QUANTITATIVE METHODS IN ECONOMICS
Volume XVII, No. 4, 2016, pp. 59 – 68

LABOUR MARKET FLEXIBILITY OF POLISH PROVINCES IN TERMS OF JOB-FINDING AND JOB-SEPARATION RATES

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Abstract: The purpose of this paper is to examine labour market flexibility for a set of Polish provinces. Particularly, labour market inequalities among Polish provinces are analysed indirectly in terms of labour force flows. The text is based on the results conducted with a structural time series model and a stock-flow model of unemployment.

Keywords: unemployment rate, Poisson process, local polynomial fitting, state-space models, stock-flow model of unemployment

INTRODUCTION

The difficult economic situation in many countries worldwide, in Europe in particular, has severely dampened growth rates in the economy which, in turn, has translated into rising unemployment. When workers are unemployed, they and the country as a whole lose. Workers do not receive wages, and the country loses the goods or services that could have been produced. In addition, the purchasing power of these workers is lost, which can lead to unemployment for yet other workers. This global problem has become a major challenge for governments, which are forced to reduce deficits, balance their national budgets and fight unemployment, searching for new, more effective forms of workers activation.

In Sztandar-Sztanderska [2009] it was shown that the activation model in Poland undergoes several limitations. It leads to reproduction of social inequalities of unemployed people and discourages employers from cooperating with employment services. So the increase of resources for the active labour market policy is not translated into an improvement in the quality of services. Consequently, low job-finding rate and low job-separation rate are expected. In addition, Polish provinces represent different economic and social development, so the difference in magnitude and dynamics of labour force flows should increase across Polish provinces, under the assumptions of the Polish activation model.

The purpose of the paper is to characterise and forecast worker flows and unemployment rate in Polish provinces since 2013. It will allow indirectly to answer the question if the disadvantages of the Polish activation model intensify in time and what will be their magnitude expressed in terms of hazard rates: job-finding and job-separating rates.

Analytic methods involving unemployment and worker flows forecast are needed. Recently it was noted in Barnichon and Garda [2015] and Barnichon and Nekarda [2015] that incorporating information from labour force flows substantially improves forecasts of the unemployment rate. A big advantage of the approach is that it can offer improvements at long forecast horizons in the case of European countries, because the magnitude of the labour market flows governs the speed of unemployment convergence to its steady state. With small flows, as in Europe (in comparison to the US) convergence occurs much more slowly (in the order magnitude of a year), so that observing the current worker flows provides information about movements in unemployment in the longer run. Barnichon and Garda [2015] pointed that for this to happen the flows must be sufficiently persistent.

It can be observed that over the last ten years the flow rates, expressed as logarithms of arrival rates, vary in the same pattern across Polish provinces. The difference between the outflow rates of any two provinces, except of some fluctuations, keeps in time (see Jaworski [2014]). The inflow rates (see Figure 1 and Figure 2) can be characterized in similar way. The time series structure of the flows is expected to have two components: linear trend and seasonality. So the flows can be regarded as persistent and the flow approach to unemployment forecasting seems to be promising with respect to Polish provinces.

