity: theoretical implications

Substantive specificity of skills is the main independent variable in discussions regarding workers’ demand for social insurance and obstacles to labour reallocation in the face of structural economic change. The above discussion offers two types of implications for these debates: regarding the measurement of substantive specificity of skills and causal mechanisms.

The dominant view holds that graduates of vocational training and workers within skilled blue-collar occupations (the main destination of vocational training graduates) rely on deep and narrow skill sets, while white-collar occupations rely on broad and shallow skills. Furthermore, it is assumed that deep and narrow skills imply difficulties in redeploying one’s skill set across occupations. For example, the Varieties of Capitalism (VoC) approach (Hall and Soskice, 2001, Estavez-Abe, et. al. 2001) argues that the German vocational training system coupled with long tenures represents an ideal type of industry-specific skills formation systems. The general skills formation system is represented by the US that is characterised by a predominance of academic education and short tenures. Somewhat similarly, the Asset Theory of Social Policy Preferences (ATSPP) relies on a measure of relative skill specificity (Iversen, 2005), which suggests that a major occupational group ‘Plant and machine operators and assemblers’ have the most specific skills, while highly skilled white-collar occupations rely on general skills.

Our analysis supports the claim that skilled blue-collar occupations (predominantly 'Plant and machine operators and assemblers') rely on deep and narrow skills. However, this does not automatically imply difficulties in changing occupations. In fact, the largest cluster of occupations with similar skill sets is within the major group 'Plant and machine operators and assemblers. This is in line with Streeck (2011) who argued that skilled plant and machine operators have substantively deep skills that are very adaptable within given working environments. We further find that skilled white-collar occupations rely on deep and broad skill sets and face limited options for cross-occupational mobility, since the number of occupations with a similar combination of skills is rather limited. In this regard, highly skilled white-collar occupations rely on substantively more specific skills than highly skilled blue-collar occupations. For example, our results suggest that it is more difficult for doctors to become engineers than for wood processing operators to become machinery assemblers, while VoC and ATSPP argue to the contrary.

The conceptualisation of substantive skill specificity also has important implications for the causal mechanisms of theories explaining workers' demands for social insurance and obstacles to labour reallocation. The first group of theories argue that workers with substantively specific skills are vulnerable, since they have a limited number of outside options. For instance, VoC argues that specific skill formation systems critically depend on the availability of employment and unemployment protection, which provides insurance in the case of economic or technological shifts. Similarly, ATSPP argues that a specificity of skills in the labour force can have an effect on voter preferences regarding their level of social protection (Iversen and Soskice, 2001; Iversen, 2005). Voters with specific skills prefer higher levels of social protection, which provides insurance against job loss.

Our findings shed doubt on these causal mechanisms. On the one hand, our analysis points to a different conclusion regarding skill specificity – it is the highly skilled white-collar occupations that should face the largest challenges in transferring their skill sets across occupation. However, this does not imply that we should expect managers and professionals to demand high social insurance. In the worst-case scenario, they can de-skill by taking up jobs requiring lower breadth or depth of skills. This option is not available for workers in low skilled white- and blue-collar occupations. On the other hand, the likelihood of finding another similar job depends more on time- and place-specific labour market conditions and institutions (see the next section on the economic dimension of skill specificity) rather than a similarity in skill sets across occupations (substantive skill specificity). There might exist a correlation between social policy preferences and occupations: workers with shallower and narrower skill sets may prefer higher redistribution, given lower incomes and more precarious working conditions. This, however, has little to do with the substantive specificity of skills.

Another group of relevant academic debates concerns the adaptability of workers and their skill sets in the face of a structural transformation of the economy. One of the most pronounced shifts in a short period of time occurred in the '90s in Central and Eastern Europe (CEE). This included a transition from a planned to a market economy, a rebalancing of the economy from agriculture and industry towards services as well as an upgrade of technology and a revamping of work organisation processes. Literature on the economics of transition argues that former planned economies in the CEE inherited highly specific skills, which were acquired as part of highly specialised vocational training and long tenures within the same firms (Micklewright, 1999; Boeri, 2000; Rashid, Rutkowski and Fretwell 2005). This diminished the capacities of the labour force to adapt to the economic restructuring brought on by a growth in services and contraction in agriculture and industry (Lamo, Messina, and Wasmer 2011). Hence, the transition resulted in high social costs as indicated by persistently high levels of inactivity and unemployment during the first decade of transition (Jeong, Kejak, and Vinogradov 2008). This led to the conclusion that specific skills (namely, workers with vocational skills in manufacturing with long tenures) impede economic restructuring.

