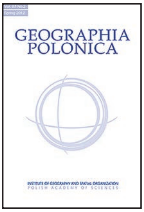

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CHANGES IN THE LABOUR MARKET DURING THE COVID-19 PANDEMIC AND THEIR SPATIAL INTERACTIONS – EVIDENCE FROM MONTHLY DATA FOR POLISH LAU

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Abstract

In addition to direct negative effects in terms of morbidity and mortality, the pandemic caused by SARS-CoV-2 also has indirect negative effects that concerned, among others, the labour market. This study analysed changes in the unemployment rate that were observed at the level of Polish Local Administrative Units (LAU) during the ten months of the pandemic. Both annual and monthly data were applied. Using cross-sectional and panel econometric modelling with spatial interactions it was shown that the observed increase in unemployment was strongly influenced by the share of employment in services, especially in less knowledge-intensive services such as: trade, accommodation and gastronomy. Moreover, it turns out that a higher share of women working in services was associated with a higher increase in unemployment than in the case of men working in services. Significant positive spatial relationships between local labour markets in LAUs were also identified. It was also shown that both the timing and severity of containment measures were significant. The strongest effect of the lockdown was observed three months after its introduction, while after six months the effect was significantly smaller. The study's findings may be important for post-pandemic recovery plans.

Key words

COVID-19 • labour market • unemployment • containment measures • spatial panel model

Introduction

Although the COVID-19 pandemic is not over yet, and it is not known when it will finally end, it is already noticeable that it caused one of the greatest crises in modern history. The crisis is triggered by many fatalities and confirmed cases, but also, perhaps to a greater extent, by unprecedented containment measures taken by the national governments to prevent the spread of the coronavirus. As a result, many businesses have been shut down temporarily and many employees have been locked in their homes. The adopted restrictions, which were probably and still are necessary to reduce mortality, have contributed to significant damage to the economy and society. The reports prepared by World Bank (Annual Report, 2020), OECD (2020a, 2020b) as well as European Commission (ESPON, 2020) provide some insight into the current global situation. We observe a growing body of research studies aimed at analysing and simulating the effects of the COVID-19 epidemic in various quantitative models (Buera et al., 2020; Eichenbaum et al., 2020; Faria-e-Castro, 2021; Guerrieri et al., 2020; Kaplan et al., 2020; among others).

The fact is that while the access to official statistical data on the various variables is still limited, it is difficult to quantify the exact magnitude of the impact of containment measures on GDP growth, but is clear that they imply sharp contractions in the level of output, household spending, corporate investment and international trade (OECD, 2020a). Notwithstanding, obtaining a better understanding of the distribution of the effects of the COVID-19 crisis is crucial to designing policy responses to sectors, enterprises as well as individuals most affected by the crisis (Adams-Prassl et al., 2020).

One of the areas that has been severely affected during the pandemic is the labour market, with noticeable increases in unemployment in most countries. The paper contributes to the literature on the impact of economic downturns on labour market outcomes (e.g., Christiano et al., 2015; Hoynes et al., 2012). Hitherto, the economic crisis was most often started with a decline in demand and production, which, with a certain delay, led to a decline in employment and an increase in unemployment. It seems that the current pandemic crisis significantly accelerated this process and changes in the labour market were taking place very rapidly. It seems that only the governments' intervention in the form of special subsidy solutions could to some extent inhibit the process. A report presenting the impact of the pandemic on unemployment in the USA, prepared by the Congressional Research Service (2021), stated that in the United States *"the unemployment rate has reached an unprecedented level that has not been observed since data collection began in 1948"*. The consequences for the labour market have been, and still are, of various types, including: employed people are losing their jobs, hiring new employees were cancelled or frozen, unemployed people stop looking for a job for family reasons, employed people could reduce working hours or simply stopped working for a time (EUROSTAT, 2021). Indubitably, it largely depends on the character of the job and the possibility of working at home (Dingel & Neiman, 2020). It is noted that workers most hit by the COVID crisis, such as young, low skilled, workers in accommodation and food sectors are often overrepresented in the low income group (Alon et al., 2020; EUROSTAT, 2020). The fact that the lockdown concerned not only working people, but also children and adolescents was also of great importance. This massively increased families' childcare needs during working hours. Moreover, bearing in mind that women have taken on a larger share of the extra childcare duties during the lockdown than men (Alon et al., 2020), this had a significant impact on the observed changes in the labour market.

