The disaggregation of the projected impacts of automation in the regional labour markets between 2019 and 2030: Case of the Czech Republic

Vít Pošta
University of Chemistry and Technology Prague, Department of Economics and Management, Prague, Czech Republic
E-mail: vit.posta@vscht.cz

The ongoing technological changes related to advances in digital technology will soon be reflected in changes in the required qualifications of workers, which will subsequently have an impact on the rate of unemployment, employment, and economic activity. The theoretical discussion in this study shows that aggregate effects will not be very strong or even negative. However, regional impacts within economies may be profound and negative. The main objective of this study is to propose a methodology to illustrate how the countrywide effects of automation can be disaggregated into regional impacts. The projection is based on population projections for the Czech Republic and its regions, and information drawn from other research related to the projection of economic activity and aggregate impacts of automation on employment in the Czech Republic. The results show that the regional impacts of automation depend on the level of education and the share of manual labour, which correlate with disposable income, and the degree to which economic activity and unemployment react to changes in employment.

Keywords:
automation,
economic activity,
employment,
regional labour markets,
unemployment

Introduction

Advances in the field of digital technologies have influenced the development of labour markets. This effect is due to the changing requirements of employee skills. On one hand, the decreasing demand for a wide range of qualifications will negatively impact employment, unemployment, and economic activity. On the other hand, positive consequences should also be considered. New branches of economic activity will come into existence, and the overall increase in productivity might lead to both increase in income and decreases in relative prices of the respective production. Therefore, aggregate impacts may be positive in various economies. However, the key question is how such an overall likely positive impact be distributed in the respective economy. The discussion shows that it is probable that the distribution will be highly uneven and dependent on the initial level of household income, level of education, and share of specific occupations.

This study focuses on the projection of the impacts of automation on regional labour markets. The results of the projections also hint at the determinants of the uneven distribution of the aggregate impacts: relatively higher regional impacts are expected in those regions where there is a lower level of education and a higher level of easily automated occupations, which correlates with the relatively lower average household income.

The results show that the regions that will be hit relatively harder are those that have also been shown to be problematic in other studies. However, the projection of the division of the negative effect on employment between unemployment and economic activity is more interesting because the reaction of unemployment to changes in employment varies across regions. The results show that, in most regions, decrease in employment leads to decrease in economic activity rather than increase in unemployment.

The paper is organized as follows: theoretical and empirical findings related to the expected impact of automation on labour markets, the methodological background of the projection, results and conclusions. The basic scenario is based on the changes in economic activity already projected for the Czech Republic, population projection at the regional level, and estimates of structural unemployment at the regional level. The second scenario focuses on the projection of the distribution of aggregate automation impacts among regional labour markets, which is based on the theoretical analysis presented in the paper.

Theory and existing results

A declining share of labour in the overall product (income) and polarization is a key characteristic of the labour market development in the last two decades, in the most developed economies where the process started earlier.

Dao et al. (2017) show that the share of labour in overall income has declined, especially in advanced economies, disproportionately. The key explanatory variable of this process is technological progress, which is captured by the decreasing relative price of the investment goods. Global integration is the most important factor. On the other hand, in the case of less developed economies, a decrease in the share of labour was also detected; however, the key driving force was global integration. They further show that in advanced economies, the industry facing decreased labour shares is manufacturing, mostly affecting the employees with secondary education. This uneven impact of technological progress on groups of employees with different levels of education is called polarisation. It leads to more severe impact on those with secondary education, and a less profound impact on those with tertiary and primary education. Besides, it is also reflected in changes in remuneration and job security.

Das–Hilgenstock (2018) show that advanced economies with a high tendency for automatised jobs at the beginning of their analysis systematically show a high level of polarisation. They also show that the possibility of automation in less-developed economies is relatively low; however, it has increased as a result of global integration which is marked by the transfer of easily automatized production from advanced economies to less-developed ones.

The polarisation of the US labour market is well documented by Acemoglu–Autor (2010), who demonstrate a sharp decrease in demand for routine labour, regardless of whether it is manual or cognitive in nature. In the context of the EU, Dachs (2018) shows a decline in the demand for employees with primary or lower secondary education. However, he does not reach a definitive conclusion as to whether it is more due to technological progress or globalisation. With respect to the presented results, it may be deduced that in the case of more developed EU economies, the key driving force of polarisation is technological progress, while in the less developed ones, the main reason is globalisation.

With regard to the Czech Republic, Dao et al. (2017) show that the economy belongs to those where labour share has increased, in this particular case by app. 1 p.p. since 1990. Since, this was induced by the reallocation of manufacturing production from more developed economies to the Czech Republic, it can be deduced that the risk of automation has increased.

Berger–Frey (2016) show that, in the context of the US labour market, the branches of economic activity most hit by technological progress stemming from digitalisation are not able to create a sufficient number of new jobs with respect to the number they destroy. On the other hand, industries that have technologically stagnated so far, especially public, personal, and health services, have been able to compensate for this difference. This result may be linked to the findings of a study by the OECD (2018) which shows that the increase in productivity related to new technologies is more detectable at the firm level than in the whole economy.

De Groen et al. (2017) based their arguments on the idea that advancing digitalisation might lower the barriers to entry into newly developed markets. However, they seem to omit the fact that many industries based on technological progress in the area of digitalisation are already populated by firms with significant monopoly power, which naturally increases barriers to entry for possible competitors.

Turning attention to the impacts of automation on labour markets, Frey–Osborn's (2013) study is the most cited. Following expert research carried out in the US, they estimated that in the next 20 years, 47% of jobs will be subject to destruction. Using the same method, Walwei (2016) estimated a loss of 42% jobs in Germany. The key problem of the Frey and Osborn analysis is that the analysed labour unit is the whole job. However, one particular job typically consists of various tasks, some of which may be automated, whereas others may not. Therefore, the process of automation can lead to the destruction of a particular job; however, this does not mean that the employee will be laid off. The result may be a change in the structure of the tasks performed, eliminating those which are automatised, and adding new ones which may not be automatised.

