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GENDER AND SKILL DIMENSIONS OF TECHNOLOGICAL TRANSITIONS AT WORKPLACES: THE CASE OF THE CZECH REPUBLIC, POLAND AND SLOVAKIA

ZMIANY TECHNOLOGICZNE W MIEJSCU PRACY W KONTEKŚCIE PŁCI I UMIEJĘTNOŚCI. PRZYPADEK CZECH, POLSKI I SŁOWACJI

Abstract: The study seeks to investigate the impact of technology on employment by gender and skills of the labour markets in the Czech Republic, Poland and Slovakia, and employs the VAR model to analyse the impact of technology on employment by gender. It also uses a panel cointegrated autoregressive distributed lag model for the impact of technology on employment by skill groups. The study finds that although technology impacts on employment of gender in the three countries, it is however gender neutral. This study also finds that in the long-term, technology impacts negatively on middle skill employment and positively on low skill and high skill employment in a similar pattern before and after the global financial crises. The impact of technology varies across countries in the short term, attributed to cross-country differences in labour market policies and institutions.

Keywords: employment, technology, gender, skill.

Streszczenie: W artykule podjęto próbę zbadania wpływu technologii na zatrudnienie według płci i umiejętności na rynkach pracy w Czechach, Polsce i na Słowacji. Do analizy wpływu technologii na zatrudnienie według płci wykorzystano model VAR. Zastosowano ponadto panelowy model autoregresji z opóźnieniami rozłożonymi, by oszacować wpływ technologii na zatrudnienie według kategorii umiejętności. Z badania wynika, że chociaż technologia wpływa na zatrudnienie według płci w każdym z trzech analizowanych krajów, jest płciowo neutralna. W badaniu tym stwierdzono również, że w dłuższej perspektywie technologia wpływa negatywnie na zatrudnienie średnio wykwalifikowanych osób, pozytywnie natomiast na zatrudnienie osób o niskich i wysokich kwalifikacjach, w podobnym zakresie przed globalnym kryzysem finansowym i po nim. W krótkim okresie wpływ technologii jest zróżnicowany w poszczególnych krajach, co przypisuje się odmiennościom polityk oraz instytucji rynku pracy.

Słowa kluczowe: zatrudnienie, technologia, płeć, umiejętności.

1. Introduction

There is growing concern about the implications of technological innovation on employment in the global economy. Jobs have been eliminated through the use of technology as evidenced in e.g. Acemoglu and Restrepo (2017). Employment has over the years received the impact of the diffusion of technology and automation in an unpredictable fashion (see Brynjolfsson and McAfee, 2012; Crespi and Tacsir, 2011). In actual fact, technological innovation is creating job opportunities in new industries and new occupations (OECD, 2017) but it also leads to job losses, as more tasks traditionally performed by humans are now executed by machines. The proponents of technological innovation argue that technology brings about product innovations and its indirect effects bring benefits that cancel out the direct effect of job destruction (see Calvino and Virgillito, 2018; Ugur, Churchill, and Solomon 2018; Vivarelli, 2014). Their opponents argue that progress in technology leaves behind the aspect of labour in terms of opportunities and welfare benefits (see Brynjolfsson and McAfee, 2012).

It is an undeniable fact that human progress occurs using technology, and the without technological progress there would be very slow economic development. It is, however, unlikely that technology affects all individuals, groups and genders, equally. A cursory look at the evidence from research in this area shows that the impact of technological innovation on gender is mixed. Women and men face the same unemployment or displacement threats from new technologies (OECD, 2017). There is a sizable literature regarding the differential effects of technology by gender, such as studies by Fox et al. (2006) and Kitetu (2008), who consider women to be underrepresented in the world of science and technology. A more recent group of literature is optimistic concerning the impact of technology on employment. According to this group, technology will enhance better gender performance rather than affect it negatively (Wajcman, 2004; Rosser, 2006).

Technology has also been addressed as the main driver of structural changes in the labour markets in literature. Seemingly diminishing middle skill jobs with a high level of routine activities might have rather negative socio-economic impact unless they have undergone re-training to find other middle skill or even high skill jobs. When middle skill workers move to low skill jobs or stay unemployed, it could have unwanted social impacts on individuals who are members of the middle societal class being considered as the median voters. Losing that middle-class way of life might lead to dissatisfied voters looking for change in terms of the political environment. These extreme groups may often become influential politically in some countries (see Hainmueller, Hiscox, and Margalit, 2014), leading to political or social unrest, Nchor and Rozmahel (2020).

Regarding the different economic history of the Visegrad countries with market economies based on the heritage of centrally planned systems, and with respect to historically strong socially-oriented labour policies, one might expect a different development of structural changes in employment in these countries. Lower flexibility, the strong role of trade unions, a different institutional background, and relying on the comparative advantage of being a low-cost economy, all provide different conditions for the impact of the technological transition on the labour markets in these countries.

The relevance of this study is based on the fact that the plethora of literature focuses on general cases of technological innovation and employment. There is less emphasis on the Visegrad countries such as the Czech Republic, Poland and Slovakia. This paper presents a descriptive and quantitative analyses that rely on two main logical building blocks typically found in the literature. Firstly, the use of the Vector Autoregressive Model (VAR) impulse responses to show the impact of technology on gender employment in each of the countries. Secondly, the use of a panel cointegrated autoregressive distributed lag model to assess the impact of technology on employment within the various skilled groups before and after the global financial crises,see Nchor and Rozmahel (2020). Technological innovation is measured using the percentage contribution of Internet Communication Technology (ICT) in Gross Domestic Product (GDP). This is because ICT captures the influence of several innovations in the production processes in firms and enterprises (OECD, 2001).

