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Job Automation Risk, Economic Structure and Trade: a European Perspective

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Abstract

Recent studies report that technological developments in machine learning and artificial intelligence present a significant risk to jobs in advanced countries. We re-estimate automation risk at the job level, finding sectoral employment structure to be key in determining automation risk at the country level. At the country level, we find a negative relationship between automation risk and labour productivity. We then analyse the role of trade as a factor leading to structural changes and consider the effect of trade on aggregate automation risk by comparing automation risk between a hypothetical autarky and the actual situation. Results indicate that trade increases automation risk in Europe, although moderately so. European countries with high labour productivity see automation risk increase due to trade, with trade between European and non-European nations driving these results. This implies that the high productivity countries do not, on the balance, offshore automation risk, but rather import it.

JEL Codes: F16, F66, O33, J24

Keywords: Automation risk for employment; Industry 4.0; Globalisation, Global Value Chains

1. Introduction

The risk of "robots" destroying employment on a large scale has been put on the agenda by Frey and Osborne (2017), who found that "47% of total US employment is in the high-risk category [risk above 70%], meaning that associated occupations are potentially automatable over some unspecified number of years, perhaps a decade or two" (p. 265). Their estimations were for the US only, but Arntz et al. (2016) and Nedelkoska and Quintini (2018) – both studies coming from the OECD – provide estimates for the entire OECD area, albeit based on a different method. Although the analysis by Nedelkoska and Quintini (2018) led the Financial Times to declare that "Job loss fears from robots overblown, says OECD" (1st April 2018), the study still concluded that the median risk of job automation is at 48% in the OECD. The main difference between the risk assessment in Frey and Osborne (2017) and Nedelkoska and Quintini (2018) lies in how many jobs are placed in the "high risk" category, but both studies agree that median or average risk is high.

In these existing studies, job automation risk is assessed only from the technological point of view, i.e., the question that they try to answer is whether a particular job may or may not be technologically replaced by machine learning and associated technologies over the next decades. However, the decision on whether or not to replace a worker by a "robot" (we use this term to refer in a colloquial way to all technologies in the field of artificial intelligence and machine learning) depends not only on technological opportunities, but also on the relative costs of the necessary capital and the potentially replaced labour (e.g., Acemoglu and Restrepo, 2017). This economic side of the automation decision is not included in the existing risk assessments.

Apart from replacing human labour by intelligent machines, firms also have the option to offshore jobs to foreign locations where labour costs are lower. Like automation, the phenomenon of offshoring is an important topic in the debate about employment loss in developed countries, e.g., Mankiw and Swagel (2006), Blinder (2006) and Blinder (2009). Offshoring refers to the "relocation" of jobs to foreign countries, in particular from developed countries to developing countries. Acemoglu and Autor (2011) find that the phenomenon has become relevant for so-called medium-skilled jobs, whereas in the past it was believed to be mainly relevant for low-skilled jobs.

Offshoring is intrinsically linked to trade, in particular to so-called Global Value Chains (GVCs) (e.g., Ali-Yrkkö et al., 2011; Los et al., 2014). The term GVCs is used to reflect the global nature of many contemporary production processes, in which production activities are fragmented across the globe. The GVC idea portrays production as a collection of activities that, under the influence of decreasing transportation costs and the potential of computer technology to coordinate processes across long distance, can be separated from each other in geographical space. Thus, we may think of the production of an individual product like a mobile phone as a collection of Research and Development (R&D), design, administration, production of various components, assembly, sales, purchasing, etc. All these activities can be performed in different locations, according to where they can be undertaken most profitably. Shipping of semi-finished products, components and even services that contribute to the final product will all yield trade flows between the locations involved in the GVC, and the final user of the product.

In this perspective, offshoring can be seen as the move of one specific activity (e.g., assembly, or after-sales service) from one country to another. This will have an impact on employment in both the country of origin (where the activity was located in the first place) as well as the host country (where the activity is moved to).[1] In other words, GVCs are a profit-responding way to re-distribute employment and the creation of value added across countries participating in the global economy. They change the employment structure of the countries involved, and, thereby, also affect a country's risk of job loss due to automation.

This paper combines the topics of trade, GVCs, offshoring and automation risk into a single analysis. The question that is addressed here is to what extent GVCs and trade in general (i.e., trade of intermediate products as well as final products) affect the average risk of a job being automated in a specific country. Of particular interest is the question of whether there are countries for which GVCs and trade increase automation risk, and others where the reverse happens.

Estimating the (causal) mechanisms behind labour market outcomes of offshoring or automation risk is a complicated business. There tend to be multiple factors at work, such as technological change, increased international trade, and the rise of China as an industrial nation and WTO member (e.g., Wright, 2014; Autor et al., 2015). Moreover, each of these factors tends to have multiple effects, often counteracting each other. Our analysis, which focusses to a large extent on the countries of the European Union, does not attempt to identify the causal effects of trade and automation on labour market outcomes. Instead, the approach that we adopt to address our research questions is more descriptive, adopting an approach that allows us to obtain an idea of the magnitude and direction of the trade/GVC effect on countries' automation risk. In terms of the direction of the effect we are specifically interested in whether trade/GVCs increase or decrease differences in (pre-trade) automation risk between (European) countries.

Our analysis reserves a central role for structural change (i.e., changes in the sectoral employment structure of a country). As automation risk varies between jobs, aggregate

[1] Note that it is not necessarily the case that employment in the origin country will decline and that in the host country will increase as a result of offshoring. From a theoretical perspective there are two main direct effects of offshoring on employment. The first being a substitution effect reflecting the destruction of jobs that occurs when firms relocate part of their production activities overseas, and the second being a scale effect that captures the creation of jobs following the expansion in industry output that may arise as a result of the productivity gains from offshoring. For evidence of the importance of these two offsetting effects, see for example Hijzen and Swaim (2007, 2010).

automation risk depends on the job structure of employment in a country. We operationalise this with sectors as an intermediate level of analysis, i.e., we look at the job structure of employment within sectors, and at the sectoral employment structure at the country level. Trade changes this structure, and we will attempt to measure such structural changes in order to assess the impact of trade on automation risk. This is implemented using the accounting framework of global input-output tables (see e.g., Koopman et al., 2014; Los et al., 2014). Among other things, we use these tables to create an autarky benchmark (e.g., Duchin, 2007; Strømman and Duchin, 2006) in which automation risk can be estimated for the jobs needed in the autarky. This benchmark is then compared to the actual situation (with trade and/or GVCs) to answer our main research question.

We show that the countries with high (low) risk tend to be the ones with comparatively low (high) labour productivity, and we ask whether this is the case because the highly productive countries were able to offshore, or use trade in other ways, jobs with high automation risk. We show that this is not the case, i.e., that automation risk in countries with high productivity actually increases due to trade. Our results further show that automation risk is "traded" mostly between the European Union (EU) and non-EU countries, and not so much within the EU.

To obtain these conclusions, the analysis will go through different stages. We start, in Section 2, by reviewing the literature on the estimation of automation risk, and applying one of the methods to a database of employment in Europe. This yields estimates of average automation risk of employment for EU countries[2] that are applied later in the analysis. Section 3 analyses the structural nature of the automation risk estimates and asks how variation in risk is related to already existing automation levels. Section 4 looks at variations in automation risk between countries, and focuses on the role of trade and global value chains. This section introduces the input-output method that is used to create the autarky benchmarks and introduces and characterises these benchmarks, and then applies these methods to estimate the impact of trade on the distribution of automation risk between countries. The final section, Section 5, summarises the argument and draws further conclusions.

2. Estimating automation risk

Frey and Osborne (2017) review the literature on machine learning and artificial intelligence and conclude that there seem to be technological bottlenecks

[2] The country list includes the 28 Member States (on 1 January 2019) of the European Union except Malta (for which necessary data are not all available), which are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom. To this set we add Norway and Switzerland, which are joined to the EU internal market by the EFTA-EU treaty. Thus, we have 29 countries in total in the analysis.

corresponding to three main job task categories: perception and manipulation tasks (i.e., recognising objects and configurations of objects, and manipulating them), creative intelligence tasks (i.e. finding non-routine solutions to non-routine problems), and social intelligence tasks (i.e. interacting with humans in a social way). They argue that jobs that contain a large degree of tasks in these three categories will not be easily automated in the near future, but other jobs will be. In order to further operationalise this, they asked a panel of experts (in machine learning) to assess a set of 70 job descriptions in terms of the potential to be automated over the coming decades. This yields a binary code (automatable or not) for each of the 70 jobs.

