Universidad del País Vasco
Euskal Herriko Unibertsitatea

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**Master in Economics: Empirical Applications and Policies**

**University of the Basque Country UPV/EHU**

**In collaboration with the ISEAK foundation**

**Master's thesis**

# The need for requalification in the Spanish labour market:

## Mapping employment with workplace skills


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Bilbao, July 29th 2021

## Abstract

This study addresses the empirical relationship between job tasks and employment share changes in Spain for the period 1997-2019. To do so, we use the novel European representative data on skills/tasks ESCO. Overall, we find a need for requalification in the Spanish workforce. We show that changes in employment shares are heterogeneously distributed by task content – there is an overall decline in the demand for routine-manual skills, while technological and social interaction skills have emerged. Next, we contrast empirically the results of the recent literature that has used the United States O*NET data. We obtain consistent results: Routine-manual intensive occupations are declining in employment share relative to non-routine cognitive occupations. Further, we find that different groups have adapted differently to these changes. Older workers are trapped in declining occupations for reasons unrelated to the tasks performed, while men are trapped in declining occupations because they hold skills of declining demand. Last, by doing a case-by-case analysis we identify workers who may need of job reallocation. For them we obtain the optimal pathway towards emerging occupations, so that the gap in terms of tasks is minimized. Following this, we find for the displaced workers the specific requalification needed to face this job reallocation.



**Keywords:** ESCO data, emerging and declining occupations, emerging and declining skills, job matching, worker requalification.


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I am grateful to mi supervisors and to the ISEAK foundation and its members for their support and dedication. I also acknowledge the European commission ESCO team for providing the data, support and suggestions.



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## Contents

# 1. Introduction

In the recent labour economics research, the analysis of skills has become greatly important. Building from Becker's (1964) human capital model, skills are considered as an investment that can be acquired with education, workplace training and experience. To approximate workers' skills, earlier empirical studies used variables such as years of schooling. In this regard, the related literature found, during the last decades, a decline in the share of middle skill occupations relative to emerging high- and low-skilled ones. This trend contrasted with the previously observed changes in the labour market. Before 1990, the low-skilled occupations were found to be declining relative to the emerging high-skilled labour (Autor, et al. [2006]).

Looking at the adoption of computer-based technologies, the literature in skill-biased technical change was able to explain the initially observed increase in demand for highly educated/skill labour (Autor, Katz, and Krueger [1998]). Instead, it could not explain the recently found hollowing out distributional trend with emerging low-skill occupations. The model accounting for skills looking at workers´ years of schooling, did not contain sufficient information about the factors determining the labour market demand. This resulted in a change of approach – putting the focus on the task content required in different occupations, rather than the assumed skills workers acquire with their educational investment. The "task framework" attempts to explain the employment changes looking at the activities that are performed in different workplaces (Autor, et al. [2003]), rather than the educational level attained by workers. This approach has proved to be more successful in explaining employment trends as a result of the computer-based technological change.

The first studies following the task framework used a rather narrow definition of tasks derived from the Dictionary of Occupation Titles (DOT) provided by the U.S. Department of Labor. This was followed by a wider dataset, called O*NET dataset, which provided a correspondence between a detailed set of occupations with a wider range of skills/tasks. O*NET has been a key tool to develop the literature explaining the recent hollowing out employment distributional change. Autor et al. (2003) used this dataset to test the Routine Biased Technological Change hypothesis, which based the explanation for the observed decline in routine manual task-intensive occupations on their risk of being automated and robotized. The declining routine-manual tasks were found to be performed by mid-educated workers, therefore explaining their decline in employment and the "U" shaped distributional change. Building from Autor et al. (2003) work, the routinization hypothesis has been widely accepted for the United States as well as for Europe, United Kingdom, and in other developed countries (Acemoglu and Autor [2010], Goos, Manning, and Salomons [2009], Anghel et al. [2014]).

In this context, in recent years, the European Commission has taken the initiative to develop an alternative to O*NET dataset by providing data on workplace task content from a European labour market perspective. By the name of ESCO (European Skills, Competences, Qualifications and Occupations) they offer European representative data on specific skills/tasks demanded in different occupations. This data can be used to replicate the previous studies focused on European countries labour market, consequently obtaining more reliable results. Moreover, the detailed and representative data on workplace skills enables the use for many other applications.

The aim of this study is to implement ESCO European workers representative data to analyse the Spanish employment distributional change from a task framework. As a result of the novel application of ESCO, this work opens the way to reliably study different European labour markets from the task perspective. In particular, the study opens a very promising avenue of future research by providing the possibility of identifying the most efficient worker reallocation, in terms of requalification, from declining to emerging occupations, given worker's competences.

The organization of the study is as follows: After a literature review in Section 2, Section 3 is devoted to the definition of the new ESCO tool, the description of the methodology to obtain the data used, and to present the implications of the resulting dataset. Whereas ESCO follows similar to O*NET procedures, it provides more detailed information and different tasks measures. Hence, a new methodology is developed, jointly with the support of the European commission ESCO team, to look for consistencies between both datasets. The outcome is a manageable dataset containing detailed information regarding the skills degree of use in different occupations. Consequently, the data enables us to measure the qualification of the different jobs and find similarities and differences between occupations task content.

Section 4 describes the Spanish labour market through the Spanish Labour Force Survey (SLFS). In particular, the structural change that it has experimented in the last decades. It shows important changes in the occupational distribution of the workforce throughout the 22-year period. The evidence indicates that those occupations employing large number of workers in 1997 are losing relative share against other incipient occupations. Moreover, it is shown that, whereas the mid- and low- skill routine-manual workers declined in employment shares, mid- and low- skill services workers, and high-skill workers increased in employment.

Section 5 uses the ESCO and the SLFS datasets together to find, based on the correspondence between occupations and tasks, the actual trends of the skills/tasks demanded. It is found, as a result of a heterogeneously distributed employment change by task content, a clear decline in the use of routine-manual skills. In contrast, non-routine cognitive skills are emerging in use, where skills related with new technology and social interaction skills stand out. Additionally, we find that skills/tasks related to construction seem to be very volatile and highly affected by the last economic cycles. Overall, the results lead to the conclusion of a need for requalification in the Spanish labour market. The observed trends are smooth and consistent suggesting, for the following years, a lower need for routine-manual skills and higher demand for non-routine cognitive tasks.

Section 6 is devoted to showing the empirical results coming from mapping skills to employment trends. First, the Routine Biased Technological Change, which implies a decline in the share of routine tasks, seems to be consistent with the evolution of the Spanish employment. Occupations more intensive in routine-manual tasks decline in employment share relative to other occupations more intensive in non-routine cognitive tasks. In addition, heterogeneity of these effects for different demographic groups is studied, with some interesting results. In particular, older workers seem to get stuck in declining occupations relative to younger workers, and males seem to get stuck performing declining in demand tasks relative to their female counterparts.

Finally, section 7 explores the possibility of an efficient reallocation of workers from declining to emerging occupations. A tool is created where the existing skills from the declining occupation are considered to suggest job reallocation paths. The tool aims to match declining occupations with emerging ones by maximising the use of already owned skills and minimizing the requalification required.

## 2. Literature review

Over the last two decades, labour market research has increasingly focused on the study of job polarisation. This phenomenon refers to the employment growth in the lower and upper tail of the wage distribution relative to the middle-wage employment. The literature has tried to explain wage polarisation from different perspectives, such as looking at workers education, or to the task content preformed.

As mentioned, the polarisation literature describes a shift in the labour market in favour of workers in the two poles of the wage distribution. In this regard, Goos et al. (2008), Dustmann et al. (2009), and Fernandez et al. (2019) find that in most of the European countries, high- and low-paying occupations expanded relative to middle-wage ones. Autor and Dorn (2009; 2013) likewise show that the wage polarization hypothesis holds true for the United Stated over the 1980-2005 period. For the specific case of Spain, Anghel et al. (2014) and Sebastian (2018), for the periods 1997-2007 and 1994-2014 respectively, find a similar hollowing out wage polarisation.

The related literature attempts to explain the observed U-shaped wage polarisation from different points of view. Autor, et al (2006), using data for workers average years of schooling, show that for the period 1980-1990, middle- and high-skill employment increase, while low-skill workers experience a decline in employment share. In contrast, for the periods from 1990 to 2000 the trend changed, low-skill workplaces started to emerge against the mid-skill ones showing a "U" shaped distributional change and explaining the recent wage polarization.

Moreover, the most prominent theory accounting for job polarization, explains the changes by focusing on the workplace tasks performed. By the name of Routine Biased Technological Change Autor, et al. (2003; 2006) explain a relative decline in employment at workplaces using routine-manual tasks, typically performed by mid-skilled/wage workers. On the contrary, there is a relative increase in employment for workers using non-routine manual and cognitive tasks. The latter are related to low- and high-skilled/wage jobs respectively.

In detail, the model for Routine Biased Technological Change comes from the seminal paper by Autor, et al. (2003). In it, they propose a classification of tasks along two different dimensions: routine (as opposed to non-routine) and manual (as opposed to cognitive) tasks. Routine tasks are defined as those requiring methodical repetition, whereas manual tasks are the ones involving physical effort. These tasks are opposed to non-routine tasks, that require problem-solving, complex and communication activities; and cognitive tasks, which involve analytical and interactive capabilities. In this regard, they explain that the way in which occupations are affected by new technologies depends to a large extent on the tasks performed. Two hypotheses are then formulated: The first hypothesis is that routine-manual tasks are declining in use as these are easy to codify, and therefore to replicate by machines. The second hypothesis is that non-routine cognitive tasks are emerging as they are difficult to be replaced by machines or complementary to computer technologies.

In addition, Autor, et al. (2003) model has been used to find implications of labour market changes on different demographic groups. In the United States, for the 1980-2005 period, Autor and Dorm (2009) find that older workers gain representativeness not only in routine manual tasks, but in declining occupations in general. Moreover, for the case of Spain and the period 1997-2012, Anghel et al. (2014) find males more affected by polarization for their higher concentration in routine intensive occupations, especially older male workers.

In summary, the task model provides a strong theoretical foundation to develop a deeper understanding of how the labour market changes may be affecting the use of the different tasks.

## 3. European data on skills

As mentioned in the introduction, one of the biggest innovations of this work comes from the usage of the new dataset connecting skills/tasks[1] to occupations called ESCO (European Skills, Competences, Qualifications and Occupations). Developed by the European Commission, ESCO contains information on the tasks that European workers perform in different workplaces. More precisely, the dataset connects, classifies and categorizes skills/tasks with occupations at ISCO-08 classification. Our interest in ESCO stems from the ability to compare qualifications of workers, find skillset similarities and differences, and find relations with employment. The dataset is a matrix connecting (# of occupations) x (# of skills), which structure will be kept along all the work specifying in each case the matrix size or granularity used.

[1] ESCO calls “skills” or “competences” to the units of classification, but we find them to be closer to tasks performed at occupations. Therefore, throughout this work we will call them interchangeably skills, tasks or competences.

To summarize, ESCO is a dictionary of occupations reflecting the European specific labour market characteristics[2]. It follows similar procedures as those used by the previous O*NET data. The latter was developed by the United States to find a correspondence between different skills/job-contents with a detailed set of occupations. This dataset has been widely used in labour economics research. ESCO contributes by providing European workers representative data which adds the possibility to reliably use it for applications in these countries. The data was created by looking at occupation classifications from Europe Member States and other classifications with an European scope, and then asking European sectoral experts (professional associations, education and training institutes, private companies, industrial associations, trade unions, etc.) to categorize the different skills/contents for the occupations based on their expertise.

Although the development of ESCO has had in O*NET dataset a clear reference, there are some differences that must be taken into account. On the one hand the granularity of tasks: ESCO works with 13,485 different skills that contain very precise tasks many of them exclusive to few occupations. Instead, O*NET includes only 35 skills (120 including Knowledge, Skills and Abilities) that are notably broader. On the other hand, ESCO provides a qualitative measure of the intensity of use of each skill/task. In particular, three categories defined – essential, optional, or not needed. Instead, O*NET provides a quantitative measure of skills importance from 1 to 100.

More specifically, the most disaggregated ESCO matrix connects 2,942 occupations (ISCO's most granular classification) with 13,485 skills/tasks. For each occupation-skill pair, ESCO provides a qualitative measure of importance, i.e., whether it is essential, optional or not used at all. However, from the most disaggregated matrix, it is possible to scale up to other more aggregated matrices, by aggregating occupations (to ISCO 4-digit, ISCO 3-digit, ISCO 2-digit or ISCO-08 1-digit) and ESCO skills. Indeed, the most aggregated ESCO skill classification contains the following 8 skills:

- S1- Communication, collaboration and creativity;
- S2 - Information skills;
- S3 - Assisting and caring;
- S4 - Management skills;
- S5 - Working with computers;
- S6 - Handling and moving;
- S7 - Constructing;
- S8 - Working with machinery and specialized equipment;

[2] The skills defined for occupations are time-invariant, meaning that the dictionary does not reflect changes in the occupations skill content over time. The European commission plans to bring in 2021 an updated version of ESCO to reflect changes in skill content and to make the dictionary dynamic.

Table 1 presents all the potential aggregation levels. It is possible to create a correspondence matrix of any occupational classification level with any ESCO classification level, and hence dealing from the most granular 2,942 x 13,485 matrix to the least granular matrix of 10 occupation x 8 skill groups.

**Table 1: occupation-skills group sizes**

| CONTENT (DEVELOPED BY) | LEVEL | SIZE (I.E. NUMBER OF GROUPS) |
|---|---|---|
| **OCCUPATION GROUPS (ISCO)** | 1 | 10 |
| **OCCUPATION GROUPS (ISCO)** | 2 | 42 |
| **OCCUPATION GROUPS (ISCO)** | 3 | 125 |
| **OCCUPATION GROUPS (ISCO)** | 4 | 426 |
| **OCCUPATION GROUPS (ISCO)** | Most granular level | 2,942 |
| **SKILL GROUPS (ESCO)** | 1 | 8 |
| **SKILL GROUPS (ESCO)** | 2 | 75 |
| **SKILL GROUPS (ESCO)** | 3 | 290 |
| **SKILL GROUPS (ESCO)** | Most granular level | 13,485 |

Source: ESCO Skill-Occupation Matrix Tables technical report – April 2021

In this study we have opted for a level of correspondence of ISCO 3-digit to ESCO level-2 skill classification. The latter contains 75 different tasks, which give us a rich enough skill heterogeneity but at the same time a manageable one. These skills (the full list is provided in Annex 2) are to some degree comparable with the ones developed in O*NET. Indeed, this is an important reason to use this disaggregation level. This amounts to a correspondence matrix between ISCO occupations and ESCO skills of 125 occupations x 75 skills, although for some visual purposes, we will use more aggregated correspondences.

