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Ciżkowicz, Piotr and Kowalczuk, Michał and Rzońca, Andrzej

Warsaw School of Economics, National Bank of Poland

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Piotr Ciżkowicz[1], Michał Kowalczuk[2], Andrzej Rzońca[3]

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Abstract

We identify determinants of large disparities in local unemployment rates in Poland using panel data on NUTS-4 level (poviats). We find that the disparities are linked to local demographics, education and sectoral employment composition rather than to local demand factors. However, the impact of determinants is not homogenous across poviats. Where unemployment is low or income per capita is high, unemployment does not depend on the late working-aged share in the population but does depend relatively stronger on the share of early working-aged. Where unemployment is high or income per capita is low, unemployment does not depend on education attainment and is relatively less responsive to investment fluctuations. Where small farms are present, they are partial absorbers of workers laid off due to investment fluctuations.

JEL classification: C23, J23, R23

Keywords: local unemployment, Poland, panel data

[1] Warsaw School of Economics, Department of International Comparative Studies, Al. Niepodleglosci 162, Warsaw, Poland. pcizko@sgh.waw.pl
[2] Warsaw School of Economics, ma.kowalczuk@gmail.com
[3] Warsaw School of Economics and Monetary Policy Council in the National Bank of Poland, andrzej.rzonca@nbp.pl

1 Introduction

Labour markets are most often studied on the country level. However, within most countries there are significant disparities in local unemployment rates (Bradley and Taylor 1997) generating social and economic costs (for more on this see, e.g. Taylor 1996).

The majority of research suggests that variation in unemployment rates across countries arises mainly from differences in labour market institutions (e.g. Blanchard 2006). As the institutions rarely differ within countries., some other factors must explain disparities in local unemployment (e.g. Elhorst, 2000).

We seek to explain this issue through analysing determinants of local unemployment rates in Polish poviats (NUTS-4 level region[4]) over the 2000-2010 period. The aim of our analysis is to confront two groups of determinants for local unemployment. The first group includes factors related to *equilibrium theory* (see, e.g. Marston 1985) combined with other structural determinants. The second group comprises factors based on *disequilibrium theory* (see, e.g. Trendle, 2012) grouped with various measures of demand changes . We also check to what extend the impact of particular variables on unemployment rate differs across poviats.

This paper makes two contributions to the existing literature. First, it deals with a country, which has been understudied in spite of significant disparities in local unemployment.[5] It takes advantage of extensive data set that has not been used in other studies. Because of the richer data set it verifies more hypotheses suggested by the literature than other research conducted for Polish local labour markets (see Appendix A, Table A.1 for comparison with other studies for Poland).

Second, our approach does not assume that identified relations are similar in all groups of poviats. We examine to what extend the impact of identified determinants depends on outlying observations and structural characteristics of poviats. To our best knowledge this approach has not been applied so far in any study on disparities in local unemployment rates not only in Poland[6], but also in other countries.[7]

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[4] Currently this level of territorial division is also described as LAU-1 in EU. In this article, however, we use NUTS-4 nomenclature as it is done in other research on Polish local unemployment (e.g. see Tyrowicz and Wójcik 2010).

[5] Local unemployment disparities in Polish poviats range from less than 5% to almost 40%.

[6] Newell and Pastore (2000) use similar approach but they restrict their analysis to only two subgroups of regions: with high and low local unemployment. Pastore and Tyrowicz (2012) also examine local unemployment determinants for different group of regions. However, they concentrate on the impact of inflows to unemployment, outflows from unemployment and labour turnover (a sum of inflows and outflows) on local unemployment. Consequently, they do not analyze structural and demand side determinants of local unemployment. In addition to this, neither of the studies inspects the influence of outlying observations on the results.

[7] Existing research on local unemployment determinants' heterogeneity often concentrates on the comparison of the West and East of Germany (see, e.g. Ammermueller et al. 2007, Lottmann 2012) and the North and South of Italy (see, e.g. Ammermueller et al. 2007). Heterogeneity analysis based not only on geographical characteristics of regions is presented by Korobilis and Gilmartin (2011), who use a mixture panel data model to describe unemployment differentials between heterogeneous groups of regions in the UK.

Our results show that large disparities in local unemployment in Poland are more related to differences in structural factors, such as local demographics, education and sectoral employment composition, rather than local demand factors including GDP or investment dynamics. However, we find a certain degree of heterogeneity across poviats in relations identified for the whole sample. In particular, where unemployment is low or income *per capita* is high, the level of unemployment does not depend on the late working-aged share in the population but does depend relatively stronger on the share of early working-aged. Conversely, where unemployment is high or income per capita is low, unemployment does not depend on education and is less responsive than elsewhere to investment fluctuations. Furthermore, small farms in some regions partially absorb reductions in employment that result from investment fluctuations.

The remainder of the paper is organized as follows. Section two describes the main theoretical approaches explaining disparities in local unemployment rates. Section three surveys previous empirical research related to our work. Section four presents some stylised facts on disparities in local unemployment in Poland. Section five discusses estimation strategy. Section six describes the data analysed in the paper. Section seven presents estimation results. Section eight examines the impact of outlying observations and heterogeneity of the obtained results. Section nine concludes and gives some policy recommendations.

2 Theories of regional unemployment

The structure of our research reflects major differences among theoretical explanations of large disparities in local unemployment rates.

Foundations for regional unemployment analysis are set up by the neoclassical theory. In its simplest form it suggests that in the long run all disparities should disappear due to labour or capital flows. The unemployed should migrate to regions where demand for labour is higher, whereas employers should relocate their production to regions of higher unemployment. However, this theory is unable to explain the observed, significant disparities in local unemployment rates (Niebuhr 2003).

There are two main theories trying to explain this issue. The first one is referred to as *equilibrium theory* (see, e.g. Marston 1985 or Molho 1995). It is based on the assumption that labour and capital flows between regions until there are no more incentives for the unemployed to migrate and for companies to relocate their production. But these incentives depend on much more factors than local unemployment level. The unemployed, when deciding whether to leave a region, may consider *inter alia* economic and social costs of migration, social security, family support and even local amenities (e.g. weather, pollution). In turn, companies' decisions on location of production are influenced by e.g. relocation costs, qualifications and wages of local labour force, public infrastructure, distance to suppliers and local markets' potential. As a result, migrations and production movements are limited and thus may not be sufficient to eliminate discrepancies among local unemployment rates.

The second theory is referred to as *disequilibrium theory* (see, e.g. Marston, 1985 or Trendle, 2012). According to that theory, disparities in local unemployment rates result from local labour market shocks and rigidities that lead to sluggishness of equilibration process. If a sufficient degree of migration and production relocation took place without any time lag, the effects of local shocks would be immediately eliminated. A symptom of disequilibrium unemployment may be a highly negative, in particular, cross-sectional correlation of unemployment rates and employment growth (Lottmann, 2012).[8]

Therefore, the above theories differ in what they consider to be the cause of disparities in local unemployment rates. The first theory emphasizes importance of structural factors, while the second - of demand-side factors. As a result, they differ in policy advices. The former recommends supply-side policies aimed at lowering migration and investment costs, improving local education and infrastructure. The latter supports actions aimed at enhancing the speed of equilibration process. However, bearing in mind that local labour market may remain in disequilibrium for a long time, the second theory recommends, in certain situations, local demand management, in particular active fiscal policy.

Taking into account the differences between the described approaches, we include both structural and demand variables in our analysis. Moreover, we check how the relative importance of both types of factors changes in subsets of poviats with various structural characteristics.

[8] However, one has to note that the layoffs responsible for that correlations may not be caused by negative demand shock. Instead they may be a result of structural changes that boosting aggregate demand cannot reverse. Such changes are signalized by persistent problems faced by the same sectors in various regions.

3 Related empirical research

The main results of previous empirical research on determinants of local unemployment disparities (cf., in particular Elhorst 2000, who runs meta-analysis of 41 empirical studies) may be summarized as follows.[9]

(i) Local unemployment is influenced by local demographics. It positively correlates with the share of the young in population (see, e.g. Cracolici et al. 2007 or Hofler and Murphy 1989). This correlation is consistent with a well-known stylised fact that unemployment among young individuals with limited professional experience is higher (Blanchard, 2006). Some research also suggests that local unemployment negatively correlates with the share of late working-aged in population (see, e.g. Lottmann, 2012 or Molho, 1995). This result may be interpreted as an effect of early retirement schemes that are available for otherwise unemployed. Yet this has been proven to be an inefficient policy for reducing unemployment.[10]

(ii) Unemployment tends to be lower in regions with well-educated labour force (Newell, 2006; Jurajda, Terrell, 2007; Trendle, 2012), provided that there is a demand for skilled labour.[11]

(iii) Local unemployment depends on local sectoral composition of employment (see, e.g. Martin, 1997; Lottmann 2012), which may result from short term industry specific demand shocks. Such shocks must be carefully controlled for.

(iv) Heterogeneity in various labour force characteristics across regions implies that 'one-size-fits-all' policies, such as a uniform minimum wage for the whole country, may contribute to disparities in local unemployment (see, e.g. Baskaya and Rubinstein 2012).

(v) There is no clear correlation between local unemployment and migration. A positive correlation, in line with neoclassical prediction, was found by e.g. Chalmers and Greenwood (1985) while a negative one by e.g. Basile et al. (2010).[12] Various explanations are provided for this discrepancy. First, it matters whether migrating people are actually unemployed or employed looking for better opportunities. Second, migration influxes

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[9] Only small part of the existing research on local unemployment uses the framework of *equilibrium* and *disequilibrium* theory. There is also no agreement on the complete list of variables related to the theories. Other studies employs in *ad hoc* manner different variables that have been shown to influence local labour markets outcomes.