The significance of the findings of this study rests in the fact that changing the employment distribution in the Visegrad countries may result in socio-economic effects such as unequal wage and income distribution across skill levels and genders, which might be even more problematic in post-communist countries with uncompleted economic and institutional convergence to the core principle of the EU. The structure of the paper is as follows: the first section introduces the objective and explains the motivation for researching the case of technology, gender, and skill groups in the Visegrad countries. This section also reviews the literature on the topic. The second section describes and explains the methods and data. The results

of the VAR and ARDL models are presented and discussed in the third section. Section 4 concludes the paper.

2. Literature review

The recent literature emphasizes the role of technological innovation on the labour markets of countries, using two theories to explain these changes in the labor market: Skill-Biased Technological Change and Routine-Biased Technological Change. The former shows that the demand for labour develops in line with rising skills and knowledge (see Acemoglu and Autor, 2011), and holds that a positive relationship exists between the demand for labour and educational skills. Due to the inability of this theory to explain all the changes in the labour markets of the countries, the Routine Biased Technological theory was introduced, which emphasizes how technology replaces jobs that are routine by nature. Obviously, technology is a driver of structural changes in the labour market. The huge socio-economic and political implications of technologically induced unemployment are the reasons why the impact of technology on gender employment makes this issue popular in recent literature. The literature regarding the Czech Republic, Poland and Slovakia remains rather heterogenous with respect to the approaches and findings.

In terms of the differences in the economic history of the three Visegrad countries, all of them have had market economies with centrally planned systems. The labour market developments are quite similar, although historically with their strong socially oriented labour policies, different developments are expected in their labour markets, in which flexibility is quite low. There is also the strong participation of the trade unions. The three countries also have the advantage of being low-cost economies and low-cost labour services.

Total levels of employment in the Czech Republic, Poland and Slovakia are estimated at 79.9%, 72.2%, 72.4% respectively, as at the end of 2018. The male employment rate is 87.4% in the Czech Republic, 79.4% in Poland and 79.2% in Slovakia using 2018 figures. The female employment rate is 72.2% in the Czech Republic, 65% in Poland and 65.5% in Slovakia as at the end of 2018. The gender employment gap is 15.2% in the Czech Republic, 14.4% in Poland and 13.7% in Slovakia, and has been declining in both the Czech Republic and Slovakia, but somehow stays steady with rises and falls in Poland. Total long-term unemployment in the Czech Republic is at 0.7% as at the end of 2018. Similarly, Poland has an estimated long-term unemployment of about 1.0%. Slovakia has the highest rate of long-term unemployment out of all the three countries, 4.0%. Long-term unemployment among males and females in the Czech Republic is 0.6% and 0.8%, respectively.

Poland has the same rate of long-term unemployment for males and females at 1.0%, while long-term unemployment for males in Slovakia is the same as the national figure, i.e. 4.0%. There is a 4.1% rate of long-term female unemployment.

The contribution of ICT to GDP varies amongst all three Visegrad countries. The percentage of ICT in GDP as at the end of 2017 was 4.42% in the Czech Republic, 3.33% in Poland and 4.3% in Slovakia. All figures for this review section were obtained from Eurostat (Eurostat, 2020).

3. Methodology

This study focuses on two research questions. The first is to investigate the impact of technology on employment by gender in the Czech Republic, Poland and Slovakia. The second is to assess the impact of technology on employment by skilled group in each of these countries. The first research question was answered using VAR impulse response functions. The second was answered using a panel cointegrated autoregressive distributed lag model. The main data source for this study is the harmonized individual European Union Labour Force Survey (ELFS) data. The ELFS contains data on employment status, using 2-digit International Standard Occupational Classification (ISCO) codes. The modelled variables for the VAR model include technology and unemployment. Technology is measured using the percentage of ICT in GDP. Unemployment is measured as a percentage of the total labour force. For each country the study runs two VAR models for males and females for a comparison of the results. The modelled variables for the panel cointegrated autoregressive distributed lag model are employment, real gross value added and technology. The measurement of technology remains the same as in the VAR model, and employment is also measured as a percentage of the total labour force as in the case of unemployment.

For the first research question using the VAR model, the study performed the time series verifications including the stationarity test, lag order selection and the cointegration test. The stationarity test was performed using the Augmented Dickey--Fuller test (Dickey and Fuller, 1979); lag order selection was carried out using the various information criteria: cf. Akaike (1979), Hannan-Quinn (1979) and Schwarz (1978). The cointegration test was conducted using the Johansen test of cointegration (Johansen, 1988). The optimum lags were decided using lag the frequency test. All the results were generated with Python software.

In contrast to many traditional VAR papers such as Bayoumi and Eichengreen (1992), more emphasis was placed on ensuring that this model is well specified, to ensure that it fulfils the issues of non-correlation, heteroscedasticity, and normality. The VAR specification in a basic form is made of a set of H endogenous variables. y_t represents the dependent variable – in this case unemployment. In each of the VAR cases, $x_{1t}, …, x_{ht}, …, x_{Ht}$ represent the set of independent variables – in this case technology (ICT). The subscripts t and h represent the time dimension and the position of the variable.

$$y_t = (x_{1t}, …, x_{ht}, …, x_{Ht}) \text{ for } h = 1…H.$$

(1)

The definition of the VAR(p)-process is given as

$$y_t = My_{t-1} + \ldots + A_p x_{t-p} + \mu_t,$$ (2)

where M_i is (H × H) coefficient matrices for $i = 1,\ldots, p$. is an H-dimensional process and E(μ_t) is 0. The covariance matrix is given by $E(\mu_t \mu_t^T) = \Sigma_\mu$ of white noise. One of the most important features of VAR(p) is stability of the system. p represents the number of lag periods. This can be checked using the characteristic polynomial:

$$\det(I_h - M_1 z - \ldots - M_p z^p) \text{ which is not equal to zero for } [z] \leq 1.$$ (3)

Given that the solution of the equation stated in (3) has a root for the value when z is equal to 1, then some variables in the process may be integrated of order one. If the variables are found to be cointegrated, then the process is appropriately analysed using a Vector Error Correction model (VECM).

