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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 relation between trade and aggregate automation risk by comparing automation risk between a hypothetical autarky and the actual situation. Results indicate that with trade, automation risk is higher in Europe, although moderately so. Automation risk in the high-productivity European countries is higher with trade, with trade between European and non-European nations driving these results. This implies that these countries do not, on balance, offshore automation risk, but rather import it. The sectors that show the largest automation risk relation to trade are manufacturing, trade, transport and finance.

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 methodology. 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.

Our aim in this paper is to investigate the relations between international trade and the exposure of countries to automation job loss risk. The analysis is aimed at identifying stylized facts, rather than causal relations. We are interested in trade in relation to automation risk because trade changes the production and employment structure of countries, and we expect that automation risk will have a strong structural dimension. The existing literature on automation risk, which we will review very briefly in the next section, clearly shows that automation risk is specific to job types, and job types are intrinsically linked to specific production activities (employment), hence structure can be expected to matter.

In the remainder of this introductory section, we will briefly discuss the mechanisms through which trade affects automation risk at the country level. This will lead to our main analysis, which is to develop a number of scenarios in which we use input-output techniques to construct counterfactual economic structures for the countries of the European Union (EU). In these counterfactuals, the countries in the analysis do not trade (autarky), or have limited trade (only intra- or extra-EU). By comparing automation risk between the counterfactuals and the actual data, we provide an estimate of the relation between trade and automation risk.

Technology is at the core of our interest in the (potential) employment effects of automation. It is technological change motivated by economic interests that creates the opportunities for substitution of

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human workers. However, it is not only the invention of technology (i.e., profit-motivated Research and Development, R&D) that is an endogenous economic process, with the application of labour-saving technology (e.g., the purchase of machinery including software) also motivated by economic factors. This is where technology and trade are closely related: 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 (see also Goos et al, 2014).[1]

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 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).[2] If the relocated jobs have a different automation risk profile than the non-relocated jobs, then offshoring will also impact on the average automation risk of jobs in a country. This is a key topic of our investigations.

The literature on the respective roles of trade versus technology in driving labour market outcomes is not a new one. A large volume of literature in the 1990s, for instance, tested empirically the relationship between indicators of both trade and technology and labour market outcomes, in particular the relative demand for skilled versus unskilled labour (see for example, Lawrence and Slaughter, 1993; Feenstra and Hanson, 1998; Haskel and Slaughter, 1998). This literature tends to conclude that while both technology and trade impacted upon developments in relative labour demand, the effect of technology was the dominant one.

This empirical literature tended to assume that trade and technology were exogenous alternatives and did not look to take account of the interactions between the two. A smaller theoretical literature, however, has looked at the interactions between technology and trade and potential labour market outcomes (see for example, Jones, 1997; Falvey and Reed, 2000; Neary, 2001; Ethier, 2002; and more recently Bustos, 2011). In these models, trade (liberalisation) by affecting relative factor prices is assumed to lead to increased equipment investment, which if biased towards certain types of workers can lead to changes in relative labour demand.[3] Under the assumptions that skilled labour and equipment are complements, while unskilled labour and offshoring are substitutes – assumptions that are more likely to hold in the context of developed countries – Ethier (2002) shows that either increased trade or technological progress will increase the demand for skilled labour.[4] Trade liberalization increases the extent of offshoring, which substitutes for unskilled labour. At the same time, offshoring will increase equipment utilisation, since equipment is complementary to skilled labour, which will further increase the demand for skilled labour. For the purposes of our analysis, this literature suggests that offshoring can encourage certain types of technological change, which in turn may impact upon the structure of labour demand.

This paper combines the topics of technological change, trade, GVCs, offshoring and automation risk into a single, combined analysis. Because we use input-output analysis to construct counterfactuals (in which trade is limited as compared to the real-world situation), we do not distinguish in detail between offshoring, GVCs and trade more generally. The core idea of the input-output method is the combination of the direct (traded final demand) and various (in principle infinite) rounds of derived trade in intermediates (see, e.g., Ahmad et al., 2017; Los et al., 2014). Thus, our limited-trade counterfactuals encompass the total effect of trade, but, importantly, contain GVCs and offshoring as a result of their emphasis on derived demand. Although the input-output approach cannot identify the causal direction of the effects, it does provide ample opportunities (explained in Section 4.1 below) to construct the counterfactuals that we seek to identify stylized facts.