The job descriptions were taken from the US O*NET database, which provides "key features of an occupation as a standardised and measurable set of variables [and] … open-ended descriptions of specific tasks to each occupation. This allows [them] to (a) objectively rank occupations according to the mix of knowledge, skills, and abilities they require; and (b) subjectively categorise them based on the variety of tasks they involve." The variables from the O*NET database are then used to estimate a range of (machine learning) models that use the binary automation variable for the 70 job codes to classify all 702 job codes in the database. This yields automation risks estimations for all job codes, which can then be applied to the actual structure of employment in the US to obtain the real-world distribution of automation risk for workers in the US.

Nedelkoska and Quintini (2018) apply a similar method, but with a broader database that covers the entire OECD area, and an estimation model that is more firmly rooted in econometrics than Frey and Osborne's machine learning algorithms. They use the PIAAC database, which is a survey among workers in OECD countries, asking them (among other things) about the kind of tasks that they perform and how often as part of their job. Nedelkoska and Quintini (2018) start by translating the expert judgments in Frey and Osborne for the 70 job codes. This involves moving from the US-based job-classification scheme in Frey and Osborne to the international ISCO (2008) job classification system. They identify the task-related variables in PIAAC that correspond to the three bottlenecks in Frey and Osborne, and then estimate a logit model for all Canadian PIAAC observations in the 70 job codes.[3] The results of this estimation are used to predict (out-of-sample) automation risk for all workers in the entire (also non-Canadian) PIAAC sample. These estimations can be aggregated to the country level to obtain their results, leading, among other things, to the 48% median risk quoted above.

Note that the procedure of Nedelkoska and Quintini (2018) differs from the one in Frey and Osborne (2017) because it estimates automation risk at the level of individuals (respondents in PIAAC), rather than at the level of jobs (as in Frey and Osborne). Thus, in Nedelkoska and Quintini (2018), two individuals in the same job-code will tend to have different automation risks, because they tend to answer differently to the task-related questions, while in Frey and Osborne automation risk cannot differ between two

[3] They only use the Canadian PIAAC data because this country has a large sample and has ISCO occupation data at the desired 4-digit level.

individuals in the same job code. This difference is presented as a main selling point of the method of Arntz et al (2016), who first introduced it.

We used a public version of the PIAAC database to reproduce, as far as possible, the results in Nedelkoska and Quintini (2018), and also to estimate new measures of automation risk that will be used in our analysis below. Because we need job codes to link automation risk to workers, we have to aggregate the results of such estimations to the job-code level. In doing this, we discovered that the estimates provided by Nedelkoska and Quintini (2018) show a very large degree of variation within job codes. Because this is an important finding that reflects on the reliability of the risk estimates, we now proceed to document this phenomenon and the way in which this arises from the estimations.

Table 1 introduces the PIAAC variables used by Nedelkoska and Quintini (2018) to operationalise the three automation bottlenecks from Frey and Osborne (2017). It is reproduced directly from their paper (p. 43). Each of the responses to these questions is scored on a pre-defined range: (1) Never; (2) Sometimes, but less than once a month; (3) Less than once a week but at least once a month; (4) At least once a week but not every day; and (5) Every day. Nedelkoska and Quintini (2018) use the numeric codes of these answers as explanatory variables in their logit model of the probability of automation.

Table 1: PIAAC variables used by Nedelkoska and Quintini (2018)

Engineering bottlenecks	Variable in PIAAC	Variable code	Variable description
Perception manipulation	Fingers, (dexterity)	F_Q06C	How often - using skill or accuracy with your hands or fingers?
Creative intelligence	Problem-solving, simple	F_Q05A	How often - relatively simple problems that take no more than 5 minutes to find a good solution?
	Problem-solving, complex	F_Q05B	Problem solving - complex problems that take at least 30 minutes thinking time to find a good solution?
Social intelligence	Teaching	F_Q02B	How often - instructing, training or teaching people, individually or in groups?
	Advise	F_Q02E	How often - advising people?
	Plan for others	F_Q03B	How often - planning the activities of others?
	Communication	F_Q02A	How often - sharing work-related information with co-workers?
	Negotiate	F_Q04B	How often - negotiating with people either inside or outside your firm or organisation?
	Influence	F_Q04A	How often - persuading or influencing people?
	Sell	F_Q02D	How often - selling a product or selling a service?

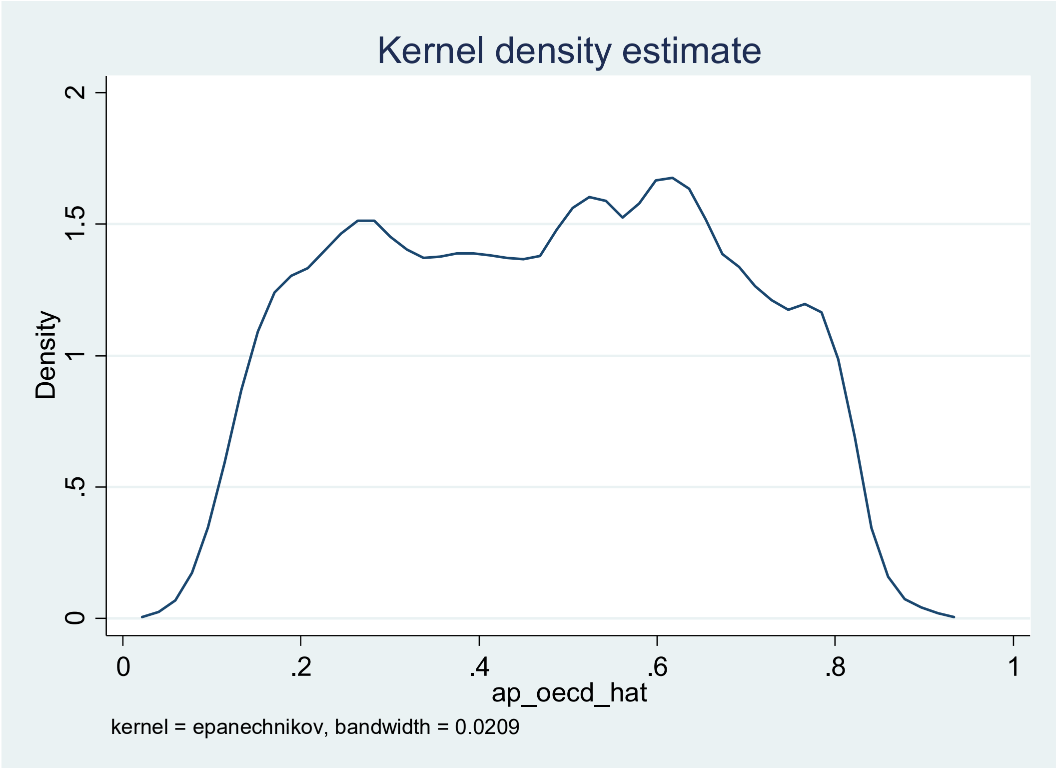
Source: Survey of Adult Skills (PIAAC) 2012, 2015

Note: this table is reproduced directly from the Nedelkoska and Quintini (2018) paper.

To implement their estimation, they use the binary variable from Frey and Osborne (yes/no expected to be automated) for the sample of job codes that are in Frey &

Osborne's data. Using this as the dependent variable, the PIAAC variables in Table 1 are used as explanatory variables in a logit model. Because the Frey & Osborne sample of job codes covers only a small fraction of all jobs, out-of-sample predictions of this model are used as estimates for automation risk for the entire PIAAC sample.

Figure 1: Distribution of automation risk ("ap_oecd_hat") at PIAAC respondent level, public PIAAC database, all observations, OECD logit model



Because all variables correspond to bottlenecks to automation, the more often these tasks are used, the smaller is the probability of automation expected to be. This means that we would expect negative signs on all variables. However, as Nedelkoska and Quintini show (their Table 4.3, p. 44), the variables "Dexterity", "Simple problems", "Negotiate", "Sell" and "Communicate" have positive and significant signs. Nevertheless, this model can be used to construct automation risk estimates, yielding the distribution in Figure 1. Note that this figure was produced using the publicly available PIAAC database, including all observations (all countries), and using the exact model estimated in Nedelkoska and Quintini's Table 4.3.[4] The kernel density estimate of this distribution does not consider PIAAC sample weights.