Many researchers are trying to answer the question of how much the labour market has been affected by the COVID-19 pandemic, what were the factors that led to different countries / regions being affected to varying degrees (Adams-Prassl et al., 2020; Alfaro et al., 2020; Bartik et al., 2020; Cajner et al., 2020; Carvalho et al., 2020; Coibion et al., 2020; Kahn et al., 2020; among others). The rise in unemployment affected different sectors to varying degrees (Kapička & Rupert, 2020) and has not been equal across countries. While in many countries unemployment rates have risen the fastest since they began to be recorded (Adams-Prassl et al., 2020; Congressional Research Service, 2021), in countries that have experienced a transformation from a centrally planned economy to a market economy, the changes currently observed do not appear to be so terrifying. Countries such as the

CEE countries, including Poland, experienced dramatic changes during the last decade of the 20th century. Moreover, the increases in unemployment that are currently observed there do not seem to be as high as reported and predicted by international institutions (ILO, 2021). The question arises as to what influenced this nature of the changes in labour markets in the CEE countries.

Additionally, as the OECD study (2020b), highlighted, different factors including region's exposure to tradable sectors, its exposure to global value chains and its specialisation, such as tourism, could be crucial. As pointed "*The regional and local impact of the crisis is highly asymmetric within countries. Some regions, particularly the more vulnerable ones, such as deprived urban areas, have been harder hit than others. Certain vulnerable populations, too, have been more affected. In economic terms, the impact of the crisis is differing across regions, at least in its initial stages. Differentiating factors include a region's exposure to tradable sectors, its exposure to global value chains and its specialisation, such as tourism*" (OECD, 2020b: 4). This means that regional and local labour markets can differ significantly. Finally, it should be emphasized that the changes in the labour market depended on the relative severity of the containment measures implemented by the economies.

The first studies are already appearing analysing the regional differentiation of the impact of pandemics and containment measures on local labour markets (Juranek et al., 2020; Meinen & Serafini, 2021). The results show that the sensitivity of the labour market depends primarily on the interaction between government containment measures, sectoral structure and trade linkages more than the spread of infections. However, it seems that the spatial interactions between regions in the changes in local labour markets caused by the pandemic have not been sufficiently analysed up to now. And yet, especially when relatively small units of spatial aggregation are investigated, where the links between local labour markets could be quite strong, the impact of what is happening in neighbouring units may be significant.

It should be noted that the analyses of changes in regional/local labour markets with spatial interactions had already been conducted. For example, Patacchini and Zenou (2007) analysed the spatial dimension of local regional labour markets in Great Britain using a simple dynamic model that explains the spatial correlation between unemployment rates. They showed a significant spatial dependence that has been growing over time and characterized by a low distance decay. Similarly, Semerikova (2015) presented a study of spatial spillover effects of the regional unemployment in Germany at the NUTS 3 level, using both spatial cross-sectional and spatial-tempral econometric models. While, Kivi (2019) presented modelling with the use of spatial econometrics tools for the relationship between all regional labour markets in the European Union at the NUTS 2 level. It should also be noted that modelling of spatial dependencies on the labour market in Polish LUAs was introduced by Pośpiech (2016). Two basic spatial models were taken into account there: the spatial error model and the spatial delay model.

The presented article is intended to fill the identified research gap by considering spatial interdependencies in researching the response of the local labour markets to the crisis caused by the COVID-19 pandemic. In particular, the aim of the presented study was to answer the following research questions:

1. Is what is observed at the level of the whole country confirmed when we look at the situation on local labour markets?
2. Was the sectoral structure of employment important?
3. Was the share of women and men in employment in various sectors (especially services) significant?
4. Did the moment imposing and severity of the containment measures matter?
5. When analysing the effects of a pandemic on local labour markets, is there a significant

importance of interdependence between local units?

Using the most recent statistical data (for January 2021) on the level of unemployment in Polish Local Administrative Units (LAU), an econometric analysis was made of the impact of the employment structure, LAU's type and other characteristics on the change in the registered unemployment rate over the last year (year of pandemic). Since many interrelations take place between LAUs, which are relatively small objects, in the econometric models the spatial interactions in the form of spatial auto-regression and spatial autocorrelation of error were considered.

Data and methods

At the time of the analysis, data on the level of the registered unemployment rate at the end of January 2021 was available. Therefore, it was possible to capture the impact of ten months of the pandemic and the related containment measures. Statistics Poland (the main provider of public statistics) published monthly data on the unemployment rate and the number of unemployed men and women in all 380 Polish LAUs. Unfortunately, as the information on the number of economically active men and women is available only for NUTS 2 regions, the monthly unemployment rate by gender LAUs is unknown. Therefore, it was not possible to conduct separate analyses for changes in the unemployment rate of women and men. The analysed variable was the yearly change of total unemployment rate. The regression analysis of such a variable was carried out both in the cross-sectional approach for the change in the unemployment rate in January 2021 compared to January 2020 and in the spatio-temporal approach for the period from March 2020 to January 2021 (ten months of the pandemic). In both cases, the dependent variable was the change in the given month of the pandemic compared to the corresponding month of the previous year.