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). Causality could be identified in a full-fledged general equilibrium approach. For example, Acemoglu and Restrepo (2017) and Nomaler and Verspagen (2020) investigate the impact of (exogenous) automation (cheap technological change strongly biased towards saving a particular type of jobs). Typically, in the general equilibrium context, factor prices will equilibrate the labour market, with repercussions in the form of changed allocations of all production factors in all markets, including international trade (automation is likely adopted at different speeds in different countries).

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, our comparison between "constructed" autarky and the real-world input-output tables simply takes automation risk levels (which were constructed to be unconditional on factor prices) as exogenous to the analysis, and adopts a descriptive approach that allows us to present (rough) indications of the order of magnitude and geographical direction of how trade/GVCs is related to aggregate countries' automation risk. In terms of the geographical direction of the effect we are specifically interested in whether trade/GVCs relate to negative or positive differences in (pre-trade) automation risk between European countries, and European vs. non-European countries.

[1] Blinder (2006 and 2009) construct indices of the 'offshorability' of particular jobs in a similar manner to that used to estimate the likelihood of jobs being automatable.

[2] 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).

[3] Blinder (2009), amongst others, argues that technological change may also lead to increased opportunities for offshoring, using the example of future technological change allowing for teaching activities to be undertaken by a 'true-to-life hologram' located in a (relatively) low-wage country.

[4] Ethier (2002), as with other contributions, concentrates on the return to labour (i.e. wages) rather than employment.

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 automation risk depends on the job structure of employment in a country. We operationalize 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 the sectoral employment structure – through specialization – and we will attempt to measure this phenomenon 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 jobs with high automation risk, or use trade in other ways. 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. Such results may indeed be consistent with the theoretical literature mentioned above, with offshoring encouraging certain types of equipment investment in the countries with higher labour productivity and changing the structure of employment towards those with higher average automation risk.

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[5] that are applied later in the analysis. Section 3 analyses the structural nature of the automation risk estimates. 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 characterizes these benchmarks, and then applies these methods to estimate the impact of trade on the distribution of automation risk between countries. The final Section 5, summarizes the argument and draws further conclusions.

2. Automation risk and economic structure

2.1. Estimating automation risk

Our estimations of automation risk at the job level follow the method proposed by Nedelkoska and Quintini (2018), who in turn base themselves on Frey and Osborne (2017). Frey and Osborne review the literature on machine learning and artificial intelligence and conclude that there seem to be technological bottlenecks corresponding to three main job task categories: perception and manipulation tasks (i.e., recognizing 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 operationalize 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.[6]

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.[7]

Nedelkoska and Quintini (2018) apply a similar method, but with a broader database that covers the entire OECD area. This, and the fact that they use ISCO occupational codes (as opposed to the US coding system) makes their method attractive when the aim is, as in our case, to analyze a large set of countries other than the USA. They also use 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 a part of their job. Nedelkoska and Quintini (2018) start by

[5] 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.

[6] Atkinson and Wu (2017) and Coelli and Borland (2019) are critical of the Frey and Osborne estimations, arguing that they overstate the expected impact of automation on employment. Berger and Frey (2016) argue that the results of Frey and Osborne (2017) are consistent with some recent evidence. They argue that one implication of the estimates of Frey and Osborne (2017) is that the pattern of skill biased technological change is likely to continue, since jobs that are typically performed by skilled workers are less likely to be automated. At the same time, routine biased technological change is likely to come to an end, since the potential scope of automation is now expanding beyond routine tasks. As such, low-skill jobs are likely to become increasingly susceptible to automation, while the remaining medium skilled jobs are likely to become less susceptible. Results of Graetz and Michaels (2015) provide support for this hypothesis. This study examines the impact of industrial robots in 17 OECD economies, and shows that while the implementation of robots increased both labour productivity and value added it reduced hours worked primarily for low-skilled workers, with less pronounced declines for workers with middling skills. The work of Deloitte (2015) on the UK further shows that occupations with a high susceptibility to automation experienced sharp employment declines between 2010 and 2015, while jobs that are less exposed experienced rapid growth. Kaltenberg and Foster-McGregor (2019) consider developments in wage inequality for a broad sample of EU countries and show that the automation risk estimates of Frey and Osborne (2017) are generally the most important predictor of developments in inequality.

