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Migrant workers and the digital transformation in the EU

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Abstract

The aim of this report is to provide insights on the implications that structural changes in the labour market related to the Digital Transformation (DT) could have on the integration of EU mobile citizens and third country nationals working in the EU. A comprehensive analysis of the changing nature of the EU labour markets and the effects of DT is provided in the upcoming European Commission's 2018 Employment and Social Developments in Europe (ESDE) review. Building upon these general findings, this report contributes to the debate from a migration-specific point of view by providing evidence on the extent to which migrants are employed in occupations that are potentially prone to automation and therefore may disappear in future. The analysis is based on data drawn from EU LFS 2015-2016 and PIAAC 2012 surveys.

The results show that:

- Third country nationals tend to be more concentrated in occupations characterized by high routine intensity and thus more prone to automation (e.g. elementary occupations), followed by EU mobile citizens and by natives.
- Both EU mobile citizens and third country nationals have a higher likelihood of being employed in jobs with high automation potential than nationals, even when socio-demographic characteristics are taken into account. However, the likelihood decreases as educational attainment increases, for all but more so for migrants.
- Major differences between EU mobile citizens and third country nationals appear when considering their length of residence. The results show that among EU mobile citizens, recent migrants have higher odds of being employed in a job with high automation potential compared to long-term migrants. On the contrary, in the case of third country nationals, long term migrants report higher odds of working in a job with high automation potential than recent migrants.
- Both EU mobile citizens and third country nationals are less likely to receive professional training in comparison to nationals. This lower investment in the human capital of migrants can hamper migrants' opportunities to transition to other jobs once they would lose their jobs due to the DT.
- Both EU mobile citizens and third country nationals are more likely to be on fixed-term contracts with a shorter horizon compared to natives, with risk of non-renewal of contract in case of economic and technological shocks.
- In summary, the vulnerability of migrants in the labour market is furthermore reinforced by the fact that they tend to be concentrated in jobs with high automation potential which, in turn, are associated to lower training and more widespread use of fixed-term contracts.

1. Introduction

The future of work has been a question at the center of academic and policy debates over the past years (Dachs, 2018; OECD, 2017; World Bank, 2016). Labour markets and business processes are being profoundly affected by the Digital Transformation (DT), interpreted as "*profound changes taking place in the economy and society as a result of the uptake and integration of digital technologies [digitalization, automation, robotics, AI, IoT, etc.] in every aspect of human life*"[1]. In our analysis we focus on the implications that DT can have on the labour markets for migrants. Animated discussions have developed following the contradictory estimates of the share of jobs at high risk of automation, ranging – for the US - from less than 10% (Arntz et al., 2016) to an alarming 48% (Frey and Osborne, 2017)[2]. However, as concluded at the 48th World Economic Forum[3], the overall impact of the DT on jobs and society will depend on how well the institutions can manage this process, rather than simply considering the proportion of jobs that are susceptible to technological change.

Over recent years the EU has actively sought to ensure the efficient management of DT by adopting a wide range of policy instruments, ranging from active labour market policies, education and training policies to fiscal policies. Today, indeed, the DT is one of the policy priorities of the EU, as set in the multiannual financial framework 2021-2027 proposal[4]. One of the main objectives in the EU's approach to address the social impacts of the DT is ensuring that "no one is left behind"[5]. This objective translates into actions aiming to mitigate the negative effects of DT and to make its opportunities beneficial to all. For that purpose initiatives such as the New Skills Agenda for Europe[6], together with the series of actions that followed[7], assign a central role to education and training, considered as tools that equip workers with appropriate skills, which enable them to cope with the labour market challenges set off by DT.

Ensuring that "*no one is left behind*" in the process of DT can, however, prove to be especially challenging for already vulnerable groups in the labour market, such as the migrant population. For migrants, labour market participation is essential in at least two dimensions. Firstly, employment is a requisite for legal stay in the EU for some categories of non-EU migrants. For example, the residence permit of labour migrants is conditional on having an employment contract. In addition to that, in some Member States, the process of family reunification is linked to sponsor's income, which basically depends upon having a job. Secondly, for all migrants, employment is considered to be the core element facilitating their full integration into society at large. In line with it, their labour market integration is set as a policy priority in the Action Plan on the Integration of Third Country

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[1] Concept Paper on Digital Transformation, Joint Research Centre, European Commission [*Forthcoming*].

[2] Differences in estimations arise from different methodological approaches adopted to assess the automability of a job. For an overview of different methodologies See: McKinsey Global Institute. (2017). "A Future That Works: Automation, Employment, and Productivity".

[3] https://www.weforum.org/agenda/2018/01/how-to-make-artificial-intelligence-inclusive/

[4] For this priority area, the European Commission proposed "to establish a new Digital Europe Programme to shape and support the digital transformation of Europe's society and economy" with an overall budget of €9.2 billion COM(2018) 321 final

[5] COM(2018)237 final

[6] COM(2016) 381 final

[7] E.g. Council Recommendation of 19 December 2016 on Upskilling Pathways: New Opportunities for Adults (2016/C 484/01),

Nationals[8], followed by numerous implementing actions[9]. Failing to ensure a successful integration of migrants into the EU labour markets and society at large can entail high financial cost, which, according to IOM (2018), would exceed the investments supporting the integration process. Moreover, a lack of labour market integration could increase the labour market segmentation and feed inequalities. Over time, the growing inequalities could erode the social cohesion of the EU through a growing social conflict, discrimination and xenophobia. Finally, labour market participation is the most straightforward and visible aspect of migrant integration. In this sense, it can shape the overall public perception of migrants, which in turn can influence policies.

The DT will eventually bring to a reconfiguration of labour market, with the likely disappearance of jobs in which migrants tend to be concentrated. This reconfiguration is likely to have consequences on the nature and number of jobs currently occupied by migrants: if these jobs will no longer be available in the future, will still be there a need for migrant workers? And for what type of profiles/skills?

In light of these considerations, it is important to understand what could be the impact on the integration of migrants in the EU of structural changes in the labour market related to the DT.

A comprehensive analysis of the future prospects of the EU labour markets and the effects of DT is provided in the upcoming European Commission's 2018 Employment and Social Developments in Europe (ESDE) review[10]. Bearing in mind these general trends, we participate to the debate from a migration-specific point of view by providing evidence on the extent to which migrants are employed in occupations that are potentially prone to automation and therefore may disappear in future.