The main explanatory factors were the ratios of employment in the main sectors of the economy: agriculture, industry and construction, total services. Furthermore, the last one was divided into less knowledge intensive services (LKIS) and knowledge intensive services (KIS). Both the ratios of women and men employed in these sectors was taken into account. The need to distinguish the LKIS and KIS sectors is related to the fact that the service sectors suffered to a different extent. The report of the International Labour Organization (ILO, 2021) identified hard-hit sectors as: accommodation and food services, arts and culture, retail, and construction. In the world economy, after three quarters of 2020, massive job losses were recorded in the above sectors, while in contrast, there was the positive job growth evident in a number of higher skilled services sectors.

Obviously, the specificity of individual LAUs was also taken into account in the regression explaining the change in the unemployment rate. The dummies were defined for big cities, that in Poland can be interpreted as local metropolises (13), units with medium-sized cities (53), while units with small towns or rural areas (314) were included as a reference group. The models based on panel data also took into account individual effects for LAUs. Due to the set goals in order to simplify the analysis and make the results more unambiguous, a number of other factors that could potentially have an impact on the observed changes in unemployment rates were not taken into account.

One of the objectives was to check how the registered unemployment rate was affected by the moment of introducing containment measures and their severity for the society. For this purpose, there was used the measure proposed by the Blovatnik School of Government at the University of Oxford analysed by so-called the COVID-19 Government Response Tracker. The proposed index collects publicly available information on 19 indicators of government responses. Eight of the policy indicators record information on containment and closure policies, such as school closures and restrictions in movement. Four of the indicators record economic policies, such as income support to citizens or provision of foreign aid. Seven of the indicators record health system policies such as the COVID-19 testing regime, emergency investments into healthcare and most recently, vaccination policies (Hale et al., 2021). The final index is given as a daily observed number from 1 to 100 reflecting the level of government action in preventing the spread of the coronavirus. The values of this index for Poland in the period from Mar 1, 2020 to the end of Jan 2021 are presented in Figure 1

It can be seen that the reaction of the Polish government was quite restrictive at the very beginning of the pandemic, while later it was rather related to the subsequent waves of the pandemic, which occurred in this part of Europe with a certain delay compared to the countries of Southern and Western Europe. As the analysis is conducted for regional data, it would seem justified to include regionalization of containment measures. However, it should be clarified that this regionalization in Poland lasted for a very short time and should not be significant for the observed changes on the labour market, therefore the strength of containment measures were assumed to be the same for all LAUs.

The spatio-temporal econometric analysis, the purpose of which was to examine how the strength of containment measures influenced the changes in unemployment, was carried out for monthly data. A variable named *lockdown* was defined as the containment measures representation, the value of which was equal to the average of the original values in a given month. As it can be expected that the introduction of restrictions in a given month brought effects not in that month, but rather in next periods, in following model specifications the *lockdown* variable was taken into account as subsequent lags.

Apart from presenting the changes in the unemployment rate in Polish LAUs observed in the analysed period on the maps, the spatial autocorrelation of the variable was also examined. For this purpose the Moran's I statistic as well as the Local Indicator of Spatial Association (LISA) proposed

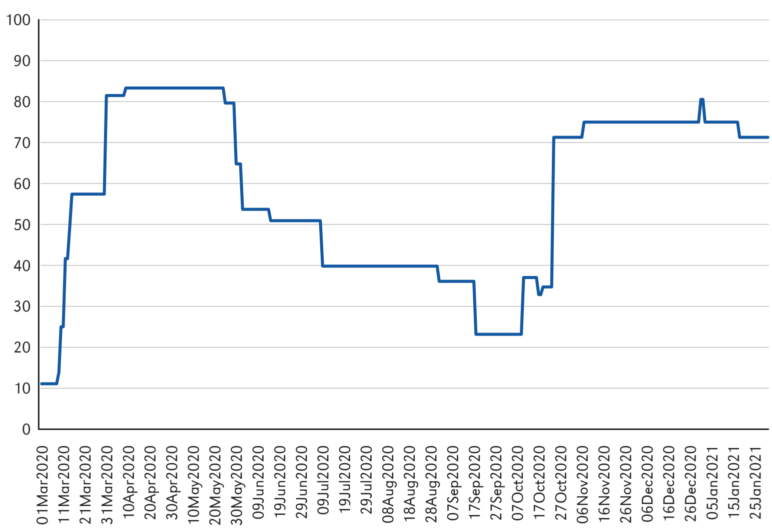

Figure 1. The strength of containment measures against the COVID-19 pandemic in Poland (from March 1, 2020 to January 31, 2021) – index ranges from 0 to 100

Source: COVID-19 Government Response Tracker, https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker#data.

by Anselin (1995) were implemented. One of the advantages of the LISA statistics is the ability to identify areas in which spatial correlation for the analysed variable is statistically significant. Moreover, it is possible to indicate where this relationship is positive and where it is negative.