[7] Since Frey and Osborne, a range of other contributions have also estimated the impact of automation on the (future) demand for labour, or wages. Felten et al. (2018, 2019) also link information on the development of AI to skills and abilities of job descriptions in O*NET. Their information on development of AI comes from the quantitative Electronic Frontier Foundation (EFF) AI Progress Measurement dataset. Webb (2019) matches job descriptions to patent descriptions, and finds that AI particularly affects high-skilled jobs. Das et al. (2020) use job descriptions in a large database of job postings. They focus specifically on AI and Big Data and find that these technologies have become a larger part of high-skilled jobs. They also fit an econometric model to predict future job demand in a broad sense. Dechezleprêtre et al. (2019) investigate whether wages have an impact on the actual implementation of automation technology. They find that higher wages for low-skilled work lead to a higher implementation of AI.

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.[8] 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 are likely to have different automation risks, because they may answer differently to the task-related questions, while in Frey and Osborne automation risk cannot differ between two 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 re-estimate and refine the results in Nedelkoska and Quintini (2018), to obtain new measures of automation risk that will be used in our analysis below. Because we need job codes to link automation risk to data on the number of workers in countries and industries, 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, likely reflecting the different contexts in which different workers are employed. Because this is an important finding that reflects on the reliability of the risk estimates, we documented this phenomenon in the online supplementary material to this paper. This material also provides details of our own estimations, which are obtained by repeating the Nedelkoska and Quintini method at the sectoral level (1-digit NACE[9]).

Fig. 1 shows the distribution of automation risk (kernel density estimate) of the PIAAC respondents used in our analysis (see Appendix I). This shows a fairly broad support, with three main peaks, and very low

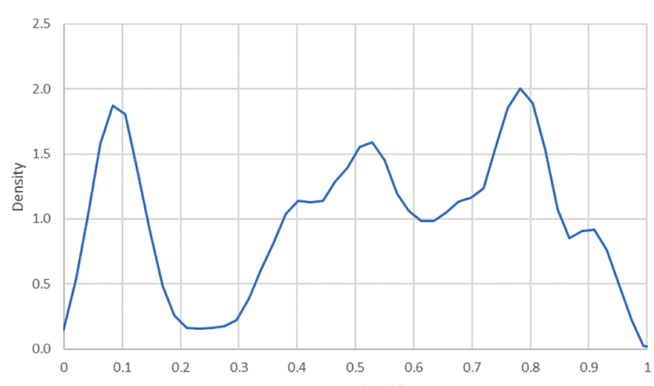

Fig. 1. Distribution of automation risk (kernel density) at job code level (ISCO08 3-digit), public PIAAC database, all observations, OECD model estimated at 1-digit industry level.

density around the 0.25 risk level. However, in our analysis, we are ultimately interested in automation risk at the country and sectoral 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.

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 sector-within-a-country level (ρ_{ri}), by calculating the weighted average over jobs and sectors:

$$\rho_{ri} = \frac{\sum_j \rho_{ji} H_{rji}}{\sum_j H_{rji}} \tag{1a}$$

$$\rho_r = \frac{\sum_j \sum_i \rho_{ji} H_{rji}}{\sum_j \sum_i H_{rji}} \tag{1b}$$

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)[10] 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

$$\rho_r = \frac{\sum_i \rho_{ri} H_{ri}}{\sum_i H_{ri}}, \tag{2}$$

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.

Thus, we see two structural factors at work in the automation risk calculation. First, because we assume that the risk estimate ρ_{ji} (automation risk of a particular job type in a particular sector) does not differ between countries, it is the share of job types in total (sectoral) employment that determines sectoral risk within the sector, in a particular country. We will call this the Type-1 structural effect. Second, structural differences between countries in terms of their sectoral employment shares also add to differences in automation risk between countries. This will be labelled as the Type-2 structural effect.

The anonymized LFS micro dataset supplied by Eurostat (we use the year 2014) 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

[8] 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.

[9] We do not have data at a finer level of disaggregation than NCE 1-digit, although we would expect that the risk estimations could be refined by performing the analysis at such a more detailed level.

[10] 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.