[10] This policy is often motivated by the idea that early retirees leave job vacancies for the young. But this effect has been refuted by several empirical research (see, e.g. Duval 2003) and there are even some proofs that early retirements may actually harm the employment of the young and total employment level (Brugiavini, Peracchi 2008).

[11] See e.g. Shearmur and Polese (2007) who show that better education does not reduce the risk of unemployment in the regions of Canada, where economic activity concentrates on fishery.

[12] Nevertheless, factors discouraging from migrations are found to contribute to higher local unemployment. Risk of being unemployed is higher when one lives in a region with higher number of sunny days, moderate climate, more generous social security schemes (see, e.g. Marston, 1985), or prevailing owner-occupied housing (see, e.g. Hughes and McCormick, 1987).

increase not only local labour supply, but also the demand for local goods and services (cf. Blanchard and Katz 1992).

(vi) Results on effects of local population size or density on local unemployment are also ambiguous. On the one hand, it is argued that higher density enhances matching process which lowers unemployment (Blackley, 1989). On the other hand, it may be an incentive for a longer job search (Burridge, Gordon 1981) or an amenity that discourages the unemployed from migration (Trendle 2012).

(vii) Local unemployment is reduced by regional industry diversification, which makes local economy more resilient to negative industry specific shocks (see, e.g. Izraeli and Murphy 2003 or Trendle and Shorney 2004). However, it is difficult to capture this effect if dominant sectors in some regions prosper over the analysed period.

(viii) Local unemployment negatively correlates with various variables linked to local demand, in line with the disequilibrium theory. Those variables include: employment growth[13] (see, e.g. Korobilis and Gilmartin 2011 or Niebuhr 2003), local output per capita (see, e.g. Elhorst 1995; Epifani and Gancia 2004 or Molho 1995) and its growth (see, e.g. Maza and Villaverde, 2007), investment growth[14] (see, e.g. Bande, Karanassou 2006 or Herbst et al. 2005), government spending on investment[15] (see, e.g. Leigh and Neill, 2011).

(ix) A limited number of studies show positive relationship between local unemployment and real wages (see, e.g. López-Bazo et al. 2002), while most of them suggest that this correlation is negative (see, e.g. Aixalá and Pelet 2010), in contrast to the neoclassical theory.[16] This result could be explained by reversed causality between the variables. Most often when economy prospers and unemployment declines, there is also an upward pressure on wages. Moreover, regions with depressed labour markets are quite often characterised by lower labour productivity and therefore lower wages.

4 Stylized facts on local unemployment in Poland

The following stylized facts on local unemployment in Poland emerge from data inspection.[17]

[13] That correlation is strong in particular in Europe, while in the US it seems to be much weaker (see, e.g. Summers, 1986). The main disadvantage of the inclusion of employment growth in the empirical model is that it does say nothing on what actually drives changes in employment.

[14] It is argued that higher investment in a given region may contribute to lower unemployment also in the long run, as larger capital stock implies higher labour productivity, which in turn encourages creation of new jobs in the region (see, e.g. Bande and Karanassou, 2006).

[15] The long run relationship between local unemployment and government spending on investment is not complex (see, e.g. OECD, 2002).

[16] Adverse impact of high real wages on local unemployment is indirectly supported by results of research on effects of regional differences in unionization (see, e.g. Hofler and Murphy, 1989; Montgomery, 1986 or Summers, 1986).

[17] Detailed data definitions and sources are described in Section 6.

(i) Today's disparities in local unemployment rates in Poland (see Figure 1) are related to distortions in development of various regions during communist regime.[18] Those distortions appear to enhance a link between unemployment rates and sectoral employment composition across regions (see also the stylized fact (iii)). The poviat with the highest unemployment rate is located in the center of Poland, near Radom city, where employment used to be dominated by several large industry plants that were closed after the economic transformation began. The highest concentration of poviats with relatively depressed labour markets encompasses the North and the West of Poland, where state owned farms used to be located. The lowest unemployment is recorded in the proximity of the largest cities, particularly Warsaw, where sectoral structure of employment has always been diversified. It is also relatively low in the South of Poland, i.e. the most industrialized part, where governments introduced generous deactivation schemes as a result of bowing to pressures from strong labour unions in the period of economic transformation.

(ii) Disparities in local unemployment rates are blurred by differences in hidden unemployment. If one uses overemployment in agriculture as a proxy of hidden unemployment, one can observe that it is particularly high in the East and South-east of Poland (Figure 2), where small area farms have partially absorbed reductions in employment.[19]

[Figure 1 and 2 here]

(iii) Disparities in local unemployment rates are very persistent. Even though the national rate of registered unemployment declined from 15.1% in 2000 to 12.5% in 2011, the correlation coefficient of 2000 and 2011 local unemployment rates stands at 0.86 (see Figure 3).[20] Notably the disparities persist despite the fact that Poland has a special algorithm that allocates active labour market policy spending with premium to more troubled poviats (Tyrowicz, Wójcik, 2009a) and has been receiving large cohesion funds since UE accession in 2004.

[Figure 3 here]

[18] For more on this, see e.g. Skodlarski (2000).

[19] Marcysiak and Marcysiak (2009) find that even 20% of farmers may work there less than three hours a day, having only marginal impact on the total production of the farms.

[20] More detailed research confirms this simple observation. Katrencik et al. (2008), Tyrowicz and Wójcik (2009b) and Tyrowicz and Wójcik (2010) find that there is no sigma or beta unconditional convergence of unemployment rates in Polish regions (even some divergence may be found), while conditional convergence is relatively weak and occurs only in small group of poviats.

(iv) Okun's law (1962) works on the local labour markets in Poland (see Figure 4). There is a negative relationship between *changes* in local unemployment rates and GDP per capita growth (r = -0.47).[21]

(v) However, disparities in local unemployment rates can hardly be attributed to disproportionate changes in local demand, at least in the analysed period (see Figure 4). There is only a weak correlation between unemployment *levels* and GDP per capita growth (r = -0.11).

[Figure 4 here] One can draw the stylised facts (iv) and (v) by comparing local unemployment rate with local employment growth (see Figure 5).[22] While local employment growth correlates strongly with *changes* in local unemployment (r = -0.67), its correlation with local unemployment *levels* is much weaker (r = -0.26).

[Figure 5 here]

5 Estimation strategy

We examine the determinants of local unemployment in Poland and check for relative validity of the theories described in Section 2 using panel data models covering 379 Polish poviats for the period of 2000-2010. As a dependent variable, we use unemployment rate (for detailed description see Section 6). The set of regressors is based on previous research as presented in Sections 2 and 3, as well as stylized facts analysed in Section 4 and contains following variables:

(i) The share of early (18-24 years old) and late (55-59/64 years old women/men) working-aged in population (*young* and *old* respectively) capture differences in demographic structure.

(ii) Due to data limitations, the share of unemployed with tertiary education (*edu*) is used as a proxy for skilled labour force. Note, however, that this variable has a high cross-section correlation coefficient (r = 0.87) with the actual data on tertiary education attainment for poviats in 2002 when census was carried out and strongly correlates with the actual data on NUTS 2 level in time dimension (r = 0.98).

(iii) The shares of manufacturing and construction, market services and non-market services in total employment (*man*, *serm*, *sernm* respectively) control for sectoral employment composition.

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[21] That comparison is done for NUTS-3 units (instead of poviats), as this is the lowest level for which estimates of regional product are available..

[22] This comparison, in contrast to GDP per capita growth, is possible for poviats.

(iv) Uniform minimum wage relative to poviat's average wage (*minw*) enables to check whether 'one-size-fits-all' policies may contribute to disparities in local unemployment.

(v) The proportion of registered migration balance to the population is used, taking into account the emphasis that local unemployment theories put on migrations.

(vi) Density of population is used (*dens*) to check its relative importance in enhancing a matching process and in lengthening a job search.

(vii) Employment diversity (*div*), as measured by the Herfindahl-Hirschmann index controls for poviats' resilience to industry specific shocks. The index is multiplied by -1 so that higher values correspond to larger employment diversity.

(viii) GDP per capita growth (*g_gdp*) allows controling for local demand fluctuations. As the respective data is only available for NUTS-3 level, the ration of investment to existing capital stock (*inv*) is also included. Lastly, in order to control for demand management by local authorities, the investment share in local government expenditure and local fiscal balance are included (*invshr* and *finbal* respectively).

(ix) We added dummy variable (*since2003*) in order to control for the effects of changes in dependent variable definition (see Section 6 for details).

All variables (see Appendix B, Table B.1 for the detailed description), except for *g_gdp,* are expressed in logs[23] and the estimated model has the following form:

$$\begin{aligned} ln\_ur_{it} &= \alpha_i + \beta_1 g\_gdp_{it} + \beta_2 ln\_inv_{it} + \beta_3 ln\_young_{it} + \beta_4 ln\_old_{it} + \\ &\beta_5 ln\_edu_{it} + \beta_6 \ln\_man_{it} + \beta_7 ln\_serm_{it} + \beta_8 ln\_sernm_{it} + \beta_9 ln\_dens_{it} + \\ &\beta_{10} ln\_div_{it} + \beta_{11} ln\_minw_{it} + \beta_{12} ln\_invshr_{it} + \beta_{13} ln\_finbal_{it} + \\ &\beta_{14} ln\_mig_{it} + \beta_{15} since2003 + \varepsilon_{it} \end{aligned} \quad (1)$$

where α_i represents time-invariant, individual effects for poviats and ε_{it} is the error term.