[4] Note that in the public PIAAC version, one cannot re-estimate this model for the same sample as Nedelkoska and Quintini did, because data on ISCO08 jobs are missing for Canada in this version of the database. However, using the coefficient estimates in Nedelkoska and Quintini's (2018) paper, one can

The resulting distribution is wide, with very little density below 10% or above 85% risk, and fairly homogenous density between the 20% and 80% level. Hence, within the 20-80% risk level, the distribution seems to be fairly uniform. We then proceed to aggregate these risk estimations into job codes. To this end, we use 3-digit ISCO08 codes, because this is the level at which our job data are available for the subsequent analysis. Note that the lowest level of aggregation in ISCO08 is 4-digit. This is not always available (i.e., some 3-digit codes are not broken down into 4-digit codes), but when it is, the 4-digit distinction will likely produce more homogenous automation risk estimates than the 3-digit.

Figure 2: Distribution of automation risk ("i_ap_oecd_hat") at job code level (ISCO08 3-digit), public PIAAC database, all observations, OECD model

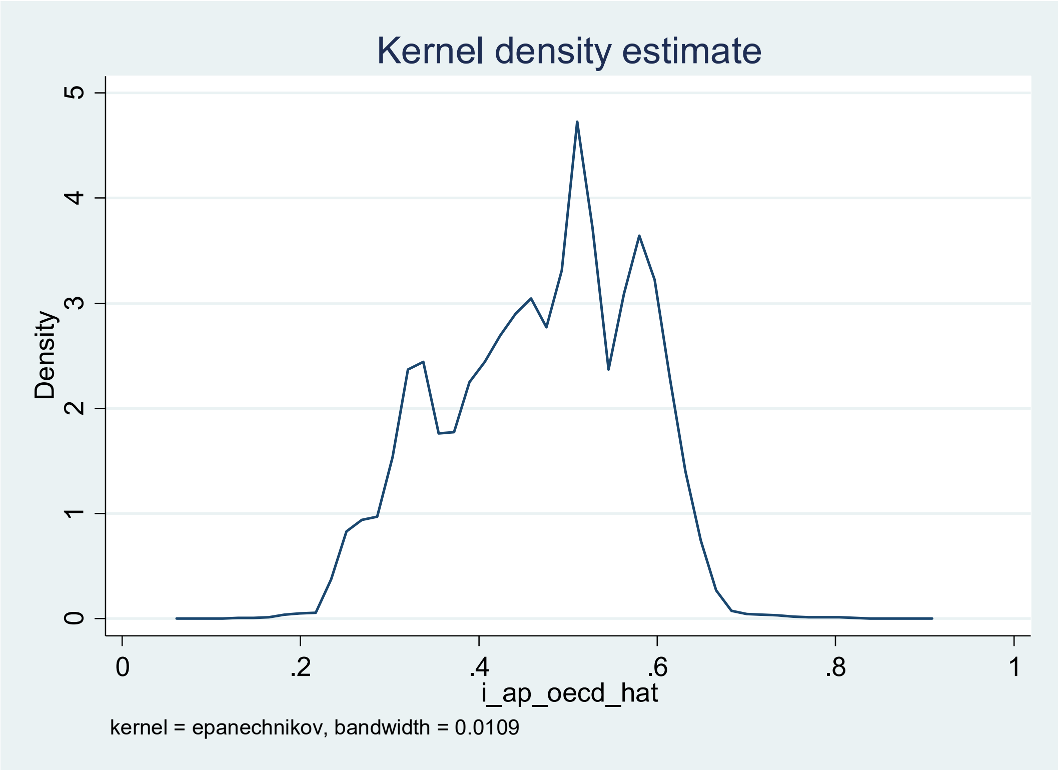


Figure 2 displays the distribution for aggregated (job level) automation risk, when using the OECD model (Nedelkoska and Quintini, 2018). This distribution is much narrower than the one in Figure 1. In other words, aggregating into job codes significantly reduces the variety of automation risk when using the PIAAC database and OECD model. In this distribution, there are almost no workers with risk lower than 20% or higher than 70%. Much of the distribution is concentrated around the peak at approximately 50% risk.

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estimate automation risk for every observation in PIAAC that has valid responses for the variables in Table 1. One can also re-estimate the model for the sample of available PIAAC observations in the public version, which is what we did for Figure 1.

The difference between Figure 1 and Figure 2 is due to the variety of tasks (i.e., scores on the variables in Table 1) within 3-digit ISCO codes, i.e., the job code is not a very good predictor of the task variables. For example, we may have one "cook" (which is a 3-digit ISCO code) who responds that she plans the activities of others every day, while another cook reports to never plan anyone else's activities. A degree of such variety is reasonable and expected (e.g., our first cook may be a chef in a large restaurant, while the second may be one of her sous-chefs). We may also expect that the variety would be lower for 4-digit ISCO codes (e.g., the 3-digit code bartenders and waiters could be broken down into those two jobs).

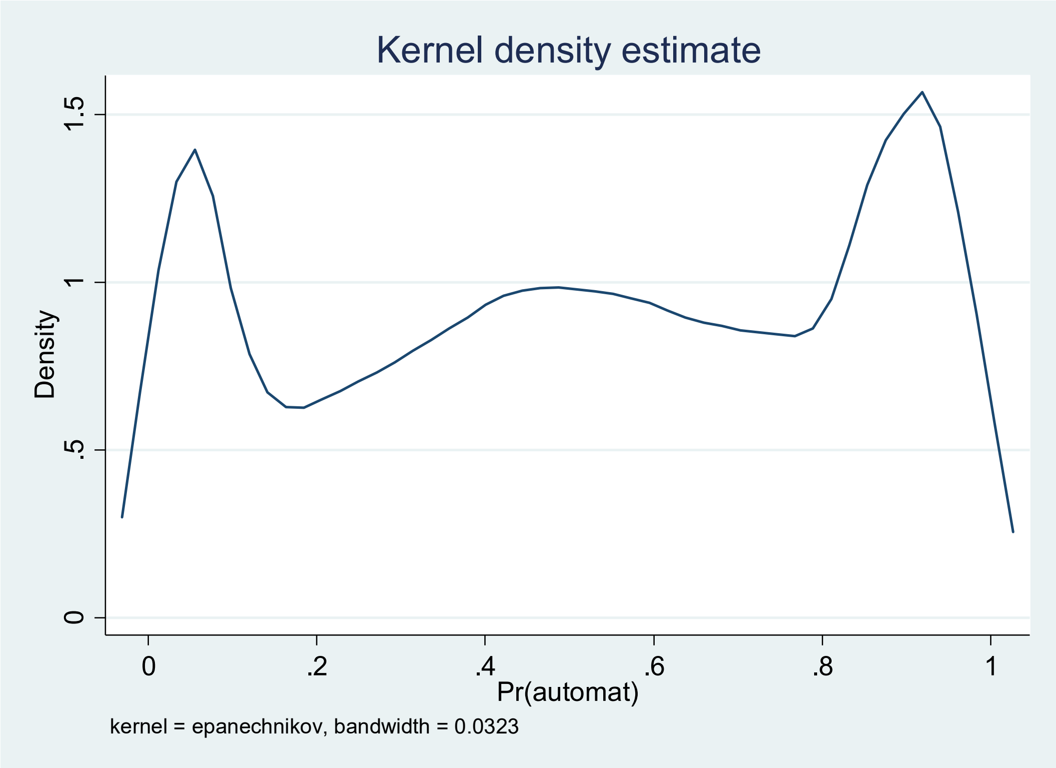
However, we would also expect that a significant degree of variation of automation risk exists between (3-digit) job codes, simply because the variables in Table 1 are intuitively related to the nature of the job. Whether the degree of variation in Figure 2 corresponds to this intuition is hard to judge objectively, but it seems fairly low. Thus, in order to avoid any potential aggregation biases in the subsequent analysis, we estimate an alternative risk measure using the PIAAC database.

This alternative measure is obtained by re-estimating the OECD model at the 1-digit industry level, i.e. the model is estimated separately for each of the 1-digit industries. We use the entire PIAAC subset that has the necessary variables to do this (note that Canada drops out because the dependent variable is not available). The idea behind using a model that is specific to 1-digit industries is that some of the task-variety within job codes will be related to variety between industries. For example, a civil engineer working for a manufacturing company may perform a different set of tasks than one working in the higher education sector.