Regarding the measure of skills use intensity, we create a quantitative measure[3], similar to the one used in O*NET, denoted by *degree of use*. The measure succeeds in being continuous capturing for each skill at ESCO level-2 (our reference, see Table 1) the share of essential subskills. The subskills are the ones at the ESCO level-3 classification (290 skills, see Table 1) and we say they are essential if at least one task in its ESCO most granular classification is essential. From here, the *degree of use* is built as the number of essential subskills relative to all possible subskills. In other words, for each skill we obtain the percentage of subskills that are performed as essential as

$$Degree\ of\ use_{i,j} = \frac{\#\ essential\ subskills_{i,j}}{\#\ subskills_{i,j}}.$$

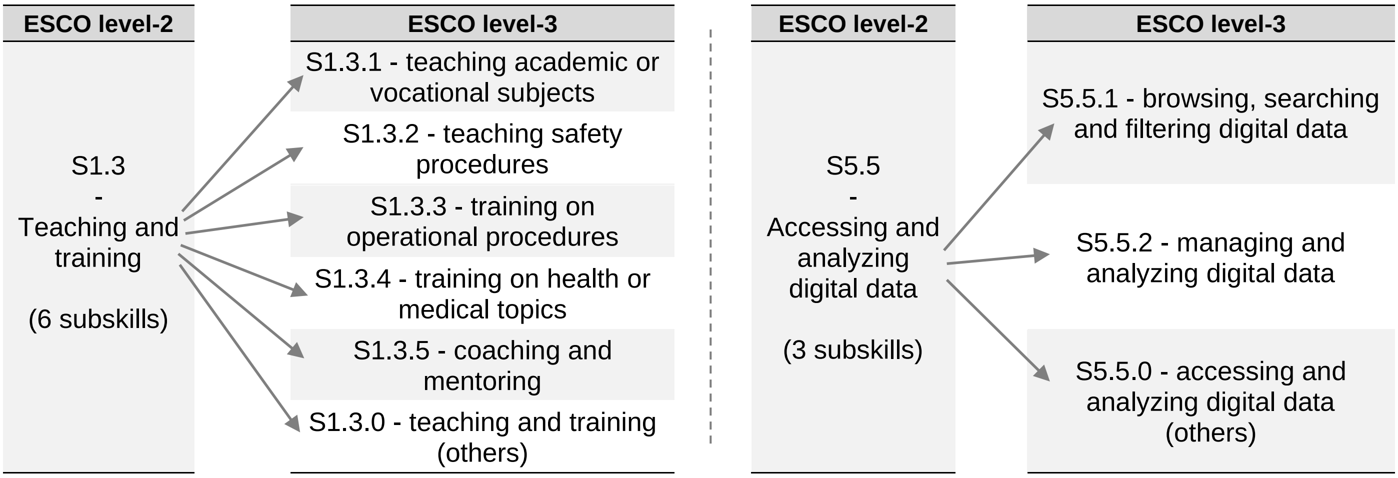
$$i = occupation,\ \ j = skill\ (level\ 2)$$

[3] To build the measure of *degree of use* we have counted with the support of the ESCO team from the European Commission. They have followed the process and have informally certify the use of ESCO data in this methodology for good practice.

For a better understanding, Example 1 depicts the computation of the *degree of use* of two skills along five different occupations. Still, greater methodological detail can be found in Annex 3.

### Example 1: ESCO Skill *degree of use* methodology

Correspondence among ESCO levels




Each skill has a different number of subskills: Teaching and training has six; Accessing and analyzing digital data has three.

Computation of the *Degree of use*

| **Degree of use** $essential\ subskills/total\ subskills$ | Teaching and training | Accessing and analyzing digital data | ··· +73 |
|---|---|---|---|
| IT managers | 2/6 = 0.33 | 2/3 = 0.66 | ··· |
| University professors | 4/6 = 0.66 | 2/3 = 0.66 | ··· |
| Electronic repairers | 1/6 = 0.16 | 1/3 = 0.33 | ··· |
| Vocational teacher | 5/6 = 0.83 | 0/3 = 0 | ··· |
| Street workers | 0/6 = 0 | 0/6 = 0 | ··· |
| ··· + 120 | ··· | ··· | ··· |

Each occupation uses a different number of subskills as essential. We say that the skill is more important for an occupation if a higher share of essential subskills are used. A complete list of occupations and skills can be found in the annexes 1 and 2.

Source: Own elaboration based on ESCO Skill-Occupation Matrix tables.

Summarizing, the measure *degree of use* let us keep the information in the granularity level-3 but working with a more manageable 75 definitions of skills. Moreover, we achieve a quantitative measure closer to the one available in O*NET. Per occupation, skills range from not essential (0) to fully essential (1). The resulting dataset contains valuable and exhaustive information regarding the skills used in different occupations. This information is presented in Figure 1 and in Table 2.

In particular, Figure 1 presents a map locating the different occupations in terms of the number of skills used and the mean *degree of use*. Specifically, the figure shows the location of the 125 occupations[4] (level-3 ISCO-08) relative to: On the one hand, the number of tasks that are essential to perform in an occupation (X-axis) – which provides an idea of the degree of multitasking. On the other hand, the mean *degree of use* out of the essential tasks (Y-axis) – which captures intensity with which the tasks are performed. Given these two dimensions, occupations can be classified in four groups:

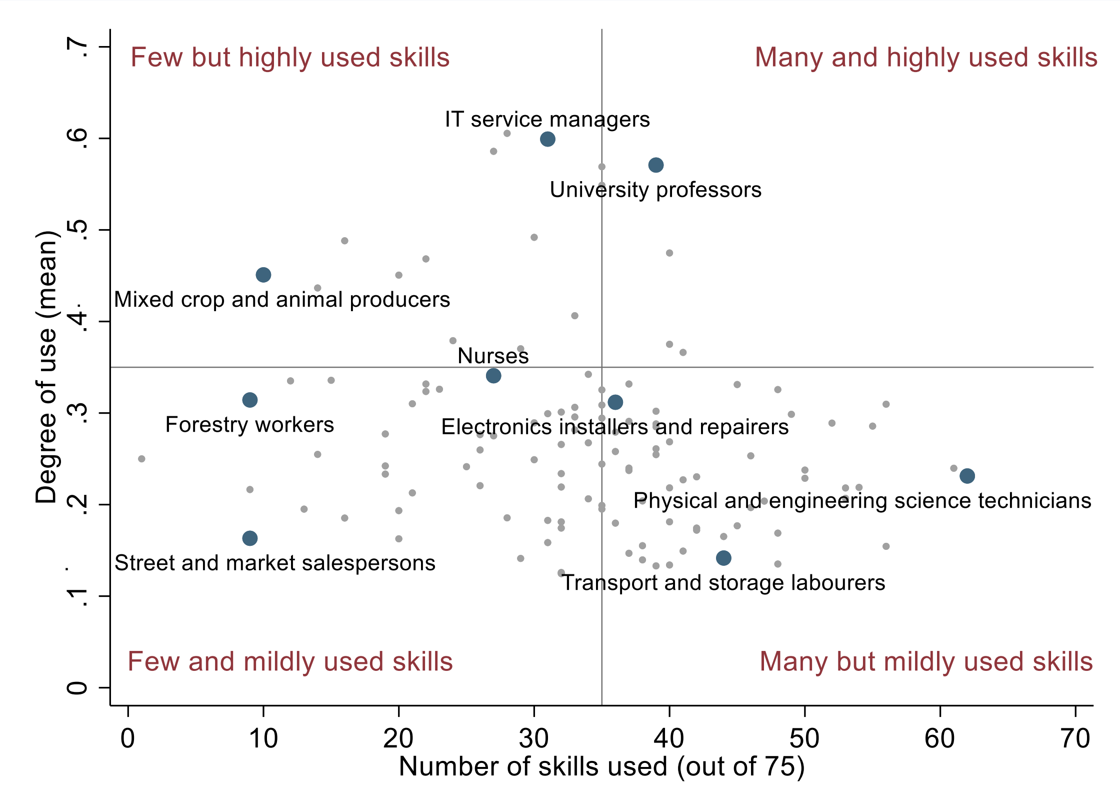
- Occupations using <u>few skills</u> with a <u>low average degree of use</u>;
- Occupations using <u>few skills</u> with a <u>high average degree of use</u>;
- Occupations using <u>many skills</u> with a <u>low average degree of use</u>;
- Occupations using <u>many skills</u> with a <u>high average degree of use</u>;

Skillsets which are more difficult to acquire are located higher and farther to the right from the origin, as it is necessary to master a higher number of skills.

Let us take some examples from Figure 1: Workers working in the occupation “Street and market salesperson” use few skills and the degree of use is low. This means that such occupation skillset would not be that hard to acquire, as there are few skills to learn and it is not necessary to master them. Second, the occupation denoted by “Mix crop and animal producer”, use a low number of skills (not many to learn) but with high degree of use of them (it is necessary to master them) – this combination leads the occupation to be in the middle of the map. On the contrary, “Transport and storage laborers” use a large number of different skills (many skills to learn), but the average degree of use is very low (not necessary to master them) – this leads to this occupation, as the former, to be in the middle of the map. Lastly, if we look at a highly skilled occupation, such as "university professor", many skills are used (a lot to learn) and require a high degree of utilization (need to master them). Therefore, acquiring the skills to work in such an occupation is more costly.

[4] For visual purposes we can only see highlighted in Figure 1 a selected sample of 9 occupations that fall at different points on the map.

**Figure 1: Occupational skills/qualification summary map**




**Number of skills used** counts all the cases for which a positive use of the skill is made. **Degree of use** captures the average share of subskills used among the skills used.

**Summarizing**, being in the upper right part points to an occupation with a set of skills that are difficult to acquire, while in the lower left part we find the less skilled ones. In the upper left, then, we have occupations that use few skills but master them, and in the lower right occupations that are truly multitasking but do not master their use.

Source: Own elaboration based on ESCO Skill-Occupation Matrix tables.

In addition to this map, to better understand the data and its structure, Table 2 presents a sample matrix linking 8 big skill groups (ESCO level-1) and 42 different occupations (ISCO-08 2-digit). This table is of great interest as it shows how close in terms of task/skill content the different occupations are, and hence, to learn about the potential reallocation of workers from one occupation to another given their particular skills. Although Table 2 aggregates occupations in wider groups than those we have used for most of the study, it offers a nice visual picture of the correspondence between occupations and tasks.

**Table 2: Occupational skills degree of use**

| ISCO level-2 \ ESCO level-1 (Mean skill Degree of use) | Communication, collaboration and creativity | Information skills | Assisting and caring | Management skills | Working with computers | Handling and moving | Constructing | Working with machinery and specialised equipment |
|---|---|---|---|---|---|---|---|---|
| Chief executives, senior officials and legislators | 0.231 | 0.201 | 0.079 | 0.631 | 0.065 | 0.000 | 0.000 | 0.000 |
| Administrative and commercial managers | 0.279 | 0.263 | 0.061 | 0.453 | 0.110 | 0.007 | 0.000 | 0.003 |
| Production and specialised services managers | 0.204 | 0.311 | 0.080 | 0.476 | 0.230 | 0.033 | 0.008 | 0.021 |
| Hospitality, retail and other services managers | 0.268 | 0.299 | 0.119 | 0.551 | 0.152 | 0.036 | 0.000 | 0.040 |
| Science and engineering professionals | 0.189 | 0.349 | 0.061 | 0.218 | 0.242 | 0.054 | 0.009 | 0.069 |
| Health professionals | 0.139 | 0.197 | 0.200 | 0.263 | 0.043 | 0.045 | 0.000 | 0.014 |
| Teaching professionals | 0.289 | 0.307 | 0.131 | 0.400 | 0.130 | 0.017 | 0.000 | 0.052 |
| Business and administration professionals | 0.269 | 0.303 | 0.083 | 0.399 | 0.170 | 0.002 | 0.000 | 0.000 |
| Information and communications technology professionals | 0.168 | 0.271 | 0.036 | 0.182 | 0.508 | 0.000 | 0.000 | 0.010 |
| Legal, social and cultural professionals | 0.259 | 0.234 | 0.083 | 0.227 | 0.107 | 0.014 | 0.003 | 0.010 |
| Science and engineering associate professionals | 0.130 | 0.240 | 0.073 | 0.233 | 0.161 | 0.061 | 0.061 | 0.187 |
| Health associate professionals | 0.102 | 0.114 | 0.193 | 0.123 | 0.058 | 0.041 | 0.001 | 0.059 |
| Business and administration associate professionals | 0.169 | 0.219 | 0.079 | 0.231 | 0.086 | 0.011 | 0.001 | 0.017 |
| Legal, social, cultural and related associate professionals | 0.235 | 0.214 | 0.163 | 0.265 | 0.059 | 0.054 | 0.012 | 0.050 |
| Information and communications technicians | 0.118 | 0.164 | 0.035 | 0.147 | 0.456 | 0.018 | 0.000 | 0.103 |
| General and keyboard clerks | 0.095 | 0.132 | 0.026 | 0.078 | 0.119 | 0.013 | 0.000 | 0.000 |
| Customer services clerks | 0.144 | 0.099 | 0.088 | 0.102 | 0.074 | 0.008 | 0.000 | 0.019 |
| Numerical and material recording clerks | 0.123 | 0.194 | 0.052 | 0.258 | 0.200 | 0.060 | 0.010 | 0.100 |
| Other clerical support workers | 0.099 | 0.116 | 0.025 | 0.042 | 0.093 | 0.010 | 0.000 | 0.017 |
| Personal service workers | 0.176 | 0.141 | 0.143 | 0.190 | 0.014 | 0.071 | 0.000 | 0.060 |
| Sales workers | 0.119 | 0.129 | 0.083 | 0.172 | 0.067 | 0.042 | 0.005 | 0.009 |
| Personal care workers | 0.158 | 0.084 | 0.219 | 0.208 | 0.032 | 0.051 | 0.000 | 0.007 |
| Protective services workers | 0.113 | 0.110 | 0.140 | 0.187 | 0.044 | 0.046 | 0.000 | 0.083 |
| Market-oriented skilled agricultural workers | 0.049 | 0.051 | 0.045 | 0.270 | 0.032 | 0.085 | 0.035 | 0.064 |
| Market-oriented skilled forestry, fishery and hunting workers | 0.058 | 0.074 | 0.084 | 0.146 | 0.028 | 0.056 | 0.008 | 0.081 |
| Building and related trades workers, excluding electricians | 0.042 | 0.117 | 0.046 | 0.040 | 0.000 | 0.124 | 0.147 | 0.065 |
| Metal, machinery and related trades workers | 0.081 | 0.121 | 0.054 | 0.164 | 0.187 | 0.168 | 0.083 | 0.226 |
| Handicraft and printing workers | 0.093 | 0.102 | 0.022 | 0.117 | 0.222 | 0.112 | 0.027 | 0.166 |
| Electrical and electronic trades workers | 0.091 | 0.150 | 0.068 | 0.128 | 0.208 | 0.054 | 0.049 | 0.235 |
| Food processing, wood working, garment and related | 0.079 | 0.117 | 0.058 | 0.102 | 0.078 | 0.122 | 0.024 | 0.114 |
| Stationary plant and machine operators | 0.061 | 0.123 | 0.055 | 0.134 | 0.128 | 0.194 | 0.035 | 0.234 |
| Assemblers | 0.080 | 0.138 | 0.061 | 0.117 | 0.074 | 0.205 | 0.088 | 0.242 |
| Drivers and mobile plant operators | 0.062 | 0.151 | 0.139 | 0.133 | 0.127 | 0.092 | 0.048 | 0.187 |
| Cleaners and helpers | 0.031 | 0.037 | 0.047 | 0.033 | 0.014 | 0.153 | 0.023 | 0.018 |
| Agricultural, forestry and fishery labourers | 0.015 | 0.038 | 0.024 | 0.031 | 0.000 | 0.120 | 0.014 | 0.129 |
| Labourers in mining, construction, manufacturing and transport | 0.034 | 0.075 | 0.050 | 0.060 | 0.041 | 0.097 | 0.079 | 0.089 |
| Food preparation assistants | 0.051 | 0.025 | 0.103 | 0.054 | 0.000 | 0.119 | 0.000 | 0.006 |
| Street and related sales and service workers | 0.067 | 0.000 | 0.048 | 0.031 | 0.000 | 0.019 | 0.000 | 0.000 |
| Refuse, waste and related elementary workers | 0.023 | 0.035 | 0.057 | 0.020 | 0.025 | 0.092 | 0.008 | 0.061 |