This report analyses job tasks performed by EU mobile citizens and third country nationals aged 15 and above that were legally residing in the EU in 2015/2016. The analysis is based on EU LFS and PIAAC data and adopts the so-called routinization hypothesis. The main assumption of this approach is that DT leads to a decline in jobs rich in routine content. In particular, we provide measures of abstract, manual and routine content for nine ISCO-08 one-digit occupations in 25 EU Member States[11]. We then analyze the distribution of EU mobile citizens, third country nationals and natives across occupations that have different level of automation potential. In addition, we provide econometric analysis of the probability of being employed in occupations with high automation potential, while controlling for many individual factors like age, gender, education etc. Finally, the report explores the working conditions, such as the type of employment contract and access to training, of migrants employed in jobs with different levels of automation potential.

Our results reveal that third country nationals tend to be more concentrated in occupations characterized by high routine intensity (e.g. elementary occupations), followed by EU mobile citizens and by natives. More in-depth multivariate analyses show that being a migrant - and more so for third country migrants - increases the odds of being employed in high routine intensity jobs and therefore in jobs

[8] COM(2016) 377 final

[9] For a detailed list of actions see: https://ec.europa.eu/migrant-integration/main-menu/eus-work/actions

[10] European Commission. (2018). *Employment and Social Developments in Europe Annual Review 2018* [forthcoming]

[11] Due to methodological issues, the analysis excludes HR, HU and MT.

with high automation potential. This finding is confirmed even when key determinants of migrant's labour market performance, such as education and length of residence, are specifically taken into account. Moreover, we show that both EU mobile citizens and third country nationals are more likely to be employed with fixed-term contract and less likely to follow any type of professional training in comparison to native workers.

Overall, the findings of this report point to a higher vulnerability of migrants and, especially, third country nationals to the effects of DT (without considering the wage discrimination). The methodology proposed in this report can be a useful tool to characterize those migrant workers that are mostly exposed to the effects of DT. This could be used to identify migrants more in need of specific interventions (e.g. education, training, social protection, etc.) that could help them transit into new career opportunities, reducing the risk of poverty and social exclusion, in line with the New Skills Agenda for Europe which introduces also a specific set of actions aiming at skills assessment and up/reskilling of third country nationals.

2. Theoretical background: digitalization and the changing nature of work

As a model for the effects of digitalization on the labour market, Autor, Levy and Murnane (2003) (hereafter, ALM) put forth the Routine Biased Technological Change (RBTC) hypothesis, later refined by Acemoglu and Autor (2011). The main purpose of their effort is to develop a theory – with testable implications – that takes into account the fact that technology, globalization and labour market institutions determine the extent to which production tasks are allocated to labour and/or capital, depending on their comparative advantages. This flexible approach is in principle able to capture the fact that some tasks – broadly defined as routine or routinizable and historically allocated to low and middle skilled workers - following the digital revolution are now allocated to capital. The implication of this is that ICT developments and digitalisation lead to a decline in jobs that are rich in the routine component (manual or cognitive) and an increase in the number of jobs that are rich in the cognitive non-routine component[12]. These effects are magnified by globalisation and free trade, since the ability to separate tasks and the availability of a technology through global trade allows for their outsourcing[13].

According to the RBTC hypothesis, the production process is defined in terms of tasks. Job tasks are allocated to workers or to capital ('machines') depending on: 1) the degree to which they are automatable (repetitive and replaceable by code and machines); 2) their separability from other tasks; and 3) the relative costs of using 'machines' versus humans. In this context, 'machines' includes hardware, software and combinations of the two, such as robots. One of the most important characteristics in this framework is the distinction between tasks and skills. According to Acemoglu and Autor (2011, p. 1045), a task is defined as a "*unit of work activity that produces output (good and services)*" whereas a skill is a "*worker's endowment of capabilities for performing various tasks*". Tasks are actions that workers perform in their jobs and, depending on the complexity of the production process, a combination of different types of tasks might be required to produce a given output. The combination of tasks required to produce output and the allocation of tasks between labour and capital might vary in time, due to technical changes and to variations in the relative price of labour. On the other hand, skills refer to workers' qualifications[14].

The main challenge of this approach is how to link the theoretical underpinning to the empirical analysis (for a discussion of the pros and cons of the RBTC approach see Sebastian and Biagi, 2018). In the theoretical model, tasks are the basic elements of the production function and they can be allocated to workers of different skill levels (including offshoring some of them) or to machines, depending on their comparative advantage (ultimately labour and capital services remain the inputs into the production function). However, the typical empirical analysis of tasks uses information from workers' surveys or from datasets describing occupational tasks such as O'NET (as opposed to firms' surveys), which really focus on jobs (i.e. those tasks that are actually performed by workers). By imposing a

[12] The RBTC theory does not make clear predictions about employment in jobs that are mostly manual and non-routine, as these are not directly affected by the digital transformation.

[13] Research has shown that these factors combined make outsourcing of middle-skilled occupation cheap and easy (e.g. Blinder, 2009).

[14] Tasks arise from the demand side while skills, which are possessed by workers, pertain to the supply side.

structure on these surveys – such as assigning a measure for the routine abstract/cognitive, manual and interactive content of a given job – it becomes possible to rank occupations as being more or less intensive in routine or in cognitive/abstract or manual or interactive activities. This information can then be aggregated at the level of occupations (more or less refined and including sectors) and countries to get aggregate indices.

The original ALM model has been later refined by others and in this paper we take the model of Autor and Dorn (2013), which combines the five original task measures[15] of Autor, Levy, and Murnane (2003) into three task aggregates: "abstract", "routine" and "manual". The three measures are then used to create a routine task intensity measure (RTI). This measure aims to capture the importance of the routine tasks relative to manual and abstract tasks.

In this report we follow Autor and Dorn and first compute separate indices for Abstract, Routine and Manual content of occupations[16] and then we aggregate them into an occupation-country-time specific RTI measure, calculated as follows:

$$RTI_{s,c,t} = \ln(T^{R}_{s,c,t}) - \ln(T^{A}_{s,c,t}) - \ln(T^{M}_{s,c,t}) \qquad [1]$$

where $T^{R}_{s,c,t}, T^{A}_{s,c,t}$, and $T^{M}_{s,c,t}$ are the routine, abstract, and manual inputs in occupation s, country c and year t. This measure rises with the importance of routine tasks in each country and declines with the importance of abstract and manual tasks.