This problem is addressed in the analysis by Arntz et al. (2016), in which the projection presented in this paper is based. They use the Programme for International Assessment of Adult Competencies (PIAAC) database, which comprises information about the socioeconomic characteristics, skills, tasks, and competencies of the workers investigated in OECD countries. The first step of their analysis is the detection of the relationship between the PIACC data and the automation rate based on research by Frey–Osborn (2013). Thus, they identified the rate of influence of various characteristics on the possibility of automation of a particular job. They first applied the method to the reality of the US and found relationships between various tasks, education, competencies, income, industries, and firm size on the one hand, and the rate of automation on the other. These estimates are then applied to other OECD countries. The fact that they focus on tasks means that they are also able to consider various compositions of particular jobs with respect to tasks in the respective countries; a particular job may consist of a higher share of tasks which may be automatised in one country, while this share may be lower in another. A job is designated as subject to the risk of automation when it consists of at least 70% of tasks that may be automatised. This means that in the context of the US, 9% of employees face a high risk of losing their jobs due to automation. The key difference between the two approaches thus rests in the fact that, while the analysis of Frey and Osborn simply detects those jobs which include some tasks which may be automatised, Arntz et al. (2016) identify the share of tasks which may be automatised and then evaluate the risk of the job being destroyed.

Other studies follow Arntz et al. (2016) but make use of a broader set of countries and/or more disaggregated data. The analysis of Nedelkoska–Quintini (2018) follows the same methodology but is based on a broader set of workers. They estimated that 15% of jobs are at high risk of automation in the Czech Republic, as compared to 10% by Arntz et al. (2016). The highest estimated percentage of jobs at high risk of automation in the Visegrad group was attributed to Slovakia (33%). Pouliakas (2018) estimated an average 14% of workers at high risk of automation in the EU28. Heald et al. (2020) make use of updated data and the same methodology and reach an estimate of 17.5% of jobs at high risk of automation in the case of the Czech Republic. As far as other Visegrad countries are concerned, their estimates point to 22.2%, 18.2%, and 18.1% in Slovakia, Poland, and Hungary, respectively.

Arntz et al. (2016) found that primary and secondary education are linked to a higher probability of automation. Second, they showed that tasks related to information exchange, selling, and manual work are also related to a higher probability of automation. This will later be used to distribute the overall effect of automation on employment in the Czech Republic among its regions.

Other findings that are not directly used in the projection are as follows. The automation rate increases with the rate at which the task is based on calculation skills, the fact that the job is located in the private sector and/or in a large firm, and the age groups of 25–29, 40–49, or 60–65. On the other hand, the rate of automation decreases with the degree to which tasks require problem solving or general literacy. The tasks which are based on reading and analysing written documents are not subject to automation. Crowley et al. (2021) show that the risk of automation does not really depend on the rate of concentration of employment in an industry per se but only on the rate of specialisation in certain occupations. These at-risk occupations are in line with the findings of Arntz et al. (2016) and others mentioned above.

Keese (2020) and Szabo (2020) conclude that Visegrad countries may be more at risk than the EU average, especially Slovakia. However, some positive results were also obtained. Szabo (2020) states that since 2011, the share of industrial robots in the Czech Republic and Slovakia has increased relatively more than the EU average; therefore, this might be considered as a positive sign for future development as a relatively large accommodation has already taken place. However, this is partially contrary to the claims of Heald et al. (2020), who expect a relatively larger share of accommodation to take place after 2030. Since their work does not consider the possible effects of recessions brought about by the measures taken to combat the spread of Covid-19 and quite probable recessions stemming from the sanctions aimed against Russia imposed in 2022, one should take note of the results of Hershbein–Kahn (2017) and Jaimovich–Siu (2018), who show that recessions in the past tended to speed the process of automation. Therefore, it is quite possible that most changes will take place sooner than Heald et al.'s (2020) claim.

Bachman et al. (2022) employed the probit regression model and showed that in countries with lower labour costs, such as the Czech Republic, Hungary, Poland, and Slovakia, automation tended to lower the separation rates and increase the job-finding rates; therefore, it contributed to better employment outcomes even in sectors relying on routine cognitive and manual jobs. These findings are explained by the context within which automation has taken place so far, which is marked by the inflow of FDI and integration into global value chains, as opposed to the introduction of new technologies in existing plants. This means that the future impact of automation will greatly depend on the overall macroeconomic context within which these countries will evolve.

Returning to the case of the Czech Republic, Marcolin et al. (2016) stated that the rate of routine tasks in the jobs in the Czech Republic is 22%. However, the authors do not examine its distribution among specific jobs, which means that their estimate is in no way comparable to the result given by Arntz et al. (2016).

At the global level, Autor–Salomons (2018) set up a model of economic growth that considers the technological progress accompanied by automation. In a sample of OECD countries, 1970 to 2007, they reached the following conclusions: a growth of technological progress of an industry by 1% leads to a decrease in employment in this industry by 0.1%, a decrease in the price of production of this industry by 0.4%, and a decrease in the share of labour in the value added of this industry by 0.3%. However, the overall impact is positive: a growth in aggregate technological progress by 1% leads to an increase in employment by 0.3% and an increase in hourly remuneration by 0.6%. The key mechanisms behind the positive impacts stem from lower production prices in the industry, influenced by technological progress, and the overall increase in income. Nevertheless, in respect of polarisation, it is expected that the possible positive impacts on the aggregate level will be distributed asymmetrically, both in the context of income groups and geographically. Therefore, it is imperative to study the effects of automation with respect to regions, and not only at the level of aggregate economies.

Methodological background

The disaggregation of the overall projected figures for the Czech economy into its regions is performed in two scenarios: the first, denoted as basic, does not consider the effects of automation, while the other one does. The key results were obtained by comparing these two scenarios.

