

Labour market matching – the case of Poland

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Abstract

Paper describes matching on Polish labour market comparing simultaneously the process mechanism – random *versus* stock – flow one. This aims at determining the role of stock and flow variables in generating outflows from unemployment. Analysed period, 1999–2010, reflects relatively consequent behaviour of the Beveridge curve. There are presented estimates of the matching function, also handling the bias resulting from data temporal aggregation. Such problem arises when discrete time data is used to describe the continuous-time process. Elements of the Markov transition matrix are exploited to approximate the magnitude of the effects corresponding to basic flows on the labour market influencing the matching process: on-the-job search, out-of-labour force search and discouraged workers.

Keywords: temporal aggregation, stock-flow matching, random matching

JEL: J63, J64

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1. Introduction

Substantial flows of both job seekers and job offers imply their co-existence on the labour market. Nevertheless such flows should also be taken into consideration in matching process analysis. If their impact was negligible short-term variations in outflow from unemployment ought to be connected to analogous variations in background stocks. However, stocks are considerably less volatile than flows. Thus, incorporating inflows into labour market matching analysis should significantly alter it, especially comparing to basic stock-stock one. On the mathematical ground the matching process is described by the matching function, most often by usage of the random matching process (compare Pissarides 2000, ch. 1). This technology assumes trade taking place between stocks what generates outflow from unemployment to employment. The other possibility is non-random (stock-flow) matching where stock on one side matches with inflow of new trading partners.

The paper aims at describing labour market matching process in Poland comparing simultaneously the process mechanism – random versus stock – flow one. Such knowledge should incorporate into better understanding of Polish labour market functioning, determining also the role of inflows and stocks in job creation. The analysis refers to period 1999-2010. Chosen time span results from data availability, as analysis takes into consideration data of newspapers ads of job offers gathered by Bureau for Investments and Economic Cycles in Warsaw.¹ This period reflects also relatively coherent behaviour of the Beveridge curve on Polish labour market. The article is organised as follows. At first there is a short descriptive analysis of Polish labour market in matching perspective referring among others to size and directions of relevant stocks and flows. Presented elements of the Markov transition matrix are counted on the basis of micro data from Labour Force Survey (LFS) for 2000-2009 period. Their values are exploited to approximate magnitudes of the effects connected to labour force flows: out of labour force search, discouraged workers and on the job search as well as the structure of the employment inflows. Further on, there is a short theoretic description of two main labour market matching mechanisms - random and non-random. This section refers also to bias arising due to data time aggregation. The problem comes out when discrete-time data is used to describe the continuous-time matching process. Third section presents results of the conducted estimates. Empirical analysis concerns random and stock-flow matching. The procedure adopted by Gregg and Petrongolo (2005) to handle the data time aggregation problem has been also applied. At the end of the article there are presented concluding remarks.

2. Data statistical analysis

Figure 1 presents Beveridge curve for Polish labour market during the period 1999–2010. According to Blanchard and Diamond model (1989, p. 6) one can state that co-movements of vacancies and the unemployed during this time span can reflect the anti-clockwise movements around the downward sloping theoretical UV curve. However period 2002–2007 situated outer from the coordinate origin may suggest a deterioration in matching efficiency comparing to 1999–

¹ Including this data should improve quality of the obtained results as registered data of job offers is constantly underestimated (Gałecka 2007, p. 48).

2002 and 2007–2010 sub-periods. V/U ratio counted on registered stock variables experienced very low values, from the range (0.003; 0.047). Such values imply relative hardness in finding a job by work seekers and relative ease finding a worker by enterprises, as on average around 70 workers competed for one job offer.

Basic conclusions regarding relative importance of stocks and flows in describing labour market matching in Poland may be enhanced by visual analysis of simultaneous changes of particular variables. Figures 2 and 3 present data of the outflow from unemployment and unemployment and vacancy stocks and flows. Visual inspection suggests that respective inflow variables affect outflow from unemployment more than stock variables do. Moreover turnover index *inflow/stock* was much higher in case of vacancies (2.8 on average) than for unemployment (0.1 on average).²