We estimate the equation described above using a set of panel data estimators. We start with the pooled estimator (*ols*) which ignores the possibility of individual effects i.e. the specific, unobservable characteristics of a given poviat that affect the dependent variable. In the case individual effects exist, the estimator is biased, hence it is regarded in literature as the first approximation only. Next, we apply the fixed effects (*fe*) and random effects estimator (*re*), which assumes homogeneous coefficients of the explanatory variables but allows for individual constant term for different poviats.

[23] Prior to log calculation a constant is added to variables with possible nonpositive observations.

The results based on the estimators mentioned may be biased due to several methodological problems. The first one is a possible cross-sectional dependence (or spatial correlation) of error terms. In the analyzed model, it is equivalent to the assumption that there are unobserved time-varying omitted variables common for all poviats which impact each poviat in a different way. Indeed, results of the Pesaran's test (2004) for cross-sectional dependence indicate that this is a characteristic of the data set used.[24] If these unobservable common factors are uncorrelated with the independent variables, the coefficient estimates based on *ols, fe* or *re* regression are consistent, but standard errors estimates are biased. Therefore, we use the Driscoll and Kraay (1998) nonparametric covariance matrix estimator (*dk*) which corrects for the error structure spatial dependence. This estimator also addresses the second problem, which is the standard errors bias due to potential heteroscedasticity and autocorrelation of error terms. We are aware of weaknesses of this estimator when number of cross-sectional units is much larger than number of time periods as in our panel. However, we take into account evidence provided by Monte Carlo simulations, according to which even for panels with very short time dimension, in the case of cross sectional dependence, it is more robust than *fe* estimator (Hoechle 2006).

The consistency of the estimators presented above may also be affected by the third issue, i.e. endogeneity due to a potential correlation between regressors and the error term. A possible solution is to use the instrumental variables estimator. The estimator is asymptotically consistent, yet it may be severely biased when applied to such short samples as ours, which prevents us from using it in the research. However, in Section 7 we address the endogeneity issue to some extent by re-estimation of the model using subsamples of data based on quartiles of the chosen exogenous variables.

Taking into account all of the above restrictions, we use four types of panel data estimators: pooled (*ols*), fixed effects (*fe*), random effects (*re*) and Driscoll-Kraay with corrected standard errors (*dk*). Because the last estimator addresses the most of above issues it is a base for interpretation of our results. At the same time, we do realize that the obtained results could be affected by some of the abovementioned problems and that conclusions drawn on their basis should be taken with caution.

[24] See Appendix C, Table C.1 for the results of specification tests.

6 Data and descriptive statistics

All data are obtained from Polish Central Statistical Office, specifically from the Local Data Bank database and from archival editions of Statistical Yearbook of the Regions. The data covers only the period of 2000-2010 for two reasons. First, poviats in Poland were introduced as part of the administration reform in 1999. Second, a large proportion of data for NUTS-4 level regions are published in Poland with a lag of several years.

There are 379 poviats in Poland. An average poviat has a population of 101 thousand and covers an area of 825 km^2. It is a good proxy for local labour market, as most inhabitants live and work within a single poviat. Research by Polish Central Statistical Office (2010) shows that 80% of working population commutes no further than 20 km and 70% of employees need less than 30 minutes to arrive at their workplace.

The numerator of unemployment rate *(ur)*, the dependent variable, is the number of individuals registered as unemployed in a particular poviat. Yet, some of them are not really "unemployed", as they either work in the shadow economy or have registered only to cover health insurance costs from public funds. The denominator (i.e. the Central Statistical Office's estimate of labour force in a particular poviat) is not a perfect measure either. For instance, it captures the number of self-employed farmers that was revised downward significantly in 2003. We control for the corresponding increase in the registered unemployment rates by including a dummy variable (*since2003*) in the regressions.

However, there are still reasons to think of registered unemployment rate as a reliable measure of unemployment in poviats. First, it is highly correlated (r = 0.92) in cross section dimension with more reliable Labour Force Survey (LFS) unemployment rates for poviats in 2002, when a census was performed. Second, on NUTS-2 level, for which regular LFS unemployment rates estimates are available, both measures are characterised by very similar trends (average correlation in time: r = 0.96). Therefore, registered rates probably do not show the actual level of local unemployment, but they capture most changes within poviats and differences among them. A full definitions of variables used in the estimations is reported in Appendix B.

There are two important conclusions which follow from descriptive statistics, as presented in Table 1. First, certain variables show very high variation (see, e.g. *inv g_gdp, dens*), suggesting the presence of outliers that may bias the results. Second, analyzing variable means for different quartiles of unemployment, it becomes visible that certain variables correlate with unemployment rate as predicted by other reserach (e.g. *edu*) while for others (e.g. *g_gdp*) there is no clear bivariate correlation. We present results of a more thorough analysis in the two subsequent sections.

[Table 1 here]

7 Estimation results

We begin with examination of variables' stationarity. We use Harris and Tzavalis (1999), Maddala and Wu (1999) and Pesaran (2007) tests. The results presented in Appendix C, Table C.2 indicate that most of variables are stationary or trend-stationary, so the model can be estimated in the form described in Section 4 with low risk of obtaining spurious results.

Estimation results are presented in Table 2. In general, the obtained results are in line with main conclusions from previous empirical research, as summarized in the Section 3. Structural factors (in particular demographics, education and composition of employment) are more important for determining local unemployment rates in Poland than fluctuations in local demand.

[Table 2 here]

The impact is the strongest in case of demographic variables. Among them the share of early working-aged has the much stronger impact on local unemployment than the share of late working-aged has (elasticity of 1.39 and -0.39 respectively). The influence of the latter is similar to the one of the share of skilled labour (elasticity of -0.34 for *edu*).

In terms of the impact on local unemployment demographic variables are followed by the set of indicators of sectoral employment composition. In this set, the share of manufacturing and construction sectors in the employment structure has the strongest impact (the second strongest among all variables in the model). In this context it is worth recalling that due to booming real estate market and considerable inflows of the EU structural funds spent on infrastructure, employment in construction sector in Poland increased by 56.8% from 2004 to 2010. Notably, the larger the is the share of nonmarket services in employment, the higher is local unemployment. The imputed elasticity of the share of agriculture in employment (which is a residual category in the model) is also positive, albeit much weaker. The interpretation of both elasticities that we consider most likely adequate is that those sectors play a role of partial absorbers of workers laid off from other sectors.

Consistently, various measures of local demand fluctuations have only weak influence on local unemployment. Acceleration of GDP per capita growth by one percentage point (which translates, on average, into an approximate change of 26%) implies a decrease of 0,59% in local unemployment . An increase of 10% in private investment relative to existing capital stock or in public investment relative to local government expenditure has similarly weak effect. The related decrease in local unemployment rates amounts to 0,66% and 0,77% respectively.[25]

The negative coefficient of local fiscal balance may, in theory, reflect either a strong impact of local fiscal stance on local unemployment or a non-Keynesian response of unemployment to local fiscal shocks. A negative (even if low) local unemployment elasticity with respect to investment share in local government expenditure supports the former.[26] The low value (in absolute terms) of the coefficient in question is in line with strong dependence of local fiscal stance on local unemployment and weak Keynesian response of local unemployment to local fiscal shock.

Non-significance of minimum wage (at least in case of *dk* estimator) suggests that if it contributes to disparities in local unemployment, then this contribution is probably made through other variables included in the model, which are most likely related to labour force heterogeneity. Such interpretation is supported by Majchrowska and Żółkiewski (2012), i.e. the research devoted specifically to effects of minimum wage in Poland.[27] Alternatively, the reverse causality (discussed with respect to real wages in Section 3) could play a role here. Over the analyzed period the minimum wage in Poland was rather low by international standards, but was raised significantly in the period of 2008-2009.

Migration balance has statistically significant positive coefficient, which is in line with the neoclassical prediction. However, its economic significance is low, which may be the result of the fact that our variable captures only officially declared part of migrations.

Population density has a statistically non-significant effect on local unemployment, It contrasts with the observed concentration of low unemployment in the largest Polish cities (see Figure 1). It could potentially be the result of a very low variation of population density in time within particular poviats (see Table 1), which is crucial for significance of variables in the framework with fixed effects. For pooled *ols* estimator, which also takes into account the variation of population density among poviats, *dens* is significant and negatively correlated with local unemployment.

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[25] Such a weak impact of local demand fluctuations on local unemployment seems to disagree with the effects observed on country level. However, note that in our analysis all poviats are treated equally regardless of their population size. Therefore, results obtained for an average poviat does not have to be representative for the whole economy.

[26] There is some evidence of non-Keynesian effects of fiscal shocks at national level in Poland (see, e.g. Afonso, Nickel and Rother, 2005; Borys et al., 2014 or Rzońca and Ciżkowicz, 2005).

[27] A survey of research for other countries notes that the impact of minimum wage on unemployment is multidimensional and its relevance remains controversial (see, e.g. Neumark and Wascher, 2006).

Industrial diversity is another variable with a non-significant effect on local unemployment. This result demonstrates that disparities in local unemployment lack a clear link with the differences in poviats' resilience to industry specific shocks. Alternatively, it may mean that no significant shocks were present in our sample.

The relative importance of structural and demand-related determinants of local unemployment does not change, if their observed variation is considered (see Table 3). The impact of one standard deviation increase in the independent variables within poviats is the highest for tertiary education attainment proxy (16.5% decrease in *ur*) and the early and late working-aged shares in the population (8.2% increase and 7.2% decrease respectively).[28]

[Table 3 here]

A comparison with other research for Poland (see Appendix A, Table A.1) indicates that our results are in line with previous outcomes with respect to the impact of higher education attainment and demographic variables (Newell and Pastore, 2000; Newell, 2006; Żurek, 2010). Our study confirms also that sensitivity of local labour market situation to cyclical fluctuations is statistically significant but low (Radziwiłł, 1999; Pastore and Tyrowicz, 2012). The impact of sectoral employment structure on local unemployment is unambiguous: some studies (Radziwiłł, 1999; Żurek, 2010) confirm our results, whereas other point to the opposite effects (Newell, 2006; Herbst et al., 2005). No previous study has analyzed the influence of fiscal variables on local unemployment.