Our findings challenge the above conclusion. Transition resulted in a shift of demand from agriculture and manufacturing (that typically employ workers with deep and narrower skill sets) to services, which rely on broader skill sets. This explains the high social and economic costs of restructuring: new jobs were not accessible because the 'inherited' skill sets lacked the necessary breadth. This should not, however, lead to the conclusion that deep and narrow skill sets always inhibit restructuring. That all depends on the trajectory of the change. On the one hand, if restructuring implied a move towards high-value-added manufacturing and the labour force was endowed with broad and shallow skill sets, workers would similarly face difficulties in accessing jobs requiring deep and narrow skill sets. On the other hand, the inherited types of skill sets could prove to be an invaluable asset, when restructuring follows the pathway of related variety: a recombination of 'inherited' assets to new productive uses (e.g. Martin, 2010; Boschma and Frenken, 2006; Hassink, 2007). This trajectory is characterized by a diversification of the structure of the economy towards new sectors or products that rely on existing region-specific resources and capabilities, such as networks of suppliers, skills of the labour force, etc. A revival of the automotive industry in Hungary, Poland, Czech and Slovak Republics would hardly have been possible without inherited skills (Radosevic and Rozeik, 2005)

The above conceptualisation and estimates of substantive skill specificity also offer two rather intuitive insights on skill mismatches during structural economic change. First, the largest skill bottlenecks are likely to appear for highly skilled white-collar occupations: they are not accessible to others lacking the necessary depth and breadth of skills. Second, low skilled occupations can only move within the clusters of similar occupations, while the highly skilled can move across occupations by de-skilling. Hence, in the face of structural economic change, workers in low skilled occupations are the most vulnerable to the risk of unemployment and dropping out of the labour market. These trends were clearly pronounced during the transition of the CEE countries from planned to market economies. The low skilled workers were the most likely to exit the labour market (Lamo, Messina, and Wasmer, 2011), workers with 'inherited' high skills took up fewer demanding jobs and new entrants with higher education qualifications entered highly skilled occupations in emerging sectors (Kertesi and Köll 2001).

Economic dimension of skill specificity

Economic dimension refers to the ease of switching jobs (as viewed by employees) and changing workers (as viewed by employers). It depends on labour market frictions, institutions, the structure of demand and supply in regional labour markets, etc. In contrast to substantial dimension, skill sets are not treated as general or specific *per se*. If the number of firms relying on a given set of skills is small and access to other labour market segments is constrained, then substantively general skills are very specific in an economic sense. Conversely, specific skills in a substantive sense may be general in the economic sense if regional labour markets are characterized by a high concentration of firms relying on that particular set of skills. The economic dimension of skill specificity encompasses two conceptualisations: portability and replaceability of skills. The next two subsections discuss these conceptualisations and outline their conceptual implications.

Portability of skills

Portability of skills refers to the ease of changing jobs as viewed by employees. The level of portability depends on two groups of factors: (i) the level and structure of demand, which affects the number of outside options an employee has and (ii) labour market frictions and institutions, which affect the costs of moving between jobs.

The first group of factors – level and structure of demand – affect the portability of skills directly: the larger the number of firms hiring workers with a given skill set, the higher the portability. This depends on the economic cycle: portability of skills declines during downturns and increases during upswings as the number of hiring firms increases. Furthermore, the portability of skills depends on the concentration of firms that rely on a given skill set. This closely follows the spatial agglomeration (Brunello and Gambarotto, 2007; Bellmann, Hohendanner, and Hujer, 2010) and market thickness (Lazear, 2003) arguments: the larger the density of (similar) firms in a region, the higher the portability of the skills of the labour force.