Size of the flows on the labour market might also be presented by the Markov matrix (transition matrix), which presents transition probabilities between states on the market.³ The Markov transition matrix for Polish labour market took values:⁴

$$P_{ij} = \begin{bmatrix} 97.53\% (0.74 \text{ p.p.}) & 1.25\% (0.46 \text{ p.p.}) & 1.22\% (0.35 \text{ p.p.}) \\ 11.04\% (3.26 \text{ p.p.}) & 81.80\% (5.49 \text{ p.p.}) & 7.16\% (3.02 \text{ p.p.}) \\ 2.17\% (0.57 \text{ p.p.}) & 2.48\% (0.98 \text{ p.p.}) & 95.34\% (1.16 \text{ p.p.}) \end{bmatrix}$$

The matrix takes the form:

$$P_{ij} = \begin{bmatrix} ee & eu & en \\ ue & uu & un \\ ne & nu & nn \end{bmatrix}$$

where:

$$i, j = e, u, n,$$

e – stock of employed,

u – the unemployment stock,

n – the out of labour force stock,

for example ue – the transition probability between the unemployment and employment stocks. Sum of the elements in each row equals by definition 1 (Kucharski 2002, pp. 17, 20–21).

These results lead to following conclusions:

The most volatile stock is the unemployment one. Probability of staying in the unemployment pool between two consecutive quarters was higher in first half of the decade (2000–2005 – almost 86% on average). Then it experienced significant declining trend ending up at 74% on average in 2009. Flows from unemployment to employment constituted on average $61\% \pm 8$ percentage points of total outflows, which is higher comparing to the registered unemployment.⁵

² Coles and Petrongolo (2008, p. 1127) report analogues indexes for Britain (period 1985–2001) on the level of 0.16 (for unemployment) and 1.08 (for vacancies).

³ In aggregate context one can think of probability of changing status being equal to average frequency of status changes (Pissarides 1986, p. 504).

⁴ The values are quarterly averages for period 2000–2009, standard deviation is presented in parentheses. The sample refers to working age population, based on the micro data from the Labour Force Survey.

 $^{^5}$ It was on average equal to 45% \pm 5 percentage points.

Another interesting observation refers to discourage worker effect, which may be approximated by transition rate between unemployment and out-of-labour-force stock.⁶ This rate was on average equal to 7.16% with substantial standard deviation what gives the coefficient of variation at the level of 42%. This rate experienced opposite changes comparing to the *uu* rate. During the period 2000–2005 its mean was 5.4% and after upward trend it finished at the level of 11% on average in 2009. Changing conditions on labour market could have boost up this rate not only due to discourage worker effect but also, for example, by job seekers' willingness to adjust qualifications to labour market requirements.

It is also worth analysing structure of employment inflows.⁷ Figure 4 presents data over such inflow structure for period 2000–2009. Its shape suggests that up to 2007 almost 50% (on average) of the inflow to employment had origin in unemployment and share of both inflows from inactivity and employment was on average equal to 25%. Since the beginning of 2007 share of the unemployment to employment flow had substantially declined and each of the inflows to employment constituted 1/3 of total employment inflow.⁸

3. Matching process on the labour market

Origins of the basic matching function come from probability theory and model of placing bills in urns (Blanchard, Diamond 1994, pp. 418–420). In this model firms are treated as urns and work seekers as balls which aim to be placed in urns. The match arises when the urn becomes productive, what happens in case it has a ball in. In aggregate, the co-existence of vacancies and unemployment arises due to the lack of coordination in placing bills in urns (coordination failure) even in the case of the same amount of participants on both sides. The thorough model description may be encountered in: Blanchard, Diamond (1990; 1994), Butters (1977), Hall (1979), Lang (1991), Montgomery (1991), Petrongolo, Pissarides (2001), Pissarides (1979).

On the other spectrum there is a stock-flow matching model, which is described for example in Coles (1999), Coles, Muthoo (1998), Coles, Petrongolo (2008), Coles, Smith (1998), Ebrahimy, Shimer (2010), Gregg, Petrongolo (2005), Lagos (2000), Petrongolo, Pissarides (2001), Taylor (1995). Basic assumptions of the model are analogous to functioning of the real estate market or taxi market (Coles, Smith 1998; Lagos 2000).

The model adapted to labour market is presented in Gregg and Petrongolo (2005, p. 1988– 1994) who partly base the analysis on that presented in Coles and Smith (1998). One of the crucial assumptions regards the process of search itself. In stock-stock mechanism job seekers apply randomly to job offers, so the systematic element of job search is omitted. Stock-flow matching model is based on the other extreme of no randomness in job applications. In this situation work seekers, having possessed full knowledge regarding available job vacancies, apply to as many of

⁶ Nevertheless, this flow consists not only of the discouraged workers (Petrongolo, Pissarides 2001, p. 412).