The basic scenario starts with the labour force and then proceeds with unemployment, which leads to the final point concerning employment. The scenario reflecting the effects of automation goes the other way round; thus, it starts with employment and proceeds with unemployment, and the result of the two is the labour force projection. The final year of the projection was 2030. Although Heald et al. (2020) expect that relatively more accommodation reflecting automation will take place after 2030, namely until 2035, given the current pre-recessionary macroeconomic environment and the results of Hershbein–Kahn (2017) and Jaimovich–Siu (2018), it can be reasonably argued that the process of automation may be faster; therefore, the final year 2030 is defendable.

The basic scenario

The key input indicator retrieved from an external source is the rate of economic activity by 2030 (EC 2021). The Ageing Report, EC (2021), considers a 0.5% decrease in the rate of economic activity in the age group 15+ between 2019 and 2030. This figure is not published directly, but can be easily deduced from the data of the report states. The key determinants behind this projection of the EC are the projected evolution of the age groups 15 to 24 years and 55 to 64 years. In the first case, the reason is that considering the increasing number of years spent in schooling, the increase in the share of this age group in the population will have a negative impact on the rate of economic activity. On the other hand, age groups 55-59 traditionally reach a high level of economic activity, while taking into account the increasing age of retirement, age groups 60-64 will show an increasing rate of economic activity. The Ageing Report considers the effects of migration in and out of EU countries. They do not consider the effects of automation.

The projected decrease in the rate of economic activity, EC (2021), by 0.5 p.p. is divided among the respective regions according to the ratios of their shares of the age groups 15-24 and 55-64 in the population of the regions with those of the Czech Republic. For this purpose, the last published population projection for the regions, the Czech Statistical Office, CZSO (2019), was used. Based on the economic activity rate of the Czech Republic in 2019, the projected working age population in 2030 (CZSO, 2019), and the projected change in the economic activity rate (EC 2021), the labour force of the Czech Republic in 2030 was calculated as follows:

$$LF_{CR}^{2030} = \frac{(REA_{CR}^{2019} + \%\Delta\, REA_{CR}) * WAP_{CR}^{2030}}{100}, \tag{1}$$

where *LF* is the labour force, *REA* is the rate of economic activity (%), and *WAP* is the working-age population. The relative change in the rate of economic activity between 2019 and 2030 was divided between regions according to an index that captured the projected changes in the shares of the key age groups in the overall population.

$$I_{region}^{REA\ loss} = \frac{\Delta ER_{region}^{15-24} - \Delta ER_{region}^{55-64}}{\Delta ER_{CR}^{15-24} - \Delta ER_{CR}^{55-64}}, \tag{2}$$

where *I* denotes the index of the change in the age composition of a particular region relative to the whole Czech Republic and ΔER is the change in the share of the particular age group in the population of the region or the Czech Republic between 2019 and 2030. By definition, the index is equal to one for the Czech economy as a whole and reaches more or less than one for its regions. The relative change in the labour force between 2019 and 2030 at the Czech Republic level is multiplied by these regional indices (2) to calculate the relative changes in the regional labour force that respect its own development of age composition with respect to the Czech Republic. These relative regional changes in the labour force are then used together with the level of the regional labour force in 2019 to calculate the projected levels of the regional labour force in 2030. The regional rates of economic activity are calculated using the projected working-age population, CZSO (2019), and the results of the previous step, that is, the regional levels of the labour force. This approach is reasonable in this particular case because the changes in the two age groups are relatively very small with respect to the changes in the working-age population at both the overall and regional levels. There is a small residuum which is not observable when the outcome is checked using the following identity, as can be verified by the reader in the next section:

$$\frac{LF_{CR}}{WAP_{CR}} = \sum_{j=1}^{14} \frac{LF_j}{WAP_{CR}} = \sum_{j=1}^{14} \frac{LF_j}{WAP_j} \frac{WAP_j}{WAP_{CR}}. \tag{3}$$

where *j* denotes a region.

The second step of the projection projects the number of unemployed and the unemployment rates. Given the long horizon of the projection, predicting the evolution of the business cycle is impossible. Thus, this projection is based on the assumption that the unemployment rate will reach its structural level by 2030. The basic scenario does not involve any structural changes in the economy. On the level of the whole economy, a broad set of methods may be used to estimate structural unemployment; at the regional level, the possibilities are rather limited.

The Ageing Report (EC 2021) follows the estimates of structural unemployment made for the purpose of estimating the potential output (Havik et al. 2014), and the anchors to which it will converge in the long run are based on Orlandi (2012). The projection assumes that convergence requires five years.

A purely statistical approach was employed for this projection. The reason is that, in the case of the Czech Republic, there are no consensual estimates or methods on how to tackle the question of structural unemployment at the regional level.

Using the Hodrick-Prescott filter and data on unemployment rates, time-varying trends are estimated for each region. Their averages over the course of the last business cycle of the Czech Republic, also estimated by the Hodrick-Prescott filter using real GDP data, are taken as anchors to which the actual rates of unemployment will converge. The last closed business cycle took place between 2005 and 2016.

The method described above was used to obtain consistent results while estimating the regional anchors. While the anchor for the Czech Republic was calculated as their weighted sum, with the regional shares in the total labour force in 2030 as the weights:

$$\frac{U_{CR}}{LF_{CR}} = \sum_{j=1}^{14} \frac{U_j}{LF_{CR}} = \sum_{j=1}^{14} \frac{U_j}{LF_j} \frac{LF_j}{LF_{CR}}. \tag{4}$$

where *j* denotes a region and *U* denotes the number of unemployed. The projected labour force is the output of the first step of the projection, as shown above.