Other than breaking down the analysis by sector and by using the (entire) public PIAAC dataset, our estimation method does not differ from Nedelkoska and Quintini (2018). The distribution that we obtain at the level of individual respondents is displayed in Figure 3. Figure 4 shows the distribution of aggregated risk (3-digit ISCO08).[5]

[5] We do not document estimation results due to space restrictions. These results are available on request.

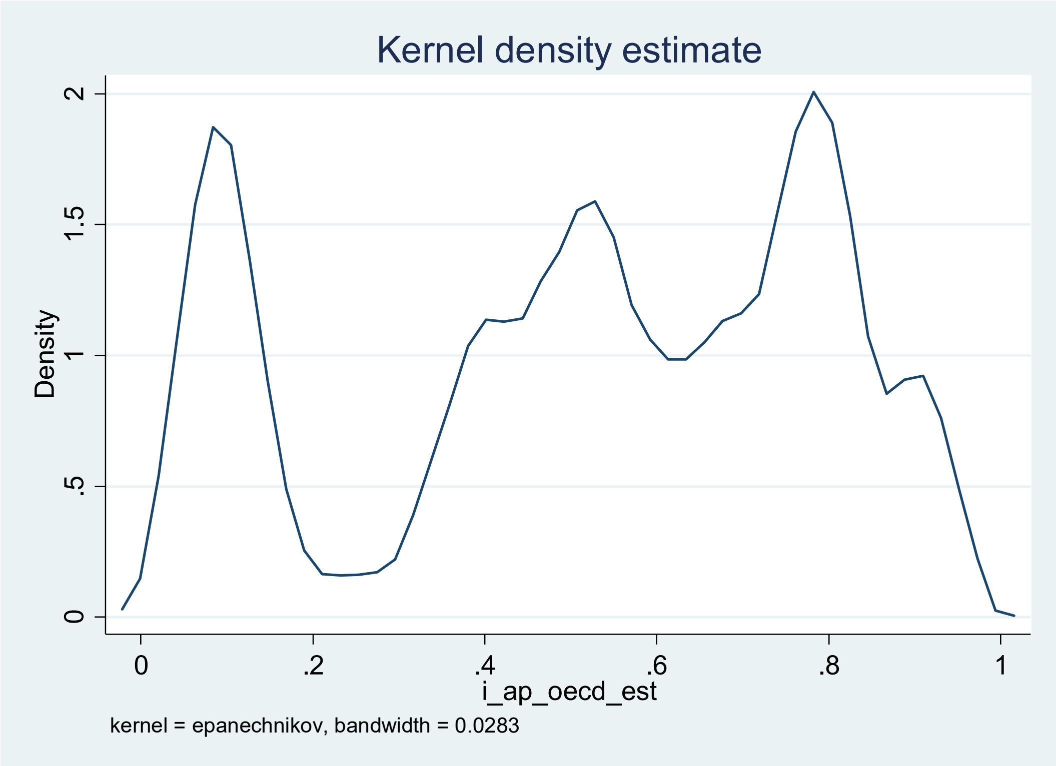
Figure 3: Distribution of automation risk ("Pr(automat)") at PIAAC respondent level, public PIAAC database, all observations, OECD model estimated at 1-digit industry level



In Figure 3, we see a distribution with a broad support, which is similar to Figure 1. What is different between Figures 1 and 3 is the double peak at the extreme ends of Figure 3. Thus, in the industry-specific version of the automation risk model, we find a relatively large density with either low or high risk, even though the middle-risk level also has significant density. In Figure 4 (aggregated to job-level), this leads to a distribution with three peaks, at low, middle and high-risk level. The very low level of density between the low- and middle peaks is remarkable.

Concluding, it seems to make a large difference whether or not we estimate automation risk by industry, especially when automation risk is aggregated to job codes rather than considered at the level of individuals. In the analysis below, we will use the automation risk estimates by industry, i.e., as in Figure 4. However, in our analysis, we are ultimately interested in automation risk at the country level. In order to aggregate the automation risk estimates at the job-industry level to the country level, and to the level of sectors within countries, we proceed as follows.

Figure 4: Distribution of automation risk ("i_ap_oecd_est") at job code level (ISCO08 3-digit), public PIAAC database, all observations, OECD model estimated at 1-digit industry level



Let us denote total employment in country r by H_r, and let us break down total employment into job-types (in the ISCO08 system) j, thus H_{rj} denotes employment in jobs of type j in country r. The index j denotes cooks, economists, bricklayers, etc. Because our measure of automation risk has been estimated at the sectoral level, we also introduce a sectoral dimension in the variable H. This is denoted by the index i, hence H_{rji} denotes employment in country r, job type j and sector i, e.g., sales clerks working in Italian retail trade.

Our measure of automation risk by job code is denoted ρ_{ji}. Note that ρ is indexed ji because it is specific for jobs within sectors. Further note that because ρ is a measure of risk, we have $0 \leq \rho \leq 1$. We aggregate automation risk to the country level (ρ_r) and to the country-sector level (ρ_{rk}), by calculating the weighted average over jobs and sectors:

$$\rho_{ri} = \frac{\sum_j \rho_{ji} H_{rji}}{\sum_j H_{rji}} \qquad (1a)$$

$$\rho_r = \frac{\sum_j \sum_i \rho_{ji} H_{rji}}{\sum_j \sum_i H_{rji}} \qquad (1b)$$

3. Economic structure and automation risk

3.1. Data

In order to calculate automation risk according to equations (1a) and (1b), we use data from two main sources. From the European Labour Force Survey (LFS), we use micro data on the job structure at the sector-country level, i.e., $H_{jri}/\sum_j H_{jri}$. Combined with the risk estimates ρ_{ji} that were obtained econometrically from the PIAAC database (as described above), this yields risk estimates at the country-sector level (ρ_{ri}), according to equation (1a). From the World Input-Output Database (WIOD)[6] we use data on the sectoral employment structure for each country, i.e., $H_{ri}/\sum_i H_{ri}$. Rewriting country risk in equation (1b) as

$$\rho_r = \frac{\sum_i \rho_{ri} H_{ri}}{\sum_i H_{ri}}, \quad (2)$$

shows that the country's overall automation risk is obtained as the weighted average of the country-sector level risks (ρ_{ri}) weighted by the employment structure of the country.

For the job-level employment data, we use micro data from the LFS. We use the anonymised micro dataset supplied by Eurostat for the year 2014. This contains data on a representative sample of the working population for all the countries in our analysis. We use job codes reported by respondents to report on the total working population by job type and by 1-digit industry (which is the most detailed level available). In doing this we include all types of employment, e.g., employees as well as self-employed, and we also include second jobs when respondents report them. Employment is calculated in full time equivalents by adjusting reported part time jobs to full time equivalents (we use reported normal work time for this, taking the average weekly working hours reported by holders of a full-time job as reference for a full time equivalent). We also used sampling weights to aggregate the data on jobs by industry.

The WIOD database has 43 countries, including all countries defined in footnote 2, and 56 sectors in the ISIC rev. 4 classification system. For the purpose of the analysis, these data need to be aggregated to the 1-digit sectoral level (because job-level data are only available at 1-digit level).

3.2. The role of economic structure

Table 2 shows the (unweighted) averages and the coefficient of variation (standard deviation divided by the average) of the estimated automation risk, by country and by sector, for 2014. Reported values for sectors are averages over countries within the

[6] We used the 2016 release of WIOD, in which the most recent year for which data are available is 2014. WIOD data were downloaded from www.wiod.org.

sector, values for countries are averages over sectors within the country. The estimated risk is highest in the finance sector (K), at approximately 0.9, and lowest in the health care sector (Q), at approximately 0.1.