⁷ The employment – employment flow was calculated by counting people having status 'working' in both consecutive quarters and being employed for 0, 1 or 2 months.

⁸ However, if the employment to employment flow is calculated by counting people having status 'working' during two consecutive quarters and being employed for 0, 1, 2 or 3 months the results differ substantially. EE flow is on average 41%, UE – 31% and IE – 18% of total inflow. UE flow's share also declines since the beginning of 2007, but since then EE share increases more than IE flow's share.

them as they seem to be acceptable. Once finding each other, parties decide whether to sign a wage contract or conduct further search of the proper partner on the labour market. Agents present on the market will not retry finding a partner among possible trading partners that have already been on the market since they were also available for match in previous period and all possible matches have been already exploited. This conclusion along with the assumption of perfect information is to reflect the fact that at first agents scan a lot of advertisement before applying to selected job offers and once an offer has been rejected reapplication is less likely than looking for new vacancies (Gregg, Petrongolo 2005, p. 1989; Petrongolo, Pissarides 2001, p. 405).

Described matching technology introduce sharp distinction between stocks and flows on the labour market as the process takes place between stock on one side with inflow on the other side of the market. Unemployment stock will try to match with inflow of vacancies, while stock of vacancies will try to match with inflow of newly unemployed. This is the motivation for the name of 'stock-flow' matching (Petrongolo, Pissarides 2001, p. 405). Such technology alters also probability of leaving the relevant pool by vacancies or the unemployed. Probability of leaving unemployment by the stock of the unemployed is negatively correlated to the magnitude of the unemployment stock due to negative external effect of crowding out, so-called congestion effect. It is, however, positively correlated to the size of the inflow of possible new matching partners what constitutes positive external effect – thick market effect and is independent of the amount of possible old matching partners (stock of vacancies) (Coles, Smith 1998, p. 240). Result of no congestion between newcomers comes from the assumption of individual appearance by agents on the market, while the matching process has the continuous time structure taking place across time periods of infinitesimal length (Petrongolo, Pissarides 2001, p. 406).

The stock-flow matching possesses two additional interesting features. Hazard rate for newcomers is likely to be bigger in comparison to the one for old agents. This comes from the fact that by relatively shorter periods of analysis stocks are likely to be relatively bigger than flows. However, time decreasing hazard rates can have many other determinants, like deterioration of human capital during unemployment. Worth noting is also the fact of increasing returns to scale, what originates from possibility of multi applications to as many job offers as work seeker wants to, which contrasts to one application available per worker in random matching model (Petrongolo, Pissarides 2001, p. 406). This feature aims at capturing the fact of larger possibilities for agents on bigger labour markets (Petrongolo, Pissarides 2001, p. 406). Moreover, increasing returns to scale in hiring imply higher efficiency of larger labour markets and may lead to appearance of high-intensity and low-intensity equilibria (Antolín 1994; Berman 1997, p. 265, 289; Diamond 1982). Brief comparison of both models leads to following conclusions (Coles, Smith 1998, p. 240):

Stock-flow model assumes perfect information on the market, whereas in random one agents need to spend some resources in order to gather knowledge about the location of possible trading partners.

Models differently justify time needed to elapse before it comes to match. In random matching possible matching partner might exist on the market but due to coordination failure match has not been realized vet. In stock-flow agents must wait for the proper partner to appear on the market.

Random matching does not differentiate agents on the market. Whereas, in stock-flow newcomers have wider, than old agents, possibilities to find a proper matching partner. Thus probability of leaving market by an agent should be a decreasing function of time spent on the market, if the match with present stock has not been realized earlier.

Another interesting feature regarding labour market matching refers to problem of a bias arising due to data time aggregation. Problem appears because discrete time data is used to describe time-continuous process, like matching (Gregg, Petrongolo 2005, p. 1990; Petrongolo, Pissarides 2001, pp. 420–422). Size of the bias might be approximated by comparison of the results obtained by using data with different frequency, so the higher the frequency of data used for the analysis the smaller the bias should be (Gregg, Petrongolo 2005, p. 1988). However, Gregg and Petrongolo (2005, p. 1990–1993) present mathematical solution for possible aggregation bias for both random and stock-flow models. Alternative solution is presented in Coles, Petrongolo (2008, pp. 1116–1123).