To compute the indices for Abstract, Routine and Manual task aggregates we use data from the Programme for the International Assessment of Adult Competencies (PIAAC) which is a survey carried out by the OECD in 24 countries in 2012. The main aim of this survey is to provide an analysis of the level and distribution of the skills used in the workplace. The data sample contains 166,000 observations of adults aged between 16 and 65 years. The survey contains information about their personal background, education and training current work status, work history, and different types of activities performed in the workplace. Particularly, using data from the workers' responses on the activities conducted at work, we construct measurements of task intensities. We measure tasks at one-digit occupational level,[17] since this is the level for which data for 13 EU MS are available.

PIAAC respondents are asked how often certain tasks are performed at work on a five-point scale ranging from one ("never") to five ("every day"). These variables on the Likert scale are then normalized to range from zero to one. To implement the definitions of each particular task, we follow the existing literature as closely as possible by selecting the task descriptions in PIAAC that resemble those

[15] In their 2003 article ALM propose a classification based on a two-dimensional typology: routine, as opposed to non-routine, and manual, as opposed to cognitive, content. The cognitive element is further divided into analytical and interactive subsets, so that, overall, the authors identify five categories of tasks: Routine manual tasks, Routine cognitive tasks, Non-routine interactive tasks, Non-routine analytic tasks, Non-routine manual tasks. The non-routine interactive and non-routine analytic in the ALM model are combined by Autor and Dorn (2013) into the "abstract task measure"; routine cognitive and routine manual are merged in the "routine task measure"; and finally non-routine manual tasks in the original model correspond to the "manual task measure".

[16] We standardize our indices with a mean of zero and a standard deviation of one.

[17] Most of the countries display the occupation at the four-digit occupation level (Belgium, Cyprus, the Czech Republic, Denmark, Spain, France, Italy, the Netherlands, Norway, Poland, Slovakia, and the United Kingdom). However, there are four countries (Germany, Ireland, Portugal, and Sweden) with occupations at the two-digit level and three countries (Austria, Estonia, and Finland) at the one-digit level.

available in the study by Autor and Dorn (2013) (Table 1).

Table 1 Task measures computed using PIAAC

PIAAC
Abstract
1) Read diagrams, maps, or schematics (g_q01h)
2) Write reports (g_q02c)
3) Prepare charts, graphs, or tables (g_q03f)
4) Use simple algebra or formulas (g_q03g)
5) Face complex problems (>30 minutes) (f_q05b)
6) Persuading/influencing people (f_q04a)
7) Negotiating with people (f_q04b)
Routine
1) Learn work-related things from co-workers (d_q13a)
2) Learning by doing from tasks performed (d_q13b)
3) Keeping up to date with new products or services (d_q13c)
4) Change sequence of tasks (d_q11a)
5) Change how do you work (d_q11b)
6) Change speed of work (d_q11c)
7) Change working hours (d_q11d)
Manual
1) Hand/finger skill accuracy (f_q06c)
2) Physical work (f_q06b)

For the abstract tasks, we retain the following items: "read diagrams", "write reports", "prepare charts, graphs, or tables", "use simple algebra or formulas", "face complex problems", "persuading and influencing people", and "negotiating with people". For the manual tasks, we resort to responses on "skill or accuracy in using hands/fingers" (e.g. to assemble or repair) and "physical work" (e.g. to work on physical activities). Finally, for the routine tasks, we select four items regarding the frequency and repetitiveness of the job (change the sequence of tasks, change how you work, change the speed of work, and change the working hours) and three items regarding the lack of adaptation (learn work-related things from co-workers, learning by doing, and keeping up to date with new products/services).

The task measures provided by PIAAC at the individual level are used to compute the Abstract, Routine and Manual indices as well as the RTI index at the ISCO-08 one-digit occupational level. This gives us (one-digit) occupation specific indices which are not country specific. Based on this measure and using the occupation and country specific weights obtained from the EU LFS, we then compute the indices for all the EU countries including those that are not in PIAAC.

3. Characterisation of migrant occupations in the EU. Descriptive results.

The analyses were carried out using the EU LFS pooled cross-sectional surveys from 2015-2016 which allow distinguishing between 3 groups of working-age population: 1) *Nationals*, that is citizens of the reporting Member State; 2) *EU mobile citizens (EU MC)*, i.e. EU citizens residing in another EU country; and 3) *Third-country nationals (TCNs)*, that is non-EU citizens residing in a EU country. The abstract, manual, routine and RTI indices – as defined in the previous paragraph – were merged with EU LFS dataset at Member State and ISCO-08 one-digit occupational level.

It should be stressed out that EU LFS sample comprises only the resident population and thus we do not have information on labour market activities of undocumented migrants. Our sample, therefore, includes nationals and legal migrants engaged in declared or undeclared work activities, nevertheless we cannot distinguish between the former and the latter activity of an individual.

Dissimilarities between migrant and non-migrant populations appear instantly evident when observing the occupational categories of three groups of workers (Table 2). In the case of nationals, the largest share is represented by "professionals" (19.80) who together with the categories of "technicians" (16.79) and "service and sales workers" (16.79) account for half of the overall work force. On the other hand, for the group of EU MC, the largest shares of workers fall under the categories "elementary occupations" (20.51), "professionals" (17.06) and "service and sales workers" (16.82), which together represent slightly more than 50.0% of the overall EU MC labour force. Finally, when looking at the group of TCN, we find that half of them is employed in only two types of occupations: "elementary occupations" (27.11) and "service and sales workers" (22.43).

These different types of occupations translate into different types of job tasks. The highest values for the Abstract index can be found (see Table 2, third column) for the categories of "managers", "professionals", and "technicians", in which EU MC and, especially, TCN have low shares of their workforce[18]. The highest values for the Manual index are found in the categories "craft and related trade workers", "elementary occupations", and "service and sales workers", where TCN and - to a lower extent – EU MC are particularly present. As for the Routine index, the highest values are found in "plant and machine operators & assemblers", "elementary occupations", "service & sales workers" and "craft & related trade workers", which – with the exception of the former, are categories in which EU MC and TCN tend to be present in large shares.

When looking at the RTI index we can see a clear pattern: nationals, who have large shares among "professionals" and "technicians" tend to have lower values for the RTI index[19]. On the other hand, EU MC and, especially TCN, which have large shares among "elementary occupations", "service & sales workers", tend to be characterized by high values for the RTI index.

[18] The partial exception is the group of EU MC professional, which corresponds to 17.06% of the EU MC workforce.

[19] However, "service & sales workers" have a high value for the RTI index and this counterbalances the effect of the first two categories.