The values range from 0 (not essential) to 1 (all the subskills essential), the shadow follows the values getting darker as the value increases. We represent 42 occupations (ISCO-08 level-2) for the aggregated 8 skill groups (ESCO level-1). The aggregation is done getting the mean value of the *degree of use* of the skills, for the occupation group.

Source: Own elaboration based on ESCO Skill-Occupation Matrix tables.

## 4. The Spanish Labour Market

Throughout the last decades, factors such as technological change and offshoring have been key determinants of important changes in the employment shares of different occupations. These have been highly related with the occupations featured tasks content. In this section, we provide evidence of these changes, which will help understand which the needed skills are to transition, if necessary, from declining to emerging occupations. To do this, we use the Spanish Labour Force Survey (henceforth SLFS) and compute the changes in employment between 1997 and 2019.

SLFS offers information about the 3-digit occupational category of a broad representative sample of the Spanish labour force. This restricts our analysis to 120 occupations[5] when we match these to the International Standard Classification of Occupations (ISCO-08) using the official correspondence tables by the Spanish National Statistics Institute.

From this dataset we compute the employment share in each of the different occupations, overall and for different demographic groups as

$$Employment\ share_{i,t} = \frac{employment_{i,t}}{total\ employment_t}.$$

$$i = occupation, \quad t = 1997, \dots, 2019$$

By doing so, we aim to identify the occupations ($i$) which emerge and which decline, by looking at their evolution along the 22 years ($t$). For this, we take absolute changes in employment shares throughout the 1997-2019 period as

$$\Delta\ Employment\ share_i = \ Employment\ share_{i,2019} - Employment\ share_{i,1997}\ .$$

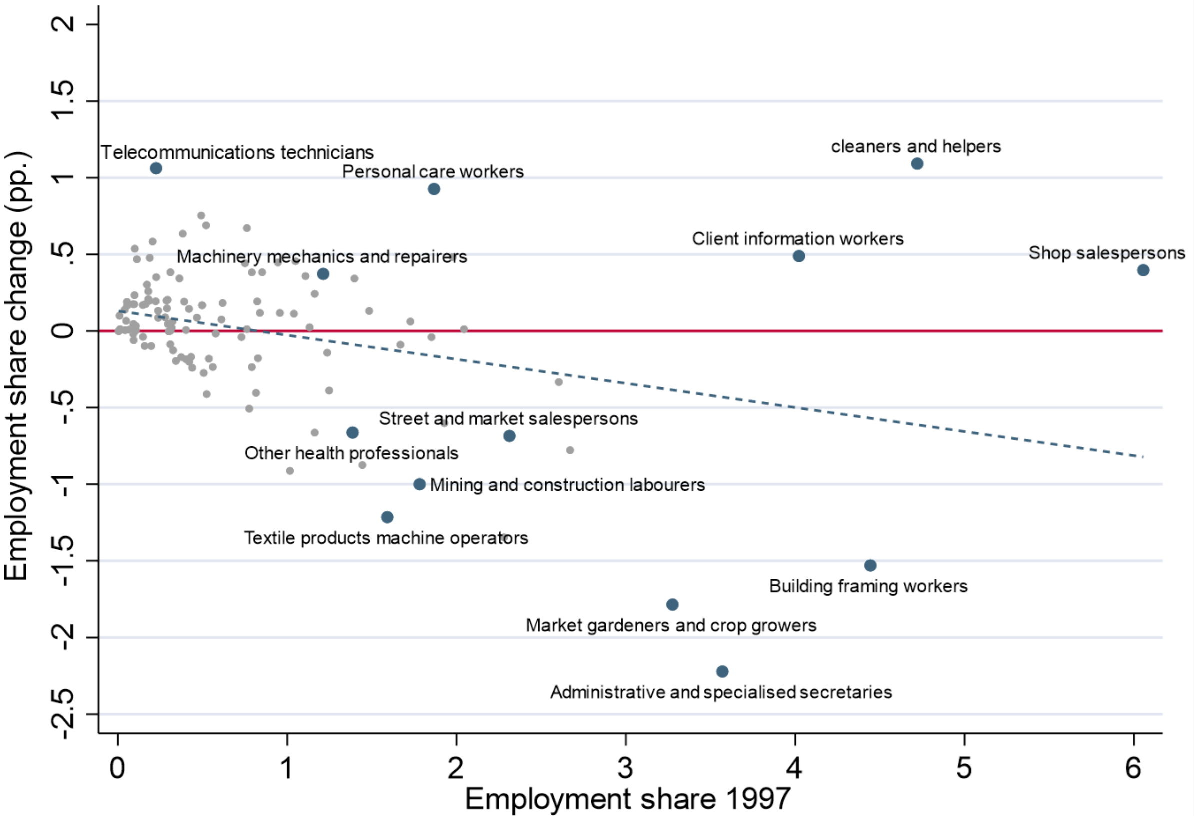
$$i = occupation$$

Figure 2 displays the 22-year changes in employment shares with respect to the initial 1997 employment share of the occupations. The graph lets us see the relatives changes in employment by comparing the employment change with the initial size of the occupations. Some lost nearly all their employment, as “Textile product machine operators” that initially with 1.5% of the employment, lost 1.2 percentage points (henceforth pp.). On the contrary, “Telecommunication technicians” quadruple its employment share from 1997 to 2019 growing in 1 pp.

[5] From the 125 occupations in ISCO-08 level-3, we drop Armed Forces (3 occupational categories), as well as “Nursing and midwifery associate professionals” as the latter has no equivalent between the ISCO classification and the Spanish CNO. Finally, the European Commission has shared with us a problem of lack of reliability of the ESCO information regarding the category denoted by “Medical doctors”, so we have also dropped it from the analysis.

In addition, fitted with a dashed line, we show a downwards sloping tendency showing that the initially small occupations gain importance, whereas the large occupations declined. Only three large occupations successfully adapted to the changing labour market, performing non-routine services and personal care tasks. These are “Client information workers”, “Cleaners and helpers”, and “Shop salespersons”. The observed trend is consistent with the hypothesis of technology, offshoring and other factors creating a structural change in the Spanish labour market in the last decades.

**Figure 2: Employment share change by initial size**



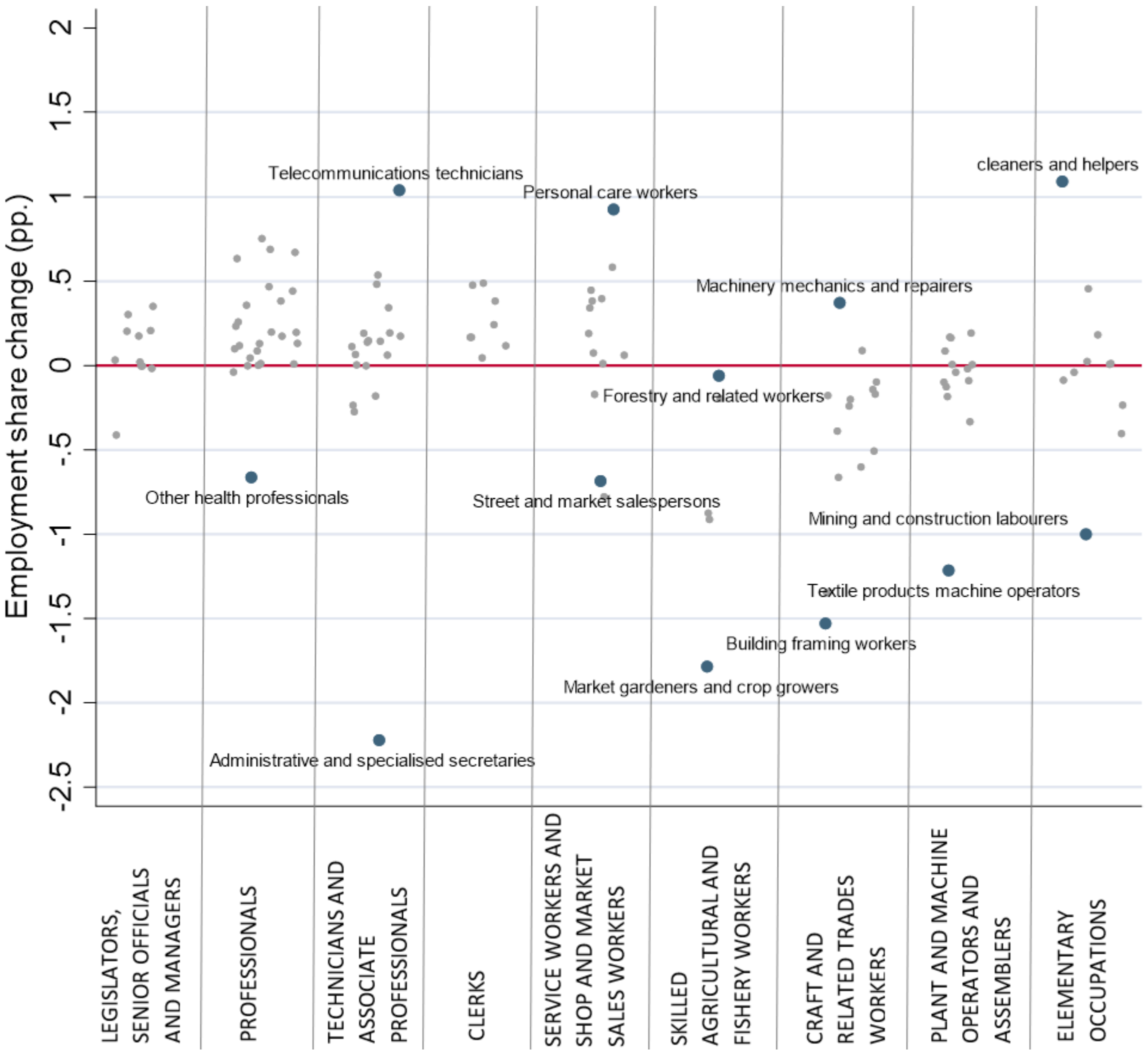

**Employment share change** shows the percentage points of total employment gained or lost by the occupations from 1997 to 2019. **Employment share 1997** gives the share of total employment hold in the initial period 1997. The dashed line represents the fitted values (Intercept = 0.13, Slope = -0.15).

Source: Spanish Labour Force Survey (SLFS), Spanish National Statistics Institute.

To better understand the relation between growing and declining occupations, Figure 3 depicts the changes in employment shares by the nine big ISCO-08 groups, therefore, aggregating occupations to 1-digit ISCO level. Most emerging occupations are represented in the first 5 groups (at ISCO 1-digit level). These cover *legislators, senior officials and managers*, *Professionals*, *Technicians and associate professionals*, *Clerks*, and *Service/Sales workers*. Moreover, within these groups we highlight the performance of high skilled technicians, analysts, computer workers, and service/care workers. Instead, occupations in decline, as their employment share diminishes along these 22 years, are mainly concentrated in columns

6 and 7, *Skilled fishery and agricultural workers*, and *Craft and related trade workers* respectively. These occupations have been heavily substituted by machines or offshored. One exception can be noted by “Machinery mechanics and repairers” that grew on 0.4 pp., as this is likely to be more a complement than substitute to automation. In regard to the last two columns, *Plant and machine operators and assemblers* and *Elementary occupations*, these include a mix of importantly emerging and declining occupations, but they can be differentiated. The emerging occupations perform personal services – clean, prepare food, aid, etc., while the declining workplaces are production orientated like textile, mining and construction.

**Figure 3: Employment share change by occupation group**




**Employment share change** shows the percentage points of total employment gained or lost by the occupations from 1997 to 2019. **X axis** separates the occupations by its biggest aggregation group (ISCO 1-digit).

Source: Spanish Labour Force Survey (SLFS), Spanish National Statistics Institute.

We see that the labour market has gone through important, heterogeneously distributed, employment changes over the last decades. Moreover, these changes seem to be related to the workplace task content. Using Autor et al. (2003) task dimensions, it can be observed that the more cognitive and non-routine occupations gained employment shares against the more routine-manual declining occupations. Especially, those workplaces featuring new technologies increase in relative employment. Consequently, these trends seem to be consistent with the literature in Routine Biased Technological Change.

Overall, the observed employment changes show that a reallocation of a significant fraction of the Spanish workforce is needed. Moreover, given that declining occupation's tasks do not seem to match with those needed in the emerging occupations, requalification is also likely to be needed at least for a considerable amount of the workforce which must engage in reallocation. To find further relationships between the skills and employment trends, given that the SLFS dataset does not provide precise job task content, we use in the following sections the ESCO data to match occupations with specific workplace tasks content.