The second group of factors – labour market frictions and institutions – affect portability of skills by altering the costs of changing jobs. In a perfectly competitive labour market there are no costs of switching jobs and workers are paid a wage corresponding to their productivity. However, search and matching costs and information asymmetries regarding the productivity of an employee can significantly increase the costs of switching jobs (Acemoglu and Pischke 1998|1999). Labour market institutions can also indirectly affect the portability of skills. Coordinated wage bargaining at the industry level sets the standard wage levels across firms for the similar occupations, which reduces incentives for poaching and switching jobs (Estavez-Abe et. al., 2001). Similar effects can be achieved through implicit agreements among firms to restrain from hiring each other's employees, as documented by case studies from Japan (Streeck, 2011). Strict employment protection legislation increases the costs of firing and makes firms more cautious when taking hiring decisions, which again increases the costs of switching jobs (Scarpetta, 1998).

Replaceability of skills

While portability of skills refers to the ease of changing employers as viewed by employees, replaceability of skills encompasses ease of replacing employees as viewed by employers. Replaceability is high when a firm 'purchases' skills in a perfectly competitive market where each employee can be easily replaced by another. Conversely, if the current workers are monopolistic providers of skill to a firm, then replaceability is low. Replaceability of skills depends on two groups of factors.

The first group refers to the size of the pool of workers with a given skill set. On the one hand, this depends on the overall supply of relevant skills, i.e. the level of unemployment, extent to which education and training institutions provide relevant skill sets, and the concentration of industry relying on similar skills. On the other hand, the size of the potential pool of workers depends on the magnitude of barriers for accessing jobs in question. The barriers include obstacles to the geographic mobility of the labour force, length of required training, as well as the existence of formal qualification barriers, such as licenses to practice law, civil engineering or medicine (Streeck, 2011).

The second group of factors refers to the extent to which performance of work relies on tacit or codified knowledge. If performance of work relies on the tacit skills of a worker, replaceability is likely to be low. Since tacit knowledge is embodied within a worker, separation with the firm inevitably leads to a loss of productive value (Goldthorpe 2000, p. 213). Furthermore, since tacit knowledge is not codified, it cannot be easily acquired in an academic setting, but rather is obtained during long apprenticeships with a 'master' and as part of learning-by-doing (Balconi 2002). This implies that it takes long periods of time to develop the skills and knowledge necessary for such jobs and workers cannot be trained in large numbers.

Conversely, if the knowledge needed to perform work is codified, the replaceability of workers is likely to be high due to several mechanisms. First, the codification of knowledge allows for the breaking down of work into small discrete tasks that have to be executed following clearly established procedures. The embodiment of knowledge within the work organisation processes implies that workers do not need to understand the full cycle of production, but rather carry out a small number of tasks in line with pre-defined instructions. As a result, such workers can be easily trained, which leads to higher replaceability (Brougham and Haar, 2017). Second, to the extent that codified knowledge is embedded within work organisation processes and technology, the loss of productive value in the case of separation of workers is lower because the knowledge stays within the firm. Lastly, the codification of knowledge also allows for an automation of routine work (Autor, 2015). In this regard, workers are replaceable by machines.

One could argue that the level of skill (in a substantive sense) affects both of the above groups of factors, i.e. the size of the pool of workers and a reliance on tacit knowledge. For example, Goldthorpe (2000) argued that unskilled workers, who 'sell' only their physical capacities, constitute a fairly homogenous pool of labour and, thus, are easily replaceable. Therefore, Goldthorpe (2000) suggested that workers in highly skilled occupations (groups 1-3 according to the ISCO classification) possess non-replaceable skills, while low skilled white-collar and blue-collar workers are highly replaceable.

Although low skilled workers could be more replaceable in some cases, the links between the substantive contents of skills and replaceability need not always hold. The size of the pool of workers with relevant skill sets depends on macroeconomic conditions, the characteristics of education systems, the legal regulation of occupations, etc. Furthermore, the extent to which a performance of work relies on codified knowledge and combinations of skills used to create value essentially reflect firms' strategies. These depend on the availability of technology (Balconi, 2002), relative costs, an abundance of skills (Acemoglu 2002), and product market orientation (Brougham, Haar, 2017; Kotha, 1995). To illustrate this, consider two cases.

First, consider different strategies of firms in the catering sector. The fast food chains employ replaceable staff, because the provision of standardised service relies on knowledge embedded within the work organisation processes and technology (Brougham, Haar, 2017). This can be contrasted with fine-dining restaurants that provide customised service (e.g. the menu depends on local produce) by relying on tacit skills acquired through apprenticeships, learning-by-doing, etc. Hence, strategic decisions regarding product market orientation within the same sector have significant effects on the level of the replaceability of skills.