Table 2 Distribution of workers by nationality and mean values of abstract, manual, routine and RTI indexes across occupations in EU

ISCO-08 1-digit	Share			Mean value			
	Nationals	EU – MCs	TCNs	Abstract index	Manual index	Routine index	RTI index[20]
Skilled agricultural, forestry & fishery workers	3,79	1,17	1,31	0,225	0,897	0,403	0,660
Managers	6,15	4,97	3,58	0,591	0,435	0,314	0,034
Clerical support workers	10,02	6,18	5,25	0,371	0,428	0,448	0,293
Plant and machine operators & assemblers	7,22	8,48	7,69	0,224	0,779	0,592	0,738
Technicians	16,79	10,55	7,62	0,468	0,485	0,395	0,218
Craft & related trade workers	11,39	14,26	12,60	0,322	0,881	0,463	0,583
Service & sales workers	16,79	16,82	22,43	0,292	0,717	0,468	0,551
Professionals	19,80	17,06	12,41	0,519	0,410	0,364	0,106
Elementary occupations	8,05	20,51	27,11	0,114	0,799	0,583	0,961

NB: HR, HU and MT are excluded from the sample.
Source: JRC KCMD elaborations of PIAAC 2012 and EU LFS 2016.

In order to have a better overview of routine task intensity across occupations, Figure 1 plots kernel density estimation for each of the population groups of reference. The *x* axis plots the RTI index of different occupations with increasing values from left to right. The *y* axis gives the share of the reference population group in each point. Notice that the variability in the values for RTI comes from a combination of observations that vary by occupation and MS. In other words, by construction, all workers in the same occupation and in the same MS have the same value for the RTI index. Hence, when providing the Kernel density for each occupation, the underlying source of variation is given by cross-MS variation.

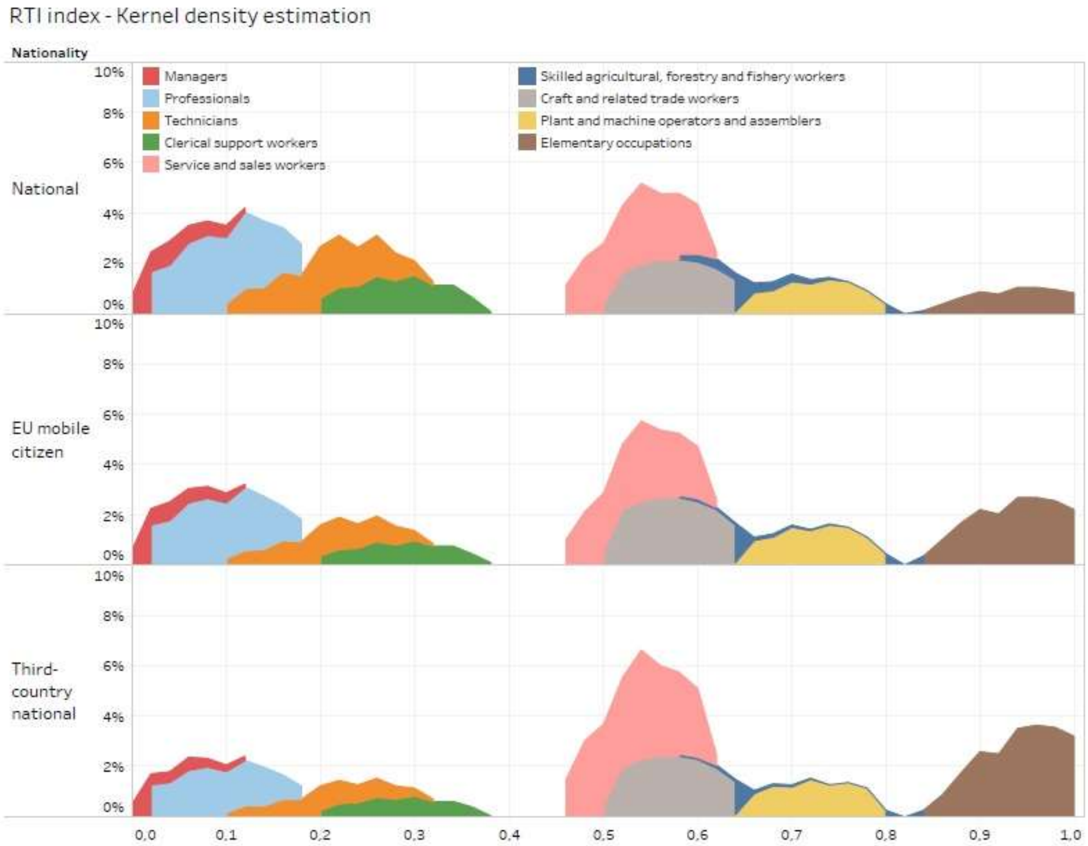
With this caveat, we can immediately see that there are clear differences among occupations: managers, professionals, technicians and clerical support workers are those with the lowest values for the RTI index (below 40%), while elementary occupation, plant and machine operators and assemblers, craft and related trade workers are those with the highest values. The remaining occupations lie someway in between, with some overlapping driven by the cross-country variability.

When we compare the three groups we can observe that the most relevant differences among reference populations appear in the left and right tails of three distributions. The height of the left tail, containing occupations with the lowest level of RTI index, decreases progressively as we pass from nationals, to EU MC and becomes the smallest in the distribution of TCNs, indicating that the share of the group-specific working population employed in these occupations decreases as we move away from nationals. On the contrary, the height of the right tail, representing "elementary occupation" with the highest routine task intensity, increases as we move from nationals to EU MC and, finally, reaches its highest density in the case of TCN. Finally, there are higher shares of migrants at the middle of the kernel distribution linked to bigger presence of service and sales

[20] Minmax normalization of RTI index defined in paragraph 2 on a scale 0-1.

workers. It can be assumed that, in future, this could be the area where migrant will still find employment opportunities.

Figure 1 Kernel density estimation of RTI index by nationality



NB: HR, HU and MT are excluded from the sample.
Source: JRC KCMD elaborations of PIAAC 2012 and EU LFS 2016.

Both Table 2 and Figure 1 show that in the EU labour market migrant workers tend to be more concentrated in occupations with higher task routine intensity, relative to nationals. When comparing the two migrant groups, this condition is even more relevant for TCN relative to EU MC.

