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THE ROUTINE CONTENT OF OCCUPATIONS: NEW CROSS-COUNTRY MEASURES BASED ON PIAAC

Luca Marcolin*, Sébastien Miroudot^, Mariagrazia Squicciarini*

ABSTRACT

This work proposes a novel measure of the routine content of occupations, built on data from the OECD PIAAC survey of adult skills mirroring the extent to which workers can modify the type and sequence of tasks performed on the job. Based on median values of individuals' responses in 3-digit occupations across 20 OECD countries, occupations are grouped into quartiles of routine intensity, namely high (HR), medium (MR), low (LR), and non-routine intensive (NR). On average, in 2012, 46% of employed persons worked in NR or LR occupations, with significant differences in the distribution between quartiles across countries. While more routine intensive occupations tend to be associated with lower skills, this relationship is not very strong. Applying the RII on employment data from Labour Force Surveys, MR and HR occupations are found to be less resilient to business cycles, with notable differences across quartiles between Europe and the United States.

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EXECUTIVE SUMMARY

This work proposes a novel measure of the routine content of occupations based on data from the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey. This measure, called the Routine Intensity Indicator (RII), is built on information about the extent to which workers can modify the sequence of their tasks and decide the type of tasks to be performed on the job. It thus captures the degree of codifiability of such tasks. The RII is selected among a number of indices built relying on a wide array of methodologies, and is used to group occupations into four routine intensity groups, namely high routine intensive (HR), medium routine intensive (MR), low routine intensive (LR), and non-routine (NR) occupations. This classification of individuals into quartiles of routine intensity, which is based on the median RII values of individuals in the 3-digit occupation, is provided for 20 OECD countries, and allows for greater precision in the allocation of occupations across different groups of routine intensity.

On average, 46% of employed persons appear to be working in non-routine (18%) or low (28%) routine intensive occupations. Canada and the United Kingdom display, respectively, the lowest and highest proportion of routine intensive workers (i.e. in medium and high routine intensive occupations). The distribution between non-routine and low routine intensive quartiles differs significantly across countries, even among countries displaying similar proportions of employment in non-routine occupations (e.g. Canada and Korea). Belgium, Denmark, and the Netherlands display the highest proportion (approximately 70%) of total employment in occupations at the middle of the routine intensity distribution (i.e. low and medium routine intensive jobs).

The paper further investigates the relationship that exists between the routine content of occupations and the skills of the workforce, intended as both the skills that workers are endowed with (i.e. independently of use) and those that they use on the job. While the correlation between skill content and routine intensity is indeed negative, i.e. more routine intensive occupations tend to be associated with lower skills, this relationship is not very strong. Non-routine and low routine intensive occupations appear to be monotonically increasing in skill intensity, when these are measured according to individuals' educational attainment or occupation type. This is not the case for medium and high routine intensive occupations, which are mostly intensive in medium skills. Also, while the proportion of workers never performing manual work is higher among routine workers, 20 % of the employed people in PIAAC perform manual work every day despite operating in non-routine or low routine intensive jobs.

Applying the RII on employment data from Labour Force Surveys, it emerges that routine intensive occupations (i.e. medium and high routine intensive occupations) are less resilient to business cycles than less routine occupations (i.e. non-routine and low routine intensive occupations). During the 2008-2009 crisis, job losses in Europe mainly concerned routine intensive occupations while in the United States they affected all groups. Conversely, in 2011-2012, in a more favourable macroeconomic scenario, both routine intensive and less routine occupations contributed to net job creation in the United States, while gains in Europe only happened in less routine occupations. This relationship may to some extent reflect the composition of routine vs non-routine workers in terms of underlying individual (e.g. age and gender) and firm characteristics (like size or technological intensity), which are correlated with the probability of an individual being employed over the business cycle.

This work sheds new light on the extent to which occupations differ in the routine content of the tasks performed on the job and on the relationship that exists between skills and the routine content of occupations, and allows comparisons of such patterns across countries and industries, in a homogenous fashion. Thanks to the richness of the data used, the routine content of occupations is investigated from a number of perspectives, including industry, firm size, gender, and the public or private nature of employers, thus providing important elements for evidence-based policy analysis.

THE ROUTINE CONTENT OF OCCUPATIONS: NEW CROSS-COUNTRY MEASURES BASED ON PIAAC

Introduction

Over the last decades, technological progress and innovation coupled with trade liberalisation and the consequent reduction and elimination of tariffs and non-tariff barriers, have led firms to organise production over an increasing number of stages and tasks, which are carried out domestically and abroad. Goods and services, as well as their components, get simultaneously or sequentially produced and assembled in different locations - often geographically clustered at the local and regional level (Baldwin, 2012) - before reaching their target markets. At the same time as production gets articulated into a wide array of horizontal, vertical and mixed settings (see Santos-Paulino *et al.*, 2008, for a discussion), the growing mobility of physical, financial and human capital, as well as of knowledge based assets, makes countries and regions progressively more economically integrated.

Cross-border flows of intermediates and goods are often accompanied by the movement of services which differ in their task, knowledge and skill content, and that relate to all stages of production, in both manufacturing and services. Firms' competitive advantage and industries' comparative advantages can therefore be defined in terms of the domestic (versus foreign) content of tasks they embed. Advanced economies generally appear to have been specialising in high-value-added activities and in high-skill tasks such as R&D and design, while developing countries have been mainly concentrating on production and assembly-related tasks and skills.

Recent analyses such as Becker *et al.* (2013) and Goos *et al.* (2014) argue that there are many factors that contribute to explaining the movements of employment across countries along the production chain. These include the degree of codifiability[1] and communicability of the tasks carried out by workers, the principal – agent relationship that can be established, and the extent to which complete contracts can be written and enforced (Rilla and Squicciarini, 2011).

In particular, an important stream of the literature investigates the link between job and wage dynamics, and the way in which the routine intensity of tasks, i.e. the extent to which tasks are carried out in a codifiable and repetitive way, affect such patterns. Anecdotal evidence suggests that the routine intensity of occupations is partially decoupled from workers' skills, as there are low-skill tasks that cannot be routinised (e.g. cleaning activities), whereas some high-skill tasks can (e.g. accounting). Also, the degree to which tasks can be routinised correlates positively with the degree of offshorability of tasks, e.g. in the form of shipments from affiliate to the headquarters (Oldenski, 2012); and negatively with employment levels at home, especially of those occupations which are intensive in such tasks (Becker *et al.*, 2013; Autor and Dorn, 2013; Goos *et al.*, 2014).

1. Seabright (2000) for instance defines as codifiable those tasks "for which a set of instructions can be given so that the task is exercised by following steps in a more or less algorithmic manner" (p.858). Autor *et al.* (2013a) underline that tasks following explicit codifiable procedures may be easily computerised and hence automated; and that codifiable tasks may be performed at a distance, possibly without substantial loss of quality, and hence appear well suited to offshoring.

The routine intensity measures used in these studies rely on classifications linking occupations to sets of tasks and skills in a given country (e.g. Autor *et al.*, 2003 and Blinder, 2009 for the U.S). While the richness of the data allows for a precise identification of the content of each occupation, and hence its routine intensity, these classifications are often based on the judgement of experts assigning scores to different indicators characterising the occupations. This is very different from asking individuals about the real content of their daily work (as in Spitz-Oener, 2006; Becker *et al.*, 2013; or Baumgarten *et al.*, 2013), which allows for a more precise identification of routine intensive tasks. What is more, the information used to identify routine intensive occupations is often chosen ad-hoc and the precision of the analyses is somewhat constrained by the limited time and country coverage of the surveys on which they rely. This leads to having to assume that the routine content of tasks is time-invariant and that it does not vary across countries, like in e.g. Goos *et al.* (2014) who rely on a task characterisation based on United States' Occupational Information Network (O*NET) to investigate job polarisation in European countries.

Motivated by the need to (re)define the routine intensity of occupations using up-to-date, country-specific information, the OECD has developed a new set of indicators to be used in analysis addressing the relationship between the routine content of occupations, participation in global value chains and employment patterns. This work exploits data from the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey to construct a novel measure of the routine content of occupations for 20 OECD countries. This measure is built on individual-level information contained in PIAAC about the extent to which workers can modify the sequence of their tasks and decide the type of tasks to be performed on the job. A number of indices synthesising this information are here used to group occupations into four routine intensity classes (high, medium, and low routine intensive, and non-routine).

Finally, this work sheds light on the relationship that exists between the routine content of occupations and the skills of the workforce, intended as both the skills that workers are endowed with (i.e. independently of use) and those that they use on the job. The ad-hoc choice of the PIAAC questions used in the study - made on the basis of a semantic analysis of their content - is also tested.

While offering new evidence on the extent to which occupations differ in the routine content of the tasks that workers perform on the job, this work has a limited ability to shed light on how these patterns change over time. As the PIAAC survey is in its first round, the information provided is cross-sectional in nature, at least until the next survey wave. To try and provide some insights on how occupational and industry patterns have changed, this work assumes that the routine intensity of any given occupation has remained basically constant over the time span considered, as done in much of the existing literature. The time dimension of routine intensity is recovered exploiting Census and Labour Force Survey-type of data, which are used to estimate employment in routine intensive occupations at the country and industry level.

This paper is structured as follows. An overview of the literature concerned with assessing the routine intensity of occupations and the extent to which more routine intensive jobs can get automated and offshored is followed by a an outline of the new methodology proposed. A brief description of the data on which the study relies follows, accompanied by a wide array of descriptive statistics portraying some of the most salient stylised facts that emerge. A characterisation of the relationship that emerges between the routine content of occupations and the skill endowment of the workforce precedes some first conclusions, highlighting some caveats and the possible work ahead.

Routine intensity, automation and offshorability: A brief survey

The literature on employment in OECD economies has recently devoted a lot of attention to the polarisation of employment (Autor *et al.*, 2006; Goos *et al.*, 2009). The latter refers to the changes occurring in employment patterns whereby the share of occupations at both ends of the skill distribution (low-skilled and high-skilled jobs) increases, while employment in the middle of the distribution (mid-skilled jobs) declines. Technological change is generally held as one of the main factors behind this employment polarisation, as suggested by the literature on “skilled-biased technological change” (see, e.g. Acemoglu, 2002; Autor *et al.*, 2003).