The final step of the study was the econometric modelling with the use of spatial analysis tools. These spatial interdependencies can be of three types (Anselin, 1988; Anselin et al., 1996; Elhorst, 2014; LaSage & Pace, 2009):

- spatial autoregression (SAR model) – the change in the unemployment rate in a given unit depended on the change in the unemployment rate in neighbouring units,
- spatial error autocorrelation (SEM model) – random factors from neighbouring locations influenced the change in the unemployment rate in a given unit,
- spatial spillover effect (SLX model) – the change in the unemployment rate in a given unit depended on exogenous factors in neighbouring units.

Analysing the spatial relationships between regions, more than one type of interaction can be included in the model at the same time. Taking into account all three interactions in practice leads to the so-called General Nesting Spatial Model (GNSM) (Elhorst, 2014), which is an unidentifiable model due to too many parameters to be estimated. The simultaneous consideration of spatial autoregression and the influence of exogenous variables from neighbouring areas leads to the so-called Spatial Durbin Model (SDM). While taking into account the spatial autoregression of the endogenous variable and the spatial autocorrelation of error gives the so-called Spatial Durbin Error Model (SDEM).

The key in this type of analysis is to adopt an appropriate tool reflecting the relative position of units in relation to each other. In the present study, a spatial weight matrix was defined as 1st order contiguity queen matrix.

The selection of the best spatial model in our analysis was made on the basis of the results of the Wald test of spatial terms as well as the values of the Akaike's information criterion (AIC). On this basis, it turned out that the SEM model is the best specification for the cross-sectional analysis. In each case, the model that takes into account, apart from spatial autoregression or spatial autocorrelation, the values of exogenous variables from neighbouring regions, turned out to be less appropriate. Hence, the applied cross-sectional regression can be written as follows:

$$\begin{aligned} y_i &= \beta_0 + \boldsymbol{\beta X} + u_i \\ u_i &= \lambda \boldsymbol{W} u_i + \varepsilon_i \\ \varepsilon_i &\sim N(0, \sigma^2 I) \quad i = 1,\ldots, 380 \end{aligned} \tag{1}$$

where:

y_i – is the change in the unemployment rate from Jun 2020 to Jun 2021 in the i-th unit,
$\boldsymbol{X}$ – are exogenous explanatory variables (including the sectoral shares in employment),
$\boldsymbol{W}$ – the common border spatial weight matrix,
$\boldsymbol{\lambda}$ – the spatial error autocorrelation parameter,
$\boldsymbol{\varepsilon}$ – the i.i.d. disturbances.

Using the same criteria, the optimal spatial model was selected for the spatio-temporal analysis and the testing procedure was in line with that proposed by Elhorst (2014) and Baltagi et al. (2003). The exogenous factors from neighbouring locations turned out not to be statistically significant for changes in the unemployment rate. Finally, for ten monthly observations from March 2020 to Jun 2021 for 380 LAUs, the model of spatial error autocorrelation was applied with the variable illustrating the periods and the severity of containment measures:

$$\begin{aligned} y_{it} &= \beta_0 + \boldsymbol{\beta X} + \theta\, lockdown_t + \alpha_i + u_{it} \\ u_{it} &= \lambda \boldsymbol{W} u_{it} + \varepsilon_{it} \\ \varepsilon_{it} &\sim N(0, \sigma^2 I) \quad i = 1,\ldots, 380 \quad t = 1,\ldots, 10 \end{aligned} \tag{2}$$

where:

$\boldsymbol{\theta}$ – parameter reflecting the impact of applied containment measures in a given month,

λ – the spatial error autocorrelation parameter,
α_i – individual effects for the i-th LAU.

In order to check whether individual effects should be considered as fixed effects or as random effects, the Hausman test adapted to the spatial panel model was used.

Results

Just like most countries affected by the COVID-19 pandemic, Poland has experienced an increase in the unemployment rate. However, these changes were not the same in all regions. Figure 2 illustrates the changes observed in all 380 LAUs in the period from Jan 2020 to the end of Jan 2021. It turns out that there were also units where there was a slight decrease in the unemployment rate, but it was only 15 units, while for 16 units the increase was higher than 2 percentage points.

It is noted that the largest increases in unemployment were recorded in the northern and western parts of Poland. This concerned the units closest to the Baltic Sea, where the tourism sector is of significant economic importance, as well as those closest to the Polish-German border. However, significant increases in unemployment were also recorded in Upper Silesia, where industry prevails. The central and eastern part of Poland was the least affected, where the agricultural sector is still of significant importance.

The Moran's I statistic was determined assuming a spatial weight matrix was defined as 1st order contiguity matrix. The value of the statistics was , which is not very high, although statistically significant.