Following the logic of the projection of the EC (2021), employment is simply the difference between the projected labour force and unemployment. The Czech Republic's employment rate in 2030 is a weighted sum of the regional employment rates, with the regional shares in the total working-age population in 2030 as the weight:

$$\frac{E_{CR}}{WAP_{CR}} = \sum_{j=1}^{14} \frac{E_j}{WAP_{CR}} = \sum_{j=1}^{14} \frac{E_j}{WAP_j} \frac{WAP_j}{WAP_{CR}}. \tag{5}$$

where *j* denotes a region and employment *E*.

The scenario with the impacts of automation

This scenario starts with the disaggregation of the overall projected impact of automation on employment.

Several estimates of employment losses are mentioned in the previous section. The calculations are based on the loss of employment at the level of the Czech Republic given by Arntz et al. (2016). the projected loss is thus 10%. Given the same methodology but slightly different data sets, Nedelkoska–Quintini (2018) and Heald et al. (2020) reach slightly higher figures of estimated loss of employment. However, none of these studies consider the possible overall macroeconomic benefits arising from the technological process, Autor–Salomons (2018), or the specific context within which automation may take place (Bachman et al. 2022). Therefore, it is not extreme to base the calculations on a lower estimate of loss.

This overall impact is divided among the regions according to their shares in the types of education and occupations that were found to be the most risky from the point of view of the analysis of Arntz et al. (2016). The most risky education levels are basic and lower secondary education (ISCED 1 and 2), and the most risky occupations are managers, service and sales workers, craft and related trade workers, plant and machine operators, and elementary occupations (ISCO 1, 5, 7, 8, and 9).

In some countries, the age structure of the labour force should also be considered. However, Nedelkoska–Quintini (2018) show that in the case of the Czech Republic, the risk of automation does not increase with age, as well as in some other countries; therefore, disaggregation does not account for the aging population. They also showed that the variation in the risk of automation between countries is explained much more by the differences in the organisation of job tasks within sectors than by the differences between the shares of the sectors in the economies (app. 70% explained by the differences in the organisation of job tasks). Therefore, possible changes in the branches of economic activity between the regions are not considered, and the organisation of job tasks is regarded as constant, given the fact that the analysis is concerned with a single working culture. A purely statistical perspective using the Czech Statistical Office data, would lead to a conclusion that the share of the most risky employment (ISCO 1, 5, 7, 8, and 9) increased by 0,9% between 2014 and 2019 at the level of the Czech Republic and, in fact, decreased in 7 out of 14 regions.

These figures show a relatively stable composition of the employed with respect to the branches of economic activity that go hand in hand with the research on occupational mobility. Vavřínová–Krčková (2015) show that app. 3% of workers changed their occupation and, at the same time, the industry of employment every year between 2002 and 2013, which is a very low figure compared with the EU average. This result was qualitatively confirmed by a more recent study by Causa et al. (2021).

Therefore, the method of disaggregation of the overall projected loss of employment considers only the structure of education and occupation. For the reasons stated above, it disregards age structure, possible changes in the structure of the branches of economic activity, and occupational mobility.

The following index is constructed for each region:

$$I_j^{E\ loss} = 0.5 * \frac{RE_j}{RE_{CR}} + 0.5 * \frac{RO_j}{RO_{CR}}. \tag{6}$$

where *j* denotes region. *RE* risk education and *RO*-risky occupation. Both the criteria had the same weights.

The next step is to project the unemployment rate. The question is to what extent will the decline in employment increase unemployment, or to what extent will it negatively affect economic activity? The approach to this question is based on the standard econometric modelling of labour market flows (Summers 2000). For this purpose, vector error correction models were set up for each region to estimate the relationship between the structural unemployment rate and the employment rate.

The time series of the rates of structural unemployment and employment are not stationary, which means that vector error correction models can be used (see Table A1 in the Appendix). The lags of the models were chosen to eliminate autocorrelation in the residuals. Three lags were required. Table A2 in the Appendix presents the structure of the cointegration vectors and confirms the supposed negative relationship between these two variables. The estimates also show that the structural unemployment rates converge to the equilibrium given by the cointegration vectors. The models were set up for the purpose of variance decomposition, which shows the extent (percentage) to which the variability in the rate of structural unemployment is explained by the rate of employment. This information is used to project the impact of loss of employment in the regions on the increase in structural unemployment in those regions.

The last step is the calculation of the rate of economic activity, which is derived directly from the results of the two preceding steps.

Results

The Czech Republic comprises 14 NUTS 3 regions: Praha (PRA), Středočeský (STR), Jihočeský (JIH), Plzeňský (PLZ), Karlovarský (KAR), Ústecký (UST), Liberecký (LIB), Královehradecký (KRA), Pardubický (PAR), Vysočina (VYS), Jihomoravský (JIM), Zlínský (ZLI), Olomoucký (OLO), Moravskoslezský (MOR). For clarity, these regions are shown in Figure 1. This section starts with a brief description of the regions, given their labour market characteristics. The section then proceeds with the presentation of the basic scenario and the scenario with the impacts of automation.

Figure 1

Map of Czech NUTS3 regions

Regional characteristics

Table 1 presents the age and educational structure of the population in each region. The projection is based on the current population projection, which is regularly published by the European Commission, especially for the analysis of aging. The analysis in this article is based on the last publication on ageing (given the time when this analysis was composed), European Commission, EC (2021).

The starting year of this report, EC (2021), was 2019. Although regional data are already available for 2020, it is more reasonable to base all of the analyses in this study on data for 2019. The data for 2020 are hugely influenced by the measures applied during the Covid-19 pandemic, and it is too soon to judge whether the data, as they are published today, capture this singular event in a reasonable manner. In this regard, the extent to which the impact of the measures might have long-term effects is not yet clear.

This publication, EC (2021), provides data on the projected rate of economic activity, that is, the ratio of the sum of employed and unemployed people to the working-age population. These data are only available for the Czech Republic.