Figure 1. The inflows of the selected provinces

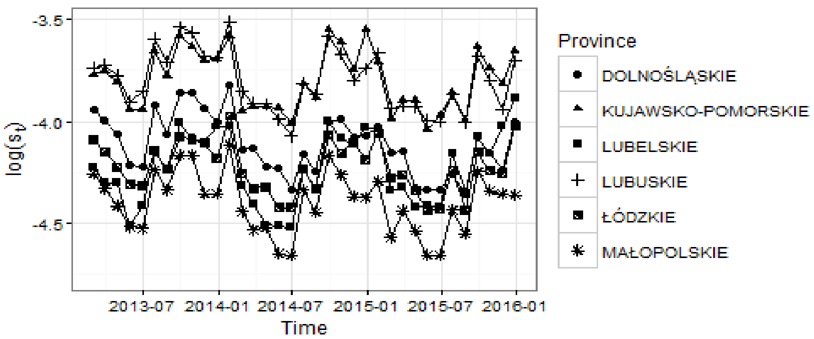

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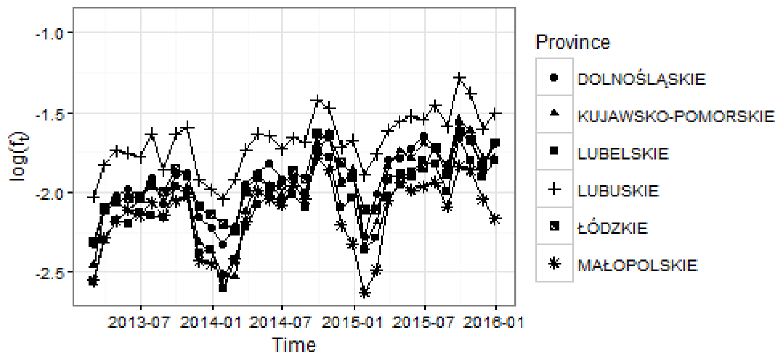
Figure 2. The outflows of the selected provinces



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THE FLOW APPROACH

This section presents the flow approach to unemployment forecasting. First, the theory underlying the approach is presented. It was developed by Shimer [2012] and Elsby et al. [2013]. The key assumption, which simplify the underling calculations, is that individuals can only be in one of two labour states: employed or unemployed, and that contribution of movements in-and-out of the labour force (with respect to unemployment fluctuations) is negligible. The approach relates to continuous time environment in which data are available at discrete dates

Second, the flow-based forecast is outlined. The forecast is non-linear and includes two stages: (i) a forecast of the worker flows, and (ii) an iteration on the law of motion of unemployment (Eq. (2)). The idea of the forecast is given in Barnichon and Garda [2015], who evaluated the approach for a set of OECD countries (France, Germany, Spain, the UK, Japan and the US). In the case of European countries large improvements were obtained at both short and long horizons (one-year ahead forecast). Quarterly data (the original or the annual duration data converted to a quarterly frequency) and a VAR model were used to forecast the flow rates (stage (i)). To generate such forecasts, they additionally included vacancy posting, claims for unemployment insurance and GDP. In this article monthly data are used and no additional variables are included. The VAR model is replaced by the linear Gaussian state space model with three components: stochastic level, fixed (or stochastic) slope and fixed seasonality.

A stock-flow model of unemployment

Let $u_{t+\tau}$ denote the unemployment rate at instant $t+\tau$ with t indexing the period (in the paper a month) and $\tau \in [0,1]$ a continuous measure of time within the period. For every $t \in [0,T]$ the interval $[t,t+1)$ will be referred to as "period t". It is assumed that in the period t all unemployed workers find a job according to a Poisson process with constant arrival rate f_t, and all unemployed workers lose their job according to a Poisson process with constant arrival rate s_t. The unemployment rate evolves according to

$$\frac{d}{d\tau}u_{t+\tau} = (1 - u_{t+\tau})s_t - u_{t+\tau}f_t \tag{1}$$

Solving Eq. (1) yields

$$u_{t+\tau} = \beta_t(\tau)u_t^* + (1 - \beta_t(\tau))u_t \tag{2}$$

where

$u_t^* \equiv \frac{s_t}{s_t+f_t}$ denotes the steady-state unemployment rate and

$\beta_t(\tau) \equiv 1 - \exp\{-\tau(s_t + f_t)\}$ is the rate of convergence to that steady state. If the flows into and out of unemployment were to remain at a fixed level, the steady state unemployment rate would prevail.