Most importantly, the impact of outliers on results obtained or potential heterogeneity of identified relations have not been also analyzed. With our paper, we aim at filling this gap. The results of the analysis are presented in the next two subsections.

8 Robustness analysis: outliers and heterogeneity of parameters.

In this section we check robustness of the conclusions obtained so far. We focus on two issues which appear to be understudied in other research devoted to local unemployment disparities: outliers detection and possible heterogeneity of parameters.

We begin with identifying of potential outliers and examine their impact on the results obtained. Four methods of outliers identification are used, and three of them in two variants (i.e. with 1 or 5% threshold). First, Mahalanobis distances from vector of means are calculated (Mahalanobis, 1936) and 1% or 5% of observations with the largest values are excluded from the sample (*mah*). Second, we control for the effect of the 1% and 5% of

[28] For one standard deviation increase in overall disparities in local unemployment it is tertiary education attainment and the share of employed in manufacturing and construction that have the strongest impact on unemployment rates (24% and 18.2% decrease respectively), The impact of population density is even stronger, but this variable is not significant for models with fixed effects.

observations with largest absolute values of residuals (*res*). Third we mark the most extreme 1% and 5% observations for every variable and exclude them from the sample (*var*). Fourth, a method developed by Verardi and Wagner (2010) is applied (*robust*).[29]

The results of regressions without identified outliers are presented in Table 4. In general, the outcome is that outliers have no strong effect on most relations identified for the whole sample.

[Table 4 here]

Demand, demographic or sectoral employment composition variables are significant in all the regressions. The same applies to fluctuations of GDP per capita and private investment. The coefficients of all aforementioned variables are quite stable and in most cases are larger in absolute terms than in the whole sample regressions. That is especially true for the share late working-aged in population. By contrast, the influence of education decreases in significance.

The share of investment in local government expenditure and fiscal balance on the one hand, and migration balance one the other hand admittedly lose their significance in the *robust* regression. However, this result should be interpreted with caution. The *robust* regression may be overfitted to data as it excludes almost 55% of observations from the sample.

Results for population density also require a comment. In three regressions the variable has a positive, highly significant coefficient. These are three estimations where most observations are excluded. Within excluded observations the mean population density is almost twice as high as in the whole sample. Thus, these estimations omit the relation between unemployment and population density in highly populated poviats.

Next, potential heterogeneity of estimated parameters is examined. If the estimated parameters varied across countries, then the standard approach would be to estimate the model separately for each country with the *ols* and to average the parameters that were obtained in this manner.[30] In our case, each of the separate country regressions would be based on 11 observations which would make the estimates impossible due to number of explanatory variables.

Instead we divide the sample into quartiles of three arbitrarily chosen variables and run separate regressions for each of them. These variables are unemployment rate (*ur*), GDP

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[29] The applied algorithm may be described in steps. First, it centers the observations by subtracting their means. Second, it runs an S-estimator (Rousseeuw and Yohai 1984) of the centered dependent variable on centered explanatory variables. Finally, it assigns outliers weights that are equal to zero and uses fixed effects estimator.

[30] This approach is called the mean group estimator method and was first proposed by Pesaran and Smith (1995).

per capita (*gdp*) and average area of arable lands (*avarea*). Unemployment quartiles are naturally of our interest, as we would like to check whether some determinants affect unemployment rates in different manner depending on the soundness of local labour markets. We use GDP per capita level as a proxy for general wealth and development, which may condition the influence of the analyzed determinants. Finally, we examine the quartiles of average area of arable lands, a variable that we consider to be a good proxy for hidden unemployment in Polish agriculture. Both GDP_per capita and average of arable lands mirror also to some extent historical conditions of particular regions. Poviats have been assigned to quartiles based on the data for the year 2000 (*ur, gdp*) and 2002 (*avarea*).[31]

The results for different quartiles estimations are presented in Figure 6 . Coefficients and significance of most variables resemble the parameters obtained for whole sample regressions. However, there are several exceptions that worth noting.

[Figure 6 here]

Heterogeneity of unemployment elasticity with respect to the share of late working-aged in the population is most distinct. The higher the GDP per capita or the lower the unemployment rate, the lower the elasticity in question. In the poviats with the highest GDP per capita or with the lowest unemployment rate, it is not significant any longer. Apparently, in these poviats late working-aged rarely leave labour force through early retirement schemes when faced with redundancy.

Heterogeneity of unemployment dependence on the share of the early working-aged is a mirror image of the heterogeneity discussed above. The higher the GDP or the lower the unemployment rate, the stronger the dependence observed. It is possible that the young from the more affluent poviats can afford a longer job search.. They are also the main group which finds it difficult to find a job in regions where unemployment is low.

Another notable result is the lack of influence of tertiary education on unemployment in poviats, where GDP per capita is low or unemployment is high. It suggests that demand for skilled labour in these regions is weak. Thus, skills improvement is not a solution for the problems of depressed poviats.

It is also worth noting the certain level of heterogeneity in estimates of local unemployment responsiveness to fluctuations in local demand. In particular, the local unemployment responds less to fluctuations in local private investment in poviats with higher unemployment. The same regularity, albeit not so unequivocal, can be observed in the case of

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[31] Data for average area of arable lands are only available for 2002 and 2010. These are the years, when a census was hold.

its response to fluctuations in local GDP per capita growth. Both these results support the claim that where unemployment is high, this is so due to structural factors that cannot be easily alleviated by a boost in local demand.

Local unemployment response to fluctuations in local private investment is also muted by large hidden unemployment in agriculture. Small farms act as an important absorber of workers laid off due to such fluctuations. This effect is less clear in the case of fluctuations in local GDP per capita or public investment.

Local public investment has the weakest influence on local unemployment in poviats with low GPD per capita. This may be caused by either structural nature of unemployment in poor poviats, or by larger productivity gains from public investment in richer poviats, where public investment leads to stronger increase in demand for labour.

9 Conclusions and policy recommendations

We find that, while local demand fluctuations have certain influence on local unemployment, large disparities in local unemployment are mainly related to demographics, education and sectoral employment composition. This conclusion is not sensitive to exclusion of outliers.

However, certain relations vary across poviats significantly. Where unemployment is low or income per capita is high, unemployment does not depend on the late working-aged share in the population but does depend relatively stronger on the share of early working-aged. Where unemployment is high or income per capita is low, unemployment does not depend on education and is less responsive to investment fluctuations. Where small farms are present, they act as partial absorbers of the employment reduced due to investment fluctuations.

The main conclusions suggested by the analysis is pessimistic. There is no easy cure for local unemployment in Poland. Skill improvement schemes appear to be a good policy with the exception of most depressed local labour markets. Certain evidence demonstrates that support of transition from employment in agriculture and non-market services to manufacturing, construction and market services may bring the desired results. It also appears that poviats with the most dense populations experience lower unemployment. Therefore, migration to more densely populated regions may decrease overall unemployment level.

However, the results obtained must be considered with caution – at the very least due to estimation issues typical for panels with a short time dimension. Certainly, there are ample oportunities for future research on the topic. In this research, it would be useful to take advantage of econometric tools which control for interconnectedness of local labour markets (e.g. spatial panel data models) and allow to divide regional markets into more homogeneous groups (e.g. mixture panel data models).

Acknowledgments

We would like to thank Maciej Stański for excellent technical assistance. The usual caveats apply.

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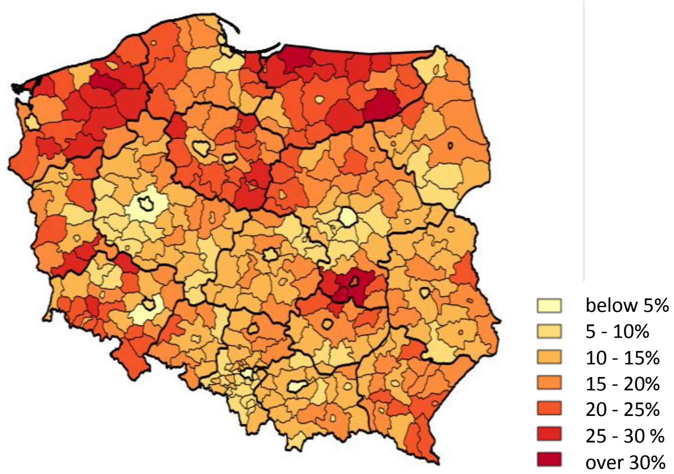
Figures and tables

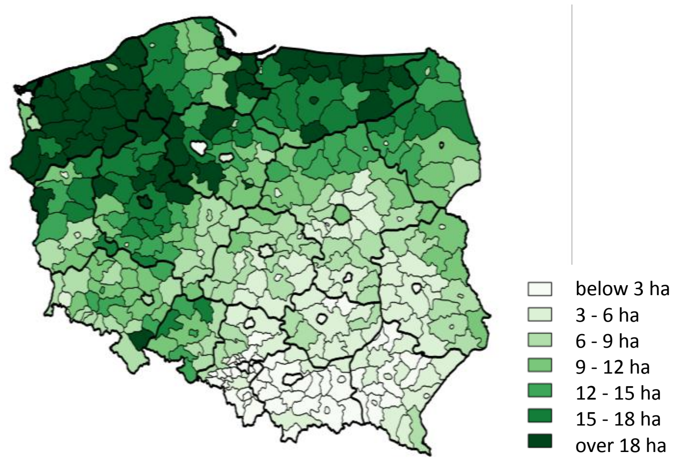
Figure 1. Spatial distribution of local unemployment