Table 2: Averages and coefficient of variation of estimated automation risk, by sector and by country, 2014

Code	Sector	Av	CoV	Country	Av	CoV
A	Agriculture	0.662	0.030	Austria	0.540	0.431
B	Mining	0.694	0.084	Belgium	0.537	0.402
C	Manufacturing	0.721	0.029	Bulgaria	0.558	0.372
D	Energy generation	0.657	0.037	Switzerland	0.533	0.402
E	Water	0.724	0.024	Cyprus	0.542	0.443
F	Construction	0.410	0.020	Czech Republic	0.546	0.440
G	Trade	0.759	0.017	Germany	0.536	0.434
H	Transport	0.825	0.025	Denmark	0.538	0.434
I	Hotels, restaurants	0.430	0.030	Spain	0.541	0.446
J	Communication	0.695	0.017	Estonia	0.543	0.422
K	Finance	0.903	0.011	Finland	0.548	0.399
L	Real estate	0.550	0.050	France	0.543	0.406
M	Professional services	0.533	0.018	United Kingdom	0.526	0.428
N	Support services	0.529	0.041	Greece	0.545	0.445
O	Public administration	0.531	0.021	Croatia	0.538	0.433
P	Education	0.137	0.114	Hungary	0.565	0.371
Q	Health services	0.103	0.051	Ireland	0.539	0.427
R	Arts, entertainment and other services	0.317	0.027	Italy	0.544	0.435
T	Household employers	0.112	0.873	Lithuania	0.557	0.375
U	International organisations	0.574	0.095	Luxemburg	0.541	0.451
	Average all sectors	**0.543**	**0.081**	Latvia	0.557	0.387
				Netherlands	0.521	0.430
				Norway	0.533	0.421
				Poland	0.543	0.409
				Portugal	0.543	0.438
				Romania	0.561	0.417
				Slovak Republic	0.554	0.432
				Slovenia	0.543	0.401
				Sweden	0.540	0.432
				Average all countries	**0.544**	**0.418**

Note: Column labelled "Av" gives average value, column labelled "CoV" gives the coefficient of variation (standard deviation divided by average). All averages are unweighted.

The average automation risk varies very little over countries within sectors, as compared to the variation over sectors within countries. The standard deviation within sectors is about 8% of average risk, with one high value in sector T (which is a very small sector in terms of employment), and otherwise always smaller than 12% of the average. On the other hand, the estimated risk within countries (over sectors) varies much more. Here, the coefficient of variation is at about 42% of the average, with 44.6% as the highest value (in Spain), and 37% as the lowest value (in Hungary).

Table 3: Automation risk estimates with alternative sectoral employment structures, 2014

	Actual	EUR	std EUR	non-EUR	std non-EUR
Romania	0.631	0.554	0.035	0.570	0.029
Bulgaria	0.608	0.554	0.034	0.573	0.031
Slovak Republic	0.590	0.553	0.036	0.572	0.035
Czech Republic	0.587	0.545	0.036	0.564	0.034
Hungary	0.584	0.555	0.035	0.574	0.031
Poland	0.583	0.545	0.033	0.563	0.030
Croatia	0.572	0.543	0.033	0.559	0.029
Latvia	0.569	0.551	0.034	0.570	0.031
Slovenia	0.569	0.542	0.034	0.561	0.032
Greece	0.554	0.540	0.035	0.558	0.031
Lithuania	0.553	0.537	0.034	0.557	0.031
Luxemburg	0.553	0.533	0.033	0.550	0.029
Estonia	0.551	0.538	0.035	0.558	0.034
Austria	0.537	0.537	0.034	0.554	0.030
Portugal	0.537	0.540	0.035	0.558	0.032
Cyprus	0.532	0.542	0.036	0.563	0.036
Spain	0.525	0.541	0.037	0.563	0.037
Italy	0.523	0.544	0.036	0.564	0.035
Germany	0.521	0.537	0.033	0.554	0.031
Ireland	0.514	0.533	0.033	0.550	0.029
Switzerland	0.512	0.524	0.031	0.540	0.026
Finland	0.504	0.538	0.033	0.557	0.029
France	0.499	0.533	0.032	0.550	0.029
Belgium	0.498	0.531	0.032	0.548	0.028
United Kingdom	0.498	0.532	0.033	0.550	0.031
Denmark	0.496	0.542	0.035	0.561	0.033
Netherlands	0.496	0.528	0.033	0.546	0.031
Sweden	0.479	0.534	0.034	0.553	0.032
Norway	0.467	0.525	0.034	0.544	0.032
Average	***0.539***	***0.540***	***0.034***	***0.558***	***0.031***

The fact that automation risk is relatively invariant within sectors suggests that variations in risk between countries are largely determined by differences in sectoral employment shares, or structural differences, between countries. This can easily be seen from equation (2), where, by and large, $\rho_{ri} \approx \rho_i$ and hence the variation in ρ_r depends mostly on the sectoral employment shares within the country ($H_{ri}/\sum_i H_{ri}$).

Table 3 documents this structural nature of the automation risk further. The first column ('Actual') documents the country automation risk as calculated using equation (2). We observe significant variation across countries, ranging from about 47% in Norway to about 64% in Romania, (i.e., a range of 17 percentage points).

The table illustrates the structural nature of automation risk by applying counterfactual calculations, in which the employment structure of other countries is used to calculate an alternative risk estimation. For example, when we apply the sectoral employment structure of Romania to the sectoral risk values of Norway, Norwegian aggregate risk increases by 14%, eliminating about 80% of the actual difference. The remaining 20% is due to different job structures within the sectors between Norway and Romania.

We conduct these counterfactual experiments for each possible combination of countries in our sample, applying in turn the sectoral employment structure of every other country in the sample to a focal country as listed on each row of Table 3.

As already mentioned, the first column in this table gives the *actual* estimated automation risk per country (ρ_r). The second column gives the average of the (alternatively) estimated automation risk when the sectoral employment structure of each and every European country is used to weigh the sectoral risk estimations of the country in the row. The next column of the table gives the standard deviation of these risk estimates when using alternative structures. The last two columns repeat this (average and standard deviation) for the sectoral structure of the non-European countries in the WIOD database.

The numbers in Table 3 show a regression to the mean, i.e., the countries with actual high risk, tend to have lower risk when the sectoral structure of other countries is applied as weights. The countries in the table are ranked in descending order of actual automation risk, and the first 13 (Romania – Estonia) show a lower value in the second column than in the first column. The bottom 15 countries (Portugal – Norway) show a higher value in the second column than in the first column.

The standard deviation of these alternative risk calculations is 0.034 on average, which is about 21% of the range between the lowest and highest risk in the sample. Average risk is slightly larger when non-European employment structures are used, at 0.558, but the standard deviation of these risk estimations is somewhat lower, at 0.031.

Having concluded that the cross-country differentials in estimated automation risk are primarily a matter of differences across countries with respect to the shares of sectors in employment, let us further explore the nature of variations in automation risk between sectors. We ask whether the relative use of the production factors capital and labour is systematically related to automation risk. Do the sectors that are already highly "mechanised" (i.e., use relatively much capital as compared to labour) provide the best opportunities for (further) automation, with high associated automation job risk, or is automation risk highest in sectors that are currently least mechanised?

In order to investigate this, we run regressions with automation risk as the dependent variable. The explanatory variable for automation risk is the capital – labour ratio (capital stock divided by employment). Underlying data for the explanatory variable is taken from the WIOD database. Observations are by country and sector, and only include European countries, for which we were able to estimate (sectoral and aggregate) automation risk.

In order to isolate the sectoral and/or country effect of the independent variable, we first run a regression of the capital labour ratio on sector and country dummies. We then take the predicted value from this regression as the part of the dependent variable that is purely related to the sector and/or country dimension, and the residual as the part that is unrelated to this. The predicted value and the residual are included separately in the risk regression. The results of these regressions are documented in Table 4.

In the regressions that estimate the impact of country and sector dummy variables on the capital-to-labour ratio, we find that sector dummies dominate the country dummies. Country dummies alone do not yield a significant F statistic in the first stage, and the regression with sector dummies alone gives a higher F statistic than when both dummy types are included.

Table 4: Regressions explaining automation risk by the capital-to-labour ratio

	Specification for capital-labour ratio regression		
	Sector dummies	Country dummies	Both dummies
Adj R^2 [F] 1st regr.	0.75 [88.76***]	0.07 [2.31]	0.87 [76.87***]
Predicted *K/L*	0.050 (0.007***)	-0.010 (0.017)	0.042 (0.006***)
Residual *K/L*	-0.008 (0.012)	0.042 (0.006***)	-0.007 (0.017)
Constant	0.308 (0.035***)	0.617 (0.087***)	0.350 (0.033***)
Adj. R^2	0.10	0.08	0.08
n	523	523	523

Notes: standard errors between brackets (). One, two and three stars indicate significance at 10%, 5% and 1% level. 2nd stage regression done with only sector dummies as instruments.