The projection of the population by the EC (2021) is based on three basic pillars: the projection of the fertility rate, the projection of the mortality rate, and migration. The projection of the fertility rate is based on the extrapolation of four variables: overall fertility, starting age of fertility, age when fertility reaches its maximum, and age when fertility decreases to half of its maximum. The projection of mortality rate follows data on various age cohorts and sex, and the results are obtained by the application of splines (Wood 1994). Migration data were extrapolated using ARIMA to project the net migration rate. The methodology is explained in EC (2017).

As argued above, the impact of automation, among other factors, depends on the age structure and structure of completed education. Table 1 shows this information from a regional perspective. As stated in the previous section, primary and secondary education jobs are the most at risk with respect to automation.

Table 1

Characteristics of the population in the regions in 2019

(%)

Region	Population characteristics			Age structure		Levels of education structure			
	POP	WAP	LF	0–14	15+	1	2	3	4
PRA	12	12	13	16	84	7	17	38	38
STR	13	13	13	18	82	12	34	36	18
JIH	6	6	6	16	84	14	37	33	16
PLZ	5	6	6	16	84	13	37	34	16
KAR	3	3	3	15	85	19	36	33	13
UST	8	8	7	16	84	21	35	32	12
LIB	4	4	4	16	84	16	37	33	14
KRA	5	5	5	16	84	12	34	36	18
PAR	5	5	5	16	84	14	36	35	15
VYS	5	5	5	15	85	13	37	35	15
JIM	11	11	11	16	84	13	32	32	23
ZLI	5	6	5	15	85	14	37	33	15
OLO	6	6	6	16	84	16	37	32	16
MOR	11	11	11	15	85	16	36	32	16
CZ	100	100	100	16	84	14	33	34	19

Notes: Population characteristics (POP: total population, WAP: working-age population, LF: labour force, shares in totals of CZ), age structure (shares in totals of region), and levels of education structure according to ISCED (1: primary education, 2: lower secondary education, 3: secondary education, 4: tertiary education, shares in totals of region).

Source: CZSO (2019), own calculations.

Table 2 presents data on employment and standard overall labour market statistics. It was stated in the previous section that the type of occupation is an important variable with respect to the risk of automation. Following the discussion in the previous section, the occupation most at risk are: clerical support workers, service and sales workers, craft and related trades workers, plant and machine operators, and elementary occupations. This does not mean that these types of occupation face the same risk of being automated. However, they represent groups of occupations with a relatively higher concentration of lower education and a higher share of manual and routine tasks.

The most frequent definition of the working-age population is a population with an age span of 15–64 years or 15–74 years. Given the fact that labour force survey data on the number of unemployed in the regions are missing in some age groups, it was not possible to use these two most frequent definitions of working-age populations. Therefore, all variables were defined for a span of 15+.

Table 2

Labour market characteristics and occupations in 2019

(%)

Region	Labour market characteristics				Occupations shares in total employed									
	REA	ER	UR	EMP	1	2	3	4	5	6	7	8	9	10
PRA	65.4	64.5	1.3	13	6	31	22	12	13	0	8	5	3	0
STR	62.1	61.3	1.3	13	5	16	18	11	16	1	15	13	5	0
JIH	59.0	57.9	1.8	6	4	13	14	9	17	2	18	16	6	1
PLZ	60.8	60.0	1.3	6	3	14	17	8	15	2	15	19	7	0
KAR	62.3	59.7	4.2	3	5	10	14	10	19	1	16	16	8	0
UST	57.3	55.8	2.5	7	3	10	17	9	17	1	18	18	8	0
LIB	57.6	56.6	1.8	4	4	14	16	8	13	1	20	18	7	0
KRA	59.6	58.6	1.6	5	5	14	16	9	17	1	15	15	6	1
PAR	60.2	59.2	1.6	5	4	12	17	11	14	1	21	14	6	0
VYS	59.5	58.7	1.4	5	4	12	18	7	14	3	20	16	6	1
JIM	60.1	58.9	2.1	11	6	19	16	10	15	1	15	11	7	0
ZLI	58.4	57.3	2.0	5	4	11	15	9	14	1	22	16	7	0
OLO	58.8	57.4	2.4	6	5	12	16	8	15	2	18	16	7	1
MOR	59.0	56.9	3.7	11	3	14	16	8	18	1	17	16	7	0
CZ	60.4	59.2	2.0	100	4	16	17	9	15	1	16	14	6	0

Notes: REA – rate of economic activity, ER – employment rate, UR – unemployment rate, EMP – shares in the number of employed in the regions in the total of CZ, occupation shares in the totals of region according to ISCO (1: managers, 2: professionals, 3: technicians and associate professionals, 4: clerical support workers, 5: service and sales workers, 6: skilled agricultural, forestry, and fishery workers, 7: craft and related trade workers, 8: plant and machine operators, 9: elementary occupations, 10: armed forces occupations).

Source: CZSO (2019), own calculations.

The initial situation in the regional markets from the perspective of the projection may also be characterised by some existing studies. Using the probability of finding a job, Pošta–Hudeček (2017) show that, even in the period of economic expansion, this characteristic increased only slightly in the regions Ústecký, Moravskoslezský, and Královéhradecký. However, these regions, as well as Olomoucký and Vysočina, were hit by a rapid decrease in the probability of finding a job during the recession years. Němec (2015), using regional data, shows that the number of unemployed 50 years and older and the number of long-term unemployed clearly and negatively influence the rate with which the vacancies match the unemployed. However, higher education positively influenced this rate. This finding with respect to the level of education directly points to conclusions concerning the effects of automation on employment, which will also be used in the projection to determine the loss in the number of employees in the respective regions. The regions recognised as problematic by Pošta–Hudeček (2017) correspond quite well with the results of Tagai et al. (2018), who used both labour market characteristics and measures of poverty and social exclusion to detect problematic regions in Hungary and Czechia. The exceptionally good standing of Praha, the capital region, was confirmed and further explained in the analysis of the metropolisation process in Central and Eastern European countries by Zdanowska et al. (2020). However, it should be noted that even the problematic regions outlined above stand quite well in international comparisons, as shown by Dudek–Sedefoğlu (2019). The analysis below shows that, on average, these already problematic regions will be hit relatively rarely. The analysis of Dudek–Sedefoğlu (2019) then implies that in some other countries, the negative impacts of the same process may be overwhelming in the deprived regions they detected.