## 5. The skills of the Spanish workforce

From this section onwards, we make use of both data sources, skills/tasks and employment, namely ESCO and SLFS. Together they show the use of skills made by Spanish workers as well as the evolution of these. We identify emerging and declining skills, as a result of the heterogeneously distributed employment changes at the occupational level described in the previous section. These show us the path that the requalification of workers may follow to accommodate the Spanish workforce to the actual and future labour market.

We start by introducing the measure to obtain the workforce use of skills. This extracts the average Spanish workforce *degree of use* of the skills, formally:

$$Spanish\ skill\ use_{j,t} = \sum_{i=1}^{122} degree\ of\ use_{i,j} \times emp.share_{i,t}\ .$$

$$i = occupation,\ \ j = skill\ (level\ 2),\ \ t = 1997, \dots, 2019$$

Where $degree\ of\ use$ measures the use of skill ($j$) in the occupation ($i$), and $emp.share$ introduces the distribution of employment across occupations ($i$) along the years ($t$). The outcome is a comparable measure of the use of skills by periods. We identify the emerging and declining skills looking at the relative change in workforce use of them as

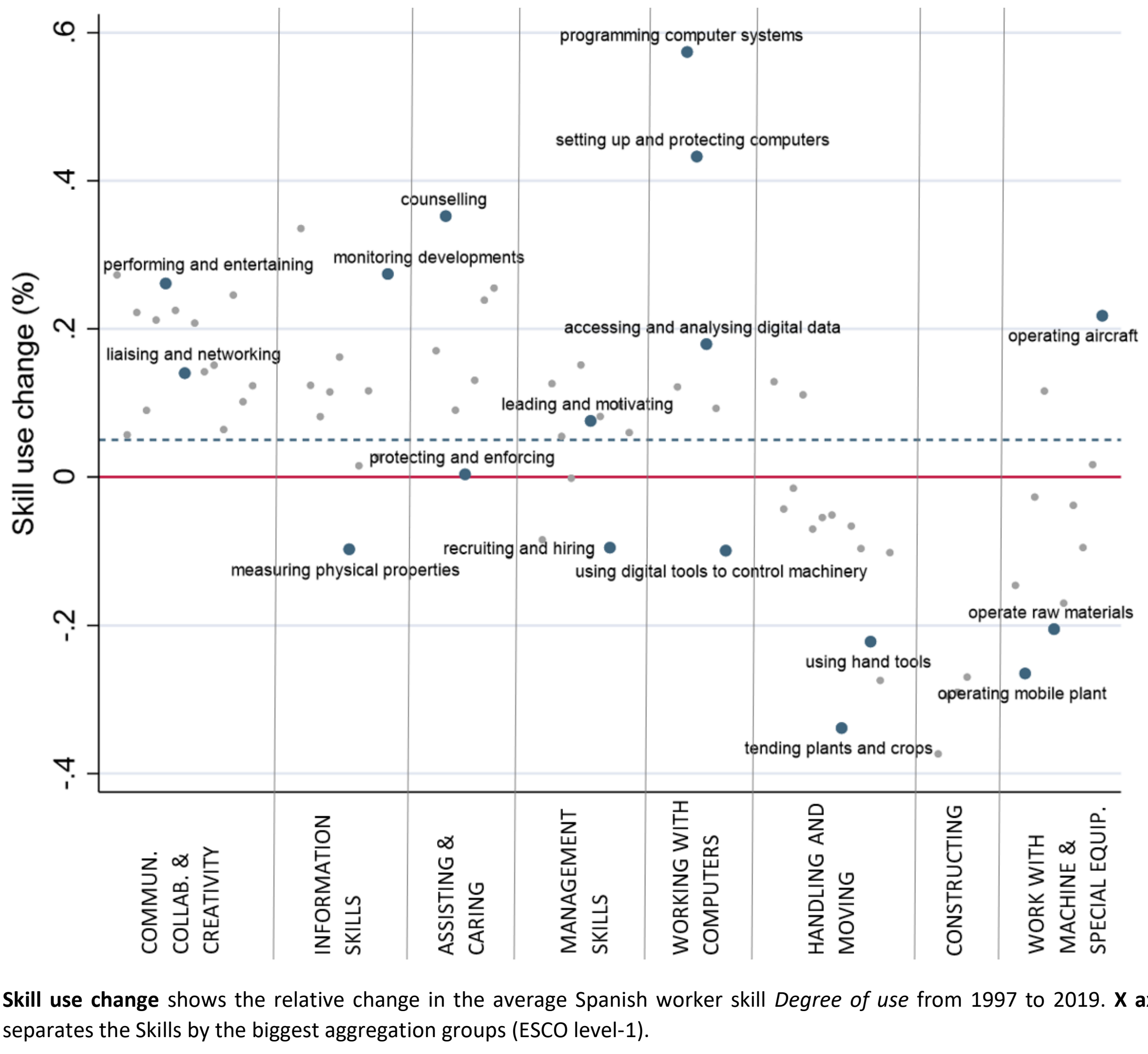
$$Skill\ use\ change_j = \frac{Spanish\ skill\ \ use_{j,2019}}{Spanish\ skill\ use_{j,1997}} - 1\ .$$

$$j = skill\ (level\ 2)$$

The resultant variable shows the percentage change in the use of skills along the period studied. A decrease means that the working population has relatively reduced the use of the skill. Instead, the increase in use signals a requalification towards skills by the Spanish workforce along the period.

Figure 4 plots the change in use of the 75 skills by their aggregated ESCO level-1 classification. We see that on average the use of skills in Spain has increased by 5% over the 22-year period (see the dashed line in Figure 4). This means that the Spanish workforce on average has moved towards more multitasking and skill intensive occupations. Regarding the variation, we find skills going from an increase in use of 57% for Programming computer systems, to decreases of 37% for Constructing.

**Figure 4: Skill use change by skill group**




**Skill use change** shows the relative change in the average Spanish worker skill *Degree of use* from 1997 to 2019. **X axis** separates the Skills by the biggest aggregation groups (ESCO level-1).

Source: Own elaboration based on the Spanish Labour Force Survey (SLFS) and ESCO Skill-Occupation Matrix tables.

Using Autor et al. (2003) task dimensions, we can separate the ESCO tasks by routine-manual and non-routine cognitive content. Routine-manual skills are represented by the skill groups *Handling and moving*, *Constructing*, and *Working with machinery and special equipment*. Instead, Non-routine cognitive are featured in the groups *Communication, collaboration and creativity*, *Information skills*, *Assisting and caring*, *Management skills*, and *Working with computers*.

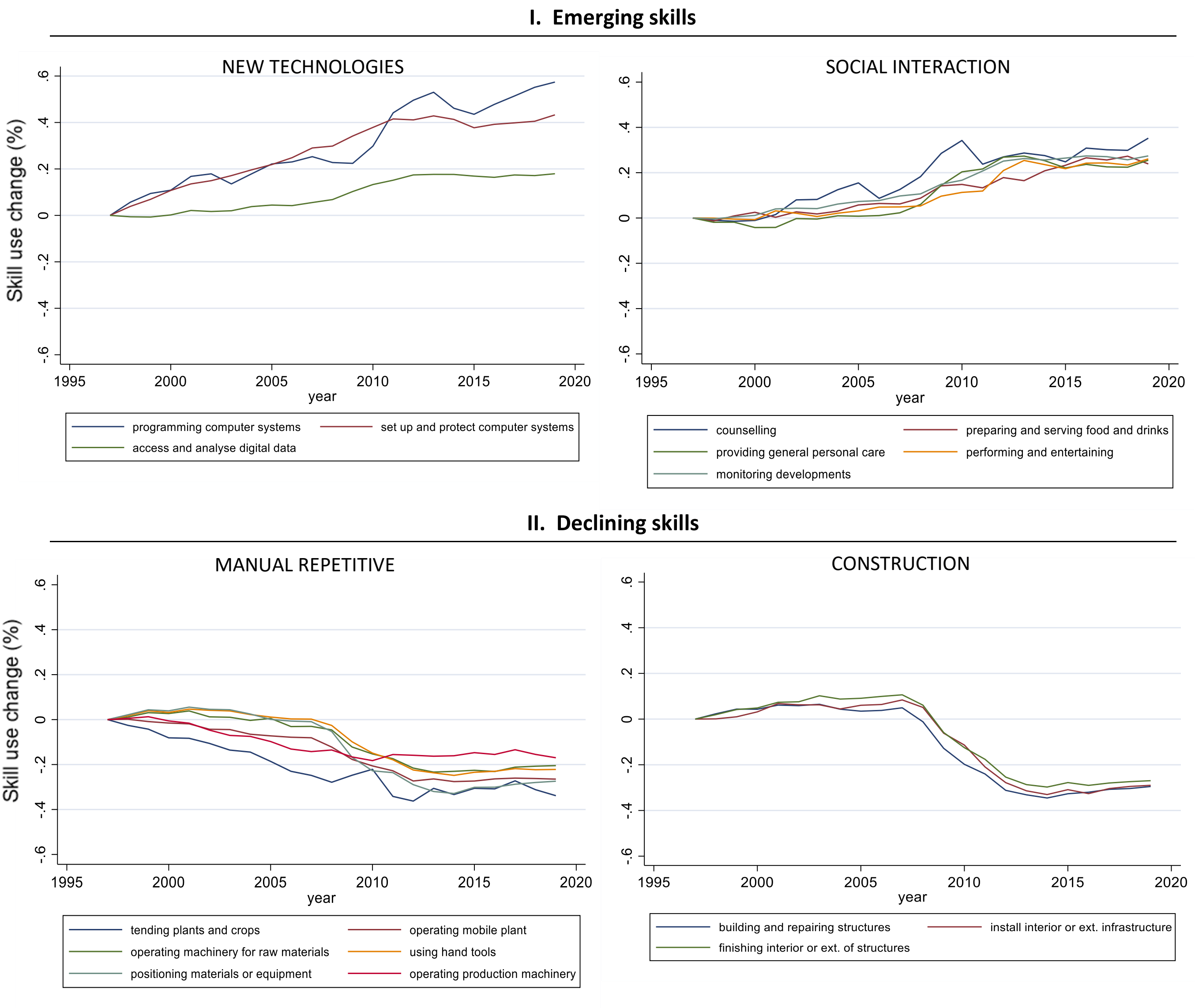
As expected from the previously analysed employment changes, and consistent with the literature in Routine Biased Technological Change, most of the emerging skills are classified under the so-called non-routine cognitive tasks. These are represented in the first five columns of Figure 4. In contrast, declining skills are those denoted by routine-manual tasks, located in the last three columns.

Looking closely at figure 4, it is interesting to observe that highly emerging skills can be separated into two groups. On the one hand, skills/tasks related to new technologies. On the other hand, skills/tasks related to social interaction. The first ones are a complement to automation, while the second group includes tasks that are more difficult to automate or offshore. Instead, for the highly declining skills, we can note a difference between construction skills and the other routine/repetitive skills. The construction sector was negatively affected by the Spanish recession explaining their decline, moreover construction has not been offshored. In comparison, the rest of highly declining routine-manual skills, have been highly offshored and substituted by robots.

While the 22-year period let us classify the emerging and declining skills during this time, it does not allow us to look at the trend. To see such trend, Figure 5 depicts the yearly change on skills with respect to the base year 1997. We plot the previously found highly emerging and highly declining skills for the 22-year period. We divide the results in four different graphs, by the task groups: new technologies, social interaction, manual-repetitive and construction.

The first result to highlight is that annual trends are in general smooth and consistent over time. From these results we can expect the labour market to keep evolving in the same direction. There is only one remarkable case, the construction skills turned out to be volatile and highly dependent on the economic cycle. Overall, the results show a great need for requalification, as there are clear winners and losers among skills/tasks. The employment change has been clearly biased against routine-manual skills. Instead, non-routine cognitive skills show positive trends, which means that there is demand from the market towards acquiring such skills.

**Figure 5: Biggest growth and declines on use of skills over time.**




**Skill use change** shows the relative change in the average Spanish worker skill Degree of use from 1997 to $t$. **Year** gives the time-period $t$ for which the change is computed.

Source: Own elaboration based on the Spanish Labour Force Survey (SLFS) and ESCO Skill-Occupation Matrix tables.

Concluding, these results only show the requalification path that the workforce should follow in the oncoming years. In fact, individual cases are much more complicated to treat. A broad recommendation of requalification towards emerging skills may not be efficient to help workers match the qualification of emerging occupations. As an example, a farmer may not benefit from acquiring programming skills, while it would be difficult for him to learn them. Instead, we find it more interesting to make appropriate personalized recommendations based on the skills already owned. In this regard, we continue the analysis and further developed requalification recommendations in section 7.

# 6. Empirical evidence of changes in skills in Spain using ESCO dataset – Heterogeneity among groups

This section is organized in three parts. First, we measure the relation between ESCO tasks and employment. Some tasks are strongly related to declining jobs, whereas others are significantly more utilized at emerging occupations. With this analysis, we aim to contrast, using ESCO, the hypothesis of Routine Biased Technological Change tested by the previous literature with O*NET.

In the second subsection, we introduce an index that measures the need for requalification of individual workers based in the occupation held. The detailed ESCO task classification allows us to assess workers skillset based on the performed tasks. Workers using declining skills, if displaced from their workplace, may need of higher requalification to move into emerging occupations as the skills they own are less demanded by the actual labour market. In this sense, we identify the position, in terms of demand for the skills, of the different occupations and, therefore, of the workers in.

Last, we perform the analysis by gender and age groups. The aim is to test whether the distribution of jobs among the different demographic groups is homogeneous, and whether it has been affected by the last decades employment changes. We build on existing literature that studies the effect of polarisation for different demographic groups. These works used O*NET data to obtain the results. We contrast the results with the European ESCO data, and, in addition, we contribute to the analysis applying the aforementioned skillset index.