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 5, 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. The role of economic structure in explaining cross-country heterogeneity in automation risk

Table 1 shows the (unweighted) averages and the coefficient of variation (standard deviation divided by the average) of the estimated automation risk, by sector and by country, for 2014. Reported values for sectors are averages over countries within the sector, reported values for countries are averages over sectors within the country. Column ρ_r also reports the actual estimated risk value for each country (this is the average weighted by sectoral shares as implied by equation 2). For sectors, 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. The coefficient of variation within sectors is about 0.08 on average, with two high values in sector T and Q (both of which are relatively small sectors in terms of employment), and otherwise always smaller than 0.085. This implies that the Type-1 structural effect is small, i.e., in a given sector, the composition of employment in terms of jobs is not very different across the European countries.

For countries, actual automation risks ρ_r shows variations in the range [0.467, 0.631] (Norway ranks lowest and Romania highest), while the variation in terms of the unweighted averages is limited to the much narrower range [0.521, 0.565]. This suggests that differences in the sectoral structure of countries is an important component of the differences in aggregated automation risk. Also observing the fact that the average automation risk varies more over sectors within countries (mean coefficient of variation 0.418; lower variation would point to the importance of the Type-1 effect), as compared to the variation over countries within sectors (mean coefficient of variation 0.083), one can already anticipate that the cross-country variation in the actual (i.e., weighted by employment share) estimated automation risk must essentially be an outcome of the Type-2 structural effect, i.e., of differences in sectoral employment shares between countries.

Let us further substantiate this argument by bringing the structural differences into the picture. The top panel of Fig. 2 shows the divergence (standard deviation) of the employment shares of each sector (over the 29 countries) on the vertical axis, and average automation risk of the sector (values from Table 1) on the horizontal axis. One would expect sectors with high values on the vertical axis and extreme (either low or high) values on the horizontal axis to make large differences in countries' aggregate automation risk. The sector Q (Health services) stands out with large variation of employment shares, and low risk. Sectors A (Agriculture) and C (Manufacturing) also have large employment variation, and automation risk on the high side. These are the sectors that are decisive for the differences in aggregate automation risk.

In the bottom panel of Fig. 2, countries are the observations. Country aggregate automation (ρ_r) risk is displayed on the horizontal axis. The vertical axis shows the correlation between the structural divergence of the country from the European average (country employment shares minus average employment shares) with the corresponding vector of sectoral average automation risk (as in Table 1). A country with a strongly negative correlation (like Sweden) tends to have large employment shares in sectors with low automation risk, while countries with a strongly positive correlation (like Hungary) tend to have high employment shares in sectors with high automation risk.

The bottom panel of Fig. 2 shows that as the correlation increases from strongly negative to strongly positive, automation risk indeed rises sharply. The R^2 of a linear regression line in this part of the figure is 0.88. This tight fit shows the importance of the employment structure of a country for its aggregate automation risk. The largest part of the variations in aggregate risk between countries is determined by differences in sectoral employment shares, or structural differences, between countries, rather than by country-specific risk factors.

4. Aggregate automation risk and trade

Having concluded that cross-country variation in overall automation risk is largely related to structural differences, we now proceed to explore the role of international trade, which is one important factor that can explain the structural differences between countries (and thereby automation risk). That is, we explore the extent to which variations in aggregate (country level) automation risk are related to trade, or differently put, to offshoring.

An important part of offshoring and GVCs seems to be driven by a search for low labour costs (e.g., Falk and Wolfmayr, 2008; Harrison and McMillan, 2011). This is why we will use country-level labour productivity to benchmark the results on the automation risk effects of trade. Labour productivity is strongly correlated to the wage rate (in our sample of 29 countries, and using country-level WIOD data, the correlation coefficient is 0.98).

The main idea behind using the labour productivity benchmark is that low-wage (low-productivity) countries will be affected differently by offshoring than high-wage (high-productivity) countries, because, for example, low-wage countries may be more often on the receiving side of the offshoring relation, or because they offshore different kinds of jobs than high-wage countries. In particular, we may expect high productivity countries to be those intensive in the use of capital and skilled labour, with offshoring involving the relocation of low-skilled jobs to third countries. By benchmarking against labour productivity, we simply mean to graph the results of the risk calculations against labour productivity, as in Fig. 3. Labour productivity is calculated from WIOD and is expressed in current (2014) US$ per worker.[11]

The figure shows a strong and negative correlation between the two variables. Our analysis above has shown that country-aggregate automation risk is primarily related to economic structure. Thus, countries with high labour productivity (and high wages) tend to have sectoral employment structures that favour sectors with low automation risk. As international trade, offshoring and GVCs impact on the employment structure of a country, we may ask whether the negative correlation in Fig. 3 is somehow connected to trade, for example because high-productivity countries offshore jobs with relatively high automation risk to lower-productivity countries. This is the subject of the last part of our analysis.