4. Empirical evidence on aggregate labour market matching in Poland

First part of empirical analysis of the matching processes on Polish labour market is based on comparison between stock-stock and stock-flow matching. In Polish literature one can find various empirical research conducted over labour market matching. Papers referring to time span 1999–2010 are among others: Gałecka (2007; 2008), Gałecka-Burdziak (2010), Kubiak (2005), Kucharski, Tokarski (2003), Roszkowska (2009), Tokarski (2005). Those empirical analyses were based on data from registered unemployment mainly using reduced form of the stock-flow model implying that the driving force of the matching process on Polish labour market is combination of unemployment stock and inflow of new vacancies.⁹

Empirical analysis focuses on comparison between stock-stock matching and stock-flow matching. Data used in the analysis comes from the registered unemployment for the period 1999–2010. Moreover, due to frequent underestimation of the number of vacancies available on the labour market, number of job offers from newspapers ads is also included.¹⁰ Data was seasonally adjusted using X-12 ARIMA.¹¹

In reference to the random matching equation takes the form:¹²

$$\ln M_t = \gamma_0 + \alpha_1 \ln U_{t-1} + \alpha_2 \ln V_{t-1} + \varepsilon_t \tag{1}$$

where:

 M_t – outflow from unemployment during month t,

- U_t unemployment stock at the end of month t,
- V_t vacancy stock at the end of month t,

⁹ Nevertheless, estimated coefficients differ substantially due to different time spans, spatial aggregation and other variables taken into consideration while estimating changes in the matching efficiency. More thorough survey over matching literature concerning Polish labour market can be found in Gałecka (2008) and Roszkowska (2009).

¹⁰ Up to 2005 sum of the stock of available vacancies plus the inflow of new ones was notoriously smaller than outflows from unemployment to employment. Data referring to newspapers job offers comes from Bureau for Investment and Economic Cycles.

¹¹ U.S. Census Bureau, http://www.census.gov/srd/www/x12a/. All seasonally adjusted time series were I(1).

¹² Analogous equations were estimated for example by Petrongolo, Pissarides (2001, p. 411), for Polish labour market by Stasiak, Tokarski (1995, pp. 28–29). Estimated equations contain also quadratic time trend to express changes in matching efficiency.

and stock-flow:13

$$\ln M_{t} = \gamma_{0} + \alpha_{1} \ln U_{t-1} + \alpha_{2} \ln V_{t-1} + \alpha_{3} \ln u_{t} + \alpha_{4} \ln v_{t} + \varepsilon_{t}$$
⁽²⁾

where:

 u_t – inflow of new unemployed during month t,

 v_t – inflow of new vacancies during month *t*.

Table 1 presents results for each of the equation using different estimation methods. First column (I) refers to results obtained using OLS method. The second one (II) also uses OLS but the restriction for the parameters concerning constant returns to scale is imposed ($\alpha_1 + \alpha_2 = 1$). Third column (III) allows for the first order serial correlation in the disturbance term. Columns IV–V present analogous to I and III estimates for the stock-flow matching model. Results obtained using OLS method showed that disturbance term includes a serially correlated component, which may lead to biases in t-Student statistics. All time series are I(1), however, Engle-Granger tests' statistics obtained for models I–V show that at 5% significance level null hypothesis of the unit root test in disturbance term should be rejected. On that basis, two additional models were created – columns VI and VII present results for Error Correction Models for random and non-random matching as a part of two-step Engle-Granger cointegration procedure (Majsterek 2008, p. 27).

Results do not vary significantly over different specifications for both random and non-random matching models. The matching function describes the hiring process with mildly decreasing returns to scale for random matching and mildly increasing returns for stock-flow matching (as the sum of parameters suggests). Unemployment stock is driving force in stock-stock matching, whereas unemployment stock and inflows of new unemployed and vacancies mainly create stock-flow matching. However, when applying Error Correction Models in short run vacancies inflow and the unemployed form the stock-flow matching. Error correction terms for both models imply relatively high efficiency of reaching long run equilibrium in the hiring process.