The basic scenario

The result of the projected division of the decrease in the rate of economic activity in the Czech Republic by 0.5 p.p. between regions is summarised in Table 3. The table also states the share of the working-age population in 2030, which is based on the population projection in the regions by CZSO (2019).

Given the value of 60.4% of the rate of economic activity in the Czech Republic in 2019 and its projected decrease by 0.5 p.p., EC (2021), it reaches 59.9% in 2030.

Table 3 presents the estimated anchors for the structural unemployment rates. The anchor for the Czech Republic was 6.1%.

Finally, Table 3 presents the rate of economic activity, unemployment, and employment in the basic scenario and their changes relative to 2019. The changes included in the basic scenario are the projected decrease in the rate of economic activity in the Czech Republic by 0.5 p.p., EC (2021), and the convergence of the unemployment rate with its anchor.

The decrease in the rate of economic activity will be most profound in Středočeský region (STR), which is due to the projected change in the age structure of the population. The projected change in the age structure of the population will have the opposite effect in the Moravskoslezský region (MOR), which is marked by the highest increase in the rate of economic activity. Considering that 2019 was located at the peak of expansion, unemployment rates were relatively low. Therefore, the projection shows a significant increase. These changes result in decreased employment rates, with the Středočeský region (STR) facing the most significant decline.

Table 3

Basic scenario

Region	Step 1 – REA				Step 2 – UR	
	$I^{REA\ loss}$	$LF^{2030/19}$	REA^{2030}	WAP share 2030	UR^{2030}	LF share 2030
PRA	2.2	4.1	62.8	13.0	2.9	13.7
STR	1.7	3.0	57.2	13.7	4.3	13.1
JIH	1.1	2.1	59.2	6.0	4.5	5.9
PLZ	1.2	2.1	59.9	5.6	4.7	5.6
KAR	0.3	0.6	64.6	2.6	8.7	2.8
UST	0.1	0.2	57.7	7.5	9.9	7.2
LIB	0.2	0.3	56.6	4.1	6.5	3.9
KRA	0.5	0.9	60.2	5.1	5.8	5.1
PAR	0.5	0.9	59.6	4.9	5.8	4.8
VYS	0.2	0.4	60.2	4.7	5.4	4.7
JIM	1.4	2.5	60.2	11.1	6.5	11.2
ZLI	0.9	1.7	55.7	5.7	6.5	5.3
OLO	0.7	1.3	65.3	5.3	7.6	5.8
MOR	0.4	0.8	61.4	10.7	9.7	11.0
CZ	1.0	1.8	59.9	100.0	6.1	100.0
Region	Summary					
	REA^{2030}	$REA^{2030/19}$	UR^{2030}	$UR^{2030/19}$	ER^{2030}	$ER^{2030/19}$
PRA	62.8	–2.9	2.9	1.6	60.9	–7.0
STR	57.2	–5.0	4.3	3.0	54.7	–11.8
JIH	59.2	0.2	4.5	2.8	56.5	–7.5
PLZ	59.9	–0.9	4.7	3.4	57.1	–8.8
KAR	64.6	2.3	8.7	4.5	59.0	–7.6
UST	57.7	0.4	9.9	7.4	52.0	–10.4
LIB	56.6	–1.1	6.5	4.7	52.9	–9.7
KRA	60.2	0.6	5.8	4.1	56.7	–7.7
PAR	59.6	–0.6	5.8	4.2	56.2	–9.1
VYS	60.2	0.7	5.4	4.0	57.0	–7.8
JIM	60.2	0.0	6.5	4.4	56.3	–7.9
ZLI	55.7	1.7	6.5	4.5	52.1	–11.1
OLO	65.3	1.8	7.6	5.1	60.3	–3.8
MOR	61.4	2.4	9.7	6.0	55.5	–7.8
CZ	59.9	–0.5	6.1	4.1	56.3	–8.5

Notes: Step 1 – REA ($I^{REA\ loss}$, see formula (2); $LF^{2030/19}$ in percentage change in the labour force between 2030 and 2019; REA^{2030} – projected rate of economic activity in % based on formula (2) and description in the previous section; WAP share 2030 – shares in the working age population, together with REA^{2030} enables check according to formula (3)) Step 2 (UR^{2030} – projected unemployment rate in % according to the description in the previous section; LF share 2030 – shares in labour force in %, together with UR^{2030} enables check according to formula (4)) Summary (ER^{2030} projected employment rate according to the description in the previous section, together with WAP share 2030 enables the check according to formula (5), changes in projections of REA, UR, and ER relative to 2019 in percentage points).

Source: CZSO (2019), EC, own calculations and estimates.

Note that the projection presented is marked by measurement errors. The projections of the European Commission do not need to respect the actual projections of the member states. These facts complicate the comparison of the basic scenario results with 2019 data. However, these inconsistencies are not important from the perspective of the main goal of this study, which is the comparison between the projection in the next section and the basic scenario in Table 3.

The scenario with the impacts of automation

Table 4 provides information on the share of the loss of employment, which is the value of index (6), as well as the resulting rate of employment. The Czech Republic employment rate is a weighted sum of the regional employment rates, with the regional shares in the total working-age population as weights. It reaches 50.6% in the Czech economy as a whole in 2030.