In addition, Information and Communication Technologies (ICT) have seemingly favoured non-routine tasks performed by high- and low-skilled workers, at the expense of routine tasks which are mainly performed by medium-skilled employees (Autor *et al.*, 2003). This can be summarised in a modified version of the skilled-biased technological change framework where ICT is rather complementary with abstract and non-routine tasks, and substitute with routine intensive tasks (Autor *et al.*, 2008, Goos *et al.*, 2014). If manual (non-routine or location-specific) occupations are mostly unaffected by automation (Autor and Dorn, 2013) but somewhat complementary to non-routine tasks, employment is expected to increase in these occupations, too. Most job losses would hence happen among middle-skilled workers, who are more likely to perform routine intensive tasks.

Offshoring and the emergence of GVCs have also been found to play a role with respect to the polarisation of employment, as routine tasks have been increasingly offshored (Autor, 2010; Goos *et al.*, 2014). In countries open to international trade, the positive employment effect due to the complementarity between ICT and non-routine tasks is enhanced by a comparative advantage-based mechanism of specialisation. In advanced economies having an incentive to specialise in non-routine occupations, greater exposure to international trade will benefit non-routine occupations the most, thus providing further incentive to specialise in this very type of occupations. The reverse holds for products which are intensive in routine tasks.

This literature crucially relies on the availability of a proxy for the routine content of tasks performed by an individual, which are mostly unobservable. A classification of individuals in routine intensity jobs thus hinges upon their occupation and how intensive occupations are in routine intensive tasks. That is why, in their seminal paper, Autor *et al.* (2003) associate a set of occupational features (skills and job requirements) contained in the Dictionary of Occupational Titles (DOT) to routine and non-routine tasks. As the DOT contains a description of all U.S. occupations according to these features, the authors classify occupations according to their intensity in routine tasks. In particular, they classify tasks as:

- *non-routine cognitive*, i.e. tasks requiring analytical reasoning skills or interactive, communication and managerial skills;
- *non-routine manual*, i.e. tasks requiring eye-hand-foot coordination;
- *routine cognitive*, i.e. tasks requiring the capability to comply with “limits, tolerances or standards”; and
- *routine manual*, in the case of tasks requiring a certain amount of “finger dexterity”, i.e. the ability to use fingers to manipulate small objects with precision and speed.

These characteristics are then aggregated to create a single index synthesising the routine intensity of occupations. An alternative index, created using principal component analysis, confirms the results of the analysis based on the ad-hoc association of tasks with routine intensity. This same classification was adopted in a number of later studies, or further elaborated in a tripartite classification (e.g. Autor *et al.*, 2006 and 2008; Autor *et al.*, 2013a and 2013b; Autor and Dorn, 2013; Goos *et al.*, 2009 and 2014).

A second stream of the literature highlights the distinction between the routine intensity and the offshorability of tasks, i.e. the easiness with which tasks can be performed abroad. As some complex, non-routine intensive tasks can also be offshored, routine intensity can be seen as one driving feature of the offshorability of tasks, albeit one that is neither sufficient nor necessary.

In Blinder (2009) and Blinder and Krueger (2013) offshorable tasks do not require face-to-face interaction with the customer and can be easily communicated electronically. Occupations are classified either using the O*NET - which can be seen as an evolution of the DOT describing the activities, context and requirements of U.S. occupations - as in Blinder (2009), or with the aid of professional coders offering their subjective judgement (Blinder and Krueger 2013).

Routine intensity is but one feature of offshorability in Firpo *et al.*'s (2011) analysis of occupational tasks and changes in the wage structure. In Oldenski (2012, 2014), routine intensity is assessed on the bases of the extent to which problem solving, creative thinking, and decision making abilities are required, as well as the easiness or difficulty with which they can be coded and communicated (especially abroad). Lastly, Spitz-Oener (2006), Becker *et al.* (2013) and Baumgarten *et al.* (2013) rely on institutional survey information to produce two different classifications of German occupations by routine intensity. In both classifications tasks and occupations are categorised by their intensity in repetitive actions (routine intensity) and face-to-face interaction (interactivity).

The methodology presented in this work takes a step away from the definitions of routine intensity above (in particular, Autor *et al.*, 2003) in several ways, and revises the importance of “finger dexterity” and “abstract reasoning” for the identification of routine intensive tasks.[2] In Autor *et al.* (2003), “finger dexterity” identifies manual routine tasks, such as baking, special kinds of sewing, or packing of agricultural products such as eggs (Appendix 1 of the original paper). The information is taken from U.S. the Dictionary of Occupational Titles (DOT) which collected information on the characteristics of jobs at the end of the 1970s. However, in the PIAAC data used for this analysis, occupations where individuals frequently require “finger dexterity” cannot be straight-forwardly identified as routinary. Such discrepancy may be attributed to the evolution of what was meant by “finger dexterity” and its relevance in the 70s (as in Autor *et al.*, 2003) and today, when finger dexterity seems to characterise manual jobs of a much higher value added such as arts and crafts.

Mathematical skills, instead, identify non-routine analytical tasks in Autor *et al.* (2003), but are not considered to define routine intensity in the present analysis. Such information will nevertheless be used in a later part of the paper to address the link between the routine content of tasks and skill endowment of the workforce. Anecdotal evidence suggests that even mathematically intensive tasks can nowadays be codified and moved abroad, as it happens for instance with data mining. Moreover, the PIAAC survey does not test respondents for advanced mathematical skills which could be typical of “abstract non-routine” tasks. Hence, this work assumes that individuals’ numerical proficiency may no longer be considered a good proxy for the routine content of tasks, and is instead used to construct one of the proxies for the skill content of occupations which is correlated with, but not perfectly mapping into, the routine content of occupations.

Measuring the routine content of occupations: A task-based approach

This work proposes a new task-based methodology for the assessment of the routine content of occupations. It exploits cross-country data and proposes the construction of a new index, the routine intensity index (RII) which can be calculated at the occupation and sector levels in an independent fashion. The availability of PIAAC data, which contains information on both the worker’s sector of employment and type of occupation, also allows producing a classification of both occupations and sectors separately.

2. In PIAAC: questions *f_q06c* and *pvpnum.*

This represents an additional step forward with respect to existing literature, where tasks are linked to occupations only. Furthermore, routine intensive tasks can be determined for more disaggregated occupations and sectors (up to the three digit level of the 2008 International Standard Classification of Occupations, ISCO08, and of 4th revision of the International Standard Industrial Classification, ISIC4, respectively).

Lastly, and perhaps more importantly, this study moves further away from ad-hoc choices in the selection of the features characterising the routine intensity of tasks. It does so exploiting PIAAC questions addressing important aspects of routinisation such as the extent to which workers can change their working plans and the type and sequence of tasks performed on the job. While such aspects of the routine content of tasks may not necessarily be more encompassing than the ones proposed in earlier literature, they nevertheless allow producing more precise proxies for the latent unobserved phenomenon, i.e. the extent to which occupations are more or less routine intensive.

An in-depth analysis of the PIAAC survey reveals the existence of four questions providing useful information with respect to the routine content of occupations.[3] Two variables of interest report the individuals' assessment of their degree of freedom in *i*) establishing the sequence of their tasks; and *ii*) deciding the type of tasks to be performed on the job.[4] These questions appear to be intuitively strongly correlated with the unobserved routine content of jobs. Moreover, and in an effort to bridge the gap with the definitions of routine intensity provided by the existing literature, two additional PIAAC questions are exploited. These variables provide relevant information on the frequency with which individuals plan their own activities and organise their own time, and links to the idea of planning and control which characterises non-routine interactive tasks in Autor *et al.* (2003).[5]

Index construction

In principle, each of the highlighted variables can be used to proxy routine intensity. Their correlation with an underlying latent variable, which can be interpreted as the routine character of an individual's job, is high, as can be seen from Cronbach's alphas (Cronbach, 1951; OECD, 2013(b)). This indicator, which allows testing for the correlation of each variable with the unidimensional latent construct, reaches 88% and confirms that all variables are positively correlated with the underlying construct[6]. This supports an operational choice where the answers provided by individuals on all four PIAAC questions are taken into account. The RII index synthesising the routine content of the task carried out by an individual *k* employed in sector *i* and occupation *o,* can thus be written as:

$$RII_{k,i,o} = w_{seq} Sequentiability_{k,i,o} + w_{flex} Flexibility_{k,i,o} + w_{planown} Plan\_own_{k,i,o} + w_{orgown} Organise\_own_{k,i,o} \quad (1)$$

Where *Sequentiability, Flexibility, Plan_own* and *Organise_own* are the frequencies with which individuals may, respectively: choose the sequence of the tasks involved by the job; change the content of work or how this is carried out; plan their own work activities; and organise their own working time. When constructing the RII, a weight *w* which is independent on the individual, her sector and occupation of employment, can be associated to each variable, in order to give more or less importance to the different routine features.

3. The exact formulation of the questions can be found in Appendix 1.
4. In PIAAC: questions *d_q11a* and *d_q11b*.
5. In PIAAC: questions *f_q03a* and *f_q03c.*
6. The estimated alpha is the square of the correlation between the composing variables and the underlying unobserved factor (0.88), i.e. 0.77 across country. The alphas calculated excluding one of the variables at a time are consistently lower (respectively: 0.72, 0.73, 0.71, 0.71), which suggests than none of the selected variables can be excluded without loss of power in explaining the underlying factor.

In PIAAC, each of the described variables is coded using a Likert scale of integer values ranging from 1 to 5, and elaborated so that 1 represents the least frequency of routine intensive activity, and 5 the highest such frequency. For instance, in the case of the question “To what extent can you choose or change the sequence of your task?” the answer “Never” (i.e. high routine intensity) is coded as “5”, “less than once a month” is coded as “4” and “less than once a week” is coded as “3”.[7] The resulting index *RII* is therefore increasing in the frequency of routine intensive tasks of the individual, that is: the higher the value of the index, the more routine intensive the occupation considered is.[8] Subjects for whom at least one of the answers to the questions of interest is missing are discarded, as they would have artificially low values of *RII* due to their missing answer to one of the index components.