Let $u_t^s(\tau)$ denote short unemployment rate, that is the number of workers who are employed at some time $t' \in [t, t + \tau]$ divided by the number of all unemployed and employed workers. The short unemployment evolves according to

$$\frac{d}{d\tau}u_t^s(\tau) = (1 - u_t)s_t - u_t^*(\tau)f_t \tag{3}$$

Equations (1) and (2) have, assuming that $u_t^s(0) = 0$, the following solutions in discrete time$t$:

$$\exp\{-f_t\} = \frac{u_{t+1} - u_t^s(1)}{u_t} \tag{4a}$$

$$u_{t+1} = \beta_t(1)u_t^* + (1 - \beta_t(1))u_t \tag{4b}$$

The flow – based unemployment forecast

We can estimate f_t and s_t for $t \in \{0,1, \dots\}$ as we know u_t and $u_t^*(1)$ from available data: f_t solving Eq. (4a) directly and s_t solving Eq. (4b) (note that $\beta_t(1)$ and u_t^* are functions of f_t and s_t). Then the forecasts of the worker flows can be generated. Given a set of worker flows forecasts: $\hat{f}_{t+j|t}$ and $=\hat{s}_{t+j|t}$ with $j \in N$, a $j-$period-ahead forecast of the unemployment rate, $\hat{u}_{t+j|t}$, can be constructed recursively from

$$\hat{u}_{t+j|t} = \hat{\beta}_{t+j|t}\hat{u}_{t+j|t}^* + \left(1 - \hat{\beta}_{t+j|t}\right)\hat{u}_{t+j-1|t} \tag{5}$$

where

$\hat{u}_{t+j|t}^* = \frac{\hat{s}_{t+j|t}}{\hat{s}_{t+j|t}+\hat{f}_{t+j|t}}$ and $\hat{\beta}_{t+j|t} = 1 - \exp\{-\left(\hat{s}_{t+j|t} + \hat{f}_{t+j|t}\right)\}$

DATA AND EMPIRICAL RESULTS

The data of the Local Data Bank in Poland are used in this article: registered unemployment persons (monthly data), registered unemployment rate (monthly data), registered inflow into unemployment rate (monthly data), number of economically active persons (quarterly data from the Labour Force Survey).

Labour force time series are available from two sources: registered at the employment office and Labour Force Survey. The dynamics of this two kind time series is different. They are shifted against themselves across vivodeships (compare with Figure 3 and the Labour Force Survey series reveal trends which are absent in the registered series (an example is shown in Figure 4).

Figure 3. Number of economically active persons. Time points and provinces are randomly selected

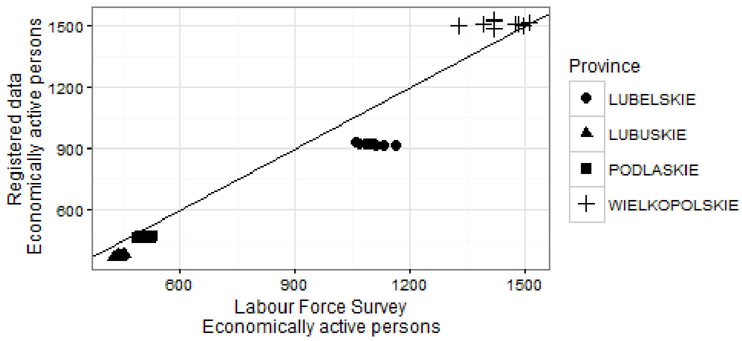

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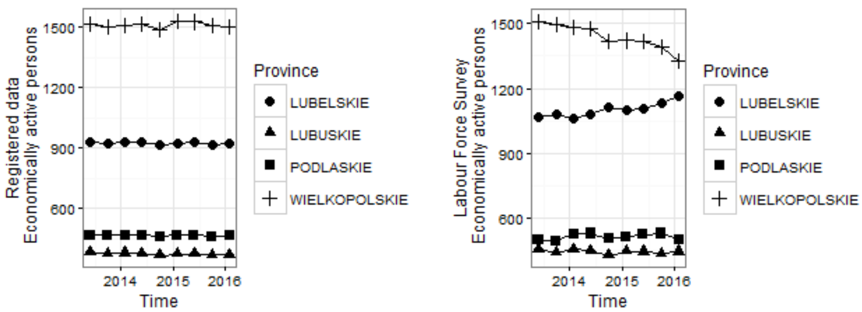
Figure 4. Example of labour force series.