Table 4 also shows the rate of reaction of structural unemployment to changes in the employment rate and the final projection of the unemployment rate. The projection for the Czech Republic is based on the weighted sum of regional figures, with regional shares in the total labour force in 2030 as weights. It reaches 7.2%.

The last step is the calculation of the rate of economic activity, which is derived directly from the results of the two preceding steps. Table 4 also presents the rate of economic activity, unemployment, and employment in the scenario with the impacts of automation and their changes relative to the basic scenario. To make a comparison with the Czech Republic as a whole, the rates of economic activity, the rate of unemployment, and the rate of employment are 55.0% (decrease by 5.0 p.p.), 7.2% (increase by 1.1 p.p.), and 50.6% (decrease by 5.6 p.p.).

The results show that in terms of the loss in employment rate, the greatest impacts will occur in the Karlovarský (KAR), Ústecký (UST), and Olomoucký (OLO) regions.

This loss of employment rate is expected to significantly increase the unemployment rate only in the Karlovarský region. In other regions, the loss of employment takes its toll, especially in the form of a decrease in the rate of economic activity.

In the previous section Ústecký (UST), Moravskoslezský (MOR) and Královéhradecký (KRA) regions were characterised as problematic given the starting point of the projection. According to the projection, further significant deterioration in labour markets is expected.

However, without surprise, the Praha region (PRA) will be the least hit. In addition, it should be expected that the possible positive macroeconomic effects of automation discussed in the theoretical section of the paper will occur, especially in regions which are closely linked to the global economy. The Czech Republic is located in the Praha region, thereby implying overall positive effects in this region, in accordance with the results of the projection and theoretical argument.

Table 4

Scenario with the impacts of automation

Region	Step 1 – ER			Step 2 – UR		
	$I^{E\ loss}$	ER^{2030}	WAP share 2030	RR	UR^{2030}	LF share 2030
PRA	0.08	57.5	13.0	0.04	3.1	13.7
STR	0.13	49.5	13.7	0.22	5.5	13.1
JIH	0.06	50.4	6.0	0.18	5.6	5.9
PLZ	0.06	51.1	5.6	0.01	4.7	5.6
KAR	0.03	52.1	2.6	0.89	14.8	2.8
UST	0.09	45.4	7.5	0.20	11.2	7.2
LIB	0.04	46.8	4.1	0.16	7.5	3.9
KRA	0.05	50.9	5.1	0.18	6.8	5.1
PAR	0.05	50.1	4.9	0.01	5.9	4.8
VYS	0.05	50.9	4.7	0.06	5.7	4.7
JIM	0.11	50.9	11.1	0.28	8.0	11.2
ZLI	0.06	46.2	5.7	0.26	8.0	5.3
OLO	0.06	53.6	5.3	0.17	8.7	5.8
MOR	0.12	49.1	10.7	0.19	10.9	11.0
CZ	1.00	50.6	100.0	0.20	7.2	100.0

Region	Summary					
	REA^{2030}	REA relative to basic sc.	UR^{2030}	UR relative to basic sc.	ER^{2030}	ER relative to basic sc.
PRA	59.5	–3.3	3.1	0.1	57.5	–3.4
STR	52.6	–4.6	5.5	1.1	49.5	–5.2
JIH	53.7	–5.5	5.6	1.1	50.4	–6.1
PLZ	54.0	–5.9	4.7	0.0	51.1	–5.9
KAR	61.7	–2.9	14.8	6.1	52.1	–6.9
UST	51.9	–5.8	11.2	1.3	45.4	–6.6
LIB	51.1	–5.5	7.5	1.0	46.8	–6.1
KRA	55.0	–5.2	6.8	1.1	50.9	–5.8
PAR	53.6	–6.0	5.9	0.1	50.1	–6.1
VYS	54.4	–5.9	5.7	0.3	50.9	–6.1
JIM	55.8	–4.4	8.0	1.5	50.9	–5.4
ZLI	50.7	–5.1	8.0	1.5	46.2	–5.9
OLO	59.3	–6.0	8.7	1.2	53.6	–6.8
MOR	55.8	–5.7	10.9	1.2	49.1	–6.4
CZ	55.0	–5.0	7.2	1.1	50.6	–5.6

Notes: Step 1 – ER ($I^{E\ loss}$– see formula (6); ER^{2030} – projected employment rate in % according to the description in the previous section; WAP share 2030 – shares in the working age population, together with ER^{2030} enables check according to formula (5)) Step 2 (RR: rate of reaction of the unemployment rate based on VECM and the description in the previous section, UR^{2030} – projected unemployment rate in % according to the description in the previous section; LF share 2030 – shares in the labour force, together with UR^{2030} enables check according to formula (4)) Summary (REA^{2030} projected rate of economic activity in % according to the description in the previous section, together with WAP share 2030 enables check according to formula (3), changes in the projections of REA, UR, and ER relative to the basic scenario in percentage points in Table 3).

Source: CZSO (2019), EC, own calculations and estimates.

Conclusions

The projection shows that the hardest impacts will take place in Karlovarský, Ústecký and Olomoucký regions. The results were based on the structure of education and occupations achieved in the respective regions. Except for the Karlovarský region, the projected decrease in employment will lead to a decrease in economic activity rather than an increase in unemployment. This is because of the estimated relationships between structural unemployment and employment in the analysed regions.

The Karlovarský, Ústecký, and Olomoucký regions also have the lowest net disposable income per capita. According to the data from the Czech Statistical Office data, the lowest figure in 2019 was observed in Ústecký region; 87.7% of the level of the Czech Republic level. In Karlovarský and Olomoucký regions, the figures were 90.5% and 89.3%, respectively. It should also be considered that the average is driven up by the Praha region, which was observed at 133.3% of the Czech Republic level. Given the theoretical discussion, these figures show that the effects of automation will further propagate income polarisation.