Expression (1) describes *RII* as a linear function of the underlying PIAAC variables. While this is clearly an ad-hoc choice, it nevertheless represents the most natural functional form that can be adopted to summarise multiple concepts which are correlated among each other and that feature a common underlying denominator, but of which the implied latent model is unknown. What is more, an additive functional form is pervasive in the relevant literature: for example, Autor *et al.* (2003) and Goos *et al.* (2014), who measure routine intensity as a sum of the considered variables.[9]

Further assumptions determine the choice of the four variable-specific weights $W_{.} = \{w_{seq}; w_{flex}; w_{planown}; w_{orgown}\}$ of the *Routine Intensity Index.* It is first established that the four weights should sum to one, so that the support of the *RII* is the same as its composing variables, and the *RII* is bound between 1 (least routine intensive task) and 5 (most routine intensive task). A second choice pertains to the value that each weight should have, as an infinite set of combinations is possible in practice. A first set of weights, W_{pca}, is derived from the principal component analysis (PCA) and computed following OECD (2008).

PCA is a statistical procedure which highlights how many groups of related variables exist in the subset of considered variables, and how well these groups can explain variation in the latent variable they describe. PCA with the four considered variables is well behaved[10] and yields a first component which can explain 60% of the total variation, and a second component which can explain further 23% of it.[11] The resulting set of weights, calculated as in OECD (2008) (p. 90) and Nicoletti *et al.* (2000), suggests that equal weights to all variables would be appropriate: $W_{pca} = \{w_{seq}; w_{flex}; w_{planown}; w_{orgown}\} = \{0.243; 0.256; 0.251; 0.25\}$. Each variable receives a precise aggregation weight, which is equal for all PIAAC individuals.[12]

7. As in all Likert scales, the distance between two responses is not exactly reflected in the numerical distance between the numbers used to code such answers, i.e. responses are ranked but intervals between values cannot be presumed equal even if this is the case for the numbers which are used to code the answers. For instance, the frequencies “Never” (coded as “5”), “less than once a month” (coded as “4”) and “less than once a week” (coded as “3”) do not represent the same intervals as 5, 4, and 3 may do.
8. Note, however, that the *RII* does not only assume integer values, due to the use of non-integer weights *w[]*. More information on this point is provided shortly hereafter.
9. Taken in logarithmic form, with unitary weight for each variable.
10. The correlation among the chosen variables is high, and the Kaiser, Meyer, Olkin (Kaiser, 1970) test is passed.
11. According to the Kaiser rule, only component 1 should be kept (eigenvalue>1), but Nicoletti *et al.* (2000) argue instead that any component explaining at least 10% of the variation should be kept. This second rule of thumb is here applied, in the interest of preserving the maximum amount of information which is provided by the data. The first rotated component has the flavour of “Sequentiability”.
12. This last condition could be relaxed, had the PCA been run differently, e.g. by occupation.

Furthermore, the current version of the analysis uses four extra arbitrary sets of weights to construct the indicator: (i) equal weights for all variables of *Routine*, i.e. $W_1 = \{1/4\,;1/4\,;1/4\,;1/4\}$; (ii) equally distanced weights in the 0-1 interval, i.e. $W_2 = \{1/10\,;2/10\,;3/10\,;4/10\}$; (iii) one weight being double than the previous one, i.e. $W_3 = \{1/15\,;2/15\,;4/15\,;8/15\}$; and (iv) the weight of the "most important" composing variable fixed at 0.5, and equal weights attributed to the other variables, i.e. $W_4 = \{1/2\,;1/6\,;1/6\,;1/6\}$.[13] Exploiting any of these four sets, the *RII* will have *non-integer* values between 1 and 5. It has to be noted that, as using equal weights for all variables yields exactly the same index as the one obtained by computing Cronbach's alpha on the same variables and sample, the remaining part of this study does not consider an index obtained with Cronbach's alpha.

A final choice relates to how each weight in last three sets (W_2, W_3 and W_4) is assigned to each of the composing variables, which is equivalent to establishing which variable should hold more weight in the computation of the *RII*.[14] Among the many possible options, this study ranks the variables based on their dispersion, so that higher weights will be attributed to variables displaying lower dispersion, as they are seemingly conveying a more coherent message. Given two questions investigating the same underlying concept, the question with more heterogeneous answers across individuals may be considered a more imprecise proxy for the latent process, and can therefore be attributed a lower weight. This study calculates dispersion in three different ways: (a) as the coefficient of variation in the 3-digit occupation or sector; (b) the coefficient of variation in the entire economy; (c) the ratio of the 90th to 10th percentile (90-10 ratio) of the distribution in the 3-digit occupation or sector.[15]

In order to compare the present analysis with Autor *et al.* (2003) and with similar studies, two extra indexes are computed using the variables in logarithm and equal weights across variables (once where *w*=0.25 and once where *w*=1), as if the *RII* could be proxied by a Cobb Douglas "production function" where the inputs are *Sequentiability*, *Flexibility*, *Plan_own* and *Organise_own*. One last index was constructed by summing up all the previous indexes when not in logarithmic form.

Measuring the routine intensity of occupations

In sum, a total of 14 different indexes are produced, i.e. two indicators obtained taking the variables in logarithms (*index3a; index3b*); one indicator from the PCA (*index2*); one from using equal weights for all variables (*index1c*); and three indicators per each set of non-equal weights (W_2, W_3, W_4), depending on how the dispersion in the answers to a given variable is calculated (a, b, d).[16] Table 1 details all the indexes produced and their acronyms.

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13. In a second phase of this analysis, a sufficiently high number (e.g. 5000) of sets of four random weights could be generated, so as to assess the robustness of the results to the choice of weights. This is not expected to matter greatly, when considering the very high correlations among values of *RII* which can be obtained with the described three sets of weights.

14. Note that the PCA provides an answer to this question as well, as it computes the four weights and assigns each of them to a precise variable.

15. As it was mentioned before, this study will produce occupation- or sector-specific measures of routine intensity and related employment, in lack of better information on the individual's working tasks. If routine intensity is believed to have a sectoral or occupational dimension, it seems appropriate to restrict the calculation of dispersion to the occupational or sectoral level as well.

16. More precisely, the suffix "_cv_occ" signals that the weight is assigned based on the dispersion within the 3-digit occupation, where the dispersion is calculated as the coefficient of variation. Similarly, "_9010_occ" signals that the dispersion is calculated as the ratio of 90th to 10th percentile within the 3-digit occupation, and "_cv_all" that the coefficient of variation is calculated pooling the data across occupations.

Table 1. Routine Intensity Indexes specification

Index	Weights for each PIAAC variable	Construction
index1a_cv_occ index1b_cv_occ index1d_cv_occ	$W_2 = \{1/10\,;2/10\,;3/10\,;4/10\}$ $W_3 = \{1/15\,;2/15\,;4/15\,;8/15\}$ $W_4 = \{1/2\,;1/6\,;1/6\,;1/6\}$	Each PIAAC variable is assigned a weight, depending on the dispersion in the value of the variable at the 3-digit occupational level. The dispersion is calculated as the coefficient of variation.
index1a_9010_occ index1b_9010_occ index1d_9010_occ	$W_2 = \{1/10\,;2/10\,;3/10\,;4/10\}$ $W_3 = \{1/15\,;2/15\,;4/15\,;8/15\}$ $W_4 = \{1/2\,;1/6\,;1/6\,;1/6\}$	Each PIAAC variable is assigned a weight, depending on the dispersion in the value of the variable at the 3-digit occupational level. The dispersion is calculated as the ratio of 90th to 10th percentile.
index1a_cv_all index1b_cv_all index1d_cv_all	$W_2 = \{1/10\,;2/10\,;3/10\,;4/10\}$ $W_3 = \{1/15\,;2/15\,;4/15\,;8/15\}$ $W_4 = \{1/2\,;1/6\,;1/6\,;1/6\}$	Each PIAAC variable is assigned a weight, depending on the dispersion in the value of the variable at the economy level. The dispersion is calculated as the coefficient of variation.
index1c	$W_1 = \{1/4\,;1/4\,;1/4\,;1/4\}$	Each PIAAC variable is assigned equal weight.
index2	$W_{pca} = \{0.243; 0.256; 0.251; 0.25\}$	Each PIAAC variable is assigned a weight which was derived from Principal Component Analysis.
index3a	$W_{log1} = \{1/4\,;1/4\,;1/4\,;1/4\}$	Each PIAAC variable is taken in logarithm and assigned equal weight.
index3b	$W_{log2} = \{1; 1; 1; 1\}$	Each PIAAC variable is taken in logarithm and assigned equal weight.
index4		All the indexes above except for index3a and index3b are linearly aggregated.
sequ		PIAAC variable *d_q11a*. Inverted to be decreasing in the frequency of *Sequentiability* of the tasks on the job. Discrete values ranging from 1 to 5.

Source: authors' own compilation.

Tables 2a and 2b below show, respectively, the pairwise and the Spearman rank correlations observed between the indicators. As can be seen, correlations are very high, and in the case of the Spearman rank correlation values range from 0.8 to 0.99. The set of highest correlations is achieved computing the index using equal weights. This is therefore used as the reference index for the entire analysis and highlighted in bold in the tables.