Figure 3 shows the LISA values that confirm the significance of the spatial autocorrelation of changes in the unemployment rate only

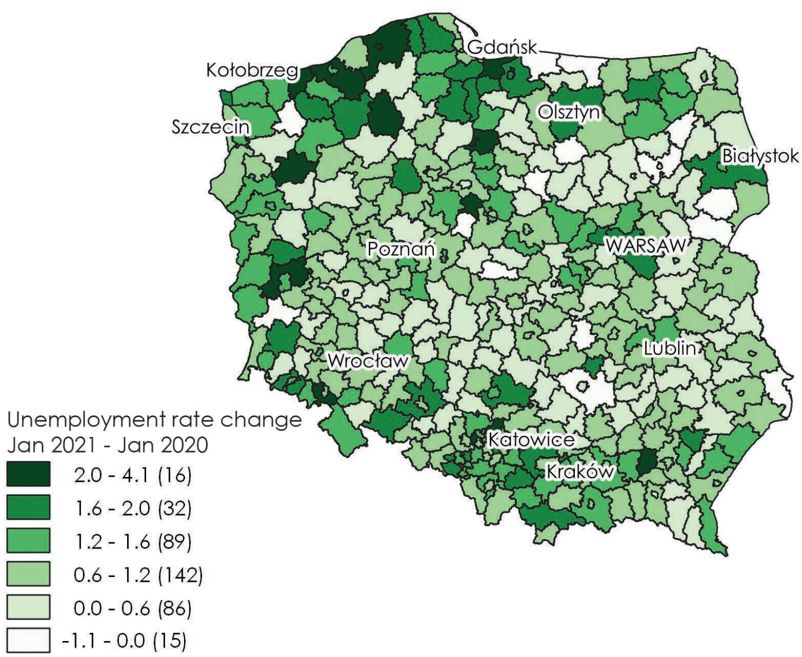

Figure 2. Changes in the registered unemployment rate in the period from Jan 2020 to Jan 2021 in Polish LAUs (p.p.)

Source: Author's calculations based on data from Statistics Poland, https://stat.gov.pl/en/.

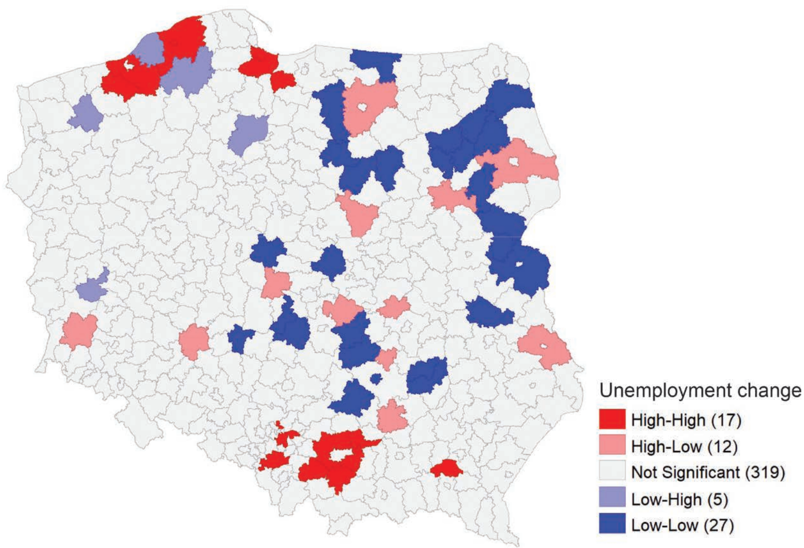

Figure 3. LISA (Local Indicator of Spatial Association) for changes in the unemployment rate in Polish LAUs during a pandemic

Source: Author's calculations based on data from Statistics Poland, https://stat.gov.pl/en/.

in a few units. The regions in which the high values of the increase in unemployment in given locations contributed to the increase in unemployment in neighbouring units were marked in red. This concerned the areas of north-west Poland related to tourism, but also industrial Upper Silesia. Thus, the spatial spillovers of negative changes was significant in those areas where the highest increases in unemployment were recorded. While blue marks the areas where the positive autocorrelation concerned low increases in unemployment. As can be seen, this was the case in units that experienced increases in unemployment to a lesser extent. In the areas where the high-high relation was identified, it can be assumed that the improvement of the situation on the labour market requires the implementation of recovery measures not only in a given unit that experienced the highest unemployment increases, but also in neighbouring units.

In January 2021, compared to January 2020, the number of registered unemployed in Poland increased by 18.2%. That increase was the result of a 21.1% increase in the number of unemployed men and only a 15.8% increase in the number of unemployed women. It can therefore be concluded that dismissals concerned more the sectors in which more men were employed than women. And which may lead to the conclusion that the work performed by women turned out to be more necessary during the pandemic, because mainly women work in such sectors as health, education, trade, and other services, and these sectors turned out to be key to maintaining functioning of society and economy in the period of a pandemic and the containment measures.