The study applies a traditional VAR because it helps with inferences and forecasting. The unrestricted VAR coefficients and the innovations generated are uninterpretable. The results are presented through impulse response functions which produced the time path of Unemployment in the VAR model to shocks from technology. Shocks decline to zero when the system of equations is stable, whilst an explosive path indicates an unstable system. This study chose the ordering to be the Cholesky decomposition. In a moving average form, the VAR process is defined as:

$$y_t = \Phi_0 \mu_t + \Phi_1 \mu_{t-1} + \Phi_2 \mu_{t-2} + \ldots,$$ (4)

where $\Phi_0 = I_H$ and Φ_S are calculated as in equation (5),

$$\Phi_s = \sum_{j=1}^{s} \Phi_{s-j} M_j \text{ for } s = 1, 2, \ldots,$$ (5)

where

$$M_j = 0 \text{ for } j > p.$$

The study answers the second research question using a panel autoregressive distributed lag model. Technology, real gross value added and employment by skill level are the three modelled variables. Technology is measured using the percentage contribution of ICT in GDP in each of the countries. Real value added is measured by dividing gross value added by inflation and it is in expressed millions of euros. Data on employment were taken from the ELFS. The classification used in this study is according to the International Standard Classification of Occupations (ISCO-08), including: Managers, Professionals, Technicians and associate professionals, Cleri-

cal support workers, Service and sales workers, Skilled Agriculture, Fishery and Forestry workers, Craft and related trades workers, Plant and machine operators and assemblers and Elementary occupations, cf. Nchor and Rozmahel (2020). The occupations are classified into skill groups based on two concepts, the nature of work performed and the concept of skill (ILO, 2012). The study also specifies three skill levels: Low skill, Middle skill and High skill. All elementary occupations are considered as Low skill (Skill level 1). Middle skill occupations include clerical and support workers, service and sales workers, skilled agricultural workers, forestry and fishery workers as well as craft and trade related workers. Managers, professionals, technicians, and associate professionals are classified as high skill occupations.

The study investigated the impact of the global financial crises on the relationship between technology and employment by dividing the dataset into two periods. The years 2000-2007 represent the period before the global financial crises and 2008--2017 the period after the financial crises. The study first tested for Unit roots in the dataset according to Levin et al. (1992). It also tested for panel cointegration using the Kao test (Kao, 1999). The choice of optimal lag lengths is based on the Akaike Information Criterion (Akaike, 1974). Logarithms of all variables were taken, and the results were generated in Python 3.4.3.

The Pooled Mean Group (PMG) estimator was used for the estimation of the model results according to the approach of Pesaran et al. (1999). The feature of the PMG estimator is to constrain all long-term coefficients as identical. It however allows for variation in short-term coefficients (Baltagi and Griffin, 1997). This means that the short-term impact of technology is allowed to vary across the Visegrad countries while a common relationship is imposed on the long-term coefficients.

The study employed the Hausman tests (Hausman, 1978) to verify the appropriateness of PMG over MG (Mean Group). The Hausman test assumes that the PMG estimator is consistent and efficient. Using the ARDL approach according to Pesaran, Shin, and Smith, (1999), the study tested the presence of a long-term relationship using a general ARDL representation of equation (6), as follows:

$$\Delta lnY_{it} = \alpha_i + \sum_{j=1}^{p}\beta_j\Delta lnY_{it-j} + \sum_{j=0}^{q}\left[\theta_j\Delta lnX_{it-j} + \gamma_j\Delta lnZ_{it-j}\right] + \varnothing_1 lnY_{it-1} \quad (6)$$
$$+\varnothing_2 lnX_{it} + \varnothing_3 lnZ_{it} + \mu_{it}.$$

Δ represents first order difference. Specific fixed effects are represented in respective countries by α_i. Employment is expressed in thousands of persons and represented by Y_{it}. Low skill employment is measured by adding up the employment of the occupations within the low skill category (elementary occupations), similarly for middle skill and higher skill. Real value added is represented by X_{it}. The ratio of gross value added to inflation gives real value added. Z_{it} refers to ICT which is the proxy for technology, and μ_{it} is the error term. For each of the models, low skill employment, middle skill employment and high skill employment are dependent variables Nchor and Rozmahel (2020). The results from the model show the impact

of real value added and technology on employment in the three Visegrad countries. Given that an impact is established, what is the magnitude and direction of the impact? Employment is determined by several factors, but for the purposes and the goal of the study, the focus is limited to technology and the impact from all the other factors, felt through real value added. In other words, growth in employment which is not related to changes in technology will be attributed to growth in real value added which is determined by other employment factors.

The expressions with summation signs in equation (6) represent dynamics in the short term, while the coefficients of the lagged regressor variables are elasticities in the long term. The long-term elasticities are obtained by multiplying the long-term coefficients by negative 1 and dividing the result by the coefficient of the lagged dependent variable. The study chose the ARDL representation using the Akaike information criterion (AIC) or the Bayesian information criterion (BIC). Maximum lags were obtained for each variable in the panel model according to the lag frequencies. For low skill employment the preferred specification was ARDL (1, 1, 3), while ARDL (1, 3, 1) was used for middle skill model. ARDL (1, 5, 1) was used in the case of high skill employment. An error-correction for the ARDL model regarding the variables in equation (6) is as follows:

$$\Delta lnY_{it} = \alpha_i + \sum_{j=1}^{p-1} \beta_j \Delta lnY_{it-j} + \sum_{j=0}^{q-1} \left[\theta_j \Delta lnX_{it-j} + \gamma_j \Delta lnZ_{it-j} \right] + \delta_1 lnY_{it-1} + \\ + \delta_2 lnX_{it} + \delta_3 lnZ_{it} + \mu_{it}. \tag{7}$$

δ_1 in equation (7) represents the speed of adjustment. A positive value for δ_1 indicates a divergence from the long-term equilibrium and a negative δ_1 shows convergence. The speed of adjustment parameter and the short-term estimates (β_j, θ_j and γ_j) in the ECM were estimated directly. The long-term elasticities were then calculated as $-\dfrac{\delta_2}{\delta_1}$ and $-\dfrac{\delta_3}{\delta_1}$. The long-term coefficients (δ_1, δ_2, δ_3) were constrained to be identical across countries, but the short-term coefficients (β_j, θ_j, γ_j and α_j) differ from country to country. The results of the VAR and ARDL models are discussed in the next section.