Table 2a. Pairwise correlations across routine intensity indices. PIAAC countries, 2011-2012

	sequ	index1a_ cv_occ	index1b_ cv_occ	index1d_ cv_occ	index1a_90 10_occ	index1b_90 10_occ	index1c	index1d_90 10_occ	index1a_ cv_all	index1b_ cv_all	index1d_ cv_all	index2	index3a	index3b	index4
Sequ	1														
index1a_cv_occ	0.845*	1													
index1b_cv_occ	0.862*	0.989*	1												
index1d_cv_occ	0.637*	0.873*	0.813*	1											
index1a_9010_occ	0.747*	0.949*	0.917*	0.927*	1										
index1b_9010_occ	0.715*	0.914*	0.886*	0.886*	0.989*	1									
index1c	0.756*	0.966*	0.921*	0.964*	0.967*	0.926*	1								
index1d_9010_occ	0.703*	0.910*	0.855*	0.926*	0.869*	0.816*	0.959*	1							
index1a_cv_all	0.850*	0.992*	0.975*	0.881*	0.944*	0.906*	0.966*	0.913*	1						
index1b_cv_all	0.867*	0.976*	0.976*	0.818*	0.909*	0.875*	0.920*	0.859*	0.989*	1					
index1d_cv_all	0.636*	0.884*	0.824*	0.982*	0.933*	0.896*	0.965*	0.924*	0.875*	0.813*	1				
index2	0.753*	0.966*	0.921*	0.964*	0.967*	0.926*	1.000*	0.959*	0.965*	0.920*	0.965*	1			
index3a	0.748*	0.952*	0.909*	0.946*	0.949*	0.908*	0.984*	0.945*	0.953*	0.909*	0.947*	0.984*	1		
index3b	0.748*	0.952*	0.909*	0.946*	0.949*	0.908*	0.984*	0.945*	0.953*	0.909*	0.947*	0.984*	1*	1	
index4	0.787*	0.981*	0.949*	0.947*	0.978*	0.945*	0.995*	0.942*	0.980*	0.946*	0.950*	0.995*	0.979*	0.979*	1

Source: authors own compilation based on PIAAC data.
Legend: * correlation significant at the 1% level. Index 4 is the additive index. Index1c is the chosen one.

Table 2b. Spearman rank correlations across routine intensity indexes. PIAAC countries, 2011-2012

	sequ	index1a_cv_ocp3	index1b_cv_occ	index1d_cv_occ	index1a_9010_occ	index1b_9010_occ	**index1c**	index1d_9010_occ	index1a_cv_all	index1b_cv_all	index1d_cv_all	index2	index3a	index3b	index4
sequ	1														
index1a_cv_occ	0.8470*	1													
index1b_cv_occc	0.8592*	0.9889*	1												
index1d_cv_occ	0.7052*	0.8963*	0.8421*	1											
index1a_9010_occ	0.7579*	0.9436*	0.9160*	0.9294*	1										
index1b_9010_occ	0.7253*	0.9069*	0.8842*	0.8904*	0.9896*	1									
index1c	0.7827*	0.9693*	0.9292*	0.9723*	0.9596*	0.9189*	1								
index1d_9010_occ	0.7355*	0.9039*	0.8553*	0.9303*	0.8352*	0.7804*	0.9482*	1							
index1a_cv_all	0.8534*	0.9887*	0.9714*	0.9104*	0.9379*	0.8976*	0.9713*	0.9118*	1						
index1b_cv_all	0.8675*	0.9732*	0.9718*	0.8585*	0.9071*	0.8704*	0.9314*	0.8663*	0.9888*	1					
index1d_cv_all	0.7149*	0.9179*	0.8675*	0.9841*	0.9422*	0.9066*	0.9789*	0.9304*	0.9119*	0.8590*	1				
index2	0.7459*	0.9632*	0.9221*	0.9720*	0.9578*	0.9175*	0.9970*	0.9440*	0.9658*	0.9256*	0.9775*	1			
index3a	0.7678*	0.9550*	0.9133*	0.9721*	0.9540*	0.9159*	0.9912*	0.9423*	0.9570*	0.9156*	0.9782*	0.9884*	1		
index3b	0.7678*	0.9550*	0.9133*	0.9721*	0.9540*	0.9159*	0.9912*	0.9423*	0.9570*	0.9156*	0.9782*	0.9884*	1.0000*	1	
index4	0.8037*	0.9825*	0.9533*	0.9529*	0.9722*	0.9391*	0.9941*	0.9254*	0.9817*	0.9519*	0.9632*	0.9903*	0.9832*	0.9832*	1

Source: authors own compilation based on PIAAC data.
Legend: * correlation significant at the 1% level. Index 4 is the additive index. Index1c is the chosen one.

While each respondent in PIAAC displays her own value of the chosen index, that is all surveyed workers are individually assigned a routine intensity score based on their answers, bridging the divide in data availability between (individual-specific) tasks and occupations (respectively, sectors) requires computing values by 3-digit ISCO08 occupations. Median values at the 3-digit ISCO08 are then used to rank occupational categories. The top quartile of this ranking (HR) represents the high routine intensity occupations. Likewise occupations are defined as non-routine intensive if they fall into the bottom quartile of occupations (NR) when they are ranked by median value of the chosen *RII*. A sample list of 3-digit occupations and their classification by quartiles of routine intensity is reported in Appendix 2.[17]

The data displayed so far are based on data pooled across all countries in the PIAAC sample. Doing so implicitly assumes that the potential routine content of tasks does not significantly change across OECD countries with respect to what could be observed in an (hypothetical) “average” OECD country. This choice was determined by the relatively low number of PIAAC individuals employed in a given 3-digit occupation or sector who were interviewed in some of the participating countries. However, one contribution of this paper is the possibility to obtain a list of routine intensive occupations based on country specific data and to compare them across countries, given that the underlying data have been collected in a harmonised fashion. Hence, with the caveat that having a relatively low number of respondents in a given cell might expose the analysis to possible outliers and to measurement error, it is nevertheless possible to assess the extent to which the routine intensity of occupations changes across countries. Country-specific classifications of occupations by routine intensive quartiles are obtained for Austria, Canada, Germany, Denmark, Estonia, France, Ireland, Japan, Korea, Poland, United Kingdom and United States, and for the following aggregates of countries which are present in PIAAC: (1) Belgium, and the Netherlands; (2) the Slovak and Czech Republic; (3) Italy and Spain; (4) Norway and Sweden.[18]

Alternative aggregation procedures would have been possible as well. For instance, one could have ranked all individuals based on their value of the chosen index, and then take the occupations most frequently associated to the workers in the bottom quartile as the routine intensive occupations. This option, however, would have been more sensitive to the existence of outliers in the individuals' values of the index. This may occur if e.g. surveyed individuals provide polarised or partially biased answers, i.e. always low or high, to any question. A second possible aggregation procedure might have entailed ranking occupations on the basis of each of the 14 routine indexes proposed and then characterise as high routine-intensive those falling in the bottom quartile of all 14 distributions. While this would avoid having to choose a preferred routine index, it would nevertheless determine a (heavy) loss of information or the need to make arbitrary choices, as robustness tests suggest that about 30% of occupations would not fall in any quartile following this methodology.

Finally, once 3-digit occupations are allocated to the corresponding quartiles of routine intensity, it is possible to compute the share of employment corresponding to the different level of routine intensive occupations. This is subject to the availability of Labour Force Survey-type of data at the same level of occupational disaggregation. It should be stressed, however, that the figures thus obtained would reflect the number of employees which are likely to have more routine intensive jobs than others, not the actual number of routine intensive jobs, nor the number of jobs which will be necessarily traded away due to their routine intensity. There will certainly be workers employed in a routine intensive occupation or sector whose job is not routine intensive in practice, for instance due to relatively low capital intensity of the company where they work compared to possible competitors. Their jobs will feature in employment statistics as "high routine intensity" ones, whereas they a not.

17. The same is done for two digit ISIC revision 4 sectors, but are not displayed or discussed here in the interest of space.

18. PIAAC data for Australia and Finland are not reported at the 3-digit ISCO2008 disaggregation level, on which this methodology relies, and had to be discarded.

Data

The principal source for the present analysis is the OECD survey of the Program for the International Assessment of Adult Competencies (PIAAC). This survey allows gathering information on the type of tasks that workers carry out on their job, as well as information on the workers themselves (e.g. gender, age, etc.), while guaranteeing maximal international comparability in terms of educational attainment, field of economic activity, and occupation. Educational attainment is measured according to the 1997 version of International Standard Classification of Education (ISCED1997), whereas industries are classified following the ISIC rev. 4 classification and occupations are defined according to the ISCO 2008 taxonomy.

In particular, PIAAC offers information on the individual's: employment status, employment sector; occupation; working hours; educational background; and a number of questions on skill use at work (OECD, 2013(a)). Among these questions, some are relevant for the degree of routine intensity of the tasks the worker is carrying out, as detailed in the methodological section above. Appendix 1 reports the exact wording of the questions taken into consideration in the analysis.

While the full PIAAC database contains information for 161,707 individuals in 22 OECD countries,[19] this study exploits information related individuals who are in employment and provide information on either their occupation or their sector (or both).[20] Self-employed individuals are kept in the sample. This may be seen as inflating the sample of non-routine jobs, as self-employed are usually freer to decide upon their schedule and organisation at work. At the same time, however, many self-employed jobs may still imply sequential and routinary activities, as for instance shop sellers or accountants. The sample is reduced by excluding all individuals with missing information for at least one of the four variables of interest (*Sequentiability*, *Flexibility*, *Plan_own* and *Organise_own*), as these individuals would display a relatively low value of *Routine* due to the missing answer rather than because of the nature of their job and its routine intensity.[21] No censoring was conversely performed on reported working hours or wages (which are more frequently subject to measurement error), as these information are not exploited in the current analysis. The current analysis therefore relies on the answers from a final sample of 105,526 PIAAC individuals, 9,373 of whom were interviewed in Australia and Finland. The resulting sample contains 128 (ISCO2008) occupations across all European countries present in PIAAC, and 127 occupations for the United States.

This mapping of 3-digit occupations into routine quartiles for the years 2011-2012 is then applied to national employment data sources, to estimate the proportion of routine intensive and non-routine jobs in 27 European countries and the United States.[22] For European countries for which PIAAC data are not

19. These are: Australia, Austria, Belgium, Canada, the Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, the UK, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Slovak Republic, Sweden and the U.S.A. For Belgium, data refer to Flanders only; for the UK data refer to England and Northern Ireland only.

20. Unemployed respondents at the time of the survey are discarded for the present analysis as the answers to the "sequentiability" and "flexibility" questions are absent for the unemployed in PIAAC. Moreover, unemployed respondents may be in unemployment exactly because the type of job they carried out and its possible routine content, so that including them in the analysis would lead to an overestimation of the routine content of their occupations and/or sectors. Conversely, such information is available for self-employed individuals.

21. A possible alternative solution to dropping these observations would be imputing the values of "sequentiability" and "flexibility" for the employed individuals who do not answer to these questions. The authors, however, are not aware of an established model which is able to explain these two phenomena, so that the imputation would be arbitrary in nature. Also, imputing possibly leads to double count some pieces of information when computing the routine index.