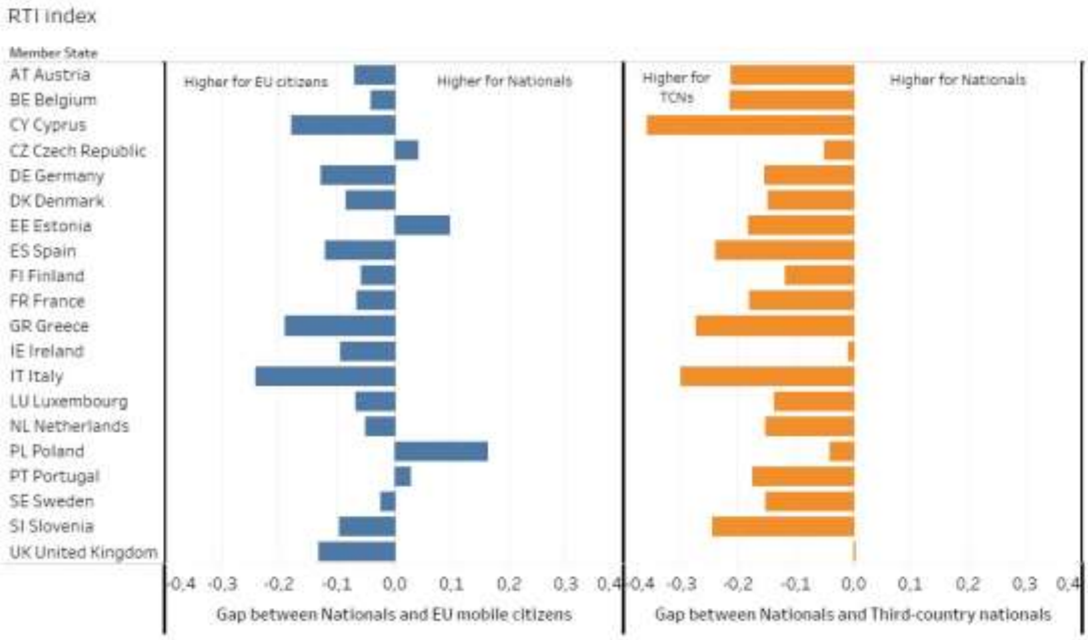
As already mentioned above, country heterogeneity – e.g. in terms of industrial structure, specialization and pace of technology adoption – plays a role in the pattern observed. Moreover, it should be considered that migrants are not evenly distributed across Member States and that their characteristics in terms of age, education, country of origin, etc. are not uniform, which again adds to the observed variability.

In order to capture better such cross-country variation (while not distinguishing by occupation), Figure 2 plots the difference in the mean value of the RTI index between *a)* nationals and EU MC (blue bars) and *b)* nationals and TCN (orange bars) for each Member State.

In a great number of Member States, EU mobile citizens perform jobs with higher routine task intensity than nationals and this gap is particularly relevant for Southern EU countries, such as IT, GR and CY. Exceptions are CZ, EE, PL and PT where EU MC are employed in jobs with lower routine task intensity compared to nationals. In the case of TCN the situation is even more uniform. In all Member

States TCN perform jobs with higher routine task intensity than nationals and this is especially striking in Southern Mediterranean countries (CY, ES, GR, IT, SL). There are however some Member States in which this national-TCN gap in terms of RTI index is almost absent (UK and IE) or very small (CZ and PL).

Figure 2 Difference in the mean value of RTI index by nationality and Member State



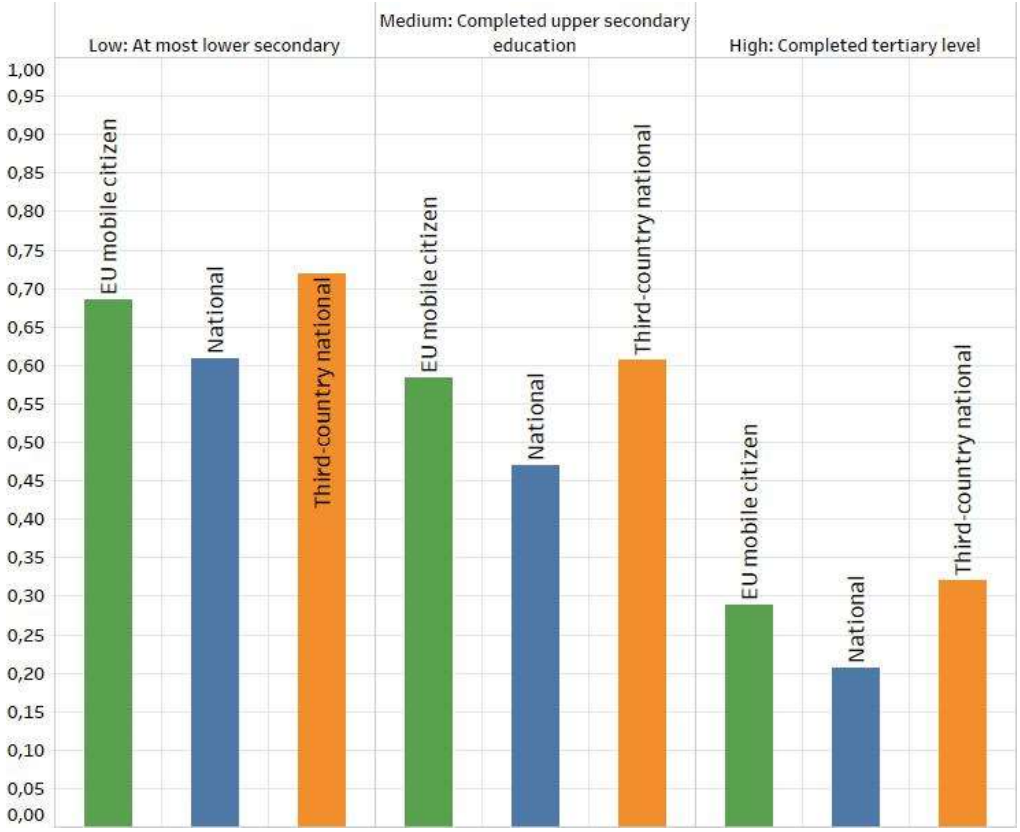
NB: HR, HU and MT are excluded from the sample; BG, LT, RO and SK excluded due to low number of observations for foreign nationals.
Source: JRC KCMD elaborations of PIAAC 2012 and EU LFS 2016.

The descriptive results at country level are in line with the general picture of migrants being more engaged in jobs characterized by higher routine task intensity than nationals. Nevertheless, important differences among Member States can be observed.

These differences are driven by separate effects. On the one hand we have compositional effects, linked to the size and the characteristics of the migrant population relative to the non-migrant one, and to differences in the cross-country occupational composition of the three groups. To this we have to add that the values for the RTI index change both across occupations and countries.