4. Results

This section contains the interpretation of the results of the VAR impulse responses and the ARDL model. It also includes a subsection that focuses on a discussion of the results and a comparison with the findings of other existing studies.

The results of the model start with the Hausman test and are followed by the results of the panel autoregressive distributed lag model. The study used the Hausman (1978) test to show that the restriction of long-term parameters (PMG) gives efficient results. The null hypothesis of the Hausman test was that all long-term slopes are homogenous. The failure to reject the null hypothesis of long-term

slope homogeneity shows that PMG is the appropriate estimator for the study. In relation to this study, the Hausman test also helped to confirm the fact that a common long-term impact of technology can be imposed on the Visegrad countries, while allowing the impact to differ across the countries in the short term.

Table 1 shows the results of the Hausman test. There are three categories each for a skill group (low skill, middle skill and high skill). All P values obtained from the tests are greater than the significance level of 0.05 and that places the Pooled Mean Group (PMG) over the Mean Group.

Table 1. Results of the Hausman test of mean group and pooled mean group models

| Variable	Low skill employment			
	(b)	(B)	(b−B)	
	MG	PMG	difference	S.E.
Log GVA(L1.)	0.907	1.151	−0.244	0.469
Log TFP (L1.)	−2.422	−3.569	1.147	3.926
Chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)	P value			
0.4	0.821			
	Middle skill employment			
Variable	(b)	(B)	(b−B)	
	MG	PMG	difference	S.E.
Log GVA (L1.)	0.228	0.428	−0.200	0.090
Log TFP (L1.)	−0.444	−1.149	0.705	0.580
Chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)	P value			
4.94	0.085			
	High skill employment			
Variable	(b)	(B)	(b−B)	
	MG	PMG	difference	S.E.
Log GVA (L1.)	0.009	0.205	−0.197	0.273
Log TFP (L1.)	1.470	1.155	0.315	2.923
Chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)	P value			
4.94	0.085			

Note: b = consistent under Ho and Ha; obtained from xtpmg, B = inconsistent under Ha, efficient under Ho; obtained from xtpmg, Test: Ho: difference in coefficients not systematic, L1 represents lag 1, sqrt (square root), (STATA, 2015)

Source: (Nchor and Rozmahel, 2020).

4.1. The impact of technology on unemployment by gender in the Czech Republic

Figure 1 shows the impulse response functions for shocks from each of the variables, but this paper focuses on shocks from technology (ICT) to male and female unemployment in the Czech Republic. The results are mixed. The initial impact of a shock from technology on newly employed workers as well as male and female

unemployment is zero. For newly employed workers the impact becomes positive after a short period and oscillates between positive and negative before discontinuing. For male and female unemployment, the impact of a shock from technology turns positive and then negative, before expiring. The positive and negative impact of technology observed shows that it destroys but also creates jobs.
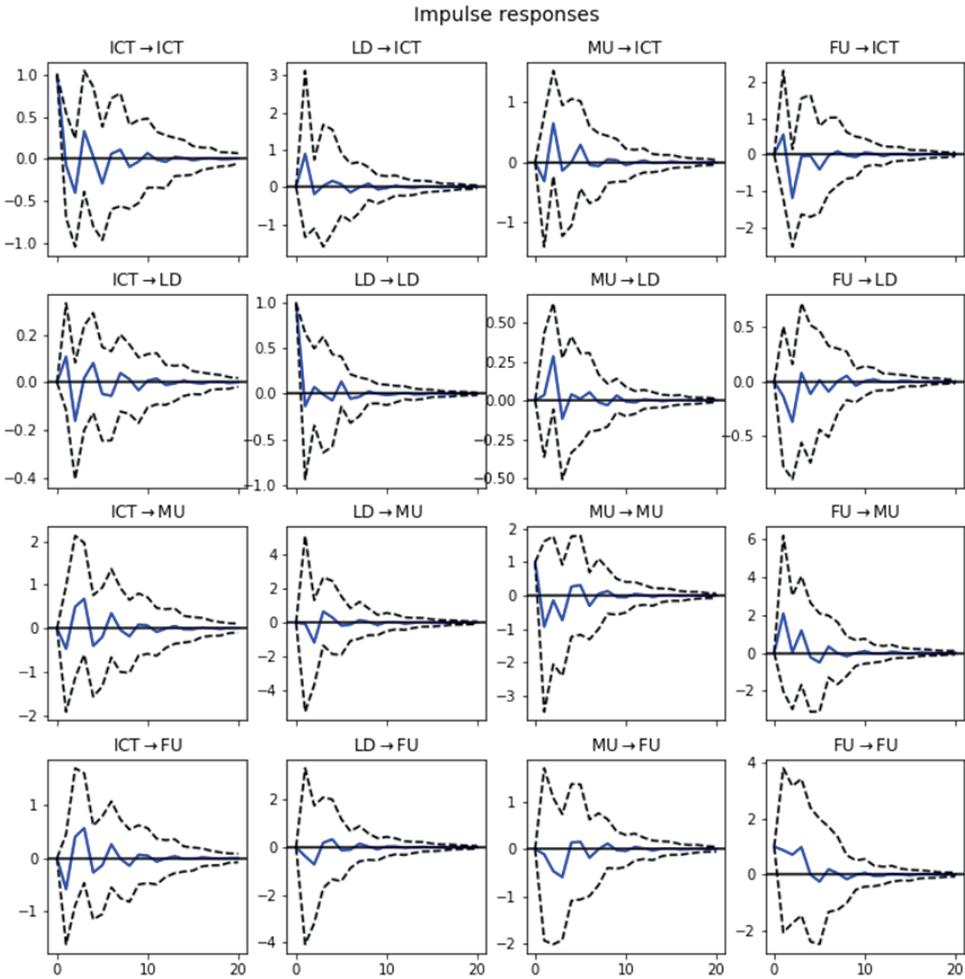
MU represents male unemployment, FU represents female unemployment, LD represents the demand for newly employed workers, ICT is the proxy for technology.