Notes: The map depicts spatial distribution of local unemployment rates for Polish poviats (NUTS-4) in 2010. Borders of most populated cities and NUTS-2 regions are marked in bold.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office

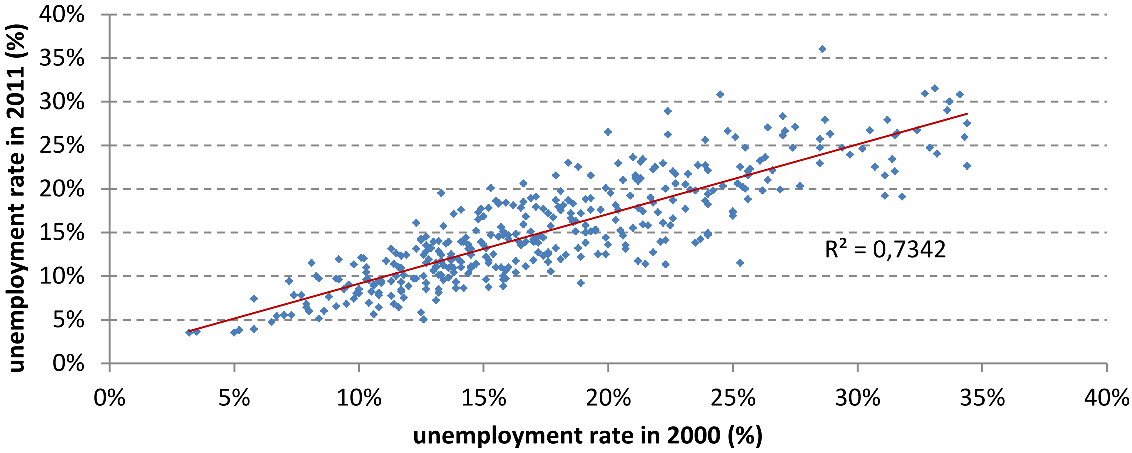
Figure 2. Average area of arable lands



Notes: The map depicts spatial distribution of average area of arable lands (in hectares) for Polish poviats (NUTS-4) in 2010. Borders of most populated cities and NUTS-2 regions are marked in bold.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office

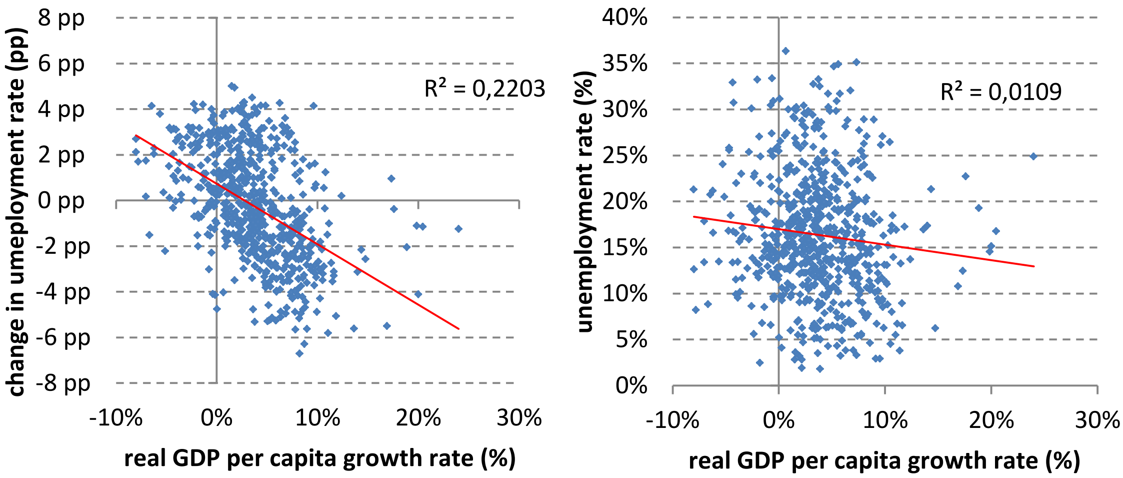
Figure 3. Correlation in time of local unemployment



Notes: the graph presents the correlation in time of local unemployment rates in Polish poviats (NUTS-4) in 2000 and 2011.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office

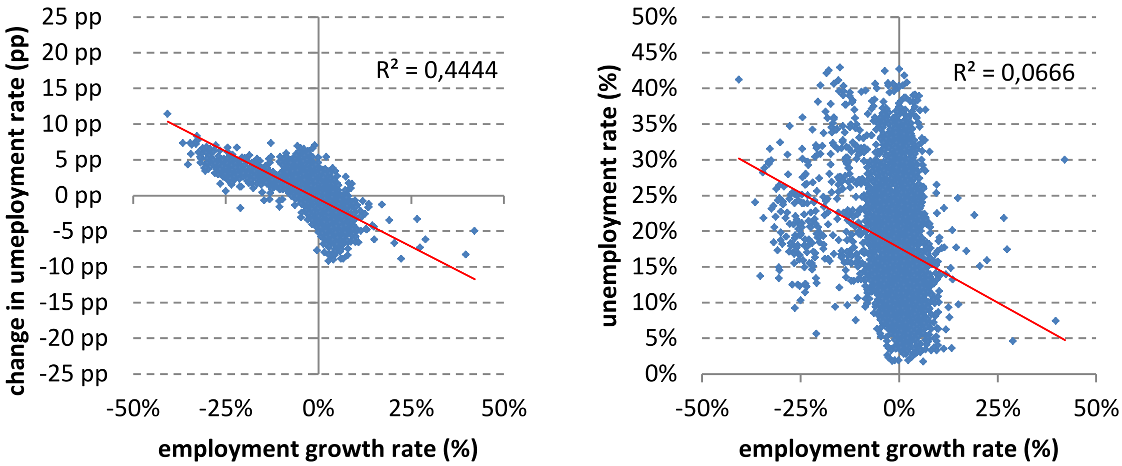
Figure 4. Correlation of local GDP growth and unemployment



Notes: the left graph presents correlation of yearly real GDP per capita growth rates with yearly *changes* in local unemployment rates for Polish NUTS-3 regions in years 2001-2000. The righ graph presents correlation of yearly real GDP per capita growth rates with yearly *levels* of local unemployment rates for Polish NUTS-3 regions in years 2001-2010. NUTS-3 data has been used, because on NUTS-4 level in Poland GDP statistics are not available.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office and Statistical Yearbook of the Regions

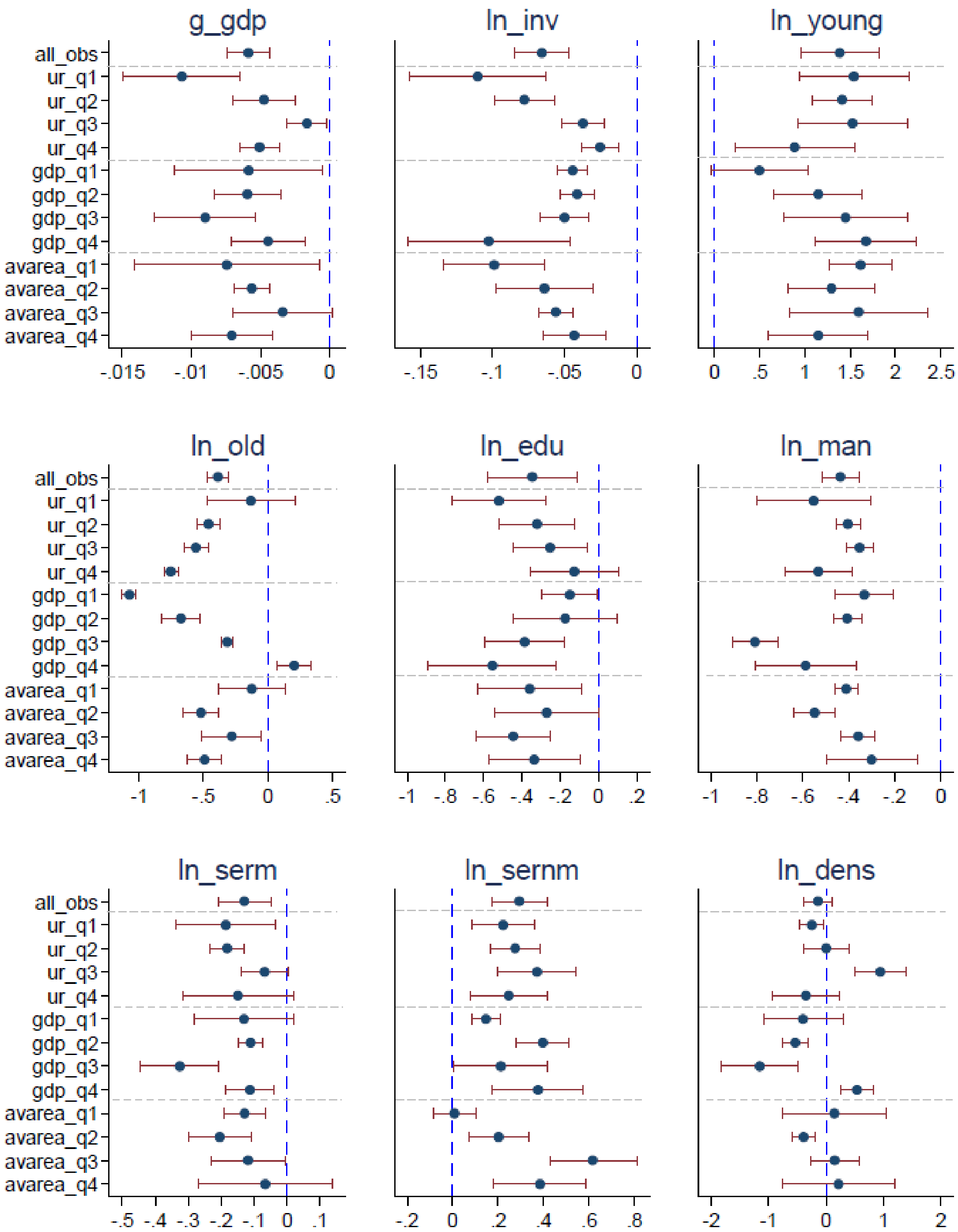
Figure 5. Correlation of local employment growth and unemployment