The higher share of employed women over men in 2019 was recorded in such sections as: education, human health and social work activities, public administration and defence; compulsory social security but also accommodation and food services financial and insurance activities as well as other services. It can be expected that sectors such as education, health care, social work and other services are the areas where employment should not have decreased. While the accommodation and food services sector, so the tourism sector, is probably the hardest hit.

The final stage of the analysis focused on econometric modelling. Firstly, the cross-sectional models were estimated in which the dependent variable was the change in the overall unemployment rate in the period Jan 2020 – Jan 2021. Table 1 presents the estimations results of models taking into account various types of spatial interactions: the Spatial Autoregressive Model (M1), the Spatial Error Model (M2), the model with spatial autoregression and spatial error autocorrelation (M3), the Spatial Durbin Model (M4) and Spatial Durbin Error Model (M5). The analysis take into account the robust standard errors of estimated parameters.

Taking into account both the values of the AIC criterion as well as the results of the Wald of spatial terms test, it can be concluded that among the presented models, the SEM model is the most adequate. Moreover, it turns out that in the Durbin type models both the explanatory variables from the neighbouring

Table 1. Estimates of the different cross-sectional spatial models for changes in LAUs' unemployment rates during the pandemic

Variables	Dependent: change of unemployment rate				
	M1	M2	M3	M4	M5
Big_cities	-0.682*** (0.202)	-0.724*** (0.203)	-0.709*** (0.204)	-0.698*** (0.202)	-0.678*** (0.204)
Big_city_neigh				0.494 (0.573)	0.312 (0.591)
Medium_cities	-0.172 (0.117)	-0.283 (0.117)	-0.240* (0.126)	-0.185 (0.121)	-0.205 (0.324)
Serv_share	0.019*** (0.003)	0.018*** (0.003)	0.018*** (0.003)	0.018*** (0.003)	0.017*** (0.003)
Serv_share_neigh				-0.002 (0.003)	0.003 (0.002)
Spatial lag	0.181*** (0.065)		0.078 (0.099)	0.212** (0.091)	
Spatial error		0.264*** (0.089)	0.183 (0.132)		0.261*** (0.090)
Constant	0.098 (0.124)	0.284** (0.130)	0.206 (0.150)	0.149 (0.136)	0.202 (0.152)
Observations	380	380	380	380	380
AIC	663.28	662.29	663.84	666.38	663.55
Wald: spatial terms p-value	7.600 0.006	8.690 0.003	8.250 0.016	8.390 0.039	11.230 0.011
Pseudo R^2	0.116	0.116	0.118	0.117	0.123
Chi^2 p-value	56.940 0.000	36.160 0.000	39.990 0.000	57.150 0.000	39.300 0.000

Source: Author's calculations.

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Spatial Models with the 1st order contiguity queen matrix; Maximum Likelihood Estimation.

locations did not have a statistically significant influence on the changes in the unemployment rate. Contrary to intuitive expectations, the location of the poviat near a large city turned out to be irrelevant.

The next conclusion from the obtained results is the confirmation of the significant spatial interactions between LAUs in terms of changes in unemployment observed during the pandemic, previously proven with the help of LISA. The positive estimates of the spatial lag parameter mean that the changes in the unemployment rate that took place in neighbouring units significantly affected the changes in unemployment in a given unit and it was a positive correlation. On average, while neighbours recorded a significant increase in unemployment, it coincided with an increase in unemployment in a given unit, and on the other hand, when neighbours experienced a lower increase in unemployment, this increase was also lower in that unit. A positive estimate of the spatial error autocorrelation parameter was also obtained, which means a positive correlation of disturbances in the neighbouring regions with changes in the unemployment rate in a given poviat.

Each spatial specification of the model showed that the growths of unemployment rate were significantly smaller in large cities

Table 2. Estimates of the cross-sectional SEM model for changes in unemployment rates with different variables of employment structure

Variables	Dependent: change of unemployment rate		
	M6	M7	M8
Big_cities	-0.342 (0.239)	-0.296* (0.173)	-0.321* (0.180)
Medium_cities	-0.050 (0.109)	-0.054 (0.098)	-0.016 (0.099)
LKIS_share	0.024*** (0.00)		
KIS_share	0.001 (0.030)		
LKIS_women		0.028*** (0.006)	
LKIS_men			0.018*** (0.005)
Constant	0.631*** (0.093)	0.572*** (0.094)	0.736*** (0.450)
Spatial error	0.316*** (0.087)	0.278*** (0.089)	0.352*** (0.085)
Observations	380	380	380
AIC	673.45	669.64	676.91
Wald test: spatial terms p-value	13.320 0.000	9.820 0.002	17.240 0.000
Pseudo R^2	0.084	0.097	0.060
Chi^2 p-value	24.230 0.000	27.550 0.000	17.650 0.001

Source: Author's calculations.