Fig. 1. IRFs the Czech Republic

Source: generated by the authors using Python 3.4.3.

4.2. The impact of technology on unemployment by gender in Poland

Figure 2 shows the impulse response functions for shocks from technology to employment in Poland. The scenario is similar to that of the Czech Republic. The initial impact of technological shock is zero for all variables. For newly employed workers, the impact turns positive after a short period and oscillates between positive and negative before discontinuing. The impact for male and female unemployment also oscillates between negative and positive but the negative impact is more than the positive. This implies that increasing automation in the workplace leads to a decrease in unemployment or an increase in employment.
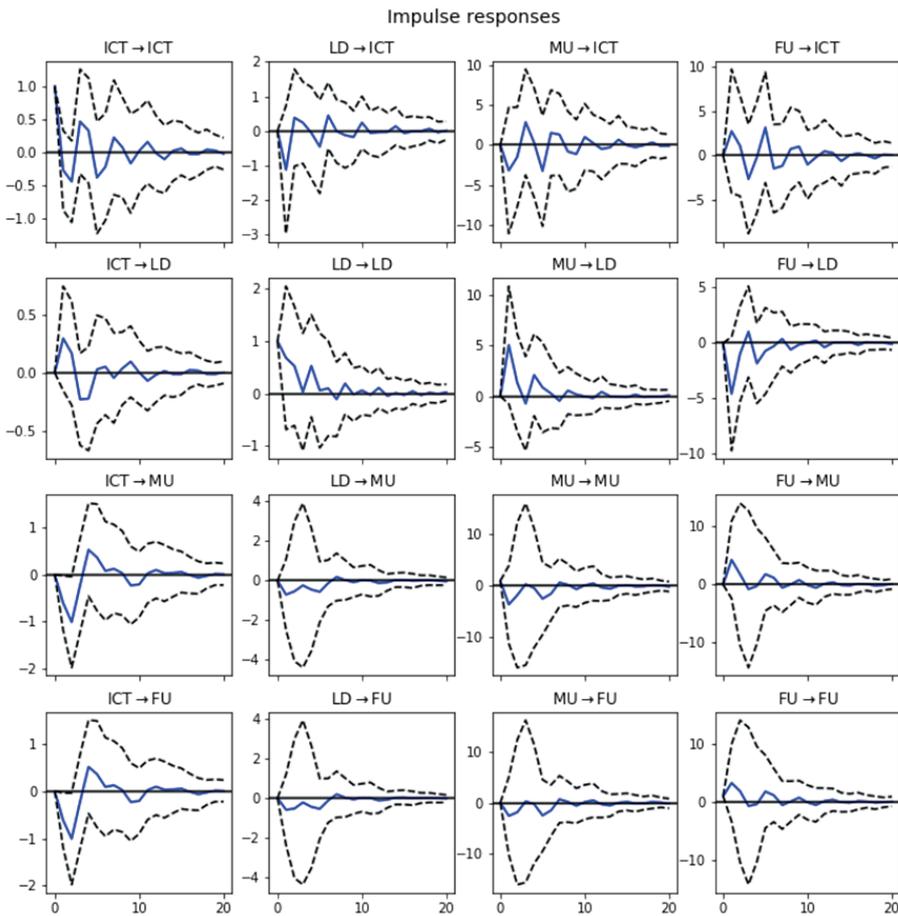

MU represents male unemployment, FU represents female unemployment, LD represents the demand for newly employed workers, ICT is the proxy for technology.

Fig. 2. IRFs Poland

Source: generated by the authors using Python 3.4.3.