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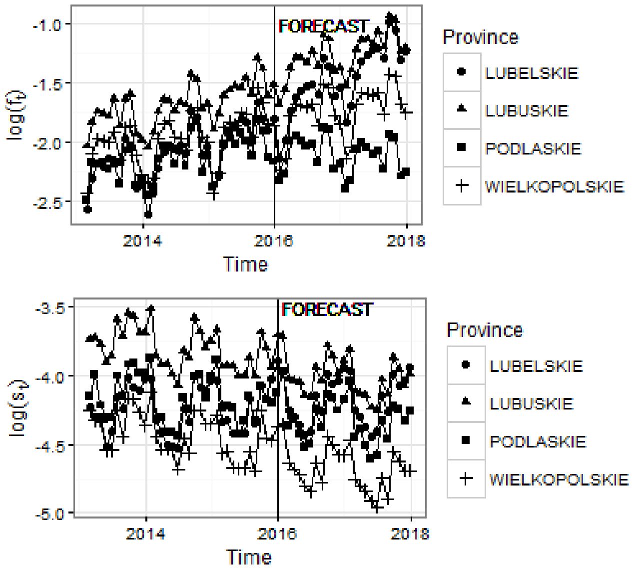
The forecast was made separately for $\{y_t = \log(f_t)\}_t$ and $\{y_t = \log(s_t)\}_t$. Dependent vector y_t was 3, 4 and 5-dimensional according to the scheme in Figure 6. For example, the observation vector $y_t = \log(f_t)$ for the first group has the following form: $y_t = [\log(f_{t1}), \log(f_{t2}), \log(f_{t3}), \log(f_{t4})]'$, where its four components relate to Dolnośląskie, Kujawsko-Pomorskie, Wielkopolskie and Zachodniopomorskie respectively. The groups of provinces were created quite arbitrary. However, it should be emphasized that the division was made to relate mainly to the east and to the west of Poland. But it was checked that some other possible divisions did not influence the adequacy of applied structural multidimensional time series models.

Figure 5. Example of labour arrival rates forecast



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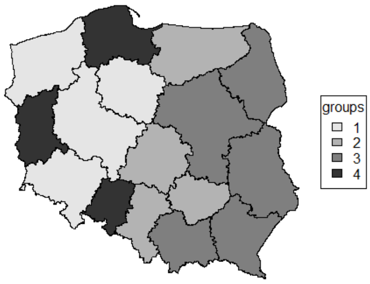
Training series covered the period since 2013-01 to 2015-12. The fit was satisfactory (coefficient of determination exceeded 0.9 in every case and normality tests did not reject null hypothesis). Using Eq. (5) the unemployment forecast was made until 2018-12.

As noted above the Labour Force Survey database is recommended for calculating the labour flows estimates. Because monthly data are not available from the source, the series of numbers of economically active persons were converted to monthly data by local polynomial regression fitting and other required variables were taken from the employment office. The unemployment rate was then calculated: registered number of unemployment persons was divided by the converted labour force number. The difference between the registered and the calculated rates can be inspected in Figure 7.