Notes: Same as table 1.

as compared to rural poviats, while changes in unemployment in medium-sized cities did not differ statistically significantly from those in poviats without cities or towns. It also turned out that higher employment shares in the overall service sector significantly contributed to higher increases in the unemployment rate in Polish LAUs during the pandemic.

In order to answer the question of how significant the shares in various types of services were, in subsequent model specifications shares in less knowledge intensive services (LKIS) and knowledge intensive services (KIS) were taken into account (M6). For LKIS, the importance of ratios of women and men employed in these sectors was also analysed (M7 and M8). The subsequent columns of Table 2 present the estimates.

Analysing the importance of the employment structure, it turned out that it was influential factor for the increase in unemployment. As was shown in Table 1, the share of services higher by one percentage point was responsible for about 0.02 percentage point increase in unemployment, controlling the kind of the LAU and spatial interactions. It was also found that the share of employment in less knowledge intensive services was more significant than the share of KIS employment. The impact of the share in KIS was not statistically significant in the analysed period. Another finding is that the higher share of female employment in LKIS contributed to a greater increase in unemployment than the share of male employment in LKIS. Thus, in those regions where the share of women working in traditional service sectors was higher, there was a significantly greater increase in unemployment during the pandemic.

Since the aim of the analysis was also to check whether the containment measures introduced by the government contributed to the increase of unemployment, it was necessary to carry out spatial-temporal modelling on monthly data. Table 3 presents the results of the estimation of the relevant panel models. Taking into account both the values of the AIC criterion, the results of significance tests as well as Hausman test the panel SEM model with random effects was selected as the most adequate in the studied relationship. (Due to space saving reasons, not all estimation results are presented in the Table 3.) This means that random, unobserved factors that contributed to the increase in unemployment in the units in which they occurred also had a significant impact on the increase in the unemployment rate in neighbouring units (positive spatial error correlation).

As in the cross-sectional model, a significant positive relation was proved between the share of employment in services and an increase in the unemployment rate. Previously, the significance of a city or town in the LAU was not unequivocally significant, while analysing monthly data, it turned out that unemployment increases in large cities, but also in units with middle-size cities, was significantly lower than in rural LAUs. This may mean that rural areas, despite perhaps a lower incidence of the disease caused by SARS-CoV-2, have experienced a greater degree of negative indirect, unobvious effects of the pandemic.

And the final findings concern the influence of the severity and timing of the containment measures. The consecutive specifications in Table 3 take into account the impact of the lockdown imposed in the previous months from the one month lag to the six month lag. As might be expected, one month after the imposition of lockdown, it did not have a significant impact on the unemployment rate, but the effect was observed already after the next month. The strongest effect of the containment measures in the form of an increase in unemployment was observed three months after the imposition. Whereas, after six months this effect was significantly smaller. Such conclusions result not only from the significance and magnitude of the parameter estimates at successive lags of the lockdown variable, but also from the value of the AIC information criterion. The lowest AIC value was obtained for the model with a three periods lag.

In addition, Table 3 also presents the standard deviation of the panel individual

Table 3. Estimates of the panel SEM for changes in LAUs' unemployment rates during ten months of the pandemic – impact of containment measures

Variables	Dependent: change of unemployment rate					
	M9	M10	M11	M12	M13	M14
Big_cities	-0.569*** (0.176)	-0.587*** (0.177)	-0.594*** (0.177)	-0.586*** (0.177)	-0.581*** (0.177)	-0.576*** (0.176)
Medium_cities	-0.237** (0.108)	-0.234** (0.107)	-0.233** (0.106)	-0.234** (0.107)	-0.235** (0.107)	-0.235** (0.107)
Services_share	0.733** (0.302)	0.789*** (0.298)	0.808*** (0.297)	0.787*** (0.298)	0.770** (0.300)	0.756** (0.300)
lockdown t-1	0.000 (0.001)					
lockdown t-2		0.006*** (0.000)				
lockdown t-3			0.007*** (0.000)			
lockdown t-4				0.005*** (0.000)		
lockdown t-5					0.004*** (0.000)	
lockdown t-6						0.003*** (0.000)
Spatial error	0.671*** (0.017)	0.607*** (0.019)	0.585*** (0.020)	0.610*** (0.019)	0.629*** (0.018)	0.645*** (0.018)
Constant	0.796*** (0.141)	0.442*** (0.134)	0.459*** (0.132)	0.554*** (0.133)	0.621*** (0.134)	0.677*** (0.135)
sigma_u	0.474*** (0.018)	0.475*** (0.018)	0.475*** (0.018)	0.475*** (0.018)	0.474*** (0.018)	0.474*** (0.018)
sigma_e	0.361*** (0.004)	0.355*** (0.004)	0.352*** (0.004)	0.354*** (0.004)	0.356*** (0.004)	0.358*** (0.004)
Observations	3,800	3,800	3,800	3,800	3,800	3,800
No of groups	380	380	380	380	380	380
AIC	4447.22	4273.72	4202.77	4260.54	4312.70	4359.53
Wald: spatial terms p-value	1555.08 0.000	1025.88 0.000	889.22 0.000	1044.00 0.000	1184.82 0.000	1314.18 0.000
Pseudo R^2	0.0338	0.0843	0.0995	0.0841	0.07	0.057
Chi^2 p-value	11.11 0.000	203.7 0.000	291.45 0.000	216.76 0.000	154.84 0.000	102.57 0.000