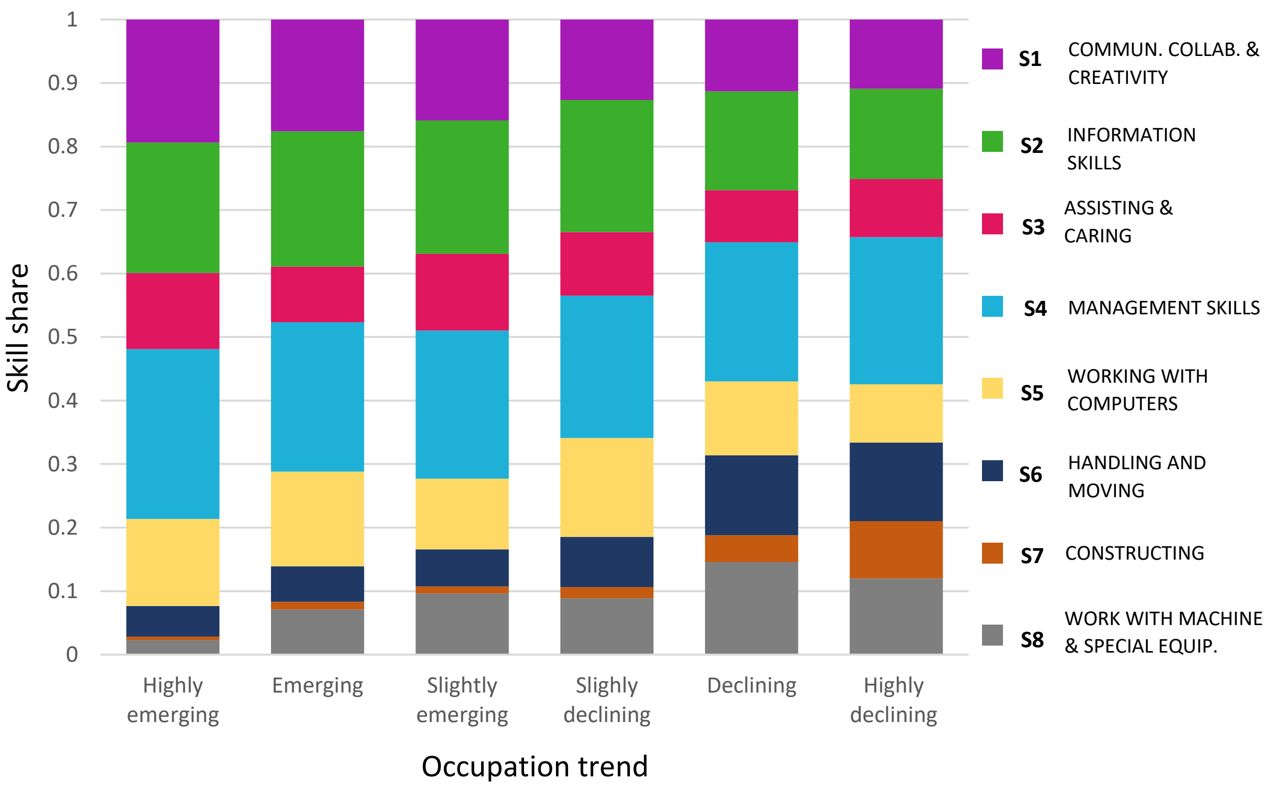
## I. Evidence of routine biased employment change

With recent technological change, machines have been able to replace certain tasks previously performed by workers. Following this argument, Autor et al. (2003), using the United States developed occupational level data on skills, namely O*NET, popularised the model that considers the task content to explain the recently found job polarisation. In this regard, for the United States, they found that tasks under a routine-manual classification are in decline due to easy automation, whereas non-routine cognitive skills emerge in use. Following this finding, the hypothesis of Routine Biased Technological Change has been accepted in most developed countries. More recently, for Spain, Angel et al. (2014) found that routine-manual intensive occupations were in decline between the period 1997-2012.

In this subsection using ESCO, instead of O*NET, we contrast the findings and measure the effect of task content on employment for the extended period 1997-2019. Following procedures comparable to Autor et al. (2003) and Angel et al. (2014), we test for routine biased employment change but with the new European dataset, so as to check whether results are consistent with those found with the previously used O*NET.

Throughout the previous sections we have noted the downward trend in routine-manual intensive occupations and the consequent decline in use of routine-manual skills. Now we move to quantify the magnitude of the decline. To test whether there is a relation between employment and task content, we first run individual regressions on each ESCO level-2 skill to explain occupations employment share changes (the table with results is included in Annex 4). Within non-routine cognitive skills (from ESCO level-2 skill 1.0 to 5.7) we do not find any significant negative relation with employment, instead, many are positively correlated with employment changes. The opposite is observed withing the routine-manual skills (from ESCO level-2 skill 6.0 to 8.9); there are no skills positively related with employment, while many of them are significantly correlated with negative changes in employment.

**Figure 6: Use of ESCO level-1 skills from emerging to declining occupations**




**Skill share** shows the shares of different skills used in average by the occupation groups. **Occupation trend** joins the occupations by its employment share change from highly emerging to highly declining. “Highly emerging” occupations are those increasing over 0.5 percentage points in employment share, “Emerging” are those between 0.5 and 0.1 pp. growth, “Slightly emerging” join occupations between 0.1 and 0 pp. growth. The classification is replicated in the opposite side: “Slightly declining” consider occupations declining in between 0 and 0.1 pp., “Declining” are those deceasing between 0.1 and 0.5 pp., “Highly declining” are the occupations falling in over 0.5 pp. of employment share.

Source: Own elaboration based on the Spanish Labour Force Survey (SLFS) and ESCO Skill-Occupation Matrix tables.

Visually, Figure 6 depicts the share of skills used (aggregated ESCO level-1 8 groups) for different groups of occupations. We have divided all occupations into six major groups – ranging from highly emerging to highly declining for the observed 22-year interval. The results reveal that indeed the declining occupations use a higher proportion of routine-manual tasks

(S6, S7 and S8), i.e., handling and moving, constructing and work with machines. In fact, these tasks absorb 33% of all tasks used in the highly declining occupations (column 6 Figure 6). If we compare the use of these tasks in highly emerging occupations (column 1 Figure 6), their share is less than 8%. On the contrary, non-routine cognitive tasks (S1, S2, S3, S4, S5) are more prevalent in emerging and highly emerging occupations.

To statistically test for routine biased employment change, we used procedures similar to the ones in Autor et al. (2003) and Angel et al. (2014) based on the O*NET dataset. Namely, we construct two variables that aggregate the ESCO level-2 granularity data into routine-manual and non-routine cognitive classification as

$$Routine\ manual_i = \sum_{j=49}^{75} skill\ degree\ of\ use_{i,j}$$

$$Non\ routine\ cognitive_i = \sum_{j=1}^{48} skill\ degree\ of\ use_{i,j}\ .$$

$$i = occupation,\ \ j = skill\ (level\ 2)$$

The variables sum the degree of skill use withing routine-manual and non-routine cognitive classifications respectively. In addition, following the work of Autor et al. (2003), we compute the Routine Task Intensity (RTI) index. This index captures the share of routine-manual content of different occupations as

$$RTI_i = \frac{Routine\ manual_i}{Routine\ manual_i + Non\ routine\ cognitive_i}\ .$$

$$i = occupation,\ \ j = skill\ (level\ 2)$$

To test whether there is a correlation between changes in the employment shares by occupations and the task measures, we regress changes in the share of employment[6] on the constructed variables for task contents: (i) Routine Task Intensity, (ii) routine-manual skills degree of use and (iii) non-routine cognitive skills degree of use. In addition, we account for heterogeneity coming from different economic situations. According to Angel et al. (2014) findings, the Spanish recession seemed to accelerate the polarization process and the routine biased employment change. Furthermore, in section 5 and Figure 5 we also find the Spanish crisis having an effect in skill use trend. To account for possible effects coming from the different periods, we separate the 22-year interval in two subperiods. The first covers the expansionary subperiod from 1997 to 2008; the second covers the recession and following expansion from 2008 to 2019. In this regard, we test whether the recession-augmented effect found in Angel et al. (2014) is still significant when the following expansionary period is included.

[6] The employment share changes are computed in yearly averages to be comparable between time periods. The coefficient explain emploiment share changes in basis points (bp.).

**Table 3:** ***Task content effect on employment***

| Dependent variable | Employment share change | | |
|---|---|---|---|
| | (1)<br>1997-2019 | (2)<br>2008-2019 | (3)<br>interacting effects |
| RTI | -3.459*** | -5.088** | -1.504 |
| | (1.037) | (2.046) | (1.550) |
| RTI x dummy (2008-2019) | | | -3.584 |
| | | | (2.567) |
| Routine manual | -0.262** | -0.327* | -0.183 |
| | (0.120) | (0.191) | (0.117) |
| Routine manual x dummy (2008-2019) | | | -0.144 |
| | | | (0.224) |
| Non routine cognitive | 0.128*** | 0.159** | 0.0902 |
| | (0.0431) | (0.0784) | (0.0588) |
| Non routine cognitive x dummy (2008-2019) | | | 0.0689 |
| | | | (0.0980) |
| Observations | 120 | 120 | 240 |

Dependent variable: yearly average change in share of employment (basis points). Each coefficient corresponds to a separate OLS regression of the dependent variable on the control variables and a constant. Robust standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Number of observations is the number of occupations at ISCO88 3 digits level. The estimations in the 3rd column also include period time dummies not reported here. All estimations are weighted by the weight of employment of each ISCO-08 3 digits occupation in total employment.

Table 3 presents the estimation results. Column 1 includes the full 22-year period, whereas column 2 shows the effect resulting from the last sub-period 2008-2019. Finally, column 3 include the two subperiods, revealing the time interacting effects. The results are consistent with the hypothesis of Routine Biased Technological Change overall the 22-year interval. When accounting for potential differences between the two aforementioned subperiods, there does not appear to be a differential impact. There are not significant employment trend variations between the first expansionary sub-period (1997-2008) and the following sub-period including the recession and the following expansion (2008-2019). Hence, for the complete period, we find comparable results to the aforementioned literature. A higher share of routine-manual tasks (RTI) is negatively related to employment. An increase in RTI by 1% is related to a decrease in the employment share of 0.76 percentage points over the 22 years. Furthermore, taking routine-manual and non-routine cognitive tasks separately, we find that the latter is positively correlated with increases in employment share changes, whereas routine-manual tasks are negatively related with changes in employment.

Overall, we find a strong relationship between the task content and employment changes in Spain over the last decades. As explained by Autor et al. (2003) and tested by Angel et al. (2014) for Spain, occupation with higher routine-manual content present a declining trend, while non-routine cognitive tasks are becoming more demanded by the labour market. Moreover, unlike Angel et al. (2014), we do not find a significant difference between the two subperiods. Although the recession seemed to accelerate the polarization process, in the following years this effect has been corrected to follow a trend similar to that prior to the recession. Therefore, it appears that the routine biased employment change is more of a structural change than an effect resulting from recessionary economic cycles.

## II. Measuring the need for requalification: Identification of outlier occupations

In this subsection we go beyond the Autor et al. (2003) task classification and the test for Routine Biased Technological Change. While we find the routinisation hypothesis consistent with the evolution of Spanish employment, we also find evidence of heterogenous effects within routine-manual and non-routine cognitive tasks (see Figure 4 and the individual ESCO level-2 skills regression with employment change in Annex 4). There is evidence of a small number of routine-manual tasks increasing in use over the last decades; in addition, few non-routine cognitive tasks also decline in use over the 22-year period. In this subsection we consider the evolution of the tasks separately to account for the precise trends of the disaggregated ESCO level-2 tasks. We aim to measure the need for requalification of individual workers in terms of the gap between workers' skills and what the labour market demands. To do so, we approximate workers' skills by its occupation task content.

To identify workers who may need requalification more intensely due to declining skills, as well as those who maintain skills increasingly in demand, an index is constructed that captures the depreciation/appreciation that the occupational skillsets have experience. The created index is a comprehensive and accurate measure to assess worker/job skills relative to what the labour market has demanded in recent decades. Formally:

**Skillset appreciation index**

$$I_i(x) = \sum_{j=1}^{75} \left( \frac{s_{i,j}}{s_i} \times \Delta\% \; skill\; use_j \right)$$

$$i = occupation, \;\; j = skill\; (level\; 2)$$

where $\frac{s_{i,j}}{s_i}$ captures the degree of use of the skill $j$ relative to the occupation $i$ skillset, while $\Delta\% \; skill\; use_j$ takes the relative change in use of the skill $j$ along the 22-year period. Interpreting, the index shows the appreciation or deprecation of the skillset in 2019 with respect to 1997 skill use. Occupations whose skillset show an overall decline in its use obtain negative values[7].

[7] The index is negatively correlated with the Routine Task Intensity measure. The occupations using higher share of routine-manual tasks have experience a higher skillset depreciation. The negative correlation is sensible as we found RTI having a negative effect on employment. Intead we observe that RTI does not capture all the information regarding the need for requalification of workers.

Corr(RTI,I)= -0.69

Table 4 presents the descriptive statistics of the Index. Alongside it, we show a sample of ISCO-08 3-digits occupations with the highest appreciation/depreciation of their skills. Moreover, to identify the outlier occupations, we include the employment growth that the occupations have had in the 22-year period. In addition, the full table is included in Annex 5.

Based on the results, we find an average appreciation of workers' skillsets. This is driven by the increase on the overall demand for skills in the las decades, as noted in section 5 and depicted in Figure 4. Nevertheless, the most depreciated skillset has undergone an overall depreciation of 9.9%, namely workers working in building frame and related trades. Conversely, the highest appreciation corresponded to mathematicians, actuaries and statisticians, with a 20% overall appreciation of their tasks performed.

**Table 4: Skillset appreciation index. Greatest appreciated/depreciated skillsets.**

| Skillset appreciation index: Descriptive statistics | | | |
|---|---|---|---|
| Mean | Max | Min | Std. dev. |
| 0.0621 | 0.2026 | -0.0999 | 0.0718 |

| ISCO-08 | Occupations: Top depreciated skillsets | Index | Emp. share change (pp.) |
|---|---|---|---|
| 711 | Building frame and related trades workers | -0.099 | -1.53 |
| 931 | Mining and construction labourers | -0.098 | -1.00 |
| 921 | Agricultural, forestry and fishery labourers | -0.095 | -0.04 |
| 814 | Rubber, plastic and paper products machine operators | -0.076 | -0.18 |
| 712 | Building finishers and related trades workers | -0.070 | -1.35 |
| 818 | Other stationary plant and machine operators | -0.065 | 0.01 |
| 932 | Manufacturing labourers | -0.064 | 0.02 |
| 817 | Wood processing and papermaking plant operators | -0.061 | 0.16 |
| 812 | Metal processing and finishing plant operators | -0.058 | 0.09 |
| 811 | Mining and mineral processing plant operators | -0.057 | -0.10 |
| 752 | Wood treaters, cabinet-makers and related workers | -0.055 | -0.51 |
| 961 | Refuse, waste and garbage workers | -0.054 | -0.40 |

| ISCO-08 | Occupations: Top appreciated skillsets | Index | Emp. share change (pp.) |
|---|---|---|---|
| 212 | Mathematicians, actuaries and statisticians | 0.202 | 0.10 |
| 252 | Database and network professionals | 0.199 | 0.17 |
| 351 | IT operations and user support technicians | 0.189 | 1.04 |
| 251 | Software and applications developers and analysts | 0.181 | 0.38 |
| 413 | Keyboard operators | 0.167 | 0.48 |
| 235 | Other teaching professionals | 0.159 | 0.75 |
| 323 | Traditional and complementary medicine associate prof. | 0.152 | 0.00 |
| 234 | Primary school and early childhood teachers | 0.149 | 0.01 |
| 264 | Authors, journalists and linguists | 0.146 | 0.20 |
| 342 | Sports and fitness workers | 0.146 | 0.34 |
| 261 | Legal professionals | 0.143 | 0.44 |

**Index** show the workers overall skillset appreciation/depreciation from 1997 to 2019 in percentages. **Employment chare change** depicts the 22-year occupational employment share change in percentage points.