Estimates of the ECT parameter were also used in three-step Engle-Yoo cointegration procedure to correct the long-term multipliers estimated from static relationship (Majsterek 2008, p. 27–28). Estimated correction terms did not alter results significantly.¹⁴

Next part of the empirical analysis was conducted handling data time aggregation problem according to procedure proposed by Gregg and Petrongolo (2005, pp. 1997–1999) where the endogenous variable was also set as the outflow from unemployment. The basic equation was:

$$O_t = a_t U_{t-1} + b_t u_t + \varepsilon_U$$

where:

- O_t outflow from unemployment during month t,
- U_{t-1} unemployment stock at the beginning of month *t*,
- u_t unemployment inflow during month *t*,
- a_t outflow rate from the stock equal to: $a_t = 1 e^{-\lambda_t}$,
- b_t outflow rate from the inflow equal to: $b_t = 1 \frac{1 e^{-\lambda_t}}{\lambda}$.

¹³ Analogous equations were estimated for example by Coles, Smith (1998, p. 248), Dmitrijeva, Hazans (2005, p. 8), Galuščák, Münich (2005, p. 17).

¹⁴ Moreover, it was not statistically significant.

Estimation was conducted for three kinds of equations:

First one refers to random matching, where Cobb-Douglas type function is assumed $(\lambda_t)^{15}$ equals:

$$\lambda_t = e^{\alpha_0 + \alpha_1 \ln\left(\frac{V_{t-1}}{U_{t-1}}\right)}$$

Second equation allows also the stock-flow matching, where *p* is the outflow probability from the unemployment inflow. Matching technology taking into consideration both methods imply λ_i equal to:

$$\lambda_t = e^{\alpha_0 + \alpha_1 \ln\left(\frac{V_{t-1}}{U_{t-1}}\right) + \alpha_2 \ln\left(\frac{v_t}{U_{t-1}}\right)}$$

while *p* is estimated as constant. Random matching implies $\alpha_1 > 0$ and p = 0, while stock-flow $\alpha_1 = 0$ and p > 0.

Third equation allows value changes of p in reference to situation on the labour market. We can assume that:

$$p_t = e^{\gamma_0 + \gamma_1 \ln\left(\frac{V_{t-1}}{u_t}\right)}$$

Estimation method was non-linear least squares including first order serial correlation in disturbance term in order to deal with autocorrelation (Gregg, Petrongolo 2005, p. 1998; Welfe 2003, p. 94). In equations XI, XII and XIII linear time trend was used in order to explore evolution of the matching efficiency in equations representing λ_t and p_t (Gregg, Petrongolo 2005, p. 1999). Results show that at 5% significance level null hypothesis of the unit root test in disturbance term should be rejected. In Table 3 one can encounter values of the probabilities of leaving unemployment pool by unemployment stock and the corresponding inflow. Values reported in square brackets or λ and p are averages of samples of models' predictions. The Table 3 contains also models predictions of mean durations of unemployment completed and incompleted and the matching function elasticities with respect to exogenous variables.

Estimates for random matching show significant impact of vacancy stock. However, when introducing vacancy inflow the stock coefficient decreases sharply. Estimated p is positive and significant at 10% significance level implying that less than 10% of newly-unemployed find a proper job offer just after coming onto the market. As previously said random matching implies $\alpha_1 > 0$ and p = 0, while stock-flow $\alpha_1 = 0$ and p > 0. Results confirm a significant role of the flows, but do not reject the stocks impact unambiguously. Estimates of third equation assuming stock-flow matching and allowing for changes in p value according to labour market situation further confirm the importance of flows. $\hat{\gamma}_t$ is positive what implies that newly-unemployed are matched with vacancy stock. Moreover, the p has increased significantly in comparison to IX column and now the unemployment inflow has a much higher matching rate than the unemployment stock. Probability of leaving unemployment stock decreases while moving from random specification through both mechanisms to pure stock-flow matching. Time trend coefficients show slight improvement in matching efficiency of the unemployed.¹⁶

 $^{^{15}}$ λ_t refers to probability outflow from the unemployment stock.

¹⁶ What can reflect, among others, changes in efficiency in functioning of Public Employment Services.