4.3. The impact of technology on unemployment by gender in Slovakia

Figure 3 shows the impulse response function of a shock from technology in Slovakia. The results show that the impact of technological shock on the newly employed is zero. The impact on male and female unemployment is initially zero, however it becomes positive and then negative before expiring. The negative impact is greater, indicating that the introduction of technological innovation to workplaces increases employment or decreases unemployment in Slovakia. Technology thus creates more jobs than destroys in this process.
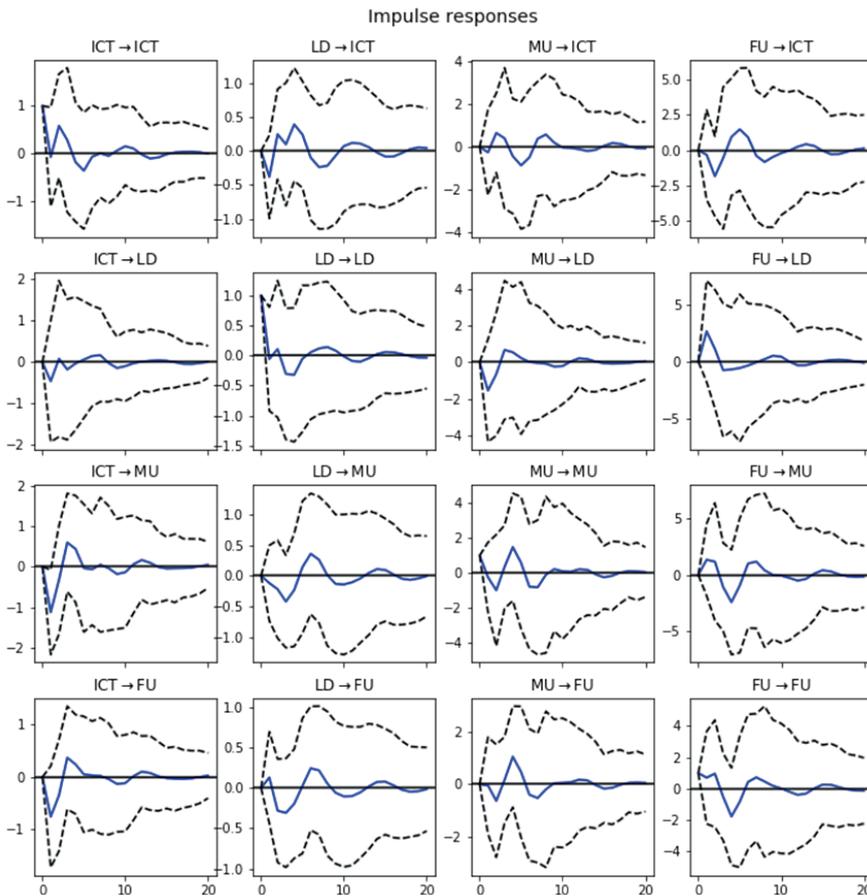

MU represents male unemployment, FU represents female unemployment, LD represents the demand for newly employed workers, ICT is the proxy for technology.

Fig. 3. IRFs Slovakia

Source: generated by the authors using Python 3.4.3.

4.4. The impact of technology on total employment by skill level before the financial crises

Given the impact the global financial crises had on economic performance and employment in European countries, it is imperative to investigate whether the relationship between technological innovation and employment within the various skill groups was affected. The dataset was split into two periods: one before the crises and anther after. The former covers the years 2000-2007, and the latter 2008--2017. The results follow the same pattern with regards to the long-term impact of technology on each of the skill groups. There is however variation in the speeds of adjustment for the two periods. Tables 1 to 3 show for employment before the crises, while Tables 4 to 6 show the numbers after the crises.

Table 2 shows the aspect of technology and low skill employment. It was observed that the long-term impact of technology was positive for all the Visegrad countries studied. The short-term impacts are different as was expected. The Czech Republic and Slovakia have positive speeds of adjustment to the long-term equilibrium indicating divergence. Deviations of low skill employment from the long-term equilibrium are corrected in Poland because of the negative speed of the adjustment parameter.

Table 2. Technology vs low skill employment before the crises

Variables	ECT	Czech R	Poland	Slovakia
ECT		1.151***	−0.130	0.004
		(0.280)	(0.106)	(0.008)
D. ln GVA		−0.000	0.002**	0.003***
		(0.001)	(0.001)	(0.001)
D.TFP		0.129***	−0.193	0.37
		(0.031)	(0.123)	(0.81)
L. ln GVA	0.004***			
	(0.000)			
L.TFP	0.121***			
	(0.004)			
Constant		−0.810***	0.995	−0.534
		(0.195)	(0.934)	(0.607)
Observations	36	36	36	36

Each variable has a maximum lag set to five. The study decided the optimal lag lengths using the Akaike Information Criterion. Standard errors are represented in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * p<0.1, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, D, D2, D3…D and its subscripts represent lags of first order difference variables. The study used L to represent the long term. ECT means Error Correction Term.

Source: generated by the authors using Python 3.4.3.

Table 3 shows middle skill employment before the crises. The observed long-term impact of technology on middle skill employment before the crises is also negative. The speed of the adjustment parameter in Poland is positive indicating divergence from the long-term equilibrium. Both the Czech Republic and Slovakia have negative speeds of adjustment parameters, indicating that deviations from the long-term equilibrium are corrected periodically. The speed of adjustment in the middle skill category is higher than the low skill category.

Table 3. Technology vs middle skill employment before the crises

Variables	ECT	Czech R	Poland	Slovakia
ECT		−0.283***	0.211	−0.197*
		(0.062)	(0.164)	(0.109)
D.ln GVA		−0.009***	0.008***	−0.003
		(0.002)	(0.002)	(0.003)
D. TFP		0.14	0.115*	0.102**
		(0.469)	(0.059)	(0.049)
L.ln GVA	0.035***			
	(0.002)			
L.TFP	−0.231***			
	(0.020)			
Constant		0.084	−0.100**	−0.115
		(0.240)	(0.047)	(0.441)
Observations	36	36	36	36

Each variable has a maximum lag set to five. The study decided the optimal lag lengths using the Akaike Information Criterion. Standard errors are represented in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, D, D2, D3…D and its subscripts represent lags of first order difference variables. The study used L to represent the long term. ECT means Error Correction Term.

Source: generated by authors using Python 3.4.3.

Table 4 shows the high skill employment before the global financial crises. The long-term speed of adjustment parameter of Poland is positive, indicating divergence from the long-term equilibrium. Both the Czech Republic and Slovakia have negative speeds of adjustment parameters, indicating that deviations from the long-term equilibrium are corrected periodically. The impact of technology is positive in the long-term across the Visegrad countries but differs from country to country in the short term.

Table 4. Technology vs high skill employment before the crises

Variables	ECT	Czech R	Poland	Slovakia
1	2	3	4	5
ECT		−0.235**	0.118***	−1.352***
		(0.101)	(0.010)	(0.000)

1	2	3	4	5
D. ln GVA		0.002*	0.001***	−0.008***
		(0.001)	(0.000)	(0.000)
D.TFP		−0.230***	−0.297***	−0.44***
		(0.033)	(0.011)	(0.000)
L. ln GVA	0.016***			
	(0.000)			
L.TFP	0.204			
	(0.000)			
Constant		−0.063	0.53**	−0.81***
		(0.104)	(0.26)	(0.000)
Observations	30	30	30	30

Each variable has a maximum lag set to five. The study decided the optimal lag lengths using the Akaike Information Criterion. Standard errors are represented in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, D, D2, D3…D and its subscripts represent lags of first order difference variables. The study used L to represent the long term. ECT means Error Correction Term.