Workers in occupations with higher depreciated skillsets may need of further requalification to match current labour market demand. In contrast, the higher appreciated skillset places workers in a better position to cope with job reallocation without the need for requalification. In addition, there is a clear positive relationship between the index values and the occupations employment change. Moreover, it is worth noting the existence of some occupations whose skills have depreciated while their employment share has increased; these are the outlier occupations. The existence of these outliers creates the possibility of reallocation of workers from declining to emerging jobs without the need of an intense requalification.

To conclude, this index makes it possible to evaluate the skillset of the different workers according to the demand for their skills. It signals the difficulty of job reallocation and the position to face the recent occupational changes observed in the Spanish labour market. Moreover, the index lets us find differences between groups depending on the jobs they occupy most frequently. Some groups of workers (age, gender, regions, nationalities, etc.) may be overrepresented in occupations with declining in use skills, causing them to need of a greater requalification to face future job reallocation.

## III. Performance of different groups towards occupational changes

A different distribution of jobs among different demographic groups may imply a greater need for worker reallocation if one group has a higher proportion of declining occupations. In addition, the existence of a task biased employment change may lead some groups to have a greater need for requalification to achieve that reallocation. In this subsection we examine the labour market structure by gender and age groups, and how it has evolved over the last decades. We study the distribution of employment between emerging/declining occupations and emerging/declining tasks performed. In addition, we introduce the link developed by Autor and Dorn (2009) with regards to the implication of the routinization theory by introducing the RTI index developed in the first subsection.

In the existing literature, it has been noted routine biased employment change to have further implication on different demographic groups and on their employment distribution. Autor and Dorn (2009) developed the framework to study the performance of different age groups over the last decades employment changes. In their paper, they find for the United States that older workers are getting stuck in declining routine task intensive jobs, whereas younger workers are moving towards non-routine and abstract jobs, thus increasing their representativeness in emerging occupations. Building on the work of Autor and Dorn (2009), Anghel et al. (2014) extended the analysis by considering a different gender distribution and accounting for age groups effects. They showed, for Spain and for the period 1997-2012, that males where overrepresented in declining occupations due to their higher concentration in routine-manual jobs. Moreover, for males only, they found that older workers performed routine-manual jobs to a greater extent.

The previous literature has used O*NET to perform this analysis at the occupational level. In this subsection, using Autor and Dorn's (2009) and Anghel et al. (2014) framework, we contribute using the novel European representative ESCO data to analyse age and gender groups separately. We contrast the results regarding the routinization theory introducing the RTI. Instead, our interest stems from introducing the skillset appreciation index to find differences in the possible need for future requalification. To this end, we study the initial (1997) distribution of the different groups and their recent changes in terms of (i) occupations employment share changes, (ii) job skillset appreciation index, and (iii) job routine task intensity (RTI).

Table 5 shows the regression analysis for age groups performance. We report the results for younger workers from 16- to 35-year-old; workers older than 35 are the counterpart. Among them we observe no differences in the 1997 distribution between emerging/declining occupations, emerging/declining tasks performed, and neither between routine-manual intensive occupations. Instead, throughout the period, we found a significant movement of young workers into emerging occupations. Moreover, this change cannot be explained by a significant movement of young workers towards performing emerging skills, nor towards less routine-intensive skills. The relatively higher reallocation of young workers towards emerging occupations seems to be caused by factors outside the task framework. This could be the caused by the higher firing costs for those over 35 years-old, as they hold indefinite contracts at a higher degree.

**Table 5: Relationship between age groups and job characteristics**

| VARIABLES | Young share 1997 | | | Young share change | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Emp. Share change | 0.0348 | | | 0.0333** | | |
| | (0.0222) | | | (0.0133) | | |
| I | | 0.177 | | | 0.117 | |
| | | (0.152) | | | (0.0956) | |
| RTI | | | 0.0281 | | | -0.00969 |
| | | | (0.0525) | | | (0.0365) |
| Young share 1997 | | | | -0.564*** | -0.552*** | -0.544*** |
| | | | | (0.0687) | (0.0686) | (0.0705) |
| Constant | 0.437*** | 0.426*** | 0.431*** | 0.0685** | 0.0560* | 0.0619** |
| | (0.0111) | (0.0136) | (0.0188) | (0.0298) | (0.0304) | (0.0296) |
| Observations | 120 | 120 | 120 | 120 | 120 | 120 |

Dependent variables: (1),(2), and (3) 16- to 35-year-old worker share; (4), (5) and (6) 16- to 35-year-old worker share change from 1997 to 2019 (percentage points). Robust standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Number of observations is the number of occupations at ISCO-08 3 digits level.

Table 6 presents the results by gender. Between males and females, there is an initial different distribution according to workplace characteristics. In 1997, males were overrepresented in routine-manual intensive occupations and, consequently, in those occupations whose skillset depreciate the most along the following years. This led males to hold, already in 1997, a higher share of declining in employment occupations. Moreover, looking at their performance over the 22-year period, the proportion of males increased even more in those occupations that use skills that are declining in demand, further widening the gap with females. As a result, they also gain more representativeness in declining occupations. The job opportunities in the emerging occupations are more often occupied by females performing less routine-manual and emerging tasks.

**Table 6: Relationship between gender and job characteristics**

| VARIABLES | Male share 1997 | | | Male share change | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Emp. Share change | -0.107* | | | -0.0591** | | |
| | (0.0584) | | | (0.0247) | | |
| I | | -1.426*** | | | -0.570*** | |
| | | (0.234) | | | (0.167) | |
| RTI | | | 0.365*** | | | 0.218*** |
| | | | (0.0976) | | | (0.0487) |
| Young share 1997 | | | | -0.0657 | -0.113** | -0.099*** |
| | | | | (0.0404) | (0.0433) | (0.0380) |
| Constant | 0.682*** | 0.771*** | 0.602*** | -0.0177 | 0.0502 | -0.0421 |
| | (0.0210) | (0.0217) | (0.0291) | (0.0302) | (0.0369) | (0.0254) |
| Observations | 120 | 120 | 120 | 120 | 120 | 120 |

Dependent variables: (1),(2), and (3) Male worker share; (4), (5) and (6) Male worker share change from 1997 to 2019 (percentage points). Robust standard errors in parentheses. *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Number of observations is the number of occupations at ISCO-08 3 digits level.

To summarize, we find our results to be consistent with those obtained by Autor and Dorm (2009) and Anghel et al. (2014). Younger workers seem to have reallocated relatively more towards emerging occupations. It must be noted that, in contrast to Autor and Dorm (2009), for Spain this effect cannot be explained with a movement of young workers towards the emerging non-routine cognitive tasks. As for the analysis by gender, females have gain representativeness in emerging occupations for being more qualified towards those emerging in demand tasks. Consequently, from these results we can expect a greater need for reallocation and requalification for males. They are getting stuck in declining occupation with the least demanded skills. To approach emerging occupations in the coming years they may need requalification towards the skills demanded by the current labour market. In contrast, among the age groups, we cannot draw further conclusions in this regard, as we find the reallocation of workers to be dependent in other factors out of job task content.

## 7. From declining to emerging occupations: Requalification suggestions

We have shown evidence of a need for job reallocation of the Spanish workforce. Moreover, it seems that the reallocation of workers may require some requalification as we found a biased by skill content employment change. Most of the declining occupations are routine-manual task intense, while the emerging ones use more non-routine cognitive skills. As a result, worker reallocation without requalification is not likely for those workers with routine-manual skills. Moreover, these are the ones who need relocation most often. In this context, we find it interesting to smooth the path to workers that are in need for requalification so that they reach emerging occupations in the most efficient way.

In previous sections we have pointed out for the overall need for requalification towards the highly emerging technological and social interacting skills. These skills are expected to increase the employability of workers towards emerging occupations. However, it must be noted that acquiring some of these skills may not be easy for displaced workers. Learning these skills can be difficult due to the complexity of the tasks, unfamiliarity with them, and the intensity of use of the new skills. Instead, we are now capable with ESCO to suggest a more efficient personalized requalification recommendation by mapping job trends with their task content. The ESCO dataset lets us, if necessary, detail the requalification needs for each job reallocation path from a declining to emerging occupation. Consequently, we can optimize the job reallocation process by maximizing the use of the existing skills and minimizing the need for requalification when approaching emerging occupations.

Henceforth, we share a tool that provide us with optimal pathways from declining to emerging jobs. For this, we use nearest neighbour matching methods, so we compute for each declining occupation, the emerging occupations that are closer in terms of task content. The methodology is as follows: Within the set of occupations, two subgroups are created for declining in employment and emerging in employment occupations respectively. At the same time, we observe the specific tasks that are performed under these occupations. In this respect, we pair each declining occupation with the emerging occupations that are as close as possible in terms of task content. To do so, a metric must be defined that measures the distance between occupations skillsets. We decide to use the inverse variance matrix weighting metric, which measures the distance in standard deviations[8]. The outcome is a set of optimal matches of declining occupations with emerging ones, where the use of skills already held is maximized while the skills to acquire are minimized. Moreover, the tool provides all the detailed information on the precise task differences.

[8] The STATA program is used to compute the nearest neighbor matches. The inverse variance distance weighting metric is selected. We use the "nnmatch" package for this purpose developed by Alberto Abadie, David Drukker, Jane Leber Herr and Guido W. Imbens. Further information in this metric and methodology can be found in Abadie, A., D. Drukker, J. L. Herr, and G. W. Imbens. (2004) "Implementing matching estimators for average treatment effects in Stata". Stata Journal 4(3), pp. 290-311.

Table 7 presents a sample of the obtained matches. Alongside this, we include the variables that further assess desirable transitions. These are: the need for requalification of the match – measured in positive distance to the emerging occupation; and the correspondence to same or similar occupational group.

**Table 7: Job reallocation paths**

| Declining occupations | Emp. Share change (pp.) | | Emerging Match | Emp. Share change (pp.) | Positive distance | Same group | Similar group |
|---|---|---|---|---|---|---|---|
| Administrative and specialised secretaries | -2.22 | → | Client information workers | 0.49 | 0.76 | | ✓ |
| Metal workers, moulders and welders, and related. | -0.38 | → | Mobile plant operators | 0.19 | 1.72 | | ✓ |
| Mining and construction labourers | -1.00 | → | Food preparation assistants | 0.18 | 1.97 | ✓ | |
| Heavy truck and bus drivers | -0.33 | → | Transport and storage labourers | 0.45 | 2.24 | | ✓ |
| Refuse, waste and garbage workers | -0.40 | → | Food preparation assistants | 0.18 | 2.33 | ✓ | |
| Wood treaters, cabinet-makers and related trades workers | -0.50 | → | Wood processing and papermaking plant operators | 0.16 | 2.56 | | ✓ |
| Blacksmiths, toolmakers and related trades workers | -0.66 | → | Machinery mechanics and repairers | 0.37 | 6.13 | ✓ | |

**Positive distance** shows the requalification need to transition from the declining to the emerging occupation as the sum of skills degree of use additionally performed in the emerging workplace. **Same group** takes into account both sides of the match to belong to the same ISCO-08 occupational group. **Similar group** considers both sides of the match to belong to the first 5 or last 4 ISCO-08 occupational groups.

Source: Own elaboration based on the Spanish Labour Force Survey (SLFS) and ESCO Skill-Occupation Matrix tables.

In addition, we can specify, for each of the different suggested transitions, the specific requalification need to cover the positive distance in skills between the declining occupation and the emerging match. In Table 8 we show the most important skills to acquire for a set of represented transitions.

As we can see from the examples in Table 7, the different job reallocation paths need of distinct requalification. Administrative and specialized secretaries, because they have experience/knowledge in highly demanded tasks, find ways to reallocate with little need for requalification. In contrast, job reallocation from declining routine-manual intensive occupations requires further requalification. This is because emerging occupations require different skills to those previously performed. In addition, as depicted in Table 8, we found that the requalification required to transition from declining to emerging occupations occurs mainly in emerging skills/tasks. Therefore, the tool allows us to suggest a specific, adequate and efficient requalification, rather than a broad recommendation towards technological and social interaction skills.

**Table 8: Requalification need to transition from declining to emerging occupation**

| Job reallocation | | | Requalification need | | | | |
|---|---|---|---|---|---|---|---|
| **Declining occupations** | **Emerging Match** | **Positive distance** | **sorting and packaging goods** | **working with computers** | **using digital tools** | **solving problems** | **processing information** |
| Heavy truck and bus drivers | Transport and storage labourers | 2.24 | 0.31 | 0.25 | 0.25 | 0.17 | 0.17 |
| **Declining occupations** | **Emerging Match** | **Positive distance** | **preparing and serving food** | **working with others** | **Allocating, controlling resources** | **monitoring, inspecting and testing** | **organising, planning, work** |
| Refuse, waste and garbage workers | Food preparation assistants | 2.33 | 0.33 | 0.28 | 0.25 | 0.19 | 0.17 |
| **Declining occupations** | **Emerging Match** | **Positive distance** | **working with machinery** | **using digital tools to control machinery** | **monitoring, inspecting and testing** | **solving problems** | **Allocating, controlling resources** |
| Wood treaters, cabinet-makers and related | Wood processing and papermaking plant operators | 2.56 | 0.33 | 0.33 | 0.25 | 0.22 | 0.17 |
| **Declining occupations** | **Emerging Match** | **Positive distance** | **maintaining and repairing equipment** | **leading and motivating** | **organising, planning work** | **Cleaning** | **monitoring developments** |
| Blacksmiths, toolmakers and related | Machinery mechanics and repairers | 6.13 | 1 | 0.5 | 0.42 | 0.375 | 0.25 |

**Positive distance** shows the requalification need to transition from the declining occupation to the emerging one. This sums the skills degree of use of the additionally performed tasks in the emerging workplace. **The last 5 columns** show the skills requiring the most requalification**.** The omitted skills complete the "positive distance" depicted.

Source: Own elaboration based on the Spanish Labour Force Survey (SLFS) and ESCO Skill-Occupation Matrix tables.