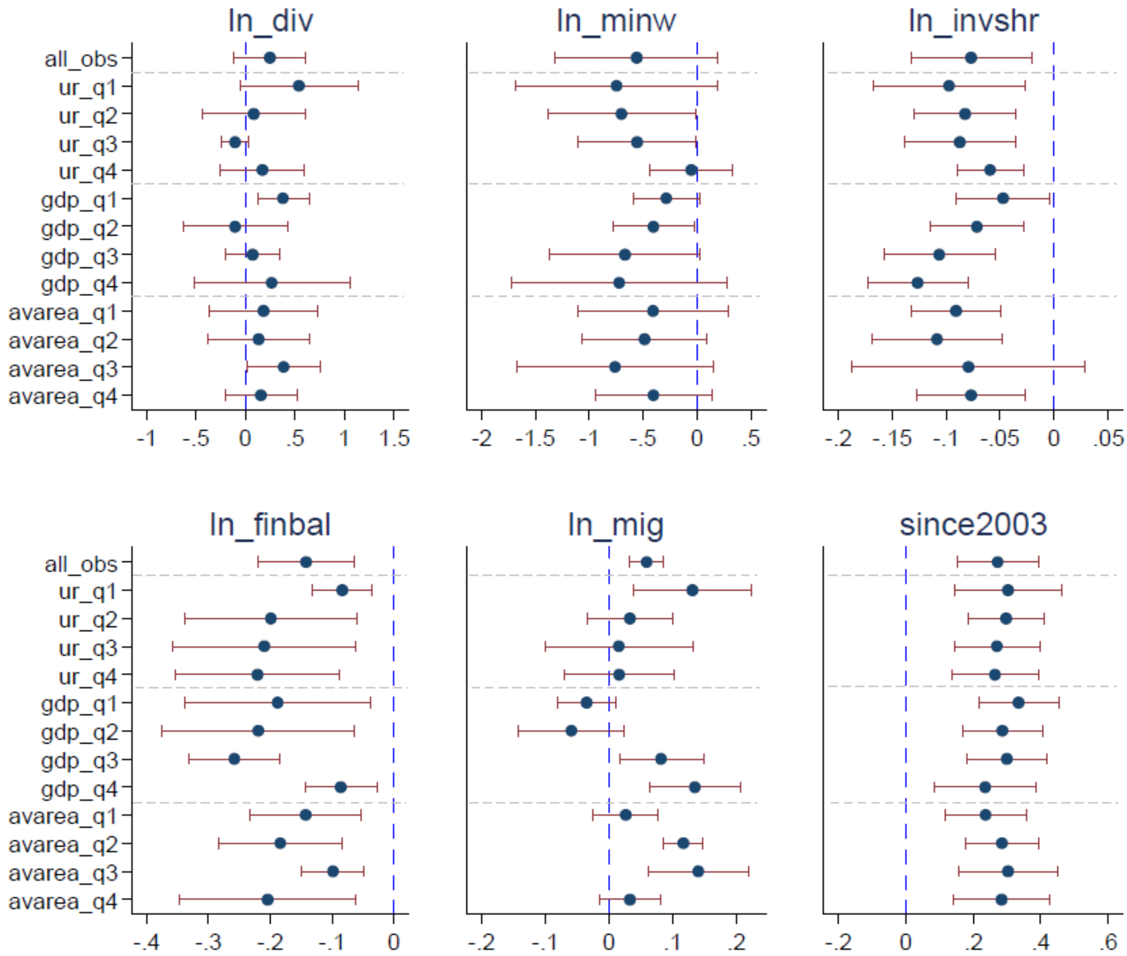


Notes: The left graph presents correlation of yearly employment growth rates with yearly *changes* in local unemployment rates for Polish poviats (NUTS 4) in years 2001-2010. The right graph presents correlation of yearly employment growth rates with yearly *levels* of local unemployment rates in Polish poviats (NUTS-4) in years 2001-2010.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office and Statistical Yearbook of the Regions

Figure 6. Regressions for poviats belonging to different quartiles of the chosen variables





Notes: The figure presents point estimates and 95% confidence intervals of structural parameters in model (1) based on subsamples corresponding to different quartiles of the following variables in Polish poviats (NUTS-4 level): *ur* – unemployment rate, *gdp* – GDP per capita, *avarea* – average arable land (*all_obs* recalls the results for the whole sample). For example, estimates and confidence intervals that correspond to *gdp_q3* are based on the separate regression for poviats with gdp per capita belonging to third quartile of this variable in 2000. All the regressions use fixed effect estimator with Driscoll and Kray (1998) standard errors.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office and Statistical Yearbook of the Regions

Table 1. Descriptive statistics

variable	mean					min	median	max	standard deviation		
	overall	ur_q1	ur_q2	ur_q3	ur_q4	overall	overall	overall	overall	within	between
ur	18.22	10.76	15.45	19.84	26.90	1.70	17.30	42.90	7.68	4.01	6.56
g_gdp	3.85	4.01	3.88	4.02	3.50	-8.10	3.83	23.38	3.99	3.87	0.97
inv	10.60	10.71	10.16	10.63	10.91	0.24	8.88	121.92	7.95	6.62	4.42
young	11.47	11.43	11.40	11.43	11.63	7.12	11.49	16.59	0.96	0.67	0.68
old	7.92	8.16	7.93	7.77	7.80	4.24	7.84	13.39	1.68	1.47	0.82
edu	5.47	7.66	6.16	4.56	3.50	0.39	4.45	28.54	3.81	2.62	2.77
man	29.28	29.94	29.27	27.68	30.25	1.74	29.62	76.45	12.26	2.35	12.05
serm	19.51	23.84	18.47	17.08	18.65	1.08	17.18	63.85	10.42	2.43	10.15
sernm	21.18	19.44	19.62	21.22	24.49	7.69	20.26	57.28	6.17	2.29	5.73
dens	387.64	653.47	380.53	372.82	141.16	19.65	89.06	4378.85	701.24	30.31	701.43
div	-0.17	-0.17	-0.18	-0.17	-0.17	-0.27	-0.17	-0.12	0.02	0.01	0.02
minw	42.48	40.11	41.84	43.02	44.98	17.79	43.13	63.16	5.49	2.41	4.94
invshr	17.00	18.79	16.62	16.74	15.57	2.00	16.00	54.00	6.00	4.83	3.67
finbal	-2.87	-3.03	-2.53	-2.88	-3.06	-32.13	-2.36	30.60	4.97	4.77	1.40
mig	-0.10	0.04	-0.12	-0.08	-0.23	-1.50	-0.16	2.67	0.40	0.13	0.38

Notes: This table presents descriptive statistics of variables in Polish poviats (NUTS-4) in years 2000-2010. Statistics labelled as *overall* correspond to the whole sample including 4169 observations. Statistics labelled as *ur_q1*, *ur_q2*, *ur_q3* and *ur_q4* have been calculated for different quartiles of poviats with respect to their unemployment rates in 2000. The table also reports the decomposition of overall standard deviations into their between and within components.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office and Statistical Yearbook of the Regions

Table 2. Estimation results

Dependent variable: ln_ur				
	ols	**re**	**fe**	**dk**
g_gdp	-0.0080***	-0.0065***	-0.0059***	-0.0059***
	(-7.059)	(-9.140)	(-8.440)	(-7.408)
ln_inv	-0.0810***	-0.0734***	-0.0658***	-0.0658***
	(-9.885)	(-11.898)	(-10.801)	(-6.905)
ln_young	0.5225***	1.1914***	1.3882***	1.3882***
	(8.126)	(22.288)	(25.658)	(6.335)
ln_old	-0.2740***	-0.3097***	-0.3880***	-0.3880***
	(-6.321)	(-8.145)	(-10.003)	(-9.537)
ln_edu	-0.3530***	-0.3495***	-0.3447***	-0.3447***
	(-29.300)	(-25.234)	(-22.622)	(-2.854)
ln_man	0.0240**	-0.1525***	-0.4355***	-0.4355***
	(2.257)	(-7.966)	(-14.767)	(-10.451)
ln_serm	-0.0701***	-0.0229	-0.1292***	-0.1292***
	(-5.198)	(-1.456)	(-6.576)	(-3.142)
ln_sernm	0.6371***	0.4557***	0.2943***	0.2943***
	(33.005)	(19.021)	(10.201)	(4.776)
ln_dens	-0.1008***	-0.0457***	-0.1381	-0.1381
	(-16.766)	(-3.666)	(-1.081)	(-1.096)
ln_div	-0.6718***	-0.1869***	0.2453***	0.2453
	(-16.433)	(-2.629)	(2.707)	(1.316)
ln_minw	-0.3100***	-0.4925***	-0.5603***	-0.5603
	(-8.324)	(-9.296)	(-9.228)	(-1.463)
ln_invshr	-0.1431***	-0.0916***	-0.0772***	-0.0772***
	(-10.088)	(-8.036)	(-6.797)	(-2.710)
ln_finbal	-0.1385***	-0.1514***	-0.1417***	-0.1417***
	(-5.998)	(-9.759)	(-9.337)	(-3.598)
ln_mig	-0.0924***	0.0123	0.0599**	0.0599***
	(-4.683)	(0.501)	(2.254)	(4.399)
since2003	0.3358***	0.2845***	0.2728***	0.2728***
	(21.130)	(26.215)	(25.344)	(4.466)
constant	4.3949***	3.8079***	5.2218***	5.2218**
	(15.738)	(11.500)	(6.929)	(2.085)
Observations	4169	4169	4169	4169
Panels		379	379	379
R2	0.659	0.594	0.360	0.360
R2-within		0.622	0.636	0.636

Notes: This table presents estimates of coefficients (t/z-statistics in parentheses, * $p<0.1$, ** $p<0.05$, *** $p<0.01$) for four applied estimators: *ols* - pooled ordinary least squares estimator, *re* – random effects estimator, *fe* - fixed effects estimator, *dk*- fixed effects estimator with Driscoll and Kray (1998) standard errors.