Obtained results suggest that mean duration of unemployment was longer than 33 weeks with relatively comparable results over different specifications. Difference in the magnitude between complete and incomplete durations of unemployment spells in stock-flow matching comes from introducing instantaneous matching probability p (Gregg, Petrongolo 2005, p. 1994). Calculated elasticities confirm important role of inflow variables, especially vacancy inflow in labour market matching processes in Poland. Introducing flow variables implied increase in elasticities with respect to flow variables and decrease with respect to stock ones. Their sums around one suggest constant returns to scale or mildly increasing ones.

Matching function elasticities are also useful when approximating the external effects size. Petrongolo and Pissarides (2001, p. 392) point out following kinds of externalities:

Positive externality (thick market effect) – occurs when actions performed by job seekers ease finding a worker by companies and analogously when search methods performed by companies ease finding a job by work seekers. Moreover, the scale of this effect may by approximated by matching function elasticities. Let's η_U be the elasticity with respect to unemployment and η_V with respect to vacancies. Then η_U measures the positive externality caused by job seekers on companies and η_V – counterpart on job seekers by firms.

The negative externality (congestion effect) – arises when intensified search actions performed by agents on one side of the market reduce transition probabilities for other agents on the same side – work seekers with respect to work seekers and firms to firms. Assuming same notions: $\eta_U - 1$ measures the crowding out effect caused by the unemployed on other unemployed workers and $\eta_V - 1$ measures the negative externality caused by firms on each other.

Conducted research implies matching elasticity¹⁷ in case of the stock – stock matching with respect to unemployment stock to be around 0.7, whereas with respect to vacancy stock around 0.3. For the stock – flow matching the average elasticity ought to be around 0.4 and 0.1 with respect to the unemployment and vacancy stocks respectively, 0.15 and 0.4 with respect to corresponding flows. Considering these values one can conclude that on Polish labour market unemployed job seekers cause higher positive externality on firms and smaller negative on each other than companies do.

5. Concluding remarks

Conducted research aimed at determining importance of stock and inflow variables in matching processes on Polish labour market. Coefficients estimates prove important role of labour market inflows in matching process. For random model function elasticity is higher with respect to unemployment stock. Introducing flows in stock-flow model shows that the driving force of the matching process on the Polish labour market consists of the unemployment stock and inflow of vacancies, proving the importance of job creation process in increasing employment on Polish labour market.

Empirical analysis of both random and stock-flow matching models handling the data time aggregation problem further confirms importance of flows in labour market matching but it does not reject the stocks impact unambiguously. However, stock-flow model implies much bigger transition rate for unemployment inflow than for the corresponding stock.

¹⁷ Taking total outflows from unemployment as endogenous variable.

Elements of the Markov transition matrix imply the unemployment stock to be the most volatile one. However the average probability of finding a job was equal to 11%. Employment inflows' structure shows a declining share of the unemployment to employment flow for the benefit of other inflows.

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Appendix

Figure 1

Beveridge curve on Polish labour market, 1999–2010 (in thousands)



Note: registered unemployment 1999-2010, data seasonally adjusted.

Figure 2

Outflow from unemployment (left axis), inflow of the unemployed (left axis) and unemployment stock (right axis) in Poland, 1999–2010 (in thousands)



Note: registered unemployment 1999-2010, data seasonally adjusted.



2003

Stock

2005

- Inflow

2007

- Outflow

Figure 3 Vacancy stock and inflow (left axis) and outflow from unemployment (right axis) in Poland, 1999–2010 (in thousands)

Note: registered unemployment 1999–2010, data seasonally adjusted.

2001

Figure 4 Employment inflows structure in Poland, 2000–2009

40

20

10 | 1999



Note: UE – flow from unemployment to employment, NE – flow from non-activity to employment, EE – flow from employment to employment.

Source: Labour Force Survey, micro data 2000–2009.