22. The European sample includes 26 EU Member States (Austria, Belgium, Bulgaria, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Iceland, Italy, Lithuania,

available, the routine classification of the PIAAC-country with the most similar economic structure is used instead. For instance, occupations in Luxembourg follow the same routine quartile classification of Belgium and the Netherlands, while for Latvia and Lithuania the one obtained with Estonian data. When such association of PIAAC and non-PIAAC countries is ambiguous (e.g., for Bulgaria), the classification based on pooled cross-country data is applied.

Information on national employment (employees and self-employed) by 3 digit occupation and sector is taken from country-specific sources, in particular from the European Labour Force Surveys (EULFS) and the United States Current Population Survey (CPS). In an effort to exploit data sources which can be compared across country, the use of LFS-type data is preferred to Census-type information, when both are available. Microdata on employment have been accessed or aggregated at the three digit ISCO2008 and two digit ISIC4 levels. A conversion table is used to transform ISCO1988 occupational classes into ISCO2008 classes for the EULFS, NAICS sectors into ISIC3 ones, and ISIC3 sectors into ISIC4 ones. In order to convert US CPS occupational classes into ISCO2008 classes, this study exploits a new mapping of SOC2010 into ISCO2008 occupations developed by Eckardt and Squicciarini (forthcoming).

Figures for Europe are based on annualised quarterly data. Figures for the United States are calculated as simple averages over monthly data, while for 2012 they are based on a simple eight-month average (i.e. May to December 2012), to avoid possible biases due to changes in the occupational codes used by the US Census Bureau (Eckardt and Squicciarini, forthcoming).

Routine intensive occupations: Stylised facts

Table 3a and 3b relates the RII (based on “index1c”) with occupational and sectoral structure of the PIAAC sample. Table 3a provides some descriptive evidence of the ability of the RII to capture the routine content of tasks embodied in occupations: the RII is lower for more sophisticated occupations (both in mean and median values), which are less likely to be routinised. The high level of aggregation (i.e. 1 digit ISCO08), however, implies relatively large standard deviations, so that most 1-digit occupations may not significantly differ in terms of RII value. The maximum value of the index (5, i.e. “most frequently routinisable”) is found only for Elementary Occupations and Plant Operators. Table 3a also suggests that the RII may be capturing a dimension of the skill, and not only of the routine content of occupations. This is tested below.

Luxembourg, Latvia, Malta, the Netherlands, Poland, Portugal, the Slovak Republic, Slovenia, Spain, Sweden and the United Kingdom), Iceland and Norway. Data for Romania and Turkey were discarded due to the short time series available or because of important changes in the number of surveyed 3-digit ISCO2008 occupations in the considered timespan.

Table 3a. Routine Intensity Index, ISCO08 1-digit occupations, all PIAAC countries, 2011-2012

ISCO	Mean	Standard Deviation	P5	Median	P95
Managers	1.61	0.61	1	1.5	2.75
Professionals	1.87	0.71	1	1.75	3.25
Technicians	2.04	0.89	1	1.75	4
Clerks	2.33	1.04	1	2	4.5
Shoppers	2.55	1.1	1	2.25	4.5
Skilled Agriculture workers	2.05	1.01	1	1.75	4.25
Crafts	2.44	1.11	1	2.25	4.75
Plant Operators	2.99	1.23	1	3	5
Elementary Occupations	2.93	1.23	1	2.75	5

Source: authors own compilation based on PIAAC data.

Greater heterogeneity in routine intensity emerges when PIAAC surveyed individuals are grouped by industry of affiliation. While this is not unexpected, as tasks are expected to be homogeneous within occupations but not necessarily within sectors, it confirms greater explanatory power of the RII in terms of occupations only. Moreover, dispersion in the values of the RII by sector, and the consequent relatively high standard deviations values observed, may be due to the pooling of data across all PIAAC countries and reflect differences in the level of sectoral specialisation across countries.

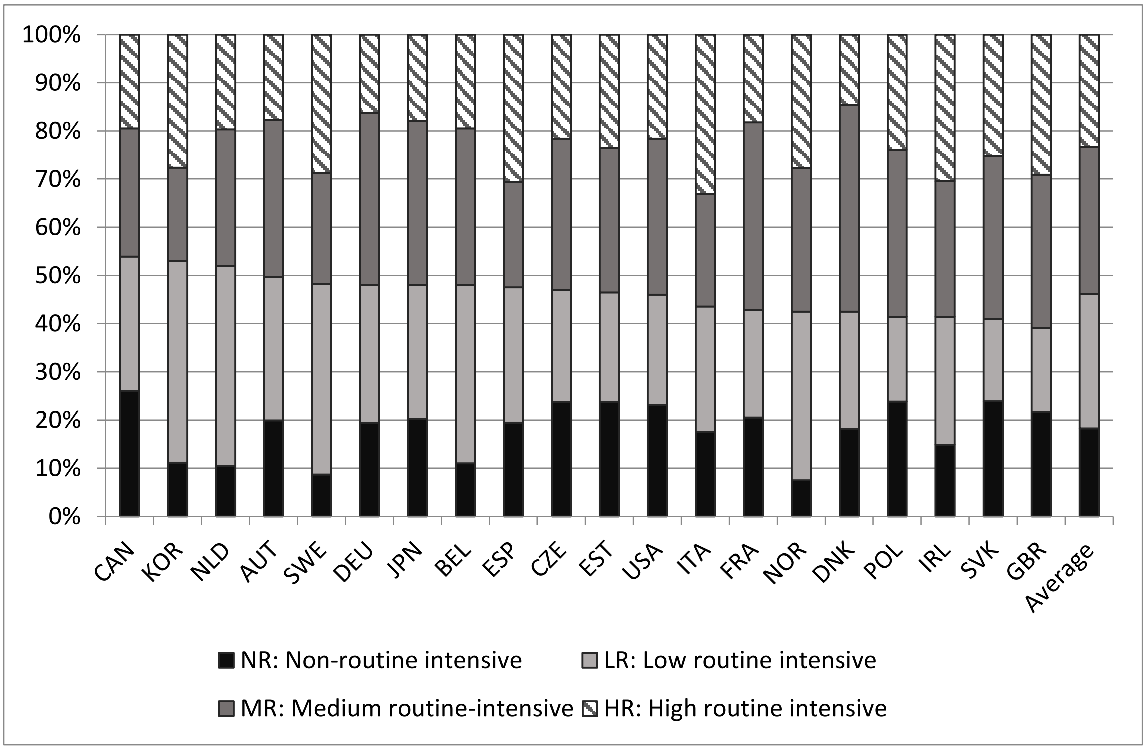
Table 3b. Routine Intensity Index by sector, (18-group classification). PIAAC countries, 2011-2012

SECTOR	ISIC4	Mean	St. Dev	P5	Median	P95
Agriculture	01-03	2.26	1.14	1	2	4.75
Mining	05-09	2.29	1.00	1	2	4.5
Food, Beverages & Tobacco	10-12	2.75	1.28	1	2.5	5
Textiles, Apparel & Leather	13-15	2.66	1.29	1	2.25	5
Wood & Paper	16-18, 58	2.31	1.13	1	2	4.75
Chemicals	19-23	2.37	1.17	1	2	5
Basic & Fabricated Metals	24, 25	2.40	1.16	1	2	4.75
Machinery n.e.c.	28	2.22	1.07	1	2	4.5
Electrical Equipment	26, 27	2.35	1.15	1	2	4.75
Transport Equipment	29, 30	2.61	1.22	1	2.25	5
Manufacturing n.e.c	31-33	2.35	1.16	1	2	4.75
Utilities	35, 36	2.12	0.91	1	2	4
Construction	41-43	2.25	1.04	1	2	4.5
Trade & Hotels	45-47, 55, 56, 95	2.41	1.12	1	2	4.5
Transport & Telecom	49-53, 61, 79	2.59	1.20	1	2.25	5
Finance	64-66	1.99	0.88	1	1.75	4
Business services	62, 63, 68, 69-78, 80-82	2.00	0.95	1	1.75	4
Personal services	37-39, 59, 60, 84-88, 90-94, 96	2.17	0.95	1	2	4.25

Source: authors own compilation based on PIAAC data. The column "ISIC4" reports the 2-digit ISIC4 classes which were used to construct the corresponding "SECTOR" category.

As mentioned, the proposed classification of individuals in quartiles of routine intensity is based on 3-digit occupations, which should grant greater precision in the estimation of the exposure of employment to routinisation. The distribution of employed individuals in PIAAC countries into quartiles of routine intensity is reported in Figure 1.[23] On average, 46% of employed persons in PIAAC countries are working in non-routine (NR, 18%) or low routine (LR, 28%) intensive occupations. Canada and the United Kingdom display, respectively, the lowest and highest proportion of routine intensive workers (MR and HR). The distribution between NR and LR routine intensity quartiles differs significantly across country, even among countries displaying similar proportions of employment in the sum of these two quartiles (e.g. Canada and Korea). Belgium, Denmark, and the Netherlands display the highest proportion (approximately 70%) of total employment in occupations at the middle of the routine intensity distribution (LR+MR).

Figure 1. Percentage of Employment (Employees & Self-Employed), by Quartile of Routine Intensity. PIAAC countries, 2011-2012.



Source: authors own compilation based on PIAAC data.

23. Figure 1 is based on reweighted employment figures, so as to guarantee the representativeness of the reported evidence, and is based on the country-specific classifications of occupations in routine quartiles. Note that figures may change with respect to Marcolin *et al.* (2016), where a similar graph (Fig.1) is constructed following the methodology described above here. However, in that study, an average over all years in the sample (2000-2011) is taken, while here it is reported the average value for 2011 and 2012 only. What is more, the graph in Marcolin *et al.* (2016) exploits both PIAAC and Labour Force Survey data, while the present one only relies on PIAAC data. For the application to LFS data, see section below.