Source: generated by the authors using Python 3.4.3.

4.5. The impact of technology on total employment by skill level after the financial crises

After the global financial crises, unemployment rose sharply in the Visegrad countries, yet its severity varied widely between countries and groups. Just as with unemployment, the demand by firms for technology also decreased since production volumes were being cut. The study sought to investigate whether the relationship between technology and employment within the various skill groups was altered by the global financial crises, comparing the results of the models from before and after the global financial crises. Table 5 shows the results for low skill employment after the global financial crises. It is observed that the long-term impact of technology was also positive just like in the pre-crises period. The short-term impacts differ with lags and across the countries. The speed of adjustment to the long-term equilibrium was negative for all the countries, indicating convergence.

Table 5. Technology vs low skill employment after the crises

Variables	ECT	Czech R	Poland	Slovakia
1	2	3	4	5
ECT		−0.169**	−0.037*	−0.112***
		(0.086)	(0.021)	(0.041)
D. ln GVA		0.001	0.001	0.003***
		(0.001)	(0.001)	(0.001)
D.TFP		−0.033	0.175	−0.044
		(0.953)	(0.873)	(0.132)

Table 5, cont.

1	2	3	4	5
L.ln GVA	0.010***			
	(0.002)			
L.TFP	0.178***			
	(0.058)			
Constant		−0.105	−0.166***	−0.79
		(0.071)	(0.056)	(0.54)
Observations	54	54	54	54

Each variable has a maximum lag set to five. The study decided the optimal lag lengths using the Akaike Information Criterion. Standard errors are represented in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, D, D2, D3…D and its subscripts represent lags of first order difference variables. The study used L to represent the long term. ECT means Error Correction Term.

Source: generated by the authors using Python 3.4.3.

Table 6 shows the results for middle skill employment after the financial crises. The impact of technology on employment in this skill group was negative in the long-term just as in the period before the financial crises. All long-term deviations were corrected in all the countries except Slovakia. Poland had the fastest speed of adjustment to the long-term equilibrium.

Table 6. Technology vs middle skill employment after the crises

Variables	ECT	Czech R	Poland	Slovakia
ECT		−0.169	−0.350***	0.512**
		(0.117)	(0.134)	(0.255)
D. ln GVA		0.002	0.006***	0.027***
		(0.003)	(0.002)	(0.007)
D. TFP		−0.142	−0.129***	−0.212*
		(0.191)	(0.019)	(0.115)
L. ln GVA	0.028**			
	(0.011)			
L.TFP	−0.161**			
	(0.067)			
Constant		0.036	0.862***	−0.921*
		(0.102)	(0.209)	(0.534)
Observations	54	54	54	54

Each variable has a maximum lag set to five. The study decided the optimal lag lengths using the Akaike Information Criterion. Standard errors are represented in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, D, D2, D3…D and its subscripts represent lags of first order difference variables. The study used L to represent the long term. ECT means Error Correction Term.

Source: generated by the authors using Python 3.4.3.

Table 7 shows the results for high skill employment after the global financial crises. They demonstrate that technology affects high skill employment positively in the long-term just as in the period before the financial crises. Deviations in employment were corrected in Poland because of the negative speed of the adjustment parameter. The Czech Republic and Slovakia had positive speed of adjustment, indicating divergence to the long-term equilibrium for high skill employment.

Table 7. Technology vs high skill employment after the crises

Variables	ECT	Czech R	Poland	Slovakia
ECT		−0.101	−0.112**	1.164*
		(0.324)	(0.051)	(0.684)
D. ln GVA		0.003	−0.002	−0.010*
		(0.005)	(0.001)	(0.001)
D.TFP		0.008	−0.104	0.950***
		(0.419)	(0.139)	(0.316)
L. ln GVA	0.011***			
	(0.000)			
L.TFP	0.798**			
	(0.363)			
Constant		0.073	0.419***	−0.341**
		(0.272)	(0.083)	(0.165)
Observations	54	54	54	54

Each variable has a maximum lag set to five. The study decided the optimal lag lengths using the Akaike Information Criterion. Standard errors are represented in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, D, D2, D3…D and its subscripts represent lags of first order difference variables. The study used L to represent the long term. ECT means Error Correction Term.

Source: generated by the authors using Python 3.4.3.

All the models were checked for autocorrelation, normality and heteroskedasticity. The results show that they were no such problems. Bounds testing was carried out to verify the existence of a long-term relationship among the variables in the panel ARDL models. The F statistics obtained from the Wald tests for all the models were greater than the upper bound of the bounds test, indicating that the variables had a long-term relationship in the three models.

4.6. Discussion

This section contains a brief discussion of the results of the paper. It also makes a comparison with the findings of prominent researchers in this field. One of the key findings of this study is that the effect of technology on employment does not vary in terms of gender. The results from the VAR impulse responses show the same pattern for both genders in all countries. In the Czech Republic, the impact of technology on both male and female employment is mixed (positive and negative),

indicating that automation both destroys and creates jobs at the same time. In Poland and Slovakia, the net effect of technology on male and female employment was positive, indicating that the digitalization and automation of workplaces leads to increased employment of both males and females.

Using the panel autoregressive distributed lag model, the study finds that technology impacts negatively on employment of middle skill labour and positively on both low and high skill labour. The impact was observed for all three countries in the long term. The short-term dynamics and speed of adjustment to the long-term equilibrium differ according to the lags and labour market policies and institutions of each country. The fastest speed of adjustment to long-term equilibrium occured in the high skill category. Low skill employment had the lowest speed of adjustment to the equilibrium.