Source Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office and Statistical Yearbook of the Regions

Table 3. Comparison of the obtained elasticities with the impact of one standard deviation change in the independent variables

variable	% change in *ur* caused by an increase in the dependent variable of:			
	1%	one standard deviation		
		within	between	overall
edu	-0.3447***	-16.4727***	-17.4335***	-23.9697***
young	1.3882***	8.1652***	8.2646***	11.6108***
old	-0.3880***	-7.1923***	-4.031***	-8.2425***
inv	-0.0658***	-4.1073***	-2.7417***	-4.9364***
man	-0.4355***	-3.4942***	-17.9181***	-18.2345***
sernm	0.2943***	3.1762***	7.9660***	8.5669***
finbal	-0.1417***	-2.8431***	-0.8309***	-3.0350***
g_gdp	-0.0227***	-2.2836***	-0.5733***	-2.3543***
invshr	-0.0772***	-2.1997***	-1.6709***	-2.7611***
serm	-0.1292***	-1.6076***	-6.7173***	-6.8992***
mig	0.0599***	0.7229***	1.3188***	1.4487***
minw	-0.5603	-3.1822	-6.5143	-7.2430
div	0.2453	1.4105	2.7505	3.0882
dens	-0.1381	-1.0796	-24.9888	-24.9821

Notes: This table compares the impact of 1% increase and one standard deviation increase in the dependent variables used in the model on the percentage change of local unemployment rate (*ur*). Calculations are based on the results obtained for fixed effects estimator with Driscoll and Kray (1998) standard errors (* p<0.1, ** p<0.05, *** p<0.01). Estimated elasticities should be rather interpreted for standard deviation in the variables *within* poviats (because of within transformation applied in fixed effects estimator). Assuming that impact of differences in the variables *between* poviats is analogous, however, one may also interpret the effects of changes in the dependent variables that are equal to their *overall* and *between* standard deviations.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office and Statistical Yearbook of the Regions

Table 4. Robustness analysis: regressions without outlying observations

Dependent variable: ln_ur								
	dk	**mah_1**	**mah_5**	**res_1**	**res_5**	**var_1**	**var_5**	**robust**
g_gdp	-0.0059***	-0.0059***	-0.0064***	-0.0063***	-0.0062***	-0.0078***	-0.0082***	-0.0033***
	(-7.408)	(-7.771)	(-7.241)	(-8.050)	(-8.460)	(-5.650)	(-10.530)	(-3.452)
ln_inv	-0.0658***	-0.0650***	-0.0601***	-0.0654***	-0.0701***	-0.0576***	-0.0503***	-0.0088***
	(-6.905)	(-8.608)	(-7.990)	(-6.793)	(-8.039)	(-6.665)	(-6.055)	(-3.669)
ln_young	1.3882***	1.3361***	1.3097***	1.4068***	1.4222***	1.3860***	1.3696***	1.1988***
	(6.335)	(6.538)	(5.877)	(6.553)	(6.644)	(6.521)	(5.386)	(28.099)
ln_old	-0.3880***	-0.3949***	-0.4433***	-0.3921***	-0.4201***	-0.4994***	-0.6181***	-0.6080***
	(-9.537)	(-9.926)	(-11.872)	(-10.448)	(-12.480)	(-15.734)	(-15.386)	(-17.355)
ln_edu	-0.3447***	-0.3318***	-0.3080***	-0.3407***	-0.3251***	-0.2970***	-0.2279**	-0.2376***
	(-2.854)	(-2.851)	(-2.817)	(-2.896)	(-2.893)	(-2.939)	(-2.526)	(-4.232)
ln_man	-0.4355***	-0.4369***	-0.4432***	-0.4480***	-0.4690***	-0.4680***	-0.4439***	-0.3635***
	(-10.451)	(-9.197)	(-9.233)	(-12.278)	(-13.849)	(-14.471)	(-16.545)	(-9.415)
ln_serm	-0.1292***	-0.1682***	-0.1848***	-0.1463***	-0.1799***	-0.1760***	-0.1643***	-0.2282***
	(-3.142)	(-3.862)	(-4.517)	(-3.723)	(-5.897)	(-4.393)	(-6.697)	(-8.026)
ln_sernm	0.2943***	0.2906***	0.2778***	0.3130***	0.3042***	0.2935***	0.3119***	0.2254**
	(4.776)	(5.310)	(4.935)	(5.189)	(5.413)	(5.963)	(5.785)	(2.453)
ln_dens	-0.1381	-0.2176*	-0.2551*	-0.1650	-0.2212*	0.2569**	0.6004***	0.6523***
	(-1.096)	(-1.693)	(-1.790)	(-1.239)	(-1.659)	(2.065)	(5.470)	(2.809)
ln_div	0.2453	0.1832	0.1271	0.2290	0.2401	0.1732	0.0253	-1.0582***
	(1.316)	(1.118)	(0.812)	(1.285)	(1.276)	(1.243)	(0.260)	(-11.675)
ln_minw	-0.5603	-0.4679	-0.4891*	-0.5608	-0.5979*	-0.4413	-0.3830	-0.4620**
	(-1.463)	(-1.395)	(-1.666)	(-1.509)	(-1.665)	(-1.551)	(-1.413)	(-2.243)
ln_invshr	-0.0772***	-0.1080***	-0.1049***	-0.0840***	-0.0824***	-0.0859***	-0.0808***	-0.0107
	(-2.710)	(-6.996)	(-6.486)	(-3.178)	(-3.129)	(-4.012)	(-3.128)	(-0.792)
ln_finbal	-0.1417***	-0.2420***	-0.2546***	-0.1487***	-0.1351***	-0.2320***	-0.2368**	-0.0003
	(-3.598)	(-2.963)	(-2.618)	(-3.749)	(-3.768)	(-3.033)	(-2.409)	(-0.014)
ln_mig	0.0599***	0.0856***	0.0844***	0.0675***	0.1178***	0.0639***	0.0228	0.0054
	(4.399)	(7.479)	(8.488)	(4.827)	(8.214)	(4.207)	(0.781)	(0.167)
since2003	0.2728***	0.2805***	0.2851***	0.2777***	0.2812***	0.2909***	0.3016***	0.2324***
	(4.466)	(4.470)	(4.564)	(4.710)	(5.034)	(4.860)	(4.998)	(13.746)
constant	5.2218**	5.7268**	6.3923***	5.3830**	5.9696**	3.4424	1.8678	3.7698**
	(2.085)	(2.344)	(2.719)	(2.167)	(2.464)	(1.559)	(0.925)	(2.041)
Observations	4169	4127	3960	4127	3960	3638	2227	1884
Panels	379	379	378	378	377	370	306	374
R2-within	0.636	0.645	0.655	0.645	0.661	0.651	0.637	0.803

Notes: This table presents estimates of coefficients (t/z-statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.0) of fixed effect regression with Driscoll and Kray (1998) standard errors without outlying observations (*all_obs* recalls the previously obtained results for the whole sample). The exclusion of observations has been done in line with following methods:
- *mah* - exclusion of x% observations with largest values of Mahalanobis distances that take into account not only outlierness of observations, but also their correlations,
res - exclusion of x% observations with most extreme residuals.-
var - exclusion of x% observations with most extreme values for every variable in the model,
- *robust* - exclusion of observations based on method designed by Verardi and Wagner (2010) for fixed effects model.
For first three methods *_1* and *_5* stand for 1% and 5% exclusion thresholds.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office and Statistical Yearbook of the Regions

Appendix A

Table A.1. Survey of previous studies on determinants of local unemployment in Poland

Notes: The table presents existing studies on the determinants of local unemployment in Poland and their results. Used notations: (ns) - not significant variable, (+) - significant variable, increase in the variable leads to increase in local unemployment, (-) - significant variable, increase in the variable leads to decrease in local unemployment. Majchrowska and Żółkiewski (2012) use local employment rate as the dependent variable. Therefore, presented results for this paper assume that the determinants that lead to increase in local employment rate also lead to decrease in local unemployment rate.