Routine intensity and skills

Table 3a suggested a possible overlapping between the routine and the skill content of occupations. “Elementary occupations” are usually classified as “low skill” (ILO, 2012), and display relatively higher routine intensity.[24] Furthermore, empirical evidence in the economic literature suggests that high skilled workers tend to specialise in non-routine tasks. However, it also suggests that some low skill tasks can be complementary to high skill ones (e.g. cleaning services). Similarly, as already mentioned, activities intensive in abstract reasoning may be exposed to the threat of offshoring nowadays too (e.g. data mining). As a consequence, understanding the link between routine intensity and the industry skill distribution in a country may be less than straight-forward. Becker *et al.* (2013), for instance, show that an increase in the offshored employment share of an economy impacts wages differently depending on whether the measure of labour force characteristics is based on education, skill or the routine content of tasks.

The correlations shown below try and provide some first descriptive elements on the relationship between the routine content of occupations and the skill level of the workforce. Results shown in Table 4 suggest the correlation between skill content and routine intensity to be indeed negative, i.e. the more routine intensive occupations tend to require less skills, but not necessarily very strong.

Such correlations rely on several measures of skill, capturing both the skill and the educational content of occupations in which the PIAAC individuals work, the skill use by individuals at work, and the skill endowment of the individuals themselves. In particular:

- *sk_occ* classifies individuals into high, medium and low-skill categories, based on their 1-digit ISCO occupations of operation, as done in ILO (2012).
- *sk_edu* classifies individuals into high, medium and low-skill categories, based on their educational attainment.
- *sk_phy* classifies individuals according to their frequency of performing physical tasks at work.
- *sk_work* classifies individuals according to their frequency of numeracy competencies at work (ranging from 0 to 5). It is a synthetic indicator obtained aggregating several PIAAC questions related to the use of numerical skills at work.
- *sk_work_cont* reflects the content of *sk_work* but using a continuous variable obtained through Item Response Theory (OECD, 2013(b)).
- *sk_num* captures the endowment of individuals in numeracy skills, as tested by the PIAAC survey itself.

All measures are constructed so that they are increasing in the skill content. Appendix 3 provides further information on these measures of skill and about the PIAAC variables which were used to construct them. Table 4 reports the correlations among proxies of skills, and their correlation with the quartile of routine intensity. The latter ones are consistently negative and significant, although the correlation is much lower (approximately 30%) for all skill measures other than those based on the classification of occupations according to ILO (2012) – *sk_occ.* This is reflected in the positive but low correlations between skill proxies, which range between 15% and 45%, except when both proxies are capturing the skill use at the workplace (*sk_work* and *sk_work_cont*).

24. ILO (2012), page 14: “High Skill” corresponds to ISCO-08 one digit occupations 1 to 3 (managers, professionals, technicians and associate professionals), “Medium Skill” to ISCO-08 occupations 4 to 8 (workers in clerical support, services and sales, skilled agriculture and forestry, crafts and related trades, plants and machine operators), and “Low Skill” to ISCO-08 occupation 9 (elementary occupations). Armed forces workers are excluded from the present analysis altogether.

Table 4. Pairwise correlations across skill intensity measures. PIAAC countries, 2011-2012

	quartile	sk_occ	sk_edu	sk_phy	sk_work	sk_work_ cont	sk_num
sk_occ	-0.747*	1					
sk_edu	-0.338*	0.445*	1				
sk_phy	-0.358*	0.362*	0.306*	1			
sk_work	-0.294*	0.255*	0.196*	0.153*	1		
sk_work_cont	-0.290*	0.258*	0.203*	0.154*	0.906*	1	
sk_num	-0.281*	0.304*	0.397*	0.294*	0.204*	0.201*	1

Source: authors own compilation based on PIAAC data. * correlation significant at the 1% level.

A further look to the link between skill and routine intensity based on pooled PIAAC data reveals that NR and LR intensive occupations are monotonically increasing in skill intensity, when these are measured according to the individual's educational attainment or his/her occupation. This is not the case for MR and HR intensive occupations, instead, which are mostly intensive in medium skills (ref. Table 5). The proportion of workers never performing manual work is higher among routine (MR+HR) rather than non-routine (LR+NR) workers. Nevertheless, 20 % of the employed people surveyed in PIAAC perform manual work every day despite operating in NR or LR jobs.

Table 5. Employment by skill and routine intensity. PIAAC countries, 2011-2012.

Skill Variable	Value	*NR: Non-routine*	*LR: Low routine intensive*	*MR: Medium routine intensive*	*HR: High routine intensive*
sk_occ	Low	0.00	0.01	0.07	0.24
	Medium	0.09	0.30	0.68	0.73
	High	0.91	0.69	0.25	0.03
sk_edu	Low	0.06	0.06	0.18	0.27
	Medium	0.30	0.38	0.51	0.57
	High	0.64	0.56	0.31	0.16
sk_phy	Every day	0.20	0.23	0.50	0.61
	At least once a week	0.10	0.10	0.11	0.10
	Less than once a week	0.06	0.06	0.05	0.04
	Less than once a month	0.14	0.13	0.07	0.06
	Never	0.50	0.48	0.26	0.19

Note: Frequencies sum up to 100 within each quartile (by skill proxy).

Source: authors own compilation based on PIAAC data.

A similar picture can be drawn when looking at the numeracy skills of individuals (*sk_num*). When pooling data across all countries, individuals display higher numeracy skills, the lower the routine intensity of their occupations (Table 6a). The average coefficients are precisely estimated for each quartile, and significantly different. When estimating the numeracy score by quartile at a country-by-country basis (shown in Table 6b), however, 90-10 intervals can substantially overlap across quartile. This is also the case when looking at skill use at work, as in Table 7, where the reported figures describe the frequency of use of numeracy skills at work, by quartile of routine intensity and by country.

Table 6a. Individuals' numeracy skills (sk_num) by quartile. PIAAC countries, 2011-12.

	Coef.	SE	95% confidence interval	
NR: Non- routine	292.85	1.09	290.71	294.99
LR: Low routine intensive	284.62	0.64	283.36	285.88
MR: Medium routine intensive	260.69	0.89	258.95	262.42
HR: High routine intensive	248.27	0.97	246.37	250.18

Note: The score ranges from 0 to 500.

Source: authors own compilation based on PIAAC data.

Table 6b. Individuals' numeracy skills by quartile and country. PIAAC countries, 2011-12.

	NR: Non- routine			*LR: Low routine intensive*			*MR: Medium routine intensive*			*HR: High routine intensive*		
	p10	*Median*	*p90*	*p10*	*Median*	*p90*	*p10*	*Median*	*p90*	*p10*	*Median*	*p90*
AUT	241	300	352	241	296	345	208	268	320	202	268	324
BEL	248	309	354	246	306	356	219	281	333	200	268	325
CAN	234	298	352	222	287	344	193	265	324	184	252	313
CZE	239	291	334	245	296	346	227	280	324	207	261	311
DEU	246	308	360	230	294	345	208	273	326	189	256	314
DNK	242	303	353	243	303	354	218	281	334	211	275	330
ESP	211	273	327	214	275	325	195	260	313	182	247	303
EST	244	300	349	238	293	342	216	271	322	208	265	314
FRA	243	303	350	226	285	336	181	258	319	175	244	302
GBR	233	293	345	234	294	350	207	271	329	185	248	310
IRL	225	289	341	215	275	331	207	269	326	189	250	306
ITA	207	273	334	196	274	331	196	260	316	177	242	299
JPN	253	308	357	252	305	351	226	282	332	220	279	330
KOR	230	285	335	215	272	323	208	269	317	186	250	298
NLD	246	305	351	245	303	351	214	282	333	202	272	325
NOR	247	308	360	246	309	358	234	292	343	196	267	322
POL	208	279	338	221	286	345	211	268	323	192	256	311
SVK	243	299	340	250	299	345	231	286	334	219	274	324
SWE	238	301	359	246	307	359	228	290	342	204	273	328
USA	218	294	348	216	279	334	177	250	314	166	242	305
Average	233	295	347	232	292	344	210	273	326	195	259	315

Note: The score ranges from 0 to 500.

Source: authors own compilation based on PIAAC data.

Table 7. Numeracy skill use at work by quartile and country. PIAAC countries, 2011-12.

	NR: Non- routine			*LR: Low routine intensive*			*MR: Medium routine intensive*			*HR: High routine intensive*		
	p10	*Median*	*p90*	*p10*	*Median*	*p90*	*p10*	*Median*	*p90*	*p10*	*Median*	*p90*
AUT	1.14	2.28	3.50	0.95	2.11	3.40	0.54	1.61	2.73	0.60	1.51	2.53
BEL	1.52	2.53	3.79	0.88	2.09	3.48	0.62	1.60	2.79	0.28	1.27	2.47
CAN	1.60	2.74	3.90	1.04	2.30	3.61	0.90	2.02	2.99	0.75	1.86	2.80
CZE	1.50	2.58	3.90	1.25	2.54	3.77	0.92	1.88	2.98	0.92	1.68	2.74
DEU	1.25	2.45	3.61	0.86	2.18	3.47	0.71	1.71	3.09	0.61	1.44	2.64
DNK	1.16	2.37	3.51	0.88	2.08	3.43	0.56	1.70	2.92	0.62	1.53	2.51
ESP	1.19	2.42	4.12	1.02	2.38	3.90	0.77	1.92	3.30	0.54	1.60	2.78
EST	1.42	2.43	3.61	0.96	2.10	3.43	0.73	1.77	2.92	0.71	1.45	2.51
FRA	1.48	2.66	4.12	1.03	2.21	3.44	0.73	1.76	2.97	0.51	1.31	2.44
GBR	1.42	2.51	3.79	0.88	2.05	3.43	0.73	1.83	3.04	0.72	1.60	2.80
IRL	1.04	2.42	3.66	0.63	1.99	3.30	0.75	1.99	3.17	0.73	1.71	2.67
ITA	0.56	2.06	3.25	0.84	2.34	3.69	0.73	1.81	3.25	0.51	1.36	2.53
JPN	1.33	2.20	3.51	1.00	1.91	3.16	0.73	1.53	2.67	0.73	1.42	2.47
KOR	1.25	2.42	3.59	1.02	2.06	3.43	0.75	1.73	2.96	0.70	1.60	2.64
NLD	1.25	2.40	3.61	0.75	2.09	3.59	0.62	1.66	2.81	0.28	1.38	2.47
NOR	1.25	2.14	2.93	1.17	2.18	3.32	0.73	1.69	2.69	0.54	1.55	2.52
POL	0.90	2.02	3.50	0.81	2.09	3.70	0.75	1.88	3.14	0.71	1.47	2.70
SVK	1.38	2.61	3.50	1.25	2.42	3.61	0.90	2.07	3.10	0.60	1.59	2.62
SWE	1.02	2.13	3.11	1.11	2.18	3.32	0.73	1.69	2.64	0.54	1.51	2.42
USA	1.39	2.50	3.93	1.17	2.40	3.61	0.77	2.10	3.09	0.90	1.86	2.97
Average	1.23	2.37	3.60	0.98	2.19	3.50	0.74	1.80	2.96	0.63	1.54	2.61

Note: The frequency values range from -0.1 to 6.7. The range of values is obtained from various PIAAC questions investigating the frequency of use of numeracy skills at work, and applying Item Response Theory (OECD, 2013(b)).