Since the occupational composition is very much related to the educational composition of the work force, it is interesting to explore the relationship between educational attainment and the RTI index (an inverse relationship between worker's education level and the routine intensity of the job is well documented in the literature: see Nedelkoska and Quintini, 2018). This relationship can be easily observed in Figure 3 where we report the values of the RTI index by (three) levels of education and for each group. For each level of education, EU MC and TCN tend to be employed jobs with higher RTI index compared to nationals.

Figure 3 Mean values of RTI index by nationality and education level



NB: HR, HU and MT are excluded from the sample.
Source: JRC KCMD elaborations of PIAAC 2012 and EU LFS 2016.

4. Migrant labour force and jobs with high degree of automation potential. Logistic regressions results.

4.1. Methodology

The desciptive analysis in the previous paragraph inform us that migrants, and especially TCN, are particularly concentrated in occupations with higher routine task intensity and thus with higher automation potential. However, this preliminary evidence does not take into account that migrants might also be characterized by a set of individual characteristics that are also associated with high routine intensity occupations, such as low education, short period of residence in the host country, young age, etc. It is hence important to analyze whether migrant status, per se, is positively associated to the likelihood of being employed in a high routine intensity occupation once we control for the other potentially relevant covariates (i.e. ceteris paribus). For this we run a series of logistic regression analysis, introducing first controls for education, length of residence and other personal characteristics such as gender and age (Table 3).

In our baseline specification:

$$Y_i = \beta_0 + \beta_1 Migrant + \beta_2 Education + \beta_3 Residence + \beta_4 X_i + \gamma_t + \varepsilon_i \qquad [2]$$

an individual *i* is considered to be employed in a job with high automation potential - and therefore Y_i=1 - if RTI is higher than its average value at the Eu level, equal to 0.415. Our first coefficient of interest β_1 measures how being a migrant (either EU MC or TCN), relative to being a native, correlates with Y_i. The vector of coefficient β_2 accounts for the role of three educational levels, namely the primary, secondary and tertiary education. Finally, the coefficient β_3 captures the importance of the length of residence, captured by a dummy variable equal to 1 if a person is a long-term resident (residing in the host country for more than 5 years) and equal to 0 if a person is a recent resident (i.e. residing in the host country for less than 5 years). Moreover, the model includes a set of controls X_i which account for individual's demographic and job characteristics such as age, gender, area of residence, country of residence, size of the firm, fixed-term contract, part-time contract and sector of employment (NACE at 1-digit level). Finally, the specification includes year γ_t fixed effects. Notice that the analysis is limited to employed individuals.

In Model 2 we add to the variables used in Model 1 a vector of indicator variables obtained combining migrant status (national, EU MC and TCN) with educational levels (primary or lower secondary; upper secondary; tertiary). These indicator variables (we refer to them collectively as *Migrant by Education*), are effectively reflecting the 9 sub-groups obtained by the crossing of migrant status and educational achievement. Therefore, in Model 2:

$$Y_i = \beta_0 + \beta_1 Migrant\ by\ Education + \beta_2 Residence + \beta_3 X_i + \gamma_t + \varepsilon_i \qquad [3]$$

Taking "Nationals with primary education" as the reference category, the β_1 separates the effect on Y_i of being an EU MC or TCN with each one of the 3 levels of education or a National with remaining education levels.

Finally, Model 3 introduces an additional variable (*Migrant by Residence*) that combines migrant status with length of residence in order to test whether the coefficient on the migrant status is affected by the length of residence in the host country. In this specification:

$$Y_i = \beta_0 + \beta_1 Migrant\ by\ Residence + \beta_2 Education + \beta_3 X_i + \gamma_t + \varepsilon_i \qquad [4]$$

the coefficient β_1 measures the effect of being long-term or recent EU MC or TCN resident on Y_i, in comparison to being National (reference category). Dealing with cross-sectional data, the contraposition between recent and long-term translates into comparing different immigration waves. More specifically, assuming that the country of residence is the first country in which the person immigrated then the category "recent migrants" refers to immigration waves occurred after 2010/2011 (included) and, vice versa, long-term residents refer to immigration waves prior to 2010/2011.

4.2. Results

Results are presented in form of Odd Ratios (OR) in Table 3. Estimates from Model 1 confirm that **migrant status** is associated to a statistically significant higher probability of working on a job with high automation potential in comparison to nationals. In addition, this migrant vs. national gap appears to be higher in case of TCN than for EU MC. Indeed, TCN have 2.9 times higher likelihood of being employed on a job with high automation potential than a national, while in case of EU MC the value goes down to 2.3. Even when combining the migrant status with education level (Model 2) or with the length of residence (Model 3), the differences between nationals and migrant groups in the current EU labour market remain persistent, as migrants tend to occupy jobs with higher automation potential than nationals.

When we look at the role of **education**, Model 1 shows that having completed upper secondary education, compared to completion of primary education or lower secondary education, reduces the likelihood of being employed in a job with high automation potential by 62%; having completed tertiary education reduces such likelihood by 95%. These results are also confirmed by Model 3 in which the length of residence is taken into account. The results show that education plays a key role in determining individual's positioning in the labour market.

Model 2 goes into more detail by providing estimates for education levels by migrant status[21]. In this case, the category "national with primary or lower secondary education" is taken as the reference category.

[21] We consider also an alternative way of accounting for education. In addition to the baseline model (Model 1) we ran an identical specification excluding the education variable (results not reported here and available upon request). The comparison of coefficients shows that the exclusion of the education variable does not affect substantially the results for the baseline model given the wide set of controls that capture the education effect.

Starting with primary or lower secondary education, it can be noted that EU MCs and TCNs have, respectively, 2.0 and 2.6 higher odds of being employed in a job with high automation potential than a national with the same level of education. Again, we find that the results for TCN are more distant from those of nationals compared to EU MC.

In line with results from Model 1 and Model 3, a National with completed upper secondary education has 62% lower probability of being employed in a job with high automation potential, relative to a national with only primary or lower secondary education. On the other hand, for a EU MC with upper secondary degree, the likelihood is only 16% lower than that of a national with primary or lower secondary education. For a TCN with upper secondary education there is no statistically significant difference with a national holding only a primary or lower secondary degree.

Finally, the smallest difference between national and migrant population can be observed at the level of tertiary education. While tertiary educated nationals have 95% lower odds of working on a job with high automation potential in comparison to a national with a primary or lower secondary degree, in the case of EU MC and TCN the likelihood is reduced by 84%.