The second example illustrates changes in skill requirements due to technological modernisation in the steel sector as discussed in Balconi (2002). Up until the 1970s – 1980s, electric furnaces were used to produce steel. The sensors and instruments for rapid chemical analysis were not widely diffused. Therefore, the operators of machines were tasked with measuring the temperature and chemical structure of liquid steel by observing its visual characteristics (e.g. colour) and taking necessary corrective actions. Such work did not require formal qualifications beyond literacy and numeracy, but it took five years of practice and experience to do the job well. In this regard, the replaceability of a worker was low. In the 1980s, the production cycle was automatized: software controlled the smelting terminals, sensors made the necessary measurements that were then automatically analysed. As a result, the content of the work of operators significantly changed: they were tasked with inputting the correct parameters into software, analysing the results of measurements and approving corrective decisions suggested by the software. Since the knowledge was codified, entry to the occupation required approx. five years of formal education in technical colleges and one year of practice. As a result, the automatisation and codification of knowledge resulted in higher requirements for formal skills and a higher replaceability of workers – firms can now draw on a larger pool of trained workers and need to invest less in on-the-job training. This stands in contrast to the above discussed association between low skills and high replaceability.

Both examples illustrate that the replaceability of skills is not predetermined by the substantive contents of skills, i.e. these are conceptually different categories. In the case of the catering industry, strategic decisions to standardise and codify lead to higher replaceability, even though the staff in fine dining and fast food restaurants work in the same occupations. In the case of the steel industry, technological advancements resulted in higher requirements for formal education and also a higher replaceability of workers.

Portability and replaceability of skills: empirical measurements

The above sub-sections argued that portability and replaceability of skills refer to two distinct concepts and these are not related to the substantive contents of skill. This sub-section aims to demonstrate that these concepts are also distinct empirically. One of the key challenges in doing so refers to a lack of established empirical strategies for measuring the two concepts.

Most past attempts to measure the portability and replaceability of skills focus on the characteristics of occupations. Iversen and Soskice (2001) and Iversen (2005) proposed an indicator of skill specificity (in a sense - of portability) based on the skill specialisation of each occupation and its share in the labour market. To capture the former, they used the hierarchical structure of the ISCO classification: the larger the number of detailed occupations covered by the sub-group of an occupation, the higher the specificity. The latter is calculated as the share of workers employed in a sub-group of the occupation. Absolute skill specialisation is obtained by dividing the share of detailed occupations in the sub-group of an occupation by the share of labour force employed in that sub-group. This indicator then covers two distinct dimensions of skill specificity: substantive dimension is covered by the skill specialisation of occupations (the number of detailed occupations in a hierarchically higher sub-group) and the portability of skills in the economic dimension (the share of employment in the sub-group of occupations). Given that this indicator covers portability as well as specificity in a substantive sense, we cannot use it.

On a similar note, Emmenegger (2009) focused on occupations to measure skill replaceability. Following Goldthorpe (2000) Emmenegger argued that persons employed in highly skilled white-collar occupations possess non-replaceable skills, while workers in semi-skilled and unskilled occupations are highly replaceable. Such operationalisation of skill replaceability is problematic, given that it focuses on skills in a substantive sense, rather than social and economic conditions that affect replaceability. Alternatively, some academics used a subjective perception of workers to find how easily they could find a similar job (portability) and how easily their employer could replace them (replaceability). For example, Iversen and Soskice (2001), in addition to the portability measurements discussed above, also used answers to the following question in the International Social Survey Programme: ‘If you were looking actively, how easy or difficult do you think it would be for you to find an acceptable job?’. The main benefit of this survey-based approach is that the estimates of the respondents could potentially cover both the number of outside options and the costs of changing jobs. However, the estimates are inherently subjective, they may reflect respondents’ self-perception/optimism, and/or the amount of labour market information the respondents have. However, due to a lack of better alternatives, we also rely on subjective perceptions of workers regarding portability and replaceability of their skills.

We estimate portability and replaceability using the European Social Survey 2010. The 2010 version of the survey was selected as it contains two relevant questions: 'How difficult or easy would it be for you to get a similar or better job with another employer if you had to leave your current job?' and 'how difficult or easy would it be for your employer to replace you if you left?'. The survey was carried out in 27 European countries and Israel. For the analysis, all the countries in the survey were used.