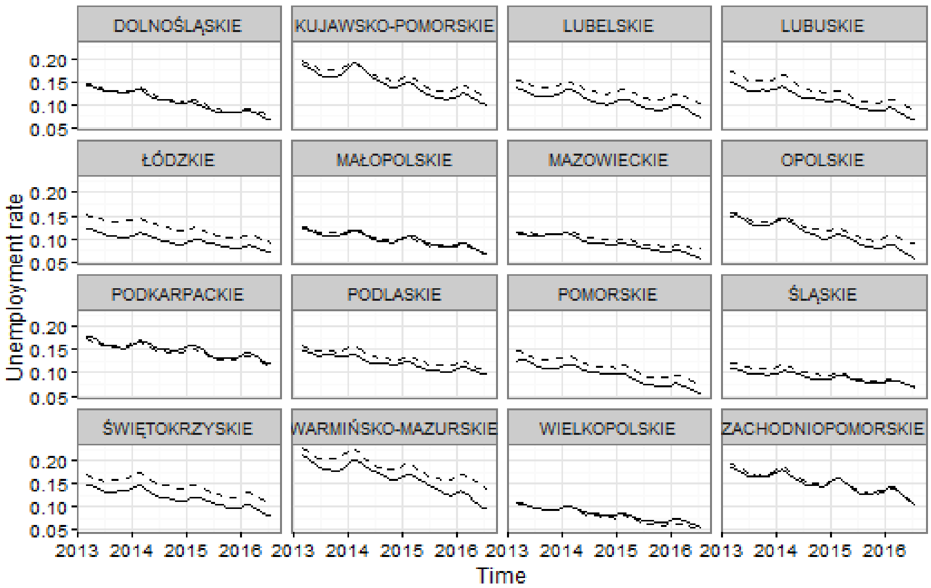
Figure 6. Groups of provinces



Model : Trend + Fixed seasonal + Irregular			
	Group 1		Group 2
y_1:	Dolnośląskie	y_1:	Łódzkie
y_2:	Kujawsko-Pomorskie	y_2:	Śląskie
y_3:	Wielkopolskie	y_3:	Świętokrzyskie
y_4:	Zachodniopomorskie	y_4:	Warmińsko-Mazurskie
	Group 3		Group 4
y_1:	Lubelskie	y_1:	Lubuskie
y_2:	Małopolskie	y_2:	Opolskie
y_3:	Mazowieckie	y_3:	Pomorskie
y_4:	Podkarpackie		
y_5:	Podlaskie		

Source: own preparation

Figure 7. Unemployment rates comparison: dashed line – registered rate, solid line – calculated rate



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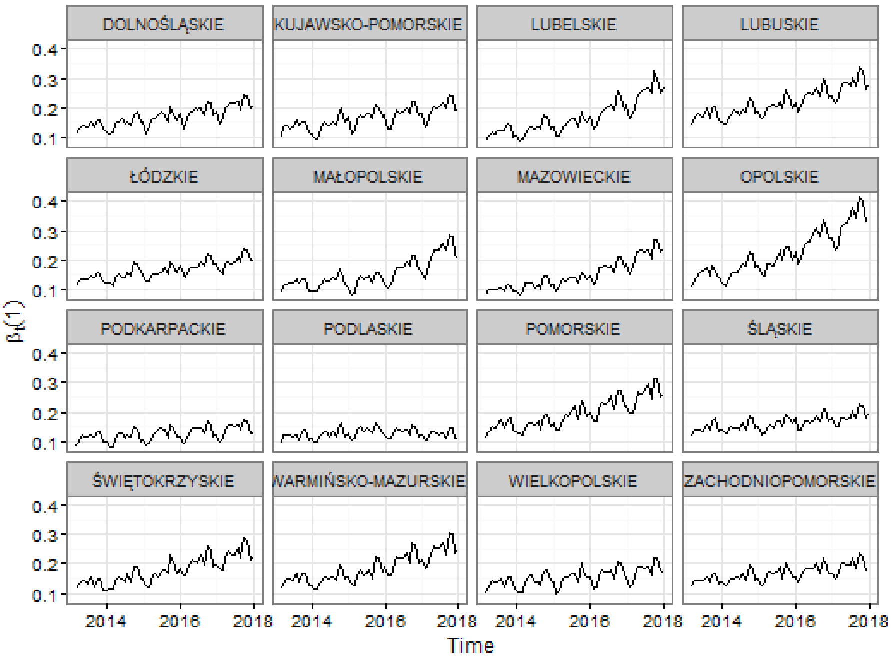
The rates series almost overlap in the case of some provinces: Dolnośląskie, Małopolskie, Wielkopolskie and Zachodniopomorskie. In other cases the series are shifted against themselves and have different slopes. However, the series keep the same seasonality pattern.