Taking into consideration these results, we confirm that migrants are more likely to be employed in occupations with higher automation potential, compared to nationals, even when accounting for the level of education. This migrant-national gap tends to diminish with higher educational level.

Lastly, the specifications allow us to consider also the role of a migrant's **length of residence** in the host country. According to Model 1 and Model 2, a long-term resident has a slightly lower – by less than 10% - likelihood of working on a job with high automation potential than a recent resident. Model 3 combines migrant status with the length of residence using "Nationals" as the reference category.

The Model 3 provides two main messages. First, in line with previous findings, migrants have higher likelihood of being employed on a job with high automation potential than nationals even when taking into account migrant's length of residence. Second, analyzing the length of residence reveals important differences between EU MC and TCN, which might be linked to the different composition of cohorts from different immigration waves and their occupational profiles. The results show that among EU MC, recent migrants have higher odds of being employed on a job with high automation potential (OR=2.8) than long-term migrants (OR=2.2). On the contrary, in the case of TCN, it is long term migrants who report higher odds of working on a job with high automation potential (OR=3.1) compared to recent migrants (OR=2.3).

Table 3 Odds of working on a job with high automation potential.

	Model 1: baseline		**Model 2: education**		**Model 3: length of residence**	
	Odd ratio	SE	Odd ratio	SE	Odd ratio	SE
Age	0.909***	0.0065	0.910***	0.0065	0.909***	0.0065
Age square	1.002***	0.0002	1.002***	0.0002	1.002***	0.0002
Age cube	1.000***	0.0000	1.000***	0.0000	1.000***	0.0000
Sex	0.568***	0.0042	0.568***	0.0042	0.568***	0.0042
Area: reference - City						
Towns and suburbs	1.170***	0.0089	1.170***	0.0089	1.170***	0.0089
Rural area	1.390***	0.0111	1.390***	0.0112	1.390***	0.0111
Size of the firm	0.886***	0.0026	0.886***	0.0026	0.886***	0.0026
Fixed-term contract	1.328***	0.0133	1.327***	0.0133	1.330***	0.0133
Part-time contract	1.815***	0.0162	1.815***	0.0162	1.815***	0.0162
EDUCATION***: reference - Primary education***						
Secondary education	0.381***	0.0038			0.381***	0.0038
Tertiary education	0.050***	0.0006			0.050***	0.0006
MIGRANT STATUS***: reference - National***						
EU mobile citizen	2.314***	0.0497				
Third-country national	2.919***	0.0644				
LONG TERM RESIDENT	0.921**	0.0315	0.963**	0.0319		
MIGRANT STATUS BY EDUCATION***: reference - National with primary education***						
National secondary education			0.379***	0.0039		
National tertiary education			0.048***	0.0006		
EU MC primary education			1.994***	0.0996		
EU MC secondary education			0.814***	0.0225		
EU MC tertiary education			0.135***	0.0047		
TCN primary education			2.653***	0.1098		
TCN secondary education			1.001	0.0322		
TCN tertiary education			0.167***	0.0061		
MIGRANT STATUS BY LENGTH OF RESIDENCE***: reference - National***						
EU MC recent resident					2.893***	0.1158
EU MC long-term resident					2.184***	0.0488
TCN recent resident					2.281***	0.1195
TCN long-term resident					3.142***	0.0741
Industry (NACE 1 digit)	yes		yes		yes	
Country	yes		yes		yes	
Year	yes		yes		yes	
Observations	2,261,233		2,261,233		2,261,233	
Pseudo R^2	0.332		0.332		0.332	

Significant at: ***p<0.01; ** p<0.05; *p<0.1
NB: HR, HU and MT are excluded from the sample.
Source: JRC KCMD elaborations of PIAAC 2012 and EU LFS 2015-2016.

5. Some indications on the future of labour market integration of migrants

In this paragraph, we explore the likelihood of attending professional training and being employed on a fixed-term contract, considering also the degree of automation potential of the job. In this we also consider whether such correlations depend upon the migrant status of the worker (National, EU MC and TCN). Results are presented in form of odd rations in Tables 4 and 5. It is important to evaluate these aspects since they may affect the possibility to transition to other occupations of the different population groups, also as a consequence of the higher probability of job loss due to digital transformation.

5.1. Professional training

Model 4 looks at the odds of receiving professional training (outside the regular education system), over the last month and it is expressed as following:

$$Y_i = \beta_0 + \beta_1\, Migrant\ by\ high\ automation\ potential + \beta_2 X_i + \gamma_t + \varepsilon_i \qquad [5]$$

where *Migrant by high automation potential* is a vector of indicator variables obtained by the crossing of the three migrant status variables with the indicator variable reflecting high automation potential (as in paragraph 4, a job is defined to have a high automation potential if RTI is higher than its average value at the Eu level, equal to 0.415). X_i incorporates demographic and job controls such as age, gender, education, length of residence, area of residence, country, size of the firm, fixed-term contract, part-time contract, occupation at ISCO-08 at 1-digit level and industry NACE at 1-digit level. The model finally includes year fixed effects γ_t.

Table 4 Odds of receiving professional training

	Model 4- Odds of receiving professional training	
	Odd ratio	Robust SE
MIGRANT STATUS BY DEGREE OF AUTOMATION OF THE JOB*:* ***reference - National employed in low automation potential job***		
National employed in job with *high* automation potential	0.309***	0.0148
EU MC employed in job with *low* automation potential	0.819***	0.0475
EU MC employed in job with *high* automation potential	0.208***	0.0185
TCN employed in job with *low* automation potential job	0.786***	0.0557
TCN employed in job with *high* automation potential	0.179***	0.0143
Controls	Yes	
Country	Yes	
Year	Yes	
Observations	1,759,477	
Pseudo R^2	0.105	

Significant at: ***p<0.01; ** p<0.05; *p<0.1
NB: HR, HU and MT are excluded from the sample.
Source: JRC KCMD elaborations of PIAAC 2012 and EU LFS 2015-2016.

Looking at the relationship between level of potential automation of the job and the likelihood of professional training in Table 4, we can provide three main conclusions. First, nationals employed on jobs with *low* automation potential have the highest likelihood of attending job-related training among all groups considered. Secondly, EU MC and TCN working in jobs with *low* automation potential have around 18-20% less likelihood of receiving training than nationals employed in occupations with similar levels of automation potential (as defined by our dichotomous variables using the average RTI). Finally, the odds of receiving professional training for all workers (National, EU MC and TCN) employed in jobs with *high* automation potential are extremely low in comparison to nationals employed in jobs with low automation potential. This likelihood is around 80% lower for EU MCs and TCNs and around 70% lower for nationals in high automation potential jobs.