article	level of aggregation	time period	estimation method
This article	approximately 379 local units	2000-2010	various panel estimators (i.a. fixed effects estimator with Driscoll-Kraay standard errors)
Majchrowska and Żółkiewski 2012	16 local units	1999-2010	Arelano-Bond and Arelano-Bundell panel estimators
Pastore and Tyrowicz 2012	approximately 379 local units	2000-2008	various panel estimators (i.a. fixed effects gls estimator)
Żurek 2010	approximately 379 local units	2007	structural equation modelling, cross-section estimation
Newell 2006	49 local units / 16 local units	1994-1998 (49 local units) /1999-2002 (16 local units)	pooled ols panel estimator (with time fixed effects)
Herbst et al. 2005	approximately 379 local units	2000Q1-2001Q4	fixed and radom effects panel estimators
Newell and Pastore 2000	49 local units, micro data for individuals	1995-1996	hazard functions of job loss, panel estimation
Radziwiłł 1999	49 local units	1996	ols, cross-section estimation
Melnyk 1996	49 local units	1991Q1-1995Q2	pooled ols panel estimator

article	**variables examined in this article**														
	gdp level / gdp growth	investment	young	old	higher education	share of construction / manufacturing in employment	share of market services in employment	share of non-market services in employment	share of agriculture in employment	population density	sectoral employment diversity	minimum wage	investment share in public expenditure	local financial balance	net migration
This article	-	-	+	-	-	-	-	+	+	ns/-	ns	ns	-	-	+
Majchrowska and Żółkiewski 2012												+			
Pastore and Tyrowicz 2012		-													
Żurek 2010					-				+	-					
Newell 2006					-		+/ns		-/ns						
Herbst et al. 2005		-							-	-					-
Newell and Pastore 2000			+	-	-	+	+			ns					
Radziwiłł 1999	-					ns	-	+	ns	ns					
Melnyk 1996												+			

Appendix B

Table B.1. Description of variables used in the analyses

variable	description	variable type	theory of unemployment
ur	local unemployment rate including the number of persons who have registered as unemployed in the particular poviat in its numerator and the Central Statistical Office's estimate of labour force in particular poviat in its denominator	dependent variable / variable used for quartile division	-
g_gdp	real gdp per capita growth rate, data on NUTS-3 level (in Poland GDP data is not available on NUTS-4 level)	independent variable	disequilibrium / demand-driven
inv	the ratio of gross fixed capital formation of enterprises with minimum 9 employees to capital stock of enterprises with minimum 9 employees in the previous year	independent variable	disequilibrium / demand-driven
young	the share of young (18-24 years old) in population	independent variable	equilibrium / structural
old	the share of working age elderly (55-59/64 years old women/men) in population	independent variable	equilibrium / structural
edu	the share of registered unemployed with tertiary education - proxy for skilled labour force (high cross section correlation coefficient (r = 0.87) with the actual data on tertiary education attainment for poviats in 2002 census data, high correlation in time dimension with actual data on NUTS-2 level (aveage r = 0.96))	independent variable	equilibrium / structural
man	the share of employed in manufacturing and construction in enterprises with minimum 9 employees in total employment covering employment in enterprises with minimum 9 employees and farmers	independent variable	equilibrium / structural
serm	the share of employed in market services in enterprises with minimum 9 employees in total employment covering employment in enterprises with minimum 9 employees and farmers	independent variable	equilibrium / structural
sernm	the share of employed in non-market services in enterprises with minimum 9 employees in total employment covering employment in enterprises with minimum 9 employees and farmers	independent variable	equilibrium / structural
dens	population density (number of people per km2)	independent variable	equilibrium / structural
div	industrial employment diversity measured by the Herfindahl-Hirschmann index (Herfindahl 1955, Hirschman 1964) multiplied by -1 (thanks to this higher values correspond to higher industrial diversity)	independent variable	equilibrium / structural
minw	the share of national minimum wage to poviat’s average wage	independent variable	equilibrium / structural
invshr	the share of investment expentidures in total expenditures of NUTS-4 and NUTS-5 local authorithies	independent variable	disequilibrium / demand-driven

finbal	aggregate financial balance of NUTS-4 and NUTS-5 local authorities = (total revenues minus total expenditures)/total revenues	independent variable	disequilibrium / demand-driven
mig	the ratio of poviat's net registered migrations to poviat's population in the previous year (much migration in Poland may be not registered)	independent variable	disequilibrium / demand-driven or equilibrium / structural
since2003	dummy variable (0 - before 2003, 1 - since 2003) controlling for the upward revision of registered unemployment rates in 2003 (caused by downward revision of the number of self-employed farmers)	independent variable	-
gdp	gdp per capita (thousands of PLN per person)	variable used for quartile division	-
avarea	average area of arable lands (in hectares) in 2002	variable used for quartile division	-

Notes: The table presents description of the variables used in the article. All the variables have been obtained for the years 2000-2010 from Local Data Bank of Polish Central Statistical Office with exception of local unemployment rates for the years 2000-2003 that have been extracted from archival editions of Statistical Yearbook of the Regions. For 17 out of the 379 poviats some observations in years 2000 and 2001 are interpolated because these poviats were either not established before 2002 or lack observations for unspecified reasons. In both cases missing values are calculated as averages of values for surrounding poviats and first available values for given poviat. The details of calculations are not presented but are available upon request.
Variables representing shares or rates are multiplied by 100. The data covers only the years 2000-2010 for two reasons. First, poviats were introduced by the administration reform in 1999. Second, many data for NUTS-4 level regions are published in Poland with a lag of several years.

Appendix C

Table C.1. Specification tests results

test name/source	what is tested	tested estimator(s)	H0	statistic	p-value
Wald test	fixed effects	ols vs fe	all fixed effects = 0 ($u_i = 0$)	F(378, 3775) = 21.51	0.000
Breusch and Pagan (1980)	random effects	ols vs re	variances across entitities = 0 (var(u) = 0)	Chi2(1) = 7218.22	0.000
Hausman (1978)	error structure	re vs fe	unique errors not correlated with regressors ($corr(u_i, X) = 0$)	Chi2(15) = 1173.51	0.000
Wooldridge (2002)	serial correlation	fe	no serial correlation ($\rho = 0$)	F(1,378) = 2939.467	0.000
Greene (2000)	heteroscedasticity	fe	homoscedasticity ($\sigma_i^2 = \sigma^2$)	Chi2 (379) = 10993.32	0.000
Pesaran (2004)	cross-sectional dependence	fe	residuals not correlated ($corr(e_i, e_j) = 0$)	CD = 363.861	0.000
Harris, Tzavalis (1999)	spurious results	dk	residuals ~ I(1)	Z = -16.4511	0.000

Notes: This table presents the results of various tests used for model specification. These tests, based on properties of error terms, support the choice of most suitable estimator. Tested estimators include: *ols* – pooled ordinary least squares estimator, *re* – random effects estimator, *fe* – fixed effects estimator, *dk* - fixed effects estimator with Driscoll and Kray (1998) standard errors.

Source Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office

Table C.2. Unit root tests results

variable	lags	H0: I(1)						H0: I(2)					
		Maddala-Wu		Pesaran		Harris-Tzavalis		Maddala-Wu		Pesaran		Harris-Tzavalis	
		no trend	trend	no trend	trend	no trend	trend	no trend	trend	no trend	trend	no trend	trend
ur	0	1.000	1.000	0.004	0.000	1.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000
	1	1.000	1.000	0.551	0.000	-	-	0.999	1.000	0.000	0.000	-	-
	2	0.000	0.000	1.000	1.000	-	-	0.000	0.020	1.000	1.000	-	-
g_gdp	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.000	0.000	0.557	-	-	0.000	0.000	0.000	0.000	-	-
	2	0.000	0.000	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
inv	0	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.000	0.000	0.000	-	-	0.000	0.000	0.000	0.000	-	-
	2	0.000	0.000	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
young	0	1.000	1.000	0.787	0.906	1.000	1.000	1.000	0.000	0.000	0.000	1.000	1.000
	1	0.001	1.000	0.998	1.000	-	-	1.000	0.000	0.002	1.000	-	-
	2	0.077	0.016	1.000	1.000	-	-	1.000	0.000	1.000	1.000	-	-
old	0	1.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000
	1	0.000	0.000	0.000	0.000	-	-	0.000	0.000	0.000	0.000	-	-
	2	0.000	0.000	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
edu	0	1.000	1.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	1.000	1.000	0.010	0.989	-	-	0.000	0.000	0.000	0.000	-	-
	2	1.000	1.000	1.000	1.000	-	-	0.117	0.000	1.000	1.000	-	-
man	0	0.000	0.000	0.030	0.000	0.002	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.000	0.867	0.000	-	-	0.000	0.000	0.000	0.296	-	-
	2	0.000	0.000	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
serm	0	0.000	0.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.026	0.000	0.580	1.000	-	-	0.000	0.000	0.005	0.000	-	-
	2	0.865	0.170	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
sernm	0	0.000	0.000	1.000	0.984	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.812	0.998	1.000	0.948	-	-	0.000	0.000	0.000	0.000	-	-
	2	1.000	1.000	1.000	1.000	-	-	0.089	0.000	1.000	1.000	-	-
dens	0	1.000	0.890	1.000	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	1.000	0.233	1.000	1.000	-	-	0.000	0.000	1.000	0.933	-	-
	2	1.000	0.000	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
div	0	0.000	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	1.000	0.000	0.000	0.001	-	-	0.000	0.000	0.000	0.000	-	-
	2	1.000	0.000	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
minw	0	1.000	1.000	0.798	0.018	0.332	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.996	1.000	1.000	1.000	-	-	0.000	0.000	0.000	0.000	-	-
	2	1.000	1.000	1.000	1.000	-	-	1.000	1.000	1.000	1.000	-	-
inv_shr	0	0.000	0.000	0.000	0.713	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.343	0.000	0.000	0.956	-	-	0.000	0.000	0.000	0.002	-	-
	2	1.000	0.000	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
finbal	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.000	0.000	0.674	-	-	0.000	0.000	0.000	0.170	-	-
	2	0.000	0.001	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-
mig	0	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.000	0.997	0.318	-	-	0.000	0.000	0.000	0.000	-	-
	2	0.000	0.000	1.000	1.000	-	-	0.000	0.000	1.000	1.000	-	-

Notes: This table presents p-values of Maddala, Wu (1999), Pesaran, (2007) and Harris, Tzavalis (1999) unit root tests for variables used in the model.

Source: Own calculation based on statistics from Local Data Bank of Polish Central Statistical Office