The discussion also highlights that the key factors behind the negative impacts of automation on the labour market are education levels and the characteristics of tasks performed with an occupation. Most studies do not consider the lowest level of education to be the most endangered from the perspective of possible employment loss. However, most of the studies state that the relative remuneration for occupations based on a relatively low level of education will decrease. In other words, income polarisation increases. In this context, the idea of supporting a shift from a higher level of education to a lower level is refuted. On an average, occupations based on lower levels of education will be more endangered by the automation process, and those that are not destroyed will be hit by decreasing relative remuneration.

The projection is based on the lowest loss in employment at the Czech Republic level, which is based on the fact that none of the estimates considers the probable overall positive macroeconomic changes associated with technological change. Using some of the higher estimated losses would not qualitatively change anything as the main accommodation will potentially take place via changes in the rates of economic activity rather than unemployment.

There are conflicting results regarding skill mismatch. Rašovec–Vavřínová (2014) concluded that about 35% of the Czech population has reached a higher level of education than the employment requirements. This signifies a positive signal with respect to accommodations. A report by CEDEFOP (2016) identified shortages of engineers and technical professionals, likely due to a lower interest in technical secondary and tertiary education. This might hinder the process of accommodating ongoing technological shifts.

From a different but closely related perspective, there has been a broad discussion about the possibility of automatic social payments to those displaced by automation. However, the economic aspect of this question may be considered least important because with expected increase in productivity, there will be mechanisms for its distribution to the displaced. The social and psychological impacts on the displaced labour force, who will function without any labour ties, are more significant for consideration than the concrete parameters of such mechanisms. The weak results of the scientific discussion of such questions did not yield clear conclusions.

The most important questions related to the diseggregation of the overall impacts between the regions are now related to the impacts of the measures applied in an attempt to combat the Covid-19 pandemic and the impacts of the upcoming recession, stemming partially from these same measures, and also provoked by the sanctions imposed against Russia in 2022. These questions are related to the time involved in the application of new technologies and, rebuilding of global value chains, resulting in changes in the functioning of Czech economy along with its employment organization, especially with respect to remote work. Since, the available data are insufficient and highly uncertain, these impacts are yet to materialise altogether, thereby building a case for remote work.

Appendix

Table A1

Unit root tests

Region	Rate of		Difference of rate of	
	structural unemployment	employment	structural unemployment	employment
PRA	–0.395	–0.461	–2.846*	–3.689**
STR	–1.058	–0.162	–2.750*	–3.338**
JIH	–1.663	–2.570	–2.770*	–3.118**
PLZ	–2.108	–1.364	–2.822*	–4.704***
KAR	–2.286	–1.496	–4.094***	–3.178**
UST	–1.573	–2.229	–4.705***	–4.442***
LIB	–1.107	–2.129	–2.881*	–4.036***
KRA	–0.816	–1.916	–3.154**	–3.146**
PAR	–1.509	–2.190	–2.820*	–4.076***
VYS	–1.924	–2.212	–2.932*	–3.862***
JIM	–2.086	–0.647	–2.980*	–3.536**
ZLI	–2.077	–2.288	–2.840*	–4.004***
OLO	–1.632	–1.907	–2.866*	–4.055***
MOR	–1.302	–1.935	–2.859*	–3.014**

Notes: The presence of unit roots was tested using the ADF test with the null hypothesis of unit root (non-stationarity). *, **, *** denotes rejection of the null hypothesis at the significance level of 10%, 5%, 1%. In any case, the null hypothesis is not rejected. The null hypothesis is rejected in all cases given the first difference of the series.

Table A2

Vector error correction models (VECM)

Region	Constant	Rate of employment (–1)	EC	LM	White	JB
PRA	11.442*	–0.249**	–0.005**	6.754	36.692	3.333
STR	36.740***	–0.557***	–0.021***	5.999	37.340	2.249
JIH	48.662***	–0.800**	–0.003***	4.809	40.718	2.476
PLZ	35.570***	–0.539***	–0.017***	2.064	43.605	2.482
KAR	43.014***	–0.622***	–0.022***	4.223	38.506	2.086
UST	35.259*	–0.564*	–0.004***	3.769	37.994	5.517
LIB	53.067***	–0.866***	–0.004**	2.143	53.502	2.111
KRA	32.558***	–0.487***	–0.029**	2.671	41.240	0.848
PAR	45.730***	–0.768***	–0.004***	3.166	45.621	2.635
VYS	61.489**	–0.927***	–0.005***	2.422	45.001	1.180
JIM	26.148***	–0.399**	–0.007***	3.113	33.019	3.999
ZLI	88.480***	–0.926***	–0.004***	4.159	44.694	2.681
OLO	38.999**	–0.617**	–0.008***	2.835	45.121	1.693
MOR	51.614***	–0.806***	–0.014***	1.945	48.407	2.492

Notes: Form of VECM: $\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{3} \Phi_i \Delta X_{t-i} + \varepsilon_t$, where $\mathbf{X}$ is a vector of endogenous variables (rate of structural unemployment and rate of employment), $\mathbf{\Pi}$ is a matrix of parameters of (a) coefficients of adjustment, denoted as *EC*; and (b) coefficients of cointegration vector, denoted as constant and coefficient of rate of employment. $\mathbf{\Phi}$ is the matrix of coefficients (three lags are necessary to eliminate autocorrelation in the residuals) and ε is the vector of residuals. The first three columns present a cointegration vector: the constant and lagged employment rates. The T tests are related to the test of the null hypothesis of the zero value of the particular coefficient. The last three columns present diagnostic residuals. LM is a statistic of the autocorrelation test with the null hypothesis of no autocorrelation at the first lag (sufficient with yearly data). White is the statistic of the heteroskedasticity test with the null hypothesis of no heteroskedasticity in the residuals. JB is a statistic of the normality test given Cholesky decomposition with the null of the normal distribution. *, **, *** denotes rejection of the null hypothesis at the significance level of 10%, 5%, 1%.

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