In the regressions explaining risk, the predicted capital-to-labour ratio has a positive and significant impact on automation risk when sector dummies are included in the first regression. In this case, the residual capital labour ratio is insignificant. When only country dummies are included, the predicted capital labour ratio is insignificant, and the residual is significant and positive. This leads us to conclude that automation risk tends to be higher in sectors where capital is relatively abundant as compared to labour. In other words, automation risk seems to be highest in sectors that are already relatively mechanised, i.e., high existing mechanisation levels indicate further opportunities for automation (with associated risk of job loss), rather than a lack of such opportunities due to saturation of some kind.

4. Aggregate automation risk and trade

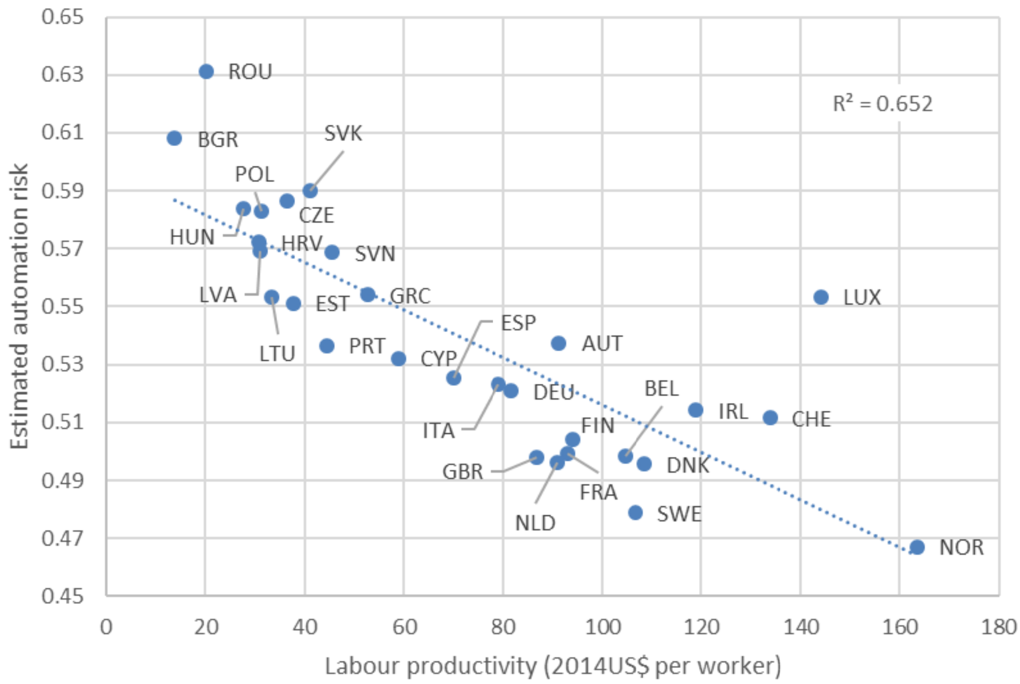
We now move to the analysis of aggregate (country level) automation risk. As a stylised fact on which our analysis will be aimed, we correlate, in Figure 5, aggregate (country) automation risk with aggregate labour productivity. We choose labour productivity because this is a direct indicator of the development level of the country, and directly speaks to the productivity effect of automation and other technologies. Labour productivity is calculated from WIOD and is expressed in current (2014) US$ per worker.

Perhaps surprisingly, the figure shows a strong and negative correlation between the two variables. At the country level, the capital-to-labour ratio and labour productivity are strongly correlated (the correlation coefficient is equal to 0.94). One could therefore expect that the positive correlation between automation risk and the capital-to-labour ratio in Table 4 leads to a positive correlation between labour productivity and risk at the country level, while the actual correlation is strongly negative.

This negative correlation results from the structural effect. Rich countries (i.e., with high labour productivity) have sectoral employment structures that favour sectors with low automation risk. This structural effect is so strong that it outweighs the positive correlation between automation risk and capital intensity at the sectoral level.

This raises the question of what factors influence these systematic differences in employment structures that gives the highly productive (rich) countries relatively low automation risk. We will focus on the role of international trade in this process. Obviously, trade influences the sectoral employment structure through its impact on specialisation patterns. Thus, we may ask whether the negative correlation in Figure 5 is the result of rich countries outsourcing jobs with relatively high automation risk to poorer countries, or other forms of international trade.

Figure 5: Estimated automation risk and labour productivity, European countries, 2014



4.1. Global value chains, trade and employment: the input-output method

The question as to how automation risk in total country-level employment is affected by trade and GVCs can be analysed using input-output methods. This section introduces these methods in their basic form, including the way in which we create autarky benchmarks.

The WIOD contains a global table that traces deliveries of one sector to all other sectors in the global economy and to final demand in a so-called transactions table. The transactions table is a matrix and consists of several sub-matrices. One important sub-matrix is the square matrix of intermediate deliveries, which we denote by the symbol U. Rows and columns in this matrix are formed by production sectors in a range of countries (covering, in principle, the entire global economy), e.g., one row /column is the food industry in Germany, another is the car industry in Japan, and so on. The element u_{ik} of matrix U denotes the intermediate deliveries of sector i to sector k, for example, the delivery of steel from the Chinese steel sector to the construction sector in the US.

Another part of the transaction table is formed by the matrix of final deliveries, which is denoted by F. This is not a square matrix: the rows are of the same order as matrix U

(i.e. country-sector specific), but the columns are of a different order. The columns are categories of final use, e.g., final consumption by households and investment and firms, and are repeated for all countries in the table, e.g., we have consumption in Italy as well as investment in Brazil. As such, the column order is equal to the product of the number of countries and the number of categories of final use.

A final part of the transaction table is formed by the matrix of value added, which we denote by V. In a general sense, this matrix can be divided into the different categories of value added, such as wages and profits. In this setting, the columns of the matrix again refer to (country-)sectors, with the rows referring to the different categories of value added. For the purposes of our work, we do not need to distinguish between categories of value added, and as such we have a single (row) vector denoting value added in a sector.[7]

The three matrices U, F and V can be arranged in the following way to form the entire transaction table (denoted by T):

$$T = \begin{array}{ccc} U & F & Q \\ V & & \\ Q' & & \end{array}$$

Here, Q is a column vector of total (gross) output by sector, and Q' is the transpose of Q. We see that matrices U and F arranged next to each other form a larger (non-square) matrix in which the rows sum to the elements of Q. Value added (elements of V) is obtained by subtracting intermediate deliveries into the sector (in the sector's column of matrix U) from gross output (the sector element in Q'). The bottom-right part of the transaction table T is empty.

Using information from the transactions table we create a new matrix, denoted by A, in which the elements a_{ik} are equal to u_{ik}/q_i, where q denotes an element of Q. The elements of matrix A are so-called input- or technical-coefficients, i.e., they specify the amount of intermediate deliveries from sector i that is necessary to produce one unit of gross output in sector k. We assume that the elements of matrix A are exogenous (determined by trade relations and by technology) and fixed over a year, which is the time horizon of the analysis. The matrix of input coefficients can be expressed as:

$$A = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1N} \\ A_{21} & A_{22} & \dots & A_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ A_{N1} & A_{N2} & \dots & A_{NN} \end{bmatrix}$$

[7] Our exposition disregards, for simplicity, transport costs and taxes – subsidies, which could be added as rows in matrix V.

Where A_{lm} refer to the sub-matrix of input coefficients for supplying country r and receiving country s, with sub-matrices along the main diagonal referring to own-country input coefficients.

It is easy to show (see, for example, Miller and Blair, 2009) that using these definitions, gross output can be calculated as:

$$Q = [I - A]^{-1}F,$$

where I is the identity matrix. The matrix $[I - A]^{-1}$ is called the inverse Leontief matrix. This equation shows that if we take final demand, F, to be exogenous, gross output levels in all sectors of the global economy are determined by technology and trade relations as embodied in A.

Since our primary interest is in employment, one additional step is necessary in the input-output analysis, i.e., the transformation of gross output into employment. To do this, we construct so-called labour coefficients. These are defined at the sector level, with the labour coefficient for sector i, l_i, being equal to employment in the sector divided by gross output in the sector. We then multiply the element q_i of vector Q by l_i to obtain employment, which is denoted by the vector H. In matrix form, this can be expressed as:

$$H = \hat{L}[I - A]^{-1}F,$$

Where $\hat{L}$ is the diagonalised row vector of labour coefficients.