Source: authors' own compilation based on PIAAC data.

An application to Labour Force data

The previous section suggests that the RII does capture a dimension of the routine intensity of occupations and is not simply approximating the skill content of occupations. The proposed classification of occupations into quartiles of routine intensity can thus be used to describe some patterns in the employment structure of OECD countries. This is achieved by applying the classification from PIAAC to Labour Force surveys-based employment data presented in the data section. Following the literature, the classification of occupations in routine quartiles is assumed to remain the same over the time-span considered.

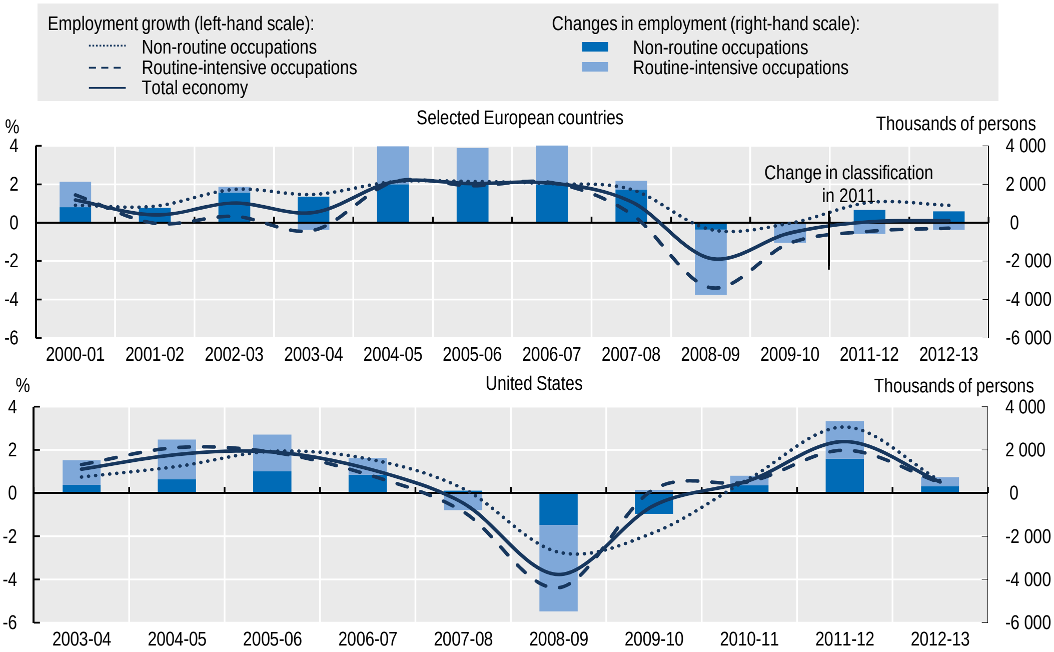
Figure 2 describes year-on-year changes in employment in selected European countries (top panel) and the United States (bottom panel) for the first decade of the year 2000s, distinguishing between routine (MR+HR) and non-routine (NR+LR) occupations. The change in employment in absolute numbers is reflected in the bars, while the percentage change is reflected in the lines of the charts.

Routine intensive occupations seem to be less resilient to the business cycle than non-routine occupations, although the United States displays more responsiveness to the business cycle in general. During the 2008-2009 crisis, job losses in Europe mainly concerned routine intensive occupations while in the US they affected both groups. About 3.4 million routine jobs were lost in Europe and 4 million in the

United States, corresponding to a negative growth rates in routine employment of 3.4% in Europe and 4.4% in the United States.

However, in 2011-2012, in a more favourable macroeconomic scenario, both routine and non-routine occupations contributed to net job creation in the United States, while gains in Europe only happened in non-routine occupations. Such comparison, nevertheless, should not be over-emphasised, as the business cycle in the two economic areas may not be strongly correlated, especially in the years following the Great Recession.

Figure 2. Employment growth by routine intensity. Selected European countries and United States, 2000-13.

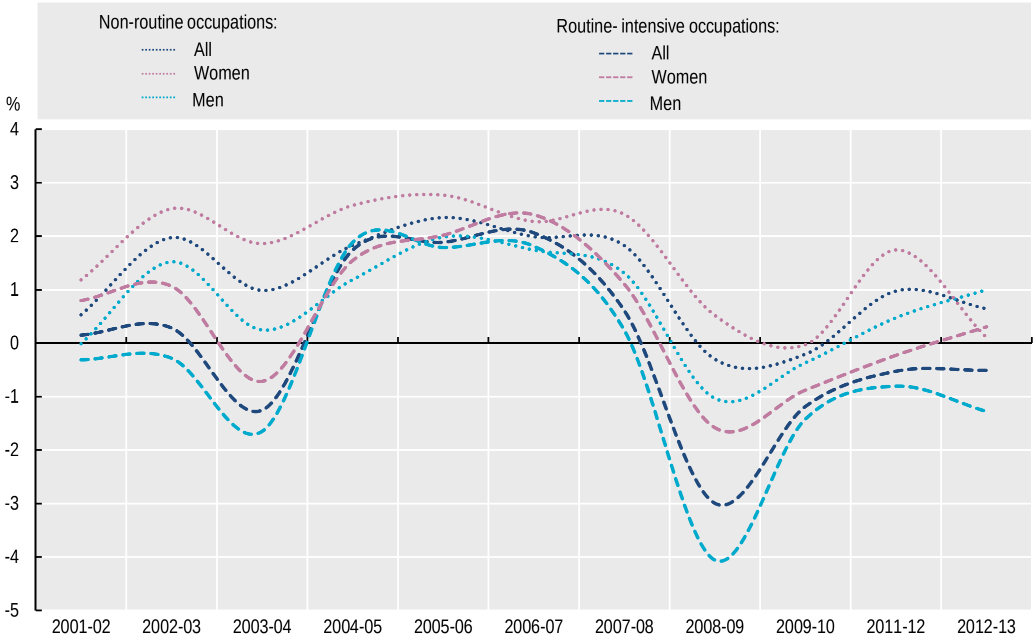


Source: OECD Science, Technology and Industry Scoreboard 2015 (http://dx.doi.org/10.1787/888933272860).

This descriptive evidence is the result of a mix of short term, cyclical patterns, and more long term trends, such as the role of ICT in substituting or complementing employment. Other economic phenomena which are only partially correlated with routine intensity may also contribute to explain the evidence presented in Figure 2, such as the industrial structure of economies, or the composition of occupations in terms of gender, education and age of the labour force.

The gender dimension is explored in Figure 3, disaggregating growth in employment in routine and non-routine occupations by gender, for a sample of European countries. While decreases in employment are more sizeable for routine occupations than non-routine ones, women in employment seem to perform better during both economic upswings and especially downswings relative to men, independently on the routine intensity of the occupations. This may be related to the different proportion of men and women in employment in the public vs private sectors or in business sectors which are not equally exposed to the business cycle. This would be the case, for instance, for employment in the construction sector, which was especially hit by the 2008-2009 crisis, and whose gender ratio is skewed towards men; the opposite could be said, for instance, for the personal care sector, which is intensive in female and public employment, and which did not suffer as many employment losses over the period.

Figure 3. Employment growth by routine intensity and gender. Selected European countries. 2001-13



Source: OECD Science, Technology and Industry Scoreboard 2015 (http://dx.doi.org/10.1787/888933272854).

Conclusions

This work exploits data from the OECD PIAAC survey to construct a novel measure of the routine content of occupations for 20 OECD countries. This measure is built on information about the extent to which workers can modify the sequence in which they carry out their tasks and decide the type of tasks to be performed on the job. A number of indices synthesising these pieces of information are used to group occupations into four routine intensity classes (high, medium, low, and non-routine intensive) and to shed light on the relationship that exists between the routine content of occupations and the skills of the workforce, intended as both the skills that workers are endowed with (i.e. independently of use) and those that they use on the job. Also, the extent to which the ad-hoc choice of the PIAAC questions used in the study - made on the basis of a semantic analysis of their content - is tested.

In particular, this study highlights that the routine intensity of occupations, as measured by the RII index, is lower for more sophisticated occupations (both in mean and median values), that is, such occupations are less likely to be routinised. On average, 46% of employed persons in PIAAC countries are working in non-routine (18%) or low routine intensive (28%) occupations. Canada and the United Kingdom display, respectively, the lowest and highest proportion of routine intensive workers (high and medium routine intensity). The distribution between non-routine and low routine intensity quartiles differs significantly across country, even among countries displaying similar proportions of employment in non-routine (non-routine + low routine) intensive occupations (e.g. Canada and Korea). Belgium, Denmark, and the Netherlands display the highest proportion (approximately 70%) of total employment in occupations at the middle of the routine intensity distribution (LR+MR).

A first look at the relationship between the routine content of occupations and the skill level of the workforce suggests a negative, but not strong, correlation between skill content and routine intensity, i.e. the more routine intensive occupations tend to require less skills. Non-routine and low routine intensive occupations appear to be monotonically increasing in skill intensity, when these are measured according to the individual's educational attainment or his/her occupation. This is not the case for medium and high-routine intensive occupations, instead, which are mostly intensive in medium skills. A similar picture can be drawn when looking at the numeracy skills of individuals. When pooling data across all countries, the higher the numeracy skills of individuals, the lower the routine intensity of their occupations.