5.2. Type of employment contract

Furthermore, we also explore how migrant status combined with the automation potential of the job of an individual is correlated with the likelihood of being employed on a fixed-term contract versus a permanent type of contract. For that purpose, in Model 5 we implement a specification analogous to that of Model 4. Naturally, in Model 5 the dummy variable fixed-term contract is excluded from controls as it becomes a dependent variable.

The results in Table 5 show, in the first place, that nationals employed in jobs with *low* level of automation potential have the lowest likelihood of being employed on a fixed-term contract. EU MC working on jobs with low automation potential have 1.38 times higher likelihood of having a fixed-term contract in comparison to nationals employed in jobs with low level of automation potential. In case of TCN this likelihood is even higher (OR=2.1).

Moreover, having a job with *high* automation potential is correlated with a relevant increase in the probability of being employed on a fixed-term contract. In case of nationals the likelihood is 3.1 times higher, while in case of EU MC and TCN the odds are 3.4 times higher in comparison to the reference group – nationals employed on low automation potential jobs.

In conclusion, the results indicate that: i) working conditions, such as access to professional training or type of contacts, are not equally distributed between migrant or non-migrant workers; ii) a job's automation potential appears to be negatively correlated with the likelihood of receiving professional training and positively correlated with the likelihood of having a fixed-term contract and both correlations are stronger for migrant workers.

Therefore, we can see two channels that can negatively affect the labour market integration of migrants determined by the DT: 1) being a migrant – all else being equal – is associated with increased likelihood of being employed in a job with high automation potential; 2) being a migrant is also associated to a higher likelihood of having a fixed-term contract and to a lower probability of receiving professional training.

Table 5 Odds of being employed on a fixed-term contract

	Model 5 - Odds of being employed on a fixed-term contract	
	Odd ratio	Robust SE
MIGRANT STATUS BY DEGREE OF AUTOMATION OF THE JOB*:* ***reference - National employed in low automation potential job***		
National employed in job with *high* automation potential	3.102***	0.1075
EU MC employed in job with *low* automation potential	1.384***	0.0539
EU MC employed in job with *high* automation potential	3.412***	0.1545
TCN employed in in job with *low* automation potential	2.070***	0.0881
TCN employed in *high* automation potential job	3.452***	0.1440
Controls	Yes	
Country	Yes	
Year	Yes	
Observations	2,261,233	
Pseudo R^2	0.192	

Significant at: ***p<0.01; ** p<0.05; *p<0.1
NB: HR, HU and MT are excluded from the sample.
Source: JRC KCMD elaborations of PIAAC 2012 and EU LFS 2015-2016.

Conclusions

This report analyzes whether EU mobile citizens and third country nationals working in the EU are more vulnerable to challenges posed by Digital Transformation relative to non-migrant workers (nationals). We perform multivariate analysis that takes into account differences in the socio-demographic composition of EU mobile citizens, third country nationals and nationals as well as heterogeneities among Member States in years 2015 and 2016.

Our results show that migrants are more likely to be employed in jobs that have high automation potential, and are thus at risk of disappearance, compared to non-migrant workers. This likelihood appears especially high in the case of third country nationals. However, the probability of being employed in jobs with high automation potential is inversely related to the educational attainment level of individuals (both for migrants and natives).

Moreover, the report indicates that both EU mobile citizens and third country nationals have lower access to professional training, which also implies that migrants tend to invest less in their own human capital and have lower opportunities to transition to better and more secure jobs. At the same time, migrants are more likely to be employed under fixed-term contracts with a shorter horizon, with risk of non-renewal of contract in case of economic and technological shocks.

This “precariousness” implies a lower resilience of migrants when facing the potential negative consequences of digital transformation or other economic shocks.

The vulnerability of migrants' in the labour market can easily extend to other socio-economic domains. On the basis of our analysis it is not possible to state the extent to which such vulnerability is the effect of individual choices vs labour market discrimination, nevertheless what appears evident is that it jeopardizes migrants' integration. Therefore, policies ensuring that migrants have the same opportunities in terms of (life-long) training and human capital accumulation could play a crucial role. In fact, migrants may be in particular need of policies directed at re-qualification in order to facilitate their transition into new occupations at lower risk of automation. At the same time, the results also point out that, the labour market vulnerability of migrants is linked to the very same migrant status of the individual. Therefore, measures favoring integration and countering discrimination more in general can furthermore contribute to mitigate the negative effects of digital transformation on migrant labour force.

The main limitation of this study lies in the fact that the theoretical framework applied in this report, and based on the RBTC hypothesis, does not take into account technical feasibility, economic benefits and costs, and the regulatory framework. Nor does it take into account that the digital transformation itself can give rise to new types of tasks and jobs[22].

Finally, our findings also raise a question on other socio-economic implications of the digital transformation that would require further analysis in future. As a direct consequence of our results, it would be interesting to understand the extent to which the (potential) loss of jobs due to DT and the difficulty to transit to new occupations could affect the employment state and thus the legal status of labour

[22] Some recent estimates on job creation due to DT were elaborated by McKinsey 2017.

migrants and their dependent families. More broadly, it would also be interesting to better understand whether the share of migrants within occupations and sectors can itself be a determinant factor in the process of technology adoption in these occupations and sectors.

Further venues for research are not concerned with the integration of the current migrants, but also about the future of immigration to the EU, considering the impacts of the DT on the demand of labour, in terms of both levels and skill composition. Currently, in the EU, migrants are mainly employed in secondary segments of the labour market (Grubanov-Boskovic and Natale, 2017), and this report has shown that changes linked to the DT may imply a reduction of demand, in particular for elementary occupations. The hypothesis that immigration may alleviate the negative consequences of the aging population in the EU may not be confirmed in a scenario where the DT will bring to a reduction of demand for labour and, at the same time, a reconfiguration towards skills which are not easily available in the supply of labour from less developed countries. If (and how) the supply of labour force linked to migration will match the future demand in countries of destination is a question which is currently not addressed in medium-long term demographic forecasts (Lutz et al., 2018).

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List of abbreviations

ALM - Autor, Levy and Murnane

EU MC - EU mobile citizen

JRC – Joint Research Centre

KCMD – Knowledge Centre on Migration and Demography

RBTC - Routine Biased Technological Change hypothesis

RTI - Routine task intensity measure

TCN – Third country national

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