As expected, the Spearman's correlation between the questions measuring portability and replaceability is very low (-0.135). Further analysis reveals that negative correlation is stronger for countries severely hit by the financial and economic crisis: here a significantly larger proportion of respondents argued that the portability of their skills is rather low while replaceability is high (see Figure 4). In line with theoretical expectations, this can be explained by the small number of hiring firms and large number of job seekers. On the other side of the spectrum we find Nordic countries that were not severely hit by crisis: here the respondents on average report lower replaceability and higher portability.

Figure 4. Average replaceability and portability of skills

Source: own calculations based on ESS 2010

We also tested whether portability and replaceability are related to substantive skill specificity, i.e. the number of occupations that rely on similar skill sets. The results in Table 3 suggest that there is a positive correlation between substantive specificity and portability as well as a negative correlation with replaceability. This could be due to some 'contamination' in the measurements. Perceptions of portability and replaceability could be influenced by both: the substantive specificity of skills as well as the structure of supply and demand, labour market frictions and institutions.

Table 3. Correlation between the number of connections and the subjective measure of portability and replaceability in each ISCO-88 level three occupations

	Portability: How difficult or easy would it be for you to get a similar or better job with another employer if you had to leave your current job?	Replaceability: How difficult or easy would it be for your employer to replace you if you left?
Substantive specificity: the number of other occupations that rely on similar combinations of skills – sets	0.415***	-0.287***

Notes: *** indicates statistical significance at 0.01. N = 100; Analysis carried out at ISCO-88 level three occupations. Spearman's correlation was used as the data is not normally distributed.

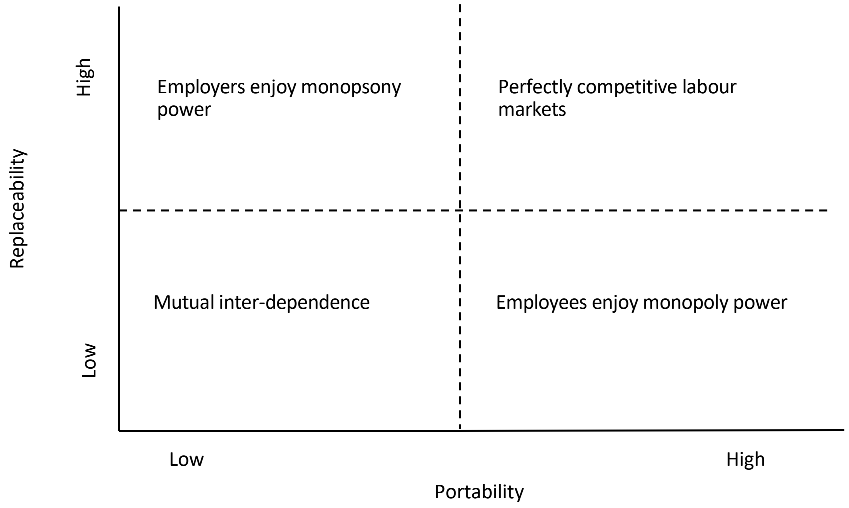
Source: own calculations based on ESS 2010.

Portability and replaceability of skills: conceptual implications

The analytical distinction between economic and substantive dimensions as well as portability and replaceability has implications for several academic debates. First, Becker (1964|1993) argued that due to the threat of poaching, firms will only invest in specific skills. The human capital literature, thus, implicitly assumed that substantive skill specificity matters and focused on the contents of training in explaining firms' investment decisions. However, Acemoglu, and Pischke (1999) demonstrated that firms can invest in substantively general skills if labour market frictions and institutions increase the costs of switching employers and effectively compress wages. This suggests that the debate on firms' investments in training should shift its focus from substantive specificity towards the portability of skills.

The second debate concerns workers' preferences for social insurance. In contrast to the literature, we did not find compelling arguments why workers with substantively specific skills would demand a higher level of insurance (see previous section). However, this can be explained by the different power relationships arising from different constellations of portability and replaceability. When both portability and replaceability are high or low, the power of employers and employees is symmetrical (see Figure 5). However, when highly replaceable workers face a limited number of outside options, employers enjoy monopsony power in the labour market. Within this power constellation we would expect workers to demand higher employment and unemployment protection.

Figure 5. The implications of portability and replaceability on employees – employer power relationships.