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

To analyze how automation risk in total country-level employment is related to trade and GVCs we use 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.

[11] Our labour productivity variable is calculated using market exchange rates, and therefore does not take into account under- or over-valuation of the country's currency. However, labour productivity as we measure it is strongly correlated to GDP per capita in international dollars (the correlation is 0.95, using Maddison's data on GDP per capita).

Table 1
Averages and coefficient of variation of estimated automation risk, by sector and by country, 2014.

	Sector	Av	CoV	Country		ρ_r	Av	CoV
A	Agriculture	0.662	0.030	Austria	AUT	0.537	0.540	0.431
B	Mining	0.694	0.084	Belgium	BEL	0.498	0.537	0.402
C	Manufacturing	0.721	0.029	Bulgaria	BGR	0.608	0.558	0.372
D	Energy generation	0.657	0.037	Switzerland	CHE	0.512	0.533	0.402
E	Water	0.724	0.024	Cyprus	CYP	0.532	0.542	0.443
F	Construction	0.410	0.020	Czech Republic	CZE	0.587	0.546	0.440
G	Trade	0.759	0.017	Germany	DEU	0.521	0.536	0.434
H	Transport	0.825	0.025	Denmark	DNK	0.496	0.538	0.434
I	Hotels, restaurants	0.430	0.030	Spain	ESP	0.525	0.541	0.446
J	Communication	0.695	0.017	Estonia	EST	0.551	0.543	0.422
K	Finance	0.903	0.011	Finland	FIN	0.504	0.548	0.399
L	Real estate	0.550	0.050	France	FRA	0.499	0.543	0.406
M	Professional services	0.533	0.018	United Kingdom	GBR	0.498	0.526	0.428
N	Support services	0.529	0.041	Greece	GRC	0.554	0.545	0.445
O	Public administration	0.531	0.021	Croatia	HRV	0.572	0.538	0.433
P	Education	0.137	0.114	Hungary	HUN	0.584	0.565	0.371
Q	Health services	0.103	0.051	Ireland	IRL	0.514	0.539	0.427
R	Arts, entertain., oth (incl. S)	0.317	0.027	Italy	ITA	0.523	0.544	0.435
T	Household employers	0.112	0.873	Lithuania	LTU	0.553	0.557	0.375
U	International organizations	0.574	0.095	Luxemburg	LUX	0.553	0.541	0.451
	Average all sectors	0.543	0.081	Latvia	LTV	0.569	0.557	0.387
				Netherlands	NLD	0.496	0.521	0.430
				Norway	NOR	0.467	0.533	0.421
				Poland	POL	0.583	0.543	0.409
				Portugal	PRT	0.537	0.543	0.438
				Romania	ROU	0.631	0.561	0.417
				Slovak Republic	SVK	0.590	0.554	0.432
				Slovenia	SVN	0.568	0.543	0.401
				Sweden	SWE	0.479	0.540	0.432
				Average		0.527	0.544	0.418

Note: Column labelled "Av" gives the unweighted average value, column labelled "CoV" gives the coefficient of variation (standard deviation divided by average). Column ρr gives the actual risk estimation as given by equation 1b and/or 2.