Source: Author's calculations.

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Spatial Error Panel Model with random effects and the 1st order contiguity queen matrix; Maximum Likelihood Estimation; *sigma_u* reflects the significance of differences in random individual effects for LAUs, while *sigma_e* means the significance of the random noise differences.

effects (*sigma_u*) and the standard deviation of the disturbances (*sigma_e*). As the panel models are estimated as random effects specifications, the random error includes both individual effects and random noise. The obtained values of *sigma_u* and *sigma_e* mean that the random variability resulting from the individual specificity of the units is greater than the random variability not explained by the model.

Conclusions

The presented research analyses one of the indirect effects of the SARS-CoV-2 pandemic, which could be observed after about ten months of struggle. From the results of analyses presented by various international institutions, it is already known that one of the most important negative effects is the increase of unemployment in most countries around the world. Poland has also experienced this problem, although so far it seems to be slightly less than other countries at a comparable level of development. However, the picture observed from the whole country level is always slightly different than what is noticeable at the regional or local level.

It was confirmed that unemployment increased significantly in most local administrative units in Poland. However, not all units were affected to the same extent. The structure of employment, and more specifically the share of employment in services, had a significant impact on the observed increases in unemployment resulting from the pandemic and the related containment measures. Similar results were also obtained by Meinen and Serafini (2021) where the intra-country regional variations in the labour market impact of the pandemic were analysed. They finds that the different economic impact across regions cannot be explained solely by the spread of infections. Moreover, the share of employment in less knowledge intensive services had a greater impact than in knowledge intensive services. Similarly, other research shows that the employment losses were disproportionately concentrated among smaller firms and lower wage workers (Adams-Prassl et al., 2020; Cajner et al., 2020). Therefore, much of the fiscal stimulus implemented during the early part of the recession was targeted towards these groups.

And on the other hand, a greater share of women working in services was related to a greater increase in the unemployment rate than in the case of men working in services. The fact that the observed effect is not so clear-cut may be the result of the fact that women are both more likely to work in occupations related to work at home and more often to work in occupations related to physical proximity. At the same time, it is possible to expect that women have experienced sharp employment losses both because their employment is concentrated in heavily affected sectors such as restaurants, and due to increased childcare needs caused by school and day-care closures, preventing many women from working. Hence, it can be expected that the employment effects of broad social distancing policies on women may be less severe, but later integration into the economy may be more difficult, which was already suggested in the researches by Mongey and Weinberg (2020) and Alon et al. (2020). Such findings may indicate the need for targeted state aid aimed at economic recovery after the pandemic. The point is for this aid to focus the sectors of traditional services and to a greater extent women than men.

The analysis of spatial interactions between labour markets of LAUs showed that the observed increases in unemployment in neighbouring units had a significant impact on each other. Also, the unobservable factors and disturbances influencing the unemployment of the neighbours also did significantly affect the workforce in a given unit. Noting such significant spatial interdependencies between LAUs means that the improvement of the situation on the labour market requires the implementation of recovery measures not only in the units that experienced the highest unemployment increases, but also in neighbouring units. On the other hand, the significant impact of the employment structure in neighbouring units (especially in services) on changes in unemployment in Polish LAUs was not confirmed. Also, the proximity of a large city did not matter in this context. Probably such results are caused by the fact that the analysed changes are short-term in nature.

The study also managed, to some extent, to capture the shift in time of the impact of containment measures. Both the moment of introduction and the severity of lockdown were taken into account. The strongest effect of the containment measures in the form of an increase in unemployment was observed three months after the imposition. Whereas, after six months this effect was significantly smaller. Perhaps this is due to the fact that the Polish labour law requires a three-month notice period when dismissing employees employed under an employment contract. Moreover, the programmes of government institutions aimed at providing financial support to enterprises in order to limit the reduction of employment were also important.

The first post-pandemic recovery plans are already under development, such as (World Bank, 2020b). The presented results indicate the need to conduct research of this type, which can provide important indications as to the assumptions of the reconstruction and development plans in the coming years.

Editors' note:
Unless otherwise stated, the sources of tables and figures are the author's, on the basis of her own research.

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