4.2. Hypothetical autarky

In order to answer our research question of how automation risk varies between a situation of autarky and the actual state of the global economy with trade, we need to modify the transactions table of the input-output system to reflect a hypothetical state of autarky. In the strictest definition of autarky, no trade takes place between countries, and this implies that all values in the A and F matrices where the row and column country are not the same must be equal to zero.

This is achieved by first setting the input coefficients and entries of F equal to zero when the row and column do not refer to the same country. We then add all values in the original matrices that were set to zero in this way to the actual domestic input coefficients of entries of F. In formal terms, the elements of matrices A and F are created as follows:

$\tilde{a}_{ij} = \sum_i a_{ij}$ if *i* and *j* belong to the same country, and $\tilde{a}_{ij} = 0$ otherwise;

$\tilde{f}_{ij} = \sum_i f_{ij}$ if *i* and *j* belong to the same country, and $\tilde{f}_{ij} = 0$ otherwise.

This adjusted input coefficient matrix is denoted $\tilde{A}$, and final demand matrix $\tilde{F}$. These are block-diagonal matrices that have only zeros outside the diagonal country blocks. This approach implies that output in autarky is produced using the same technology (i.e. input coefficients) that is available in the domestic economy under trade, and that the same amount of final demand is exercised by each country, but by domestic firms only.

With these new values, we can use the standard input-output expression and find gross output under autarky as:

$$\tilde{Q} = \left[I - \tilde{A}\right]^{-1}\tilde{F}$$

Using the labour coefficients (unchanged under autarky), we can then calculate employment under autarky from gross output under autarky. Using equation (1), employment and the automation risk coefficients (ρ) per sector (also assumed to be unchanged under autarky) can then be used to calculate aggregate automation risk under autarky.

It should be borne in mind that the autarky benchmark that is calculated in this way is based on a number of restrictive assumptions, which are mainly due to a lack of data. This leads to various factors that cannot be considered in the autarky benchmarks. One such factor is the size of the labour force. We have no information on what would be a full employment situation at the sectoral level, and therefore we assume that there is no particular employment restriction under autarky. What determines employment levels in autarky is final demand, which is assumed to be equal to what is observed in the actual situation with trade. We also assume that the job structure of sectoral employment does not change between autarky and trade. This is unlikely to be true in reality, as specific activities are offshored and others are not, and the job structure of these activities is likely to be different. However, because we have no information on which jobs are involved in which activities within the sector (e.g., the production of intermediate goods vs. final goods), we cannot include this effect in the calculations.

4.3. Autarky, trade and automation risk

We report results on aggregate automation risk under various forms of autarky, and compare them to the actual data, which represent a situation with relatively unrestricted trade (as compared to our autarky constructs). The basic results are displayed in Table 5, which compares automation risk and the number of jobs affected between hypothetical autarky and the actual situation with trade for the European countries in our analysis, for the year 2014.

Interestingly, trade creates employment in the 29 European countries that we analyse. Total actual employment in the 29 countries is at about 234.5 million persons engaged in 2014, and this is 3.0% higher than employment under autarky in the same year. Employment increases with trade as compared to autarky in 20 of the 29 countries, at an average rate of 5.1%. It decreases with trade in 9 of 29 countries, at an average rate of -5.3%. The countries where employment decreases with trade are Cyprus, Finland, France, Greece, Croatia, Latvia, Norway, Portugal and Slovenia.

Note that this increase in overall employment with trade is a direct consequence of our definition of autarky, which does not put any restrictions on employment (or capital, or any other production factors), and instead keeps final demand constant. Thus, the way in which we define autarky does not correspond well with the way this would be done in pure trade theory, which would normally keep the production factors (labour) constant between trade and autarky, while demand (and hence production) adjusts. Consequently, our results mainly provide insights into the structural change that comes with trade, and the impact of that on aggregate automation risk.

Total aggregate automation risk in the 29 countries together is (slightly) higher with trade: it stands at 0.527 with trade and 0.522 without trade. While this is "only" a difference of about 0.005 (i.e., half a percent), there are 4.8 million more jobs at risk in the 29 countries with trade as compared to autarky.

Table 5: Difference in automation risk and number of jobs at risk between hypothetical autarky and actual situation (with trade), European countries, 2014

Country	Risk increase with trade	Increase # jobs at risk with trade	Country	Risk increase with trade	Increase # jobs at risk with trade
Austria	0.006	104	Latvia	-0.005	-25
Belgium	0.008	138	Lithuania	0.007	39
Bulgaria	-0.001	64	Luxemburg	0.056	52
Croatia	-0.007	-15	Netherlands	0.012	467
Cyprus	-0.043	-78	Norway	-0.004	-36
Czechia	0.015	328	Poland	0.004	390
Denmark	0.009	98	Portugal	-0.008	-194
Estonia	0.003	6	Romania	0.000	31
Finland	0.000	-13	Slovakia	0.000	55
France	-0.001	-117	Slovenia	0.004	1
Germany	0.014	2,234	Spain	0.002	83
Greece	-0.012	-278	Sweden	0.010	152
Hungary	0.012	208	Switzerland	0.014	211
Ireland	0.012	51	United Kingdom	0.002	114
Italy	0.009	754	Total 29 countries	0.005	4,824

Note: increase of number of jobs denoted in 1,000s (of persons engaged).

Table 6: Difference in automation risk and number of jobs at risk between full autarky and two partial autarky situations, European countries, 2014

	Opening up extra-European trade (intra-European autarky)		*Opening up intra-European trade (extra-European autarky)*	
Country	**Risk increase with trade**	**Increase # jobs at risk**	**Risk increase with trade**	**Increase # jobs at risk**
Austria	0.009	165	-0.001	-35
Belgium	0.004	60	0.007	83
Bulgaria	0.004	119	-0.005	-73
Croatia	0.006	85	-0.012	-92
Cyprus	-0.011	-26	-0.043	-75
Czechia	0.003	69	0.016	346
Denmark	0.017	164	-0.003	-11
Estonia	0.008	24	-0.006	-26
Finland	0.009	79	-0.007	-74
France	0.004	334	-0.005	-492
Germany	0.013	2,107	0.003	433
Greece	0.004	30	-0.017	-316
Hungary	0.006	90	0.012	234
Ireland	0.013	79	0.038	319
Italy	0.007	638	0.004	317
Latvia	0.003	15	-0.014	-64
Lithuania	0.009	59	0.004	28
Luxemburg	0.051	90	0.002	8
Netherlands	0.000	-81	0.011	445
Norway	0.010	95	-0.016	-134
Poland	-0.003	-231	0.004	535
Portugal	0.004	84	-0.014	-298
Romania	0.002	168	-0.004	-231
Slovakia	0.000	23	0.001	39
Slovenia	0.002	-4	0.002	-8
Spain	0.002	117	0.002	103
Sweden	0.013	204	-0.003	-51
Switzerland	0.019	423	-0.003	-149
United Kingdom	0.006	581	-0.004	-675
Total 29 countries	0.006	5,559	0.001	86

Note: increase of number of jobs denoted in 1,000s (of persons engaged).

There are eight countries in Table 5 for which the number of jobs at automation risk decreases with trade (these are the same as where total employment decreases with trade, except Slovenia, which has a small decrease of total employment, but also a small increase of jobs at risk). These eight countries lose about 0.76 million jobs at risk of automation from trade. In the other 21 countries, the number of jobs at automation risk increases with trade, with an additional 5.6 million jobs at risk. Germany takes by far the largest share of this increase, with about 2.2 million extra jobs at risk.

The average absolute deviation of risk between trade and autarky among the European countries is exactly 1 percentage point. This can be compared to the structural calculations that were introduced in Table 3: the average of the standard deviation in the second column of this table is 3.4 percentage points. Thus, on average, the structural changes associated with trade realise about 30% (0.010/0.034) of the effect of the hypothetical structural differences on automation risk in Table 3.

We consider two more hypothetical situations, both representing partial autarky. The first one is where the 29 European countries in the analysis do not trade with each other, but do trade with countries outside Europe.[8] We call this the intra-Europe autarky. This is implemented in a similar way to that described in Section 3.1 above: all trade with European countries in the original input-output table is re-assigned to the country itself, while cells in the table that reflect trade with non-European nations are unaffected.