The study also noted that the pattern of relations between technology and employment within the various skill groups (low skill, high skill and middle skill) was not altered by the global financial crises. The impact of technology was positive on low and high skill occupations both before and after the financial crises. The impact on middle skill was negative both before and after the financial crises.

The findings of this study were then compared with several other findings in this field. The results are similar to a large extent. According to OECD studies (OECD, 2017) technological innovation might lead to increased unemployment due to reduced labour demand in the short term. Long-term adjustment will however lead to a long-term increase in employment. Other studies similarly conclude that technological innovation is gender neutral. The impact depends on the skill and routine nature of the jobs performed by the labour force (cf. Autor, Kartz, and Kearnery, 2006; Marcolin, Miroudot, and Squicciarini, 2016; OECD, 2017).

Studies with findings that technology impacts on employment within skill groups include (Harrigan, Reshef, and Toubal, 2017), which concluded that technology plays a significant impact on employment. Tüzemen and Willis (2013) attributed the vanishing middle skill jobs and the increase of low and high skill jobs to the growing use of technology by companies. Spitz-Oener (2006), and Acemoglu and Autor (2011) argued that within-skill group employment changes are often regarded as evidence consistent with the pervasive effect of technology. Rotman (2013) and Deane (2013) concluded that the growing use of machines significantly affects employment, causing a decline in middle skill jobs and a rise in low and high skill jobs.

The differences in the speed of adjustments and responses to technology are attributed to country specific differences in labour market policies and institutions. The findings are similar to those of (Arpaia, Kiss, Palvolgyi, and Turrini, 2014), which concluded that the speed and dynamism of the impact of technology differ across countries due to differences in the labour markets. (Dustmann, Glitz, and Frattini, 2008) as well as (Naticchioni, Ragusa, and Massari, 2014) also highlighted

the important role of labour market policies and institutions in the dynamic relations between employment and technology.

This study confirms that several other factors determine employment dynamics, and it would be difficult to attribute all changes to the labour markets in the Visegrad countries only to the influence of technology. Some of the challenges encountered include the fact that in the build-up to the ARDL model, routine and non-routine tasks were bundled together within the same skill group, making it difficult to predict the impact of technology across the skill groups just as in the findings of Autor and Dorn (2013).

This paper concludes that even though technology impacts on employment within the skill groups in the Visegrad countries, changes in the occupational structure of the Visegrad labour market over the years cannot be understood as being dominated by RBTC alone. The growing demand for education has contributed significantly to the main aspect of the changing employment process. In other words, the increased demand for labour with higher education results in the reallocation of employment from middle to top skill occupations. Even though the employment structure is changing, there is no clear case of decreased employment of labour in its totality, thus increasing digitalization or technological innovation might not necessarily cause an increase in unemployment in the Czech Republic, Poland and Slovakia, as was concluded in the studies of Davis and Haltiwanger (2014), (Wadhwa, 2012) as well as by Atkinson, Piketty, and Saez (2010).

4.7.   Policy recommendations

Policy interventions are certainly necessary to forestall any future negative consequences of the impact of technology in the form of rising poverty and inequality. The impact of digitalization on gender gap in the labour market depends to some extent on the policy responses by government. The study results may show the gender neutrality of technology, but with the obvious negative impact of technology on middle skill employment, pragmatic policies should be put in place to avert the possible consequences of inequality and rising poverty.

Firstly, the inclusion of 'high-risk' labor in most opportunities in the labor market is paramount; this implies providing more and better job opportunities. Labour market policy should increasingly focus on enhancing legal and social protection of employees without compromising quality and efficiency of firms and businesses. Policy simulation might have little impact if the unemployment is occurring due to displacement by technology.

Secondly, there should be a policy focus on part-time jobs and short-term contracts. Many of these jobs are low earning and do not have social security protection. There is a low rate of transition from non-standard forms of employment to full-time jobs, which increases the risk of unemployment in this category.

Given the situation of the job mismatch in the labour markets of some of the Visegrad countries, workers should be equipped with the skills that can help with

a transition to jobs in growing sectors – in the case of displacement by technology. The long-term goal of equipping workers in the Visegrad countries should be approached differently. There is much emphasis on educational achievement as the demand for highly educated college and university graduates increases. As important as education is to the individual, it is necessary to emphasize the development and training of workers to acquire non-routine skills, as this helps to make their labour valuable during the periods of robotization of routine tasks.

5. Conclusion

The study aimed to investigate the impact of technology on employment by gender and skill in the Czech Republic, Poland and Slovakia. For the impact by gender, the study employed the VAR model and for the impact by skill group it used a panel autoregressive distributed lag model. The authors found that technology has an impact on employment in the three Visegrad countries both by gender and by skill. Technology is however gender-neutral, meaning that the impact for all three countries does not vary between males and females. Thus the issue about technological innovation leading to inequality might be just a false alarms. The impact of technology is more skill-based than gender-based. The study also observed that for both the period before and after the global financial crises, technology impacted negatively on middle skill employment and positively on both low skill and high skill employment. The study pooled a common technological effect for the Visegrad region in the long term using the Pooled Mean Group estimator. The short-term dynamics were different for each of the countries, but the long-term dynamics had common patterns. The differences in short-term coefficients and speeds of adjustments to long-term equilibrium are attributed to the cross-country differences in labour market policies and institutions. The study noted that the speed of adjustment of employment to long-term equilibrium was higher in the high skill group than in the low skill and middle skill groups. Although this study established a relation between technology and employment in the various skill levels, the authors suggest that there are several other causes of employment in the Visegrad countries that were not accounted for. The study also concluded that even though there is increased digitalization, it will not necessarily cause an increase in unemployment in the studied Visegrad countries.

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