Source: own compilation

The third debate concerns the adaptability of the labour force in the face of a structural transformation of the economy. The economic conceptualisation of skill specificity points to the role of two factors affecting labour reallocation. First, as already well documented in the literature (e.g. see Krause and Uhlig, 2012; Holmlund, 2013; Donovan et al., 2018), labour market institutions can affect the pace of movement of labour from declining sectors/regions to growing ones. Second, a discussion on the replaceability of skills points to an interplay between exogenous technological or economic shocks and the strategies of firms. Firms facing skill shortages are likely to codify necessary knowledge and embed it within its work organisation processes and technology so as to increase the replaceability of workers. Conversely, if the pool of workers with the necessary skills is large, firms are likely to use it as a source of competitive advantage and rely more on the tacit rather than on codified knowledge. This argument has been already put forward in a number of studies. For example, Acemoglu (2002) argues that the shortage of artisans and a large influx of unskilled workers to the US at the beginning of the nineteenth century 'created profit opportunities for firms to exploit by introducing technologies that could be used with unskilled workers' (p. 12). In other words, the knowledge of artisans was codified and embedded within the work organisation processes and technology. Acemoglu further argues that technological progress since the mid-20th century has resulted in a growing demand for higher levels of skills, because an increasing supply of tertiary education graduates induced the development of skill complementary technologies. That is, firms changed their strategies so as to reap the profits offered by the ample supply of necessary skills.

Conclusions and implications

This paper argues that we need to move beyond Becker's (1964|1993) distinction between general and specific skills as being valuable to a large number or to only a few firms. This distinction under-defines the concept, which can lead to significant confusion. For example, a unique skill set such as proficiency in the Estonian and Russian languages, programming, and money-laundering regulations could be highly portable and easily replaceable in Tallinn, but not elsewhere. Is this a general or specific skill set in Becker's terms? To address the resulting theoretical and empirical confusion we proposed a new multidimensional approach for estimating skill specificity based on four dimensions: accessibility and similarity of skill sets as well as the portability and replaceability of skills. The former two refer to skills acquired by an individual (i.e. skills are substantively specific), while the latter two depend on the structure of labour market demand and supply, institutions, and firm strategies (i.e. on economic factors) that are time-and place-dependent. In this regard, the paper further supports Lazear's (2003), Streeck's (2011), and others' criticism on Becker's (1964|1993) dichotomy of skills, as well as highlights the need for a careful definition and use of concepts.

The introduction of multi-dimensionality has significant theoretical implications. We demonstrate that the long-standing explanations of firms' investment in training, demand for social insurance, and obstacles to a reallocation of labour in the face of structural economic change implicitly focused on the contents of skills, i.e. substantive skill specificity. However, the causal mechanisms of these explanations implicitly refer to economic factors behind skill specificity. This leads to significant conceptual confusion. Furthermore, a distinction between the dimensions and conceptualisations of skill specificity provide numerous new hypotheses that could significantly enrich our understanding of the above questions.

In line with the conceptualisation of substantive skill specificity, this paper proposed a novel approach for measuring the similarity of skill sets and the accessibility of occupations based on the depth and breadth of required skills. We find that high skilled blue-collar occupations rely on skill sets that are shared across a larger pool of occupations. This stands in contrast to the assumption in the literature that these occupations rely on substantively specific skills.

Empirical measurement of the different conceptions of skill specificity, however, remains challenging. One of the key weaknesses of the proposed approach of measuring substantive specificity is that it relies on the O*NET database, which is US based and is relatively static (i.e. it is only marginally updated annually). This could lead to poor measurements if the required skills in occupations significantly change over time and/or they differ quite substantially between countries. We also propose using the subjective perceptions of workers for measuring the economic specificity of skills. However, this strategy is far from perfect, as it also captures the substantive dimension of skill specificity. Hence, further work is needed in building better measurements for the portability and replaceability of skills.