A second form of partial autarky is extra-European autarky. Here the European countries trade with each other (including also Malta), but do not trade with countries outside Europe. This is implemented by re-assigning the relevant (i.e., extra-European) cells in the original input-output table to the country itself, while leaving other cells (intra-European trade) unaffected.

We look at these two partial autarky situations as limited (hypothetical) ways of opening up trade from full autarky. In the case of intra-Europe autarky, trade with non-European nations is opened up, in the case of extra-European autarky, trade within Europe is opened up. The overall employment effects in the total set of 29 countries differ greatly between the two scenarios. Opening up extra-European trade (intra-European autarky) creates 3.5% extra employment, as compared to full autarky. Opening up intra-European trade (extra-European autarky) creates -0.1% employment, i.e., employment falls as compared to full autarky.

These differential effects also translate to largely different effects on automation risk. These results are documented in Table 6. Opening up extra-European trade increases European-wide automation risk by 0.6%, while opening up intra-European trade increases it only by 0.1%. When extra-European trade is opened up, all countries except Cyprus and Poland see automation risk increase, and 4 countries (Cyprus, Netherlands, Poland and Slovenia) see the number of jobs at risk increase. With intra-European trade opening up, a majority of countries (16) see automation risk decrease, and see the number of jobs at risk decrease.

Finally, we come to the question how trade affects the relationship between aggregate labour productivity and aggregate automation risk, as displayed in Figure 5 above. To

[8] In this case, the 29 countries also do not trade with Malta.

assess this, we created data on aggregate (country) labour productivity for each of the three hypothetical (partial) autarky situations, and regressed automation risk on these data. This creates alternative versions of Figure 5.

Table 7. The relation between automation risk and labour productivity in the (partial) autarky scenarios and with trade

	constant	Labour productivity slope	adj R^2	F-test for difference from autarky cons	slope
Actual data (trade)	0.598 (0.009***)	-0.0008 (0.0001***)	0.64	1.79	5.67**
Autarky	0.610 (0.008***)	-0.0011 (0.0001***)	0.82		
Trade with non-EU	0.604 (0.009***)	-0.0009 (0.0001***)	0.68	0.60	4.10*
Trade within EU	0.602 (0.008***)	-0.0010 (0.0001***)	0.75	0.96	1.16

Notes: standard errors between brackets. One, two and three stars indicate significance at 10%, 5% and 1% level.

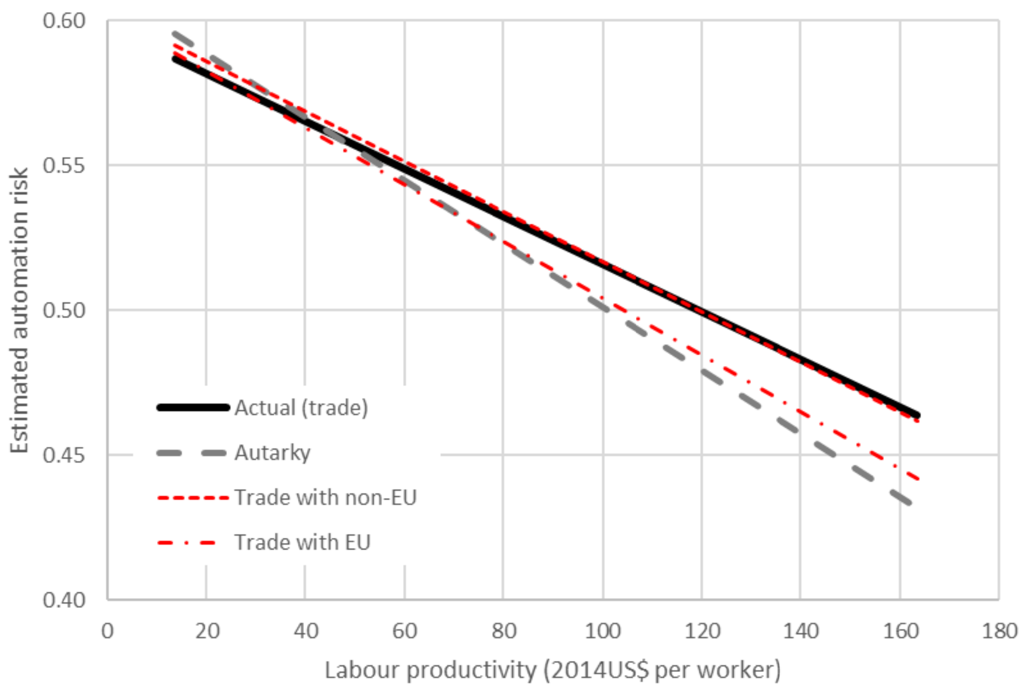


Figure 6. Regression lines for automation risk - labour productivity relation, countries, 2014, actual trade situation and various autarky scenarios

Table 7 documents the estimated regression lines between automation risk and labour productivity. The first row refers to the regression line in Figure **5**, the other rows give results for the (partial) autarky scenarios. Figure 6 displays the regression lines in the table. The final two columns in the table test whether the parameters of the regression line are different from the line for autarky. This is implemented with a simple F-test that tests the null hypothesis that the parameter is equal to the estimated value for autarky. The estimated constant terms never differ significantly from autarky, but two of the slopes do: the slope for actual trade, and the one for trade with non-EU countries.

This leads to three clear conclusions. First, trade actually increases automation risk of the rich countries, rather than reducing it. This is obvious from the fact that on the right-hand side of the graph, the regression line for autarky lies below all other lines. Thus, we can firmly conclude that automation risk is not offshored from rich to poorer countries in Europe. In fact, the effect is opposite, with rich countries increasing their automation risk by trade.

Second, the effects of trade on automation risk are very small for the poorer (less productive) European countries in our sample. The four regressions lines are very close to each other for values of labour productivity up to about 60. Trade makes very little difference, on average, for countries at these productivity levels.

Third and finally, we see that trade between Europe and non-European countries is responsible for the largest part of the effect that countries with high productivity levels experience. On the right-hand side of the figure, the line for intra-European trade is only slightly above the line for autarky (this is also confirmed by the F-tests in Table 7), while the line for extra-European trade is well above autarky.

5. Summary and Conclusions

This paper presents descriptive empirical evidence on the nature of automation risk for employment in European countries. Automation risk was estimated using a method proposed by researchers at the OECD. The estimation of automation risk provided by the analysis confirm the generally high amount of risk, with the average number of jobs potentially at risk of automation at the country level varying between 47% and 64%.

The analysis also revealed a very strong role of the sectoral employment structure in determining automation risk at the country level. Automation risk varies little (between countries) within sectors, and relatively much (within countries) between sectors. Automation risk also seems to be higher in sectors with already high productivity and high capital intensity, i.e., sectors that have already benefited from mechanisation. However, at the country level, countries with high (low) labour productivity tend to have low (high) automation risk. This illustrates the effect of structural differences between countries: the rich (highly productive) countries have high employment shares in sectors with low automation risk.

Because international trade is one factor that causes such structural differences, we ask whether it was trade that induced the observed negative relationship between aggregate automation risk and labour productivity. In order to investigate this and estimate the impact of trade on automation risk (through the sectoral employment structure), we compare automation risk between hypothetical autarky and actual employment (with trade).

The main results of the analysis suggest that trade plays a role in determining automation risk, but that this role is limited. We found that in the 29 European countries combined, automation risk increases by about half a percentage point as a result of trade. However, in individual countries, this effect is often larger, because at the European level countries with positive and negative effects of trade on automation risk compensate each other. Overall, countries that have high labour productivity and associated low automation risk (without trade) have increasing risk due to trade. In other words, in terms of automation risk, trade comparatively benefits the countries with low productivity, not those with high productivity. Also, we find that opening up of trade with countries outside Europe has a much stronger effect on automation risk than opening up intra-European trade.

Although these results have little to say about the causal mechanisms behind the effects of trade and offshoring of automation risk, they do point to interesting conclusions and invite further research. Offshoring and "trading" of automation risk seems to be a relevant empirical phenomenon, but goes in the opposite direction than what we are used to in the debate on the relations between employment, technology and trade. Thus, in addition to giving research and policy attention to the direct substitution of work by "robot capital", we should also be looking at how the interplay of globalisation and technology affects the reallocation of labour across the globe. While our results only refer to Europe, there may be even stronger tendencies if we widen the scope to include countries at a lower level of development.

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