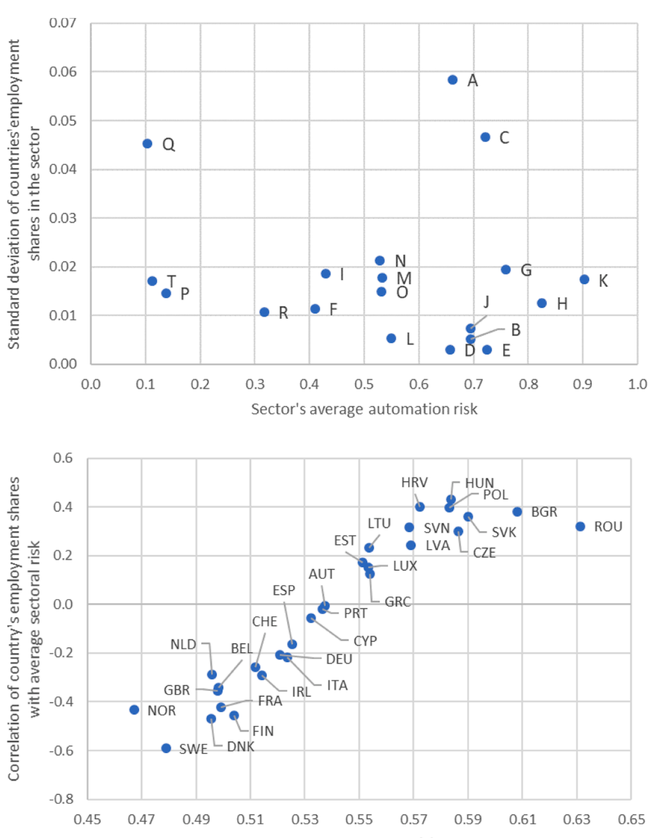

Fig. 2. The structural nature of country automation risk.

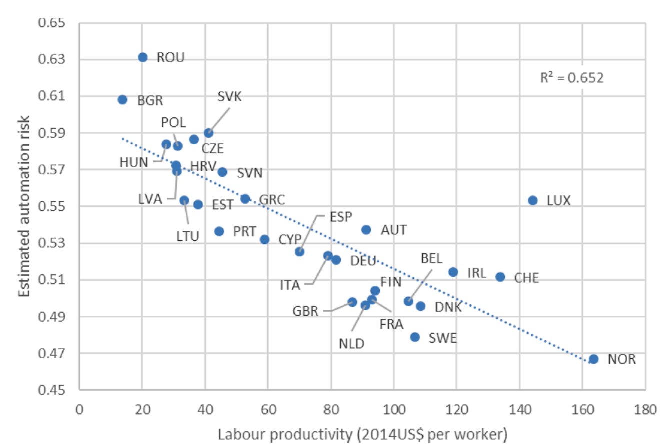

Fig. 3. Estimated automation risk and labour productivity, European countries, 2014.

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. In our analysis, U is 2464×2464, where 2464 is a result of having 56 sectors and 44 countries.

Another part of the transaction table is formed by the matrix of final deliveries, which is denoted by F, in our analysis it is 2464×220. 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 5 categories of final use, e.g., final consumption by households and investment and firms, and are repeated for all 44 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, i.e., 220.

A final part of the transaction table is formed by the matrix of value added, which we denote by $\boldsymbol{V}$. 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 (1×2464) denoting value added in a sector.[12]

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

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

Here, $\boldsymbol{Q}$ is a column vector (2464×1) of total (gross) output by sector, and $\boldsymbol{Q}$' is the transpose of $\boldsymbol{Q}$. We see that matrices $\boldsymbol{U}$ and $\boldsymbol{F}$ arranged next to each other form a larger (non-square) matrix in which the rows sum to the elements of $\boldsymbol{Q}$. Value added (elements of $\boldsymbol{V}$) is obtained by subtracting intermediate deliveries into the sector (in the sector's column of matrix $\boldsymbol{U}$) from gross output (the sector element in $\boldsymbol{Q}$'). The bottom-right part of the transaction table $\boldsymbol{T}$ is empty.

Using information from the transactions table we create a new matrix, denoted by $\boldsymbol{A}$, in which the elements $\boldsymbol{a_{ik}}$ are equal to $\boldsymbol{u_{ik}} / \boldsymbol{q_i}$, where $\boldsymbol{q}$ denotes an element of $\boldsymbol{Q}$. The elements of matrix $\boldsymbol{A}$ are so-called input- or technical-coefficients, i.e., they specify the amount of intermediate deliveries from sector $\boldsymbol{i}$ that is necessary to produce one unit of gross output in sector $\boldsymbol{k}$. We assume that the elements of matrix $\boldsymbol{A}$ 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:

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

where $\boldsymbol{A_{rs}}$ refers to the sub-matrix of input coefficients for supply from country $\boldsymbol{r}$ to country $\boldsymbol{s}$, 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:

$$\boldsymbol{Q} = [\boldsymbol{I} - \boldsymbol{A}]^{-1}\overline{\mathbf{F}},$$

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

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 $\boldsymbol{i}$, $\boldsymbol{l_i}$, being equal to employment in the sector divided by gross output in the sector. We then multiply the element $\boldsymbol{q_i}$ of vector $\boldsymbol{Q}$ by $\boldsymbol{l_i}$ to obtain employment, which is denoted by the vector $\boldsymbol{H}$. In matrix form, this can be expressed as:

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

Where $\widehat{\boldsymbol{L}}$ is the diagonalized (2464×2464) 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 tables in the input-output system to reflect a hypothetical state of autarky. Our method for making these modifications draws on the existing literature in the input-output field (e.g., Duchin, 2007; Strømman and Duchin, 2006; Feenstra and Sasahara, 2018).