The training set of the series in Figure 7 covers the period since 2013-02 to 2015-12 and the test set the period since 2016-01 to 2016-06. Mean absolute/relative prediction error for Dolnośląskie, Małopolskie, Wielkopolskie and Zachodniopomorskie province is equal to 0.6%/7.8%, 0.2%/3.1%, 0.6%/10% and 0.2%/0.6% respectively. The values measure the difference between available registered unemployment rate and forecast of the calculated unemployment rate. The values are meaningful as they relate to the overlapping series.

According to Eq. (4b), the unemployment rate u_{t+1} is a weighted average of the previous unemployment rate u_t and the time t steady-state u_t^* with the weights $\beta_t(1)$ determined by the speed of convergence to the steady state. If $\beta_t(1)$ is greater then faster actual unemployment rate converges to its flow steady-state value: the level at which the unemployment rate would settle if the inflow and outflow rates stay constant at their current levels. It can be shown, that $1 - \beta_t(1) = (1 - F_t)(1 - S_t)$, where F_t is the job finding probability and S_t is the separation probability. So $\beta_t(1)$ can be regarded as a measure of the flexibility of the labour market. An estimate of $\beta_t(1)$ is presented in Figure 8. So it can be inspected that two Polish provinces, Podkarpackie and Podlaskie, have relatively low market flexibility: $\beta_t(1) < 0.2$. In contrast to the other provinces, this low level will be holded until 2018. The best market flexibility in 2018 is expected for Lubelskie, Lubuskie and Opolskie.

In general the inflow rates in provincec decrease and the outflow rates increase. Simultaneously the impact of the labour flows increase (see Figure 8) what implies the unemployment rate have to decrease.

Figure 8. Estimate of $\beta_t(1)$



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CONCLUSIONS

The main question is about variables used in this article for calculations. The variables are mixed from two sources. They are not compatible as for example they relate to slightly different definitions of unemployment or economically active persons. They are also collected in different ways. However as they relate to empirical data they may be perceived as labour market indicators or measures. So in this article the estimated unemployment rate is treated as one of the labour market indicator reflecting differences between provinces. The ex-post mean absolute difference between the calculated unemployment indicator and the registered unemployment rate is in range 0.34 – 2.68 percent points (for the overlapping series the difference is less then 0.47 percent points). The difference is not high and in the case of four provinces: Dolnośląskie, Małopolskie, Wielkopolskie and Zachodniopomorskie, the levels of error prediction errors indicate high forecast precision.

The influence of changing labour force data source for unemployment rate can be observed. As can be seen in Figure 7, the influence imply changes in trend but not in seasonal pattern.

Unemployment rate forecast was done on the basis of inflows and outflows into unemployment. It required to forecast the flows previously. The flows expressed in log arrival rates have clear time series structure with linear trend and fixed seasonality. Components of each dependent vectors were related to one of the arbitrary selected groups of provinces. In every case the model fit was satisfactory. So the multidimensional time series models reflected mutual relationships between labour markets of Polish provinces.

The flow approach gives possibility to measure and compare the impact of the inflows and outflows on the unemployment rate across provinces. The impact is increasing in almost every province (see Figure 8). For example in Lubelskie and Opolskie the impact is expected to increase faster then in Podkarpackie and Zachodniopomorskie. In Podlaskie the impact is going to be averagely holded at the same low level. So the main question about the Polish activation model can be answered. Generally, economic activity of Polish population keeps going up since 2013 but there are some Polish provinces, where the activity is at the low level and nothing can be expected to be changed in that matter. It means that the Polish activation model works locally in some provinces only. Consequently, it will deepen labour market inequalities among Polish provinces.

SUMMARY

The flow approach to forecast unemployment rate was applied for a set of Polish provinces. First, worker flows into and out of unemployment were estimated by Gausian state space models. The models fit was satisfactory. Second,

forecast unemployment rate was done according to a stock-flow model. The estimated unemployment rates were discussed with respect to data source and forecast accuracy. At last the impact of the flows on unemployment rate was investigated and conclusion about growing labour market inequalities among Polish provinces was drawn.

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