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Appendix

111	Legislators and senior officials	322	Nursing and midwifery associate professionals	711	Building frame and related trades workers
112	Managing directors and chief executives	323	Traditional and complementary medicine associate professionals	712	Building finishers and related trades workers
121	Business services and administration managers	324	Veterinary technicians and assistants	713	Painters, building structure cleaners and related trades workers
122	Sales, marketing and development managers	325	Other health associate professionals	721	Sheet and structural metal workers, moulders and welders, and related workers
131	Production managers in agriculture, forestry and fisheries	331	Financial and mathematical associate professionals	722	Blacksmiths, toolmakers and related trades workers
132	Manufacturing, mining, construction, and distribution managers	332	Sales and purchasing agents and brokers	723	Machinery mechanics and repairers
133	Information and communications technology service managers	333	Business services agents	731	Handicraft workers
134	Professional services managers	334	Administrative and specialised secretaries	732	Printing trades workers
141	Hotel and restaurant managers	335	Regulatory government associate professionals	741	Electrical equipment installers and repairers
142	Retail and wholesale trade managers	341	Legal, social and religious associate professionals	742	Electronics and telecommunications installers and repairers
143	Other services managers	342	Sports and fitness workers	751	Food processing and related trades workers
211	Physical and earth science professionals	343	Artistic, cultural and culinary associate professionals	752	Wood treaters, cabinet-makers and related trades workers
212	Mathematicians, actuaries and statisticians	351	Information and communications technology operations and user support technicians	753	Garment and related trades workers
213	Life science professionals	352	Telecommunications and broadcasting technicians	754	Other craft and related workers
214	Engineering professionals (excluding electrotechnology)	411	General office clerks	811	Mining and mineral processing plant operators
215	Electrotechnology engineers	412	Secretaries (general)	812	Metal processing and finishing plant operators
216	Architects, planners, surveyors and designers	413	Keyboard operators	813	Chemical and photographic products plant and machine operators
221	Medical doctors	421	Tellers, money collectors and related clerks	814	Rubber, plastic and paper products machine operators
222	Nursing and midwifery professionals	422	Client information workers	815	Textile, fur and leather products machine operators
223	Traditional and complementary medicine professionals	431	Numerical clerks	816	Food and related products machine operators
224	Paramedical practitioners	432	Material-recording and transport clerks	817	Wood processing and papermaking plant operators
225	Veterinarians	441	Other clerical support workers	818	Other stationary plant and machine operators
226	Other health professionals	511	Travel attendants, conductors and guides	821	Assemblers
231	University and higher education teachers	512	Cooks	831	Locomotive engine drivers and related workers
232	Vocational education teachers	513	Waiters and bartenders	832	Car, van and motorcycle drivers
233	Secondary education teachers	514	Hairdressers, beauticians and related workers	833	Heavy truck and bus drivers
234	Primary school and early childhood teachers	515	Building and housekeeping supervisors	834	Mobile plant operators
235	Other teaching professionals	516	Other personal services workers	835	Ships' deck crews and related workers
241	Finance professionals	521	Street and market salespersons	911	Domestic, hotel and office cleaners and helpers
242	Administration professionals	522	Shop salespersons	912	Vehicle, window, laundry and other hand cleaning workers
243	Sales, marketing and public relations professionals	523	Cashiers and ticket clerks	921	Agricultural, forestry and fishery labourers
251	Software and applications developers and analysts	524	Other sales workers	931	Mining and construction labourers
252	Database and network professionals	531	Child care workers and teachers' aides	932	Manufacturing labourers
261	Legal professionals	532	Personal care workers in health services	933	Transport and storage labourers
262	Librarians, archivists and curators	541	Protective services workers	941	Food preparation assistants
263	Social and religious professionals	611	Market gardeners and crop growers	951	Street and related service workers
264	Authors, journalists and linguists	612	Animal producers	952	Street vendors (excluding food)
265	Creative and performing artists	613	Mixed crop and animal producers	961	Refuse workers
311	Physical and engineering science technicians	621	Forestry and related workers	962	Other elementary workers
312	Mining, manufacturing and construction supervisors	622	Fishery workers, hunters and trappers	011	Commissioned armed forces officers
313	Process control technicians	631	Subsistence crop farmers	021	Non-commissioned armed forces officers
314	Life science technicians and related associate professionals	632	Subsistence livestock farmers	031	Armed forces occupations, other ranks
315	Ship and aircraft controllers and technicians	633	Subsistence mixed crop and livestock farmers		
321	Medical and pharmaceutical technicians	634	Subsistence fishers, hunters, trappers and gatherers		

[i] A survey of employees carried out in different time periods by The Federal Institute for Vocational Education and Training of Germany (BBIB) and the German Institute for Employment Research (IAB). Its main goal is to gain a detailed picture of employees' job characteristics.