Overall, the tool, which recommends optimal job transitions from declining to emerging occupations, provides valuable and comprehensive information to help facilitate workers' job reallocation. We find it interesting for many applications: It can be used, along with other tools, to improve public policies regarding the employability of displaced workers. Additionally, the tool can help public employment services match jobseekers with employers and find the right training to facilitate this. The provided information can be also valuable for recruitment agencies to find workers with low cost of entry into the workplace. Many other institutions, as well as individuals, can take advantage of the developed tool.

## 8. Conclusions

This work has addressed the empirical relationship between employment changes and the tasks performed in them. Early empirical evidence on such a relationship was based on O*NET data, representative of the United States labour market. However, our study has used the novel, European representative, ESCO data that enable us to study the European labour market more reliably. Based on this, we further explore the changes in the Spanish labour market changes over the period 1997-2019 to study distributional changes from the task perspective.

Based on O*NET and the surrounding literature, we have developed a methodology to operate with the European ESCO data. The resulting dataset has allowed us to assess the occupations skills used, degree of use of them and, consequently, the overall job qualification. Thereby we have been able to compare occupations, find skillset similarities and differences and find relationships with employment. In addition, the detailed and accurate data on task content have enabled us to find worker reallocation paths and requalification needs to ease the transition of workers from declining to emerging occupations.

We first address whether Spanish employment experienced a structural change to then go deeper into its characteristics. Using the Spanish Labour Force Survey (SLFS), we assess the employment changes along the last decades. It is found that the recent employment changes have been heterogeneously distributed by job content. The employment share of mid- and low-skill routine-manual jobs declined, while that of mid- and low-skill service jobs and high-skill jobs increased. This finding leads to a further analysis on the relation of task with employment. Introducing the ESCO data, we identify the specific tasks that are declining and emerging in use given the recent employment changes. It is found that routine-manual tasks are declining in use in Spain, as they are easily codified and performed by machines, or offshored to be performed in other countries. On the other hand, the technological and social interacting tasks are emerging as they are complementary to machines or cannot be substituted by them. Moreover, we found the construction skills to be volatile in response to the different economic cycles. All in all, these results lead to the conclusion that a requalification of workers is needed. As most workers are being displaced from routine-manual occupations, they have to reallocate towards emerging occupations with greater use of technological and social interaction skills. Therefore, there is need to acquire new skills to meet the qualification demanded by emerging occupations.

We then contrast the results of the literature on Routine Biased Technological Change. We constructed two task classifications, routine-manual and non-routine cognitive, derived from the broad ESCO classification. In this regard, we find routine-manual content highly related with the declining occupations. In contrast, the non-routine cognitive skills were significantly more demanded by the emerging occupations. The results coming from ESCO data turned out to be comparable to the ones from the literature using O*NET. Moreover, we find that the routine biased employment change is more structural rather than driven by the different economic cycles.

Nevertheless, we go beyond the literature in Routine Biased Technological Change task classification to assess skills individually. We construct an index that manages to capture the depreciation of workers skillset. This is based on the labour market demand for the tasks performed at their jobs. In this way we can determine whether an individual worker may need more requalification than another based on the demand for their skills. Workers with the least demanded skillset, if displaced, may need of a considerable amount requalification to learn the skills demanded by the current labour market. Instead, we find that some outlier occupations have emerge while employing workers with declining in use skills. This creates the possibility of reallocation of some workers into those occupations without the need for intense requalification.

However, the implications found in the employment composition are not homogeneous across different demographic groups. The work finds a gender gap, where males are overrepresented in declining occupations. Moreover, this gap has tended to widen over the 22 years analysed. This gender gap is explained by looking at the task content, as men are notably more represented performing declining in use tasks. Conversely, women are more represented in emerging occupations performing tasks that are increasing in demand. In contrast, for the age groups, the only implication found is a greater movement of young workers into emerging occupations over the 22 years analysed. Instead, this appears not to be related to the task content performed but driven by other factors. The results lead us to the conclusion that men may need greater reallocation in the near future with a necessary requalification to meet the skills currently in demand. In contrast, for the age groups, we find that the tasks performed do not play a central role in their employment distribution.

Last but not least, as we consider it as one of the main contributions of this study, this work opens the promising avenue of suggesting efficient reallocation pathways for workers. The ESCO database, representative of European workers and with very detailed information on the task content of occupations, has allowed us to find optimal, well-informed job transitions from declining occupations to emerging occupations. We have created a tool that provides the best possible job reallocation by maximising the skills the worker possesses and minimising the need for new skills or requalification. In addition, the precise tasks gap between the emerging and declining occupations is observed to suggest the specific requalification needed. The tool can be used for many applications, from improving public policies to individuals' assessment of their job opportunities and the skills they need to acquire.

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# Annexes

## Annex 1: List of ISCO-08 level-3 occupations

| ISCO-08 | Label |
|---|---|
| 011 | Commissioned armed forces officers |
| 021 | Non-commissioned armed forces officers |
| 031 | Armed forces occupations, other ranks |
| 111 | Legislators and senior officials |
| 112 | Managing directors and chief executives |
| 121 | Business services and administration managers |
| 122 | Sales, marketing and development managers |
| 131 | Production managers in agriculture, forestry and fisheries |
| 132 | Manufacturing, mining, construction, and distribution managers |
| 133 | Information and communications technology service managers |
| 134 | Professional services managers |
| 141 | Hotel and restaurant managers |
| 142 | Retail and wholesale trade managers |
| 143 | Other services managers |
| 211 | Physical and earth science professionals |
| 212 | Mathematicians, actuaries and statisticians |
| 213 | Life science professionals |
| 214 | Engineering professionals (excluding electrotechnology) |
| 215 | Electrotechnology engineers |
| 216 | Architects, planners, surveyors and designers |
| 221 | Medical doctors |
| 222 | Nursing and midwifery professionals |
| 223 | Traditional and complementary medicine professionals |
| 225 | Veterinarians |
| 226 | Other health professionals |
| 231 | University and higher education teachers |
| 232 | Vocational education teachers |
| 233 | Secondary education teachers |
| 234 | Primary school and early childhood teachers |
| 235 | Other teaching professionals |
| 241 | Finance professionals |
| 242 | Administration professionals |
| 243 | Sales, marketing and public relations professionals |
| 251 | Software and applications developers and analysts |
| 252 | Database and network professionals |
| 261 | Legal professionals |
| 262 | Librarians, archivists and curators |
| 263 | Social and religious professionals |
| 264 | Authors, journalists and linguists |
| 265 | Creative and performing artists |
| 311 | Physical and engineering science technicians |
| 312 | Mining, manufacturing and construction supervisors |
| 313 | Process control technicians |
| 314 | Life science technicians and related associate professionals |
| 315 | Ship and aircraft controllers and technicians |
| 321 | Medical and pharmaceutical technicians |
| 322 | Nursing and midwifery associate professionals |
| 323 | Traditional and complementary medicine associate professionals |
| 324 | Veterinary technicians and assistants |
| 325 | Other health associate professionals |
| 331 | Financial and mathematical associate professionals |
| 332 | Sales and purchasing agents and brokers |
| 333 | Business services agents |
| 334 | Administrative and specialised secretaries |
| 335 | Regulatory government associate professionals |
| 341 | Legal, social and religious associate professionals |
| 342 | Sports and fitness workers |
| 343 | Artistic, cultural and culinary associate professionals |
| 351 | Information and communications technology operations and user support technicians |
| 352 | Telecommunications and broadcasting technicians |
| 411 | General office clerks |
| 412 | Secretaries (general) |
| 413 | Keyboard operators |
| 421 | Tellers, money collectors and related clerks |
| 422 | Client information workers |
| 431 | Numerical clerks |
| 432 | Material-recording and transport clerks |
| 441 | Other clerical support workers |
| 511 | Travel attendants, conductors and guides |
| 512 | Cooks |
| 513 | Waiters and bartenders |
| 514 | Hairdressers, beauticians and related workers |

| ISCO-08 | Label |
|---|---|
| 515 | Building and housekeeping supervisors |
| 516 | Other personal services workers |
| 521 | Street and market salespersons |
| 522 | Shop salespersons |
| 523 | Cashiers and ticket clerks |
| 524 | Other sales workers |
| 531 | Child care workers and teachersâ€™ aides |
| 532 | Personal care workers in health services |
| 541 | Protective services workers |
| 611 | Market gardeners and crop growers |
| 612 | Animal producers |
| 613 | Mixed crop and animal producers |
| 621 | Forestry and related workers |
| 622 | Fishery workers, hunters and trappers |
| 711 | Building frame and related trades workers |
| 712 | Building finishers and related trades workers |
| 713 | Painters, building structure cleaners and related trades workers |
| 721 | Sheet and structural metal workers, moulders and welders, and related workers |
| 722 | Blacksmiths, toolmakers and related trades workers |
| 723 | Machinery mechanics and repairers |
| 731 | Handicraft workers |
| 732 | Printing trades workers |
| 741 | Electrical equipment installers and repairers |
| 742 | Electronics and telecommunications installers and repairers |
| 751 | Food processing and related trades workers |
| 752 | Wood treaters, cabinet-makers and related trades workers |
| 753 | Garment and related trades workers |
| 754 | Other craft and related workers |
| 811 | Mining and mineral processing plant operators |
| 812 | Metal processing and finishing plant operators |
| 813 | Chemical and photographic products plant and machine operators |
| 814 | Rubber, plastic and paper products machine operators |
| 815 | Textile, fur and leather products machine operators |
| 816 | Food and related products machine operators |
| 817 | Wood processing and papermaking plant operators |
| 818 | Other stationary plant and machine operators |
| 821 | Assemblers |
| 831 | Locomotive engine drivers and related workers |
| 832 | Car, van and motorcycle drivers |
| 833 | Heavy truck and bus drivers |
| 834 | Mobile plant operators |
| 835 | Ships deck crews and related workers |
| 911 | Domestic, hotel and office cleaners and helpers |
| 912 | Vehicle, window, laundry and other hand cleaning workers |
| 921 | Agricultural, forestry and fishery labourers |
| 931 | Mining and construction labourers |
| 932 | Manufacturing labourers |
| 933 | Transport and storage labourers |
| 941 | Food preparation assistants |
| 951 | Street and related service workers |
| 952 | Street vendors (excluding food) |
| 961 | Refuse, waste and garbage workers |
| 962 | Other elementary workers |

## Annex 2: List of ESCO level-2 skills

| ESCO | Label |
|---|---|
| 1.0 | communication, collaboration and creativity |
| 1.1 | negotiating |
| 1.11 | designing systems and products |
| 1.12 | creating artistic, visual or instructive materials |
| 1.13 | writing and composing |
| 1.14 | performing and entertaining |
| 1.15 | using more than one language |
| 1.2 | liaising and networking |
| 1.3 | teaching and training |
| 1.4 | presenting information |
| 1.5 | advising and consulting |
| 1.6 | promoting, selling and purchasing |
| 1.7 | obtaining information verbally |
| 1.8 | working with others |
| 1.9 | solving problems |
| 2.0 | information skills |
| 2.1 | conducting studies, investigations and examinations |
| 2.2 | documenting and recording information |
| 2.3 | managing information |
| 2.4 | processing information |
| 2.5 | measuring physical properties |
| 2.6 | calculating and estimating |
| 2.7 | analysing and evaluating information and data |
| 2.8 | monitoring, inspecting and testing |
| 2.9 | monitoring developments in area of expertise |
| 3.0 | assisting and caring |
| 3.1 | counselling |
| 3.2 | providing health care or medical treatments |
| 3.3 | protecting and enforcing |
| 3.4 | providing information and support to the public and clients |
| 3.5 | preparing and serving food and drinks |
| 3.6 | providing general personal care |
| 4.0 | management skills |
| 4.1 | developing objectives and strategies |
| 4.2 | organising, planning and scheduling work and activities |
| 4.3 | allocating and controlling resources |
| 4.4 | performing administrative activities |
| 4.5 | leading and motivating |
| 4.6 | building and developing teams |
| 4.7 | recruiting and hiring |
| 4.8 | supervising people |
| 4.9 | making decisions |
| 5.0 | working with computers |
| 5.1 | programming computer systems |
| 5.2 | setting up and protecting computer systems |
| 5.5 | accessing and analysing digital data |
| 5.6 | using digital tools for collaboration, content creation and problem solving |
| 5.7 | using digital tools to control machinery |
| 6.0 | handling and moving |
| 6.1 | sorting and packaging goods and materials |
| 6.11 | cleaning |
| 6.12 | washing and maintaining textiles and clothing |
| 6.13 | handling and disposing of waste and hazardous materials |
| 6.2 | moving and lifting |
| 6.3 | transforming and blending materials |
| 6.4 | tending plants and crops |
| 6.5 | assembling and fabricating products |
| 6.6 | making moulds, casts, models and patterns |
| 6.7 | using hand tools |
| 6.8 | positioning materials, tools or equipment |
| 6.9 | handling animals |
| 7.0 | constructing |
| 7.1 | building and repairing structures |
| 7.2 | installing interior or exterior infrastructure |
| 7.3 | finishing interior or exterior of structures |
| 8.0 | working with machinery and specialised equipment |
| 8.1 | operating mobile plant |
| 8.2 | driving vehicles |
| 8.3 | operating watercraft |
| 8.4 | operating machinery for the extraction and processing of raw materials |
| 8.5 | operating machinery for the manufacture of products |
| 8.6 | using precision instrumentation and equipment |
| 8.7 | installing, maintaining and repairing mechanical equipment |
| 8.8 | installing, maintaining and repairing electrical, electronic and precision equipment |
| 8.9 | operating aircraft |

## Annex 3: ESCO methodology

With the matrix size selected we build the approach to give importance values to the skills by occupation. Recalling that we have just a qualitative measure (essential, optional or not needed) at the most disaggregated level, we can deal with that as we move to lower-level matrixes. There exist many options to aggregate the values, summing essential skills by groups, taking means, normalizing, etc., and also many ways to handle the optional classification as weighting them down or others. From our perspective and with the approval of the ESCO team, our way to proceed has been the following:

- Dismiss the "optional" classification for its lack of preciseness. We just want to work with the essential skills for the different workplaces, we do not find appropriate to work with task that are optional for an occupation. An alternative approach would have been to weight down its value to be comparable to essential skills. The latter force us to introduce and arbitrary weight and assume all sectoral experts understood optional skill in the same way.

- Classify the ESCO level-3 skills. The 429 different skill groups at 3$^{rd}$ level of granularity (see Table 1) is the biggest classification where the highly precise tasks are grouped. To avoid really small and occupation specific task like "describe flavour of different wines", "run a media server", "plan surface slope", etc. having an effect, we say that a skill in ESCO level-3 is essential if at least one subtask is essential for the occupation.