Assuming that the routine content of occupations does not change much over time, allows shedding light on the extent to which routine intensity relates to employment over time. Data suggests that routine intensive occupations are less resilient to the business cycle than non-routine occupations, although the United States displays more responsiveness to the business cycle in general.

While this work can be considered to be still in its 'infancy' and can be improved in many ways, it nevertheless contributes to shed new evidence on the extent to which occupations differ in the routine content of the tasks that workers perform on the job, and allows comparisons of such patterns across countries, in a homogenous fashion. To this end, and in the interest of external validation, the median values of the RII at the country-occupation level, appropriately standardised, are being made available to the broader public.[25]

Thanks to the richness of PIAAC data, this paper is also able to look at the routine content of occupations from a number of dimensions including industry, firm size, gender, and the public or private nature of employers. Furthermore, Marcolin *et al.* (2016) exploit the RII to investigate the role of global value chains (GVCs), workforce skills, ICT, innovation and industry structure in explaining employment levels by routine intensity in 28 OECD countries over 2000-2011. They provide evidence that a higher ICT intensity of industries is positively associated to employment, except for high-routine jobs, where ICTs seemingly displaces workers. Technological intensity in the form of patented inventions, instead, is found to relate positively to employment in all routine quartiles. GVCs generally do not appear to contribute to the displacement of routine workers. This is especially true in manufacturing, where input offshoring and domestic outsourcing are positively associated with routine employment.

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APPENDIX 1: LIST OF PIAAC QUESTIONS USED FOR THE DEFINITION OF ROUTINE INTENSITY

This Appendix reports all questions which were exploited in the methodological section of this study.

- D_Q11a: "To what extent can you choose or change the sequence of your tasks?" (Not at all, Very little, To some extent, To a high extent, To a very high extent)

- D_Q11b: "To what extent can you choose or change how you do your work?" (Not at all, Very little, To some extent, To a high extent, To a very high extent)

- F_Q03a: "How often your current job involves planning your own activities?" (Never; Less than once a month; Less than once a week but at least once a month; At least once a week but not every day; Every day)

- F_Q03c: "How often your current job involves organising your own time?" (Never; Less than once a month; Less than once a week but at least once a month; At least once a week but not every day; Every day)

APPENDIX 2:
EXAMPLES OF OCCUPATIONS BY QUARTILE OF ROUTINE INTENSITY

Box 1. Routine intensity of occupations: some examples based on the cross-country classification

Non-routine occupations (NR)

Legislators and senior officials; Managing directors and chief executives; Sales and purchasing agents and brokers; Authors, journalists and linguists.

Low routine intensive occupations (LR)

Secondary education teachers; Hotel and restaurant managers; Administrative and specialised secretaries; Hairdressers, beauticians and related workers.

Medium routine intensive occupations (MR)

Machinery mechanics and repairers; Shop salespersons; Medical and pharmaceutical technicians; Other clerical support workers.

High routine intensive occupations (HR)

Assemblers; Food preparation assistants; Tellers, money collectors and related clerks; Metal processing and finishing plant operators.

APPENDIX 3: USED DEFINITIONS OF SKILLS

Variable	*Description*
Skill by occupations (**SK_OCC**)	3= skilled = ISCO 1dig occupations 1 to 3 (managers) 2= med skilled= ISCO 1dig occupations 4 to 8 1 = low skilled = ISCO 1dig occupation 9 PIAAC variables: *isco08_c, isco1c, isco2c*.
Skill by education (**SK_EDU**)	3 = skilled = masters and above 2 = medium skilled = levels 5 to 10 = upper secondary 1= low skilled = up to isced 3c = upper secondary education (but up to 2 years) PIAAC variable: *b_q01a*
Manual work **(SK_PHY)**	Frequency of performing physical tasks at work. 4 = never 3= less than once per month 2 = less than once a week 1 = at least once a week 0 = every day PIAAC variable: *f_q06b*
Numeracy skill use **(SK_WORK)**	Frequency of numerical skills use at work. Summary index of several PIAAC questions related to numeracy skills use. It ranges from 0 to 5 in discrete jumps. Increasing in the frequency of skill use at work. PIAAC variable: *numwork_wle_ca*
Numeracy skill use **(SK_WORK_CONT)**	Frequency of numerical skills use at work. Summary index of several PIAAC questions related to numeracy skills use. It ranges from -0.1 to 6.7 as a continuous variable. Increasing in the frequency of skill use at work. PIAAC variable: *numwork*
Numeracy skills **(SK_NUM)**	Numerical skills (endowment). Variable ranging from 0 to 500. Increasing in the endowment. PIAAC variable: *pvnum*

REFERENCES

Acemoglu, D. (2002), "Technical Change, Inequality, and the Labor Market", *Journal of Economic Literature*, Vol. 40/1, pp.7-72.

Autor, D. (2010), "The Polarization of Job Opportunities in the U.S. Labor Market. Implications for Employment and Earnings", paper jointly released by Center for American Progress and The Hamilton Project.

Autor, D.H., and D. Dorn (2013), "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market". *American Economic Review*, Vol. 103/5, pp.1553–1597.

Autor, D. H., D. Dorn and G. H. Hanson (2013a), "The Geography of Trade and Technology Shocks in the United States", *American Economic Review*, Vol. 103/3, pp.220-25.

Autor, D. H., D. Dorn and G. H. Hanson (2013b), "The China Syndrome: Local Labor Market Effects of Import Competition in the United States", *American Economic Review*, Vol. 103/6, pp.2121-2168.

Autor, D.H., F. Levy, and R. Murnane (2003), "The Skill Content of Recent Technological Change: an Empirical Exploration", *Quarterly Journal of Economics*, Vol. 118/4, pp.1279-1333, http://dx.doi.org/10.1162/003355303322552801.

Autor, D.H., L.F. Katz, and M.S. Kearney (2006), "The Polarization of the U.S. Labour Market", *American Economic Review*, Vol. 96/2, pp.189-194, http://dx.doi.org/10.1257/000282806777212620.

Autor, D.H., L.F. Katz, and M.S. Kearney (2008), "Trends in U.S. Wage Inequality: Revising the Revisionists", *Review of Economics and Statistics*, Vol. 90/2, pp.300-323.

Baldwin, R. E. (2012), "Global Supply Chains: Why They Emerged, Why They Matter, and Where They Are Going", Centre for Economic Policy Research Discussion Paper N. 9103.

Baumgarten, D., I. Geishecker, and G. Holger (2013), "Offshoring, Tasks, and the Skill-Wage Pattern", *European Economic Review*, Vol. 61/C, pp.132-152.

Becker, S.O., K. Ekholm, and M.A. Muendler (2013), "Offshoring and the Onshore Composition of Tasks and Skills", *Journal of International Economics*, Vol. 90/1, pp.91-106, http://dx.doi.org/10.1016/j.jinteco.2012.10.005.

Blinder, A. (2009), "How Many U.S. Jobs Might be Offshorable?", *World Economics*, Vol. 10/2, pp.41-78. http://dx.doi.org/10.1.1.360.5806

Blinder, A., and A.B. Krueger (2013), "Alternative Measures of Offshorability: A Survey Approach", *Journal of Labor Economics*, Vol. 31/S1, S97 - S128, http://dx.doi.org/10.1086/669061.

Cronbach, J. (1951), "Coefficient Alpha and the Internal Structure of Tests", *Psychometrika*, Vol. 16/3, pp.297-334.

Eckardt, D., and M. Squicciarini (forthcoming), "Mapping SOC-2010 into ISCO-08 occupations: a New Methodology Using Employment Weights", Mimeo.

Firpo, S., N. M. Fortin, and T. Lemieux (2011), "Occupational Tasks and Changes in the Wage Structure", Mimeo.

Goos, M., A. Manning, and A. Salomons (2014), "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring", *American Economic Review*, Vol. 104/8, pp.2509-26, http://dx.doi.org/10.1257/aer.104.8.2509.

Goos, M. , A. Manning, and A. Salomons (2009), "Job Polarization in Europe", *American Economic Review*, Vol. 99/2, pp.58–63.

ILO (2012), "International Standard Classification of Occupations ISCO-08", Vol. 1.

Kaiser, H.F. (1970), "A Second Generation Little Jiffy", *Psychometrika*, Vol. 35: pp.401-415.

Marcolin, L., S. Miroudot, and M. Squicciarini (2016), "Routine jobs, Employment and Technological Innovation in Global Value Chains", *OECD Science, Technology and Industry Working Papers*, 2016/01, OECD Publishing, Paris, http://dx.doi.org/10.1787/5jm5dcz2d26j-en.

Nicoletti, G., S. Scarpetta, and O. Boylaud (2000), "Summary Indicators of Product Market Regulation with an Extension to Employment Protection Legislation", *OECD Economics Department Working Papers* N.226, OECD Publishing, Paris, http://dx.doi.org/10.1787/215182844604.

OECD (2013a), "OECD Skills Outlook 2013: First results from the Survey of Adult Skills", OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264204256-en.

OECD (2013b), "The Survey of Adult Skills: Reader's Companion", OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264204027-en.

OECD (2013c), "Interconnected Economies: Benefiting from Global Value Chains", OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264189560-en.

Oldenski, L. (2012), "The Task Composition of Offshoring by U.S. Multinationals", *Economie Internationale*, Vol. 131, pp.5-21.

Rilla, N., and M. Squicciarini (2011), "R&D (Re)location and Offshore Outsourcing: a Management Perspective", *International Journal of Management Reviews*, Vol. 13/4, pp.393-413.

Santos-Paulino, A. U., M. Squicciarini, and P. Fan (2008), "R&D (re)location : a bird's eye (re)view", Working Paper Series RP2008/100, World Institute for Development Economic Research (UNU-WIDER).

Seabright, P. (2000), "Skill versus Judgement and the Architecture of Organisations", *European Economic Review*, Vol. 44/4, pp.856-868.

Spitz-Oener, A. (2006), "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure", *Journal of Labor Economics,* Vol. 24/2, pp.235-270.