190

170

150 130

2009

Independent variable/ statistics	Parameters estimates (t-student statistics)							
	Ι	II	III	IV	V	VI	VII	
ln U _{t-1}	0.611 (16.37)	0.689 (81.91)	0.592 (11.94)	0.417 (25.38)	0.379 (11.64)	_	_	
$\ln V_{t-1}$	0.281 (16.89)	0.311	0.266 (11.99)	0.160 (10.21)	0,100 (4.80)	-	-	
$\ln u_t$	-	-	-	0.347 (9.55)	0.208 (3.51)	-	-	
$\ln v_t$	-	-	-	0.290 (7.92)	0.434 (9.54)	-	-	
$d\ln U_{t-1}$	-	-	-	-	-	$0.890 \\ (4.10)$	0.466 (2.92)	
$d\ln V_{t-1}$	_	_	_	_	_	0.200 (4.90)	_	
$d\ln u_t$	_	-	-	-	_	_	_	
$d \ln v_t$	_	-	-	-	_	_	0.493 (13.45)	
ρ	_	_	0.297 (3.59)	_	0.542 (7.18)	_	_	
ECT parameter	-	-	-	-	-	-0.652 (-7.93)	-0.524 (-7.46)	
R^2 (adj. R^2)	$0.930 \\ 0.928$	$0.928 \\ 0.927$	$0.936 \\ 0.934$	$0.952 \\ 0.951$	$0.960 \\ 0.958$	$0.375 \\ 0.361$	$0.666 \\ 0.659$	
Engle-Granger statistics [*] p-value	-5.54 (0.00)	-5.44 (0.00)	5.51 (0.00)	-8.50 (0.00)	-12.54 (0.00)	-5.68 (0.00)	-12.76 (0.00)	

Table 1

Estimates for random and stock-flow matching models for Polish labour market, 1999–2010

Note: data seasonally adjusted, dependent variable: outflows from unemployment, ho presents the AR(1) coefficient in error term. *ADF test for residuals.

Source: registered unemployment 1999-2010, BIEC.

Independent variable/	Parameters estimates (t-student statistics)							
statistics	VIII	IX	Х	XI	XII	XIII		
$\lambda_{_U}$	[0.0945]	[0.0884]	[0.0789]	[0.0936]	[0.0899]	[0.0645]		
α_{0}	-0.8669 (-14.62)	-0.3696 (-5.05)	-0.6940 (-4.83)	-1.5395 (-8.87)	-0.7685 (-10.61)	-0.9470 (8.16)		
α,	0.3374 (25.58)	0.0954 (4.02)	-	0.2357 (8.39)	0.0531 (2.28)	-		
α ₂	-	0.5026 (11.44)	0.5656 (16.14)	-	0.4711 (12.62)	0.5000 (18.33)		
p_u	-	0.0777 (1.67)	[0.1680]	-	0.0600 (1.87)	[0.2519]		
γ_0	-	-	-0.8051 (-3.22)	-	-	-1.5012 (-3.72)		
γ_1	-	-	0.4753 (3.48)	-	-	0.4803 (3.20)		
ρ	0.6694 (10.40)	0.6886 (10.73)	0.701 (11.00)	0.7196 (12.00)	0.4369 (5.68)	0.4742 (6.24)		
R^2 (adj. R^2)	$0.921 \\ 0.920$	$0.963 \\ 0.962$	$0.963 \\ 0.962$	$0.931 \\ 0.929$	$0.970 \\ 0.969$	$0.970 \\ 0.969$		
Engle-Granger statistics [*] p-value	-15.62 (0.00)	-12.96 (0.00)	-12.87 (0.00)	-16.65 (0.00)	-12.04 (0.00)	-12.04 (0.00)		

Table 2

Estimates for random and stock-flow time aggregated matching models for Polish labour market, 1999–2010

Note: data seasonally adjusted, dependent variable: outflows from unemployment, ρ presents the AR(1) coefficient in error term.

*ADF test for residuals.

Source: registered unemployment 1999-2010, BIEC.

Independent variable/ statistics	Parameters estimates (t-student statistics)					
	VIII	IX	X	XI	XII	XIII
λ_{U}	[0.0945]	[0.0884]	[0.0789]	[0.0936]	[0.0899]	[0.0645]
p_u	_	0.0777 (1.67)	[0.1680]	-	0.0600 (1.87)	[0.2519]
Mean duration: – completed – incompleted Elasticities:	34.41	33.89 36.74	34.27 41.19	34.71	33.96 36.13	34.43 38.01
U	0.683	0.372	0.358	0.763	0.442	0.442
V	0.346	0.088	0.081	0.235	0.049	0.045
u	0.047	0.116	0.127	0.045	0.099	0.089
ν	-	0.462	0.465	-	0.436	0.442
Sum	1.076	1.038	1.031	1.043	1.027	1.018

Table 3

Outflow probability from the unemployment stock and inflow, mean unemployment duration, matching function elasticities for VIII–XIII estimates

Source: Table 2.