- Obtain the value of skill importance. The value of *degree of importance* for the 75 level-2 skills (our reference, see Table 1) is the share of essential subskills in ESCO level-3 skills (See Example 1). In this way we can compare skills across occupations and within occupations. We say that a skill is more important for a workplace if they use a higher share of subskills.

This methodology comes with some limitations. We may be losing some information for not considering optional tasks. Moreover, we are not considering the amount of essential specific tasks at the most granular level of ESCO. These limitations were also noted by the ESCO developers when we shared with them the methodology but given the structure of ESCO we agreed in being of good praxis.

## Annex 4: Individual skill OLS regression: ESCO skills relation with employment changes

A OLS regression is performed explaining the 22-year employment share change with the different ESCO level-2 skills. 75 separate regressions are run for the great multicollinearity between tasks. The following table shows the results for the different skills relation with employment change. The significance of the effect is shown with asterisk, namely *** probability to reject the hypothesis of having an effect lower than 1%, ** provability < 5%, * provability < 10%.

### Relation of ESCO skills with employment changes

| ESCO | Label | Emp. change |
|---|---|---|
| 1.0 | communication, collaboration and creativity | 0.414*** |
| 1.1 | negotiating | 0.237 |
| 1.11 | designing systems and products | 0.592** |
| 1.12 | creating artistic, visual or instructive materials | 0.241 |
| 1.13 | writing and composing | 0.615** |
| 1.14 | performing and entertaining | 0.685*** |
| 1.15 | using more than one language | 0.441 |
| 1.2 | liaising and networking | 0.613*** |
| 1.3 | teaching and training | 0.621*** |
| 1.4 | presenting information | 0.710** |
| 1.5 | advising and consulting | 1.228*** |
| 1.6 | promoting, selling and purchasing | 0.254 |
| 1.7 | obtaining information verbally | 0.671*** |
| 1.8 | working with others | 0.520* |
| 1.9 | solving problems | 0.461** |
| 2.0 | information skills | 0.355** |
| 2.1 | conducting studies, investigations and examinations | 0.646** |
| 2.2 | documenting and recording information | 0.811* |
| 2.3 | managing information | 0.133 |
| 2.4 | processing information | 0.660* |
| 2.5 | measuring physical properties | -0.345 |
| 2.6 | calculating and estimating | 0.0827 |
| 2.7 | analysing and evaluating information and data | 0.480** |
| 2.8 | monitoring, inspecting and testing | 0.198 |
| 2.9 | monitoring developments in area of expertise | 0.418*** |
| 3.0 | assisting and caring | 0.0127 |
| 3.1 | counselling | 0.611* |
| 3.2 | providing health care or medical treatments | 0.269 |
| 3.3 | protecting and enforcing | 0.046 |
| 3.4 | providing information and support to the public and clients | 0.595*** |
| 3.5 | preparing and serving food and drinks | 0.699*** |
| 3.6 | providing general personal care | 1.298*** |
| 4.0 | management skills | -0.161 |
| 4.1 | developing objectives and strategies | 0.553** |
| 4.2 | organising, planning and scheduling work and activities | 0.275* |
| 4.3 | allocating and controlling resources | -0.00527 |
| 4.4 | performing administrative activities | 0.875* |
| 4.5 | leading and motivating | 0.157 |
| 4.6 | building and developing teams | 0.109 |
| 4.7 | recruiting and hiring | -0.182 |
| 4.8 | supervising people | 0.23 |
| 4.9 | making decisions | 0.118 |
| 5.0 | working with computers | 0.194 |
| 5.1 | programming computer systems | 0.308** |
| 5.2 | setting up and protecting computer systems | 0.437* |
| 5.5 | accessing and analysing digital data | 0.524*** |
| 5.6 | using digital tools for collaboration, content creation and problem solving | 0.477 |
| 5.7 | using digital tools to control machinery | -0.124 |

| | | |
|---|---|---|
| 6.0 | handling and moving | 0.158 |
| 6.1 | sorting and packaging goods and materials | -0.248 |
| 6.11 | cleaning | -0.0836 |
| 6.12 | washing and maintaining textiles and clothing | 0.383 |
| 6.13 | handling and disposing of waste and hazardous materials | -0.279 |
| 6.2 | moving and lifting | -0.268 |
| 6.3 | transforming and blending materials | -0.19 |
| 6.4 | tending plants and crops | -1.456* |
| 6.5 | assembling and fabricating products | -0.479 |
| 6.6 | making moulds, casts, models and patterns | -0.363 |
| 6.7 | using hand tools | -1.109*** |
| 6.8 | positioning materials, tools or equipment | -1.208*** |
| 6.9 | handling animals | -0.262 |
| 7.0 | constructing | -2.509** |
| 7.1 | building and repairing structures | -3.457*** |
| 7.2 | installing interior or exterior infrastructure | -3.343*** |
| 7.3 | finishing interior or exterior of structures | -2.129*** |
| 8.0 | working with machinery and specialised equipment | -0.228** |
| 8.1 | operating mobile plant | -1.326*** |
| 8.2 | driving vehicles | -0.0627 |
| 8.3 | operating watercraft | 0.0763 |
| 8.4 | operating machinery for the extraction and processing of raw materials | -0.607 |
| 8.5 | operating machinery for the manufacture of products | -0.483 |
| 8.6 | using precision instrumentation and equipment | -0.172 |
| 8.7 | installing, maintaining and repairing mechanical equipment | -0.305 |
| 8.8 | installing, maintaining and repairing electrical, electronic and precision equipment | 0.0421 |
| 8.9 | operating aircraft | 0.467 |
| **Observations** | | **120** |

## Annex 5: Table for occupations skillset appreciation/depreciation index

| ISCO-08 | Label | Index | Emp. change |
|---|---|---|---|
| 711 | Building frame and related trades workers | -0.100 | -1.53 |
| 931 | Mining and construction labourers | -0.098 | -1.00 |
| 921 | Agricultural, forestry and fishery labourers | -0.095 | -0.04 |
| 814 | Rubber, plastic and paper products machine operators | -0.077 | -0.18 |
| 712 | Building finishers and related trades workers | -0.071 | -1.35 |
| 818 | Other stationary plant and machine operators | -0.065 | 0.01 |
| 932 | Manufacturing labourers | -0.064 | 0.02 |
| 817 | Wood processing and papermaking plant operators | -0.061 | 0.16 |
| 812 | Metal processing and finishing plant operators | -0.058 | 0.09 |
| 811 | Mining and mineral processing plant operators | -0.058 | -0.10 |
| 752 | Wood treaters, cabinet-makers and related trades workers | -0.055 | -0.51 |
| 961 | Refuse workers | -0.054 | -0.40 |
| 834 | Mobile plant operators | -0.050 | 0.19 |
| 612 | Animal producers | -0.047 | -0.87 |
| 611 | Market gardeners and crop growers | -0.042 | -1.79 |
| 721 | Sheet and structural metal workers, moulders, welders and related. | -0.040 | -0.39 |
| 722 | Blacksmiths, toolmakers and related trades workers | -0.040 | -0.66 |
| 816 | Food and related products machine operators | -0.034 | 0.17 |
| 821 | Assemblers | -0.031 | -0.04 |
| 813 | Chemical and photographic products plant and machine operators | -0.019 | -0.13 |
| 713 | Painters, building structure cleaners and related trades workers | -0.017 | -0.18 |
| 313 | Process control technicians | -0.009 | -0.27 |
| 731 | Handicraft workers | -0.009 | -0.24 |
| 741 | Electrical equipment installers and repairers | -0.008 | -0.60 |
| 751 | Food processing and related trades workers | -0.004 | -0.14 |
| 962 | Other elementary workers | -0.002 | -0.23 |
| 815 | Textile, fur and leather products machine operators | 0.004 | -1.21 |
| 833 | Heavy truck and bus drivers | 0.008 | -0.33 |
| 613 | Mixed crop and animal producers | 0.010 | -0.91 |
| 831 | Locomotive engine drivers and related workers | 0.012 | -0.02 |
| 835 | Shipsâ€™ deck crews and related workers | 0.018 | 0.01 |
| 732 | Printing trades workers | 0.020 | -0.20 |
| 314 | Life science technicians and related associate professionals | 0.021 | 0.07 |
| 324 | Veterinary technicians and assistants | 0.022 | 0.14 |
| 911 | Domestic, hotel and office cleaners and helpers | 0.023 | 1.09 |
| 912 | Vehicle, window, laundry and other hand cleaning workers | 0.024 | -0.09 |
| 723 | Machinery mechanics and repairers | 0.025 | 0.37 |
| 622 | Fishery workers, hunters and trappers | 0.026 | -0.19 |
| 754 | Other craft and related workers | 0.027 | -0.10 |
| 742 | Electronics and telecommunications installers and repairers | 0.028 | 0.09 |
| 941 | Food preparation assistants | 0.028 | 0.18 |
| 512 | Cooks | 0.032 | 0.34 |
| 131 | Production managers in agriculture, forestry and fisheries | 0.036 | 0.18 |
| 312 | Mining, manufacturing and construction supervisors | 0.036 | -0.24 |
| 933 | Transport and storage labourers | 0.037 | 0.46 |
| 753 | Garment and related trades workers | 0.045 | -0.17 |
| 432 | Material-recording and transport clerks | 0.051 | 0.38 |
| 522 | Shop salespersons | 0.052 | 0.40 |
| 225 | Veterinarians | 0.058 | 0.05 |
| 311 | Physical and engineering science technicians | 0.059 | 0.11 |
| 951 | Street and related service workers | 0.064 | 0.01 |
| 213 | Life science professionals | 0.065 | 0.23 |
| 315 | Ship and aircraft controllers and technicians | 0.068 | 0.00 |
| 142 | Retail and wholesale trade managers | 0.069 | -0.02 |
| 541 | Protective services workers | 0.071 | 0.06 |
| 343 | Artistic, cultural and culinary associate professionals | 0.071 | 0.19 |
| 832 | Car, van and motorcycle drivers | 0.073 | -0.09 |
| 141 | Hotel and restaurant managers | 0.077 | 0.21 |

| ISCO-08 | Label | Index | Emp. change |
|---|---|---|---|
| 321 | Medical and pharmaceutical technicians | 0.077 | 0.19 |
| 515 | Building and housekeeping supervisors | 0.078 | 0.08 |
| 121 | Business services and administration managers | 0.079 | 0.20 |
| 112 | Managing directors and chief executives | 0.082 | -0.41 |
| 132 | Manufacturing, mining, construction, and distribution managers | 0.084 | 0.02 |
| 214 | Engineering professionals (excluding electrotechnology) | 0.084 | 0.64 |
| 952 | Street vendors (excluding food) | 0.087 | 0.01 |
| 516 | Other personal services workers | 0.087 | -0.17 |
| 325 | Other health associate professionals | 0.088 | 0.15 |
| 111 | Legislators and senior officials | 0.091 | 0.03 |
| 621 | Forestry and related workers | 0.092 | -0.06 |
| 521 | Street and market salespersons | 0.094 | -0.68 |
| 335 | Regulatory government associate professionals | 0.094 | 0.15 |
| 143 | Other services managers | 0.095 | 0.35 |
| 211 | Physical and earth science professionals | 0.096 | -0.04 |
| 331 | Financial and mathematical associate professionals | 0.099 | -0.18 |
| 524 | Other sales workers | 0.100 | -0.78 |
| 332 | Sales and purchasing agents and brokers | 0.100 | 0.48 |
| 265 | Creative and performing artists | 0.101 | 0.13 |
| 334 | Administrative and specialised secretaries | 0.102 | -2.22 |
| 532 | Personal care workers in health services | 0.103 | 0.93 |
| 226 | Other health professionals | 0.105 | -0.66 |
| 241 | Finance professionals | 0.105 | 0.47 |
| 133 | Information and communications technology service managers | 0.107 | 0.00 |
| 514 | Hairdressers, beauticians and related workers | 0.110 | 0.38 |
| 333 | Business services agents | 0.110 | 0.54 |
| 122 | Sales, marketing and development managers | 0.112 | 0.30 |
| 513 | Waiters and bartenders | 0.112 | 0.45 |
| 412 | Secretaries (general) | 0.113 | 0.17 |
| 216 | Architects, planners, surveyors and designers | 0.114 | 0.12 |
| 222 | Nursing and midwifery professionals | 0.118 | 0.36 |
| 242 | Administration professionals | 0.119 | 0.69 |
| 243 | Sales, marketing and public relations professionals | 0.119 | 0.20 |
| 422 | Client information workers | 0.120 | 0.49 |
| 431 | Numerical clerks | 0.120 | 0.24 |
| 421 | Tellers, money collectors and related clerks | 0.123 | 0.05 |
| 352 | Telecommunications and broadcasting technicians | 0.124 | 0.17 |
| 511 | Travel attendants, conductors and guides | 0.124 | 0.19 |
| 411 | General office clerks | 0.124 | 0.17 |
| 523 | Cashiers and ticket clerks | 0.126 | 0.01 |
| 262 | Librarians, archivists and curators | 0.126 | 0.01 |
| 232 | Vocational education teachers | 0.126 | 0.00 |
| 341 | Legal, social and religious associate professionals | 0.129 | 0.06 |
| 215 | Electrotechnology engineers | 0.130 | 0.26 |
| 231 | University and higher education teachers | 0.133 | 0.09 |
| 263 | Social and religious professionals | 0.133 | 0.67 |
| 441 | Other clerical support workers | 0.133 | 0.12 |
| 233 | Secondary education teachers | 0.134 | 0.13 |
| 223 | Traditional and complementary medicine professionals | 0.136 | 0.00 |
| 134 | Professional services managers | 0.136 | 0.00 |
| 531 | Child care workers and teachersâ€™ aides | 0.138 | 0.58 |
| 261 | Legal professionals | 0.143 | 0.44 |
| 342 | Sports and fitness workers | 0.146 | 0.34 |
| 264 | Authors, journalists and linguists | 0.146 | 0.20 |
| 234 | Primary school and early childhood teachers | 0.149 | 0.01 |
| 323 | Traditional and complementary medicine associate professionals | 0.153 | 0.00 |
| 235 | Other teaching professionals | 0.159 | 0.75 |
| 413 | Keyboard operators | 0.167 | 0.48 |
| 251 | Software and applications developers and analysts | 0.182 | 0.38 |
| 351 | Information and communications technology and user support technicians | 0.190 | 1.04 |
| 252 | Database and network professionals | 0.200 | 0.17 |
| 212 | Mathematicians, actuaries and statisticians | 0.203 | 0.10 |