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:

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

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

This adjusted input coefficient matrix is denoted $\widetilde{A}$, and final demand matrix $\widetilde{F}$. 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.[13]

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

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

Using the labour coefficients (unchanged under autarky), we can then calculate employment under autarky from gross output under autarky. Using equation (1a), 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 2, which compares

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

[13] By fixing the level of final demand we concentrate on the relocation effect (see footnote 2), which allows us to focus on the question of whether highly productive countries have offshored automation risk.

Table 2
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).

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 analyze. 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 relation of that to 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. In the countries with increased risk, the increased number of jobs at risk amount to about 6.1% of total (actual) employment. For countries with decreased risk, the fall in the number of jobs at risk amounts to about 9.1% of their actual employment.

There are eight countries in Table 2 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, which is small as compared to the 16.4%-points difference between the countries with highest and lowest automation risk in our sample.

Fig. 4 provides more information about which sectors are driving the results. In this figure, the employment effect of each sector has been averaged over the 29 countries in the analysis. At the sectoral level, the employment effect is the change in the employment share due to trade, multiplied by the automation risk level of the sector in the country. The bar labelled "overall" gives the average over the 29 countries for this effect. We notice that the sectors G (Trade), H (Transport) and K (Finance) have a moderate average positive impact, while sectors B (Mining) and C (Manufacturing) have a moderate average negative impact. Most other sectors have a small to negligible average impact. Thus, given that automation risk is fixed between autarky and trade, these results imply that trade involves a net movement of employment out of mining and manufacturing and into trade, transport and finance. Countries (usually the highly productive ones) who have large shares of these sectors (G, H and K) will tend to see their average automation risk increase.

The other two bars in this figure display the averages over subgroups of countries, i.e., only those with either a negative or a positive impact. Here we see that most of the sectors that have a substantial overall impact in fact both have countries with negative and positive impact. For example, in Manufacturing (C), the countries with a negative impact of trade on automation risk have an average effect of almost -3%, but there are also countries that see automation risk due to the manufacturing sector rise, on average by slightly more than 1.5%. Sectors without large negative effects are H (Transport) and K (Finance). Agriculture has a fairly sizeable negative and positive average, but a small overall average effect. The Health care sector (Q), which was rather influential in Fig. 2, is very small here, because it is predominantly a non-tradeable sector.

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.[14] 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 3. 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 decrease. With intra-European trade opening up, a majority of countries (16) see automation risk decrease, and see the number of jobs at risk decrease.

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

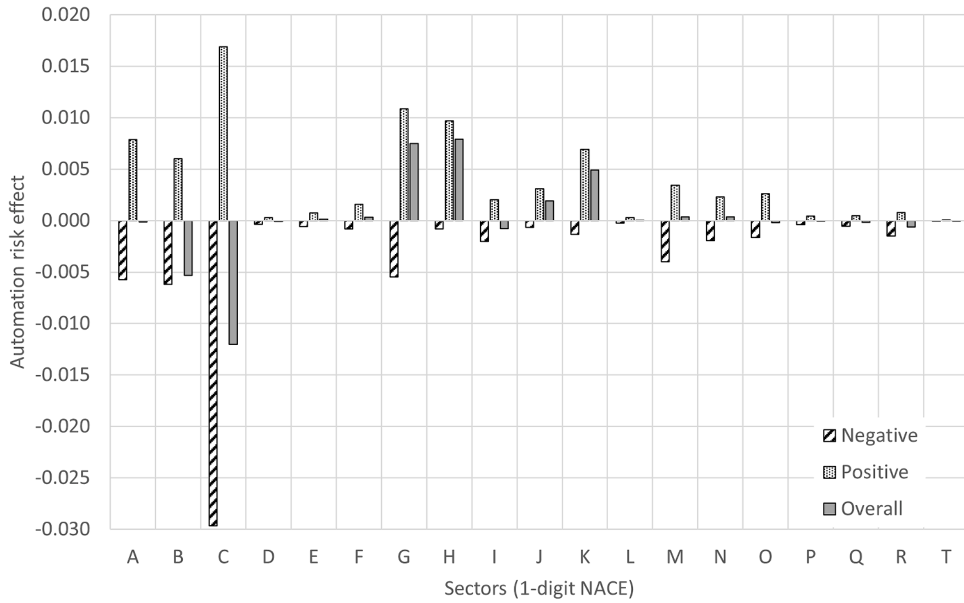

Fig. 4. Average automation risk effect of trade over 29 countries, overall and by negative/positive effect.

Table 3
Difference in automation risk and number of jobs at risk between full autarky and two partial autarky situations, European countries, 2014.

Country	Opening up extra-European trade (intra-European autarky) Risk increase with trade	Increase # jobs at risk	Opening up intra-European trade (extra-European autarky) 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).

Finally, we come to the question of how trade affects the relationship between aggregate labour productivity and aggregate automation risk, as displayed in Fig. 3 above. To assess this, we created alternative versions of Fig. 3 for each of the three hypothetical (partial) autarky situations, and regressed automation risk on these data. Note that both variables in this regression, labour productivity and automation risk, are endogenously determined in the (partial) autarky simulation.

Table 4 documents the estimated regression lines between automation risk and labour productivity. The first row refers to the regression line in Fig. 3, the other rows give results for the (partial) autarky scenarios. Fig. 5 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, with trade, automation risk of the high-productivity countries increases, rather than decreases. This is obvious from the fact that on the righthand 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 higher- to lower-productivity countries in Europe. In fact, the effect is opposite, with high-productivity countries increasing their automation risk by trade.

Second, the effects of trade on automation risk are very small for the 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-

Table 4
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.

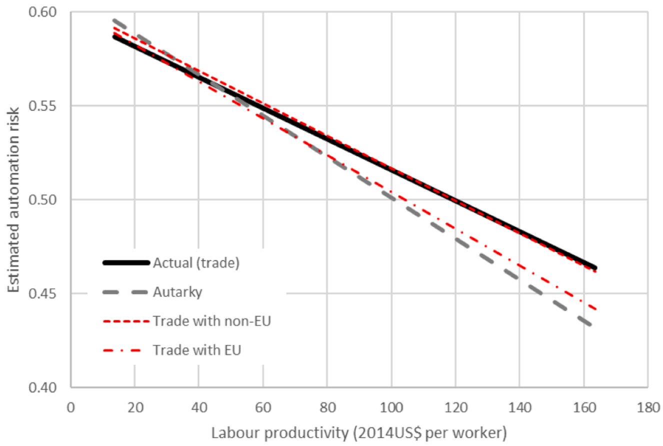

Fig. 5. Regression lines for automation risk - labour productivity relation, countries, 2014, actual trade situation and various autarky scenarios.

European countries is responsible for the largest part of the effect that countries with high productivity levels experience. On the righthand 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 4), while the line for extra-European trade is well above autarky.

5. Summary and Conclusions

This paper presents descriptive empirical evidence – or stylized facts – 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. Aggregate automation risk also seems to be lower in countries with high productivity and high wages. This illustrates the effect of structural differences between countries: the 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 in the without-trade scenario, the observed negative relationship between aggregate automation risk and labour productivity changes. In order to investigate this and explore the relationship between trade and 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 is related to 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 in the actual situation with trade as compared to a scenario without trade. However, in individual countries, the difference is often larger, because at the European level countries with positive and negative differences 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 obtaining low levels 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 shows a much stronger difference in automation risk than opening up intra-European trade. The sectors that show the largest automation risk differences with trade are mainly manufacturing, trade, transport and finance.

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 globalization 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.

With research on new methods to estimate automation risk burgeoning in the literature (see, e.g., footnotes 6 and 7), it may also be interesting to apply alternative methods of risk estimation to our calculations (as in, e.g., Webb, 2019), provided that these risk automations can be applied to data other than the US, or to develop and apply non-input-output methods to analyse international trade.

Credit statement

All authors contributed equally to this paper.

Declaration of Competing interest

The authors declare no conflict of interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2021.104269.

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