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Iva Tomić

The Efficiency of the Matching Process: Exploring the Impact of Regional Employment Offices in Croatia

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The efficiency of the matching process: Exploring the impact of regional employment offices in Croatia

Iva Tomić*

The Institute of Economics, Zagreb

&

Faculty of Economics, University of Ljubljana

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Abstract:

This paper investigates the efficiency in job placement in Croatian labour market by estimating matching function on a regional level using the Croatian Employment Service data on a monthly basis over the 2000-2011 time period. The efficiency of the matching process is analysed via panel stochastic frontier estimation. Results suggest that the efficiency in the labour market is rising over time, with great variations across regions. Additionally, in order to get consistent estimates, first-difference transformation of the original panel stochastic frontier model is applied. However, preliminary results from this transformed model show that there are no major differences in estimated technical efficiency coefficients in comparison to the original panel stochastic frontier model.

In order to explore regional variations in estimated technical efficiency coefficients structural characteristics of the labour market as well as some policy variables, like ALMPs coverage or regional CES office staff caseload, are included into the second-stage estimation. Even though most of the structural as well as policy variables proved to be significant, none of the estimated coefficients is large enough to explain high regional variations in matching efficiency. This indicates that matching (in)efficiency is highly determined by demand fluctuations. Nevertheless, being that the allocation of funds to regional employment offices is mostly driven by the absorption capacity of the respective office based on historical records, it is argued that in the future local needs should have larger weight when allocating funds to CES regional offices.

Key words: matching function, stochastic frontier, employment offices, efficiency, Croatia

JEL classification: C33, J64, J69, P3

* Email: itomic@eizg.hr; Postal address: Trg J. F. Kennedyja 7, 10000 Zagreb, Croatia.

1. Introduction[1]

Even though it is often considered that labour market institutions reduce the size of the market by introducing a wedge between labour supply and labour demand they are still needed because of different inefficiencies, inequities and policy failures in modern labour markets (Boeri and van Ours, 2008). In order to respond to these market failures, intermediaries between workers and firms arise, usually in the form of state or private employment agencies, labour unions, craft guilds and similar. However, the precise economic function of these intermediaries is questionable (Autor, 2008). Nevertheless, the study of the situation in the labour market would not be complete if the labour market institutions are left out of the analysis.

A traditional rationale for labour market institutions has been to facilitate the matching process in the labour market (Calmfors, 1994; Tyrowicz and Jeruzalski, 2009). This is especially true in the case of transition countries that experienced huge changes in their labour markets after the breakdown of the former socialist system and shift towards market economy. Croatia belongs to this group of countries as well. However, even though the shift in the (un)employment was less than expected in the early years of transition, high unemployment rates, combined with low employment and activity rates, persisted to date. The problem was only highlighted with the prolonged economic and financial crises that started in the second half of 2008. Fahr and Sunde (2002) explain how reasons for high and persistent unemployment may lie on the labour supply side, with inadequate incentives for unemployed to search for a job actively and inefficient labour market in terms of matching unemployed job-seekers and vacant jobs, or on the labour demand side, with insufficient demand for labour as the main culprit for high unemployment. Hence, right form of institutions (intermediaries) in the Croatian labour market is needed now more than ever. Kuddo (2009), for instance, explains how in addition to (inadequate) funding, public policies to combat unemployment largely depend on the capacity of relevant institutions.

However, even in the case of Croatia, there are huge regional differences in the labour market. Some regions (counties) have pretty low unemployment, while others are struggling with high and increasing unemployment rates. That is why this paper examines the efficiency of the labour market on a regional level. Namely, the main objective of the paper is to estimate and explain the efficiency changes that may have taken place both over time and across regions. Additionally, the impact of regional employment offices on the matching efficiency is taken into account. Even though Croatian Employment Office is centralised in a way that financial structure and main policies are brought at the central level, the sole implementation of the policy is local specific. Thus, the aim of the paper is to investigate the role played by employment offices in increasing successful matchings between

[1] I am grateful to Miss Joanna Tyrowicz for her comments and ideas at a very early stage of this research. I would also like to thank Croatian Employment Service (CES), especially Ms Biserka Bulić, for granting access to their data.

vacancies and unemployment in Croatia while controlling for different regional characteristics of the labour markets.

The paper is organised into five parts. After a brief introduction, second section presents a background for the topic in form of a relevant literature review as well as a description of the main ‘intermediary’ in Croatian labour market – the Croatian Employment Service (CES). In addition to that, data used in subsequent empirical analysis are also described in this section. Third section presents methodology used for the empirical assessment of the matching efficiency on a regional level, while results of the conducted analysis are presented in the fourth section. Section five gives some concluding remarks.

2. Background and data description

2.1. Literature review

The literature on regional unemployment persistence in transition economies and the difference of regional unemployment from that in market economies is thoroughly examined by Ferragina and Pastore (2006). They explain how the process in transition countries was driven by massive and prolonged structural change, while the differences persisted over time for three main reasons: (i) restructuring is not yet finished; (ii) foreign capital concentrated in successful regions for many years; and (ii) various forms of labour supply rigidity impeded the full process of adjustment (Ferragina and Pastore, 2006). This topic was further elaborated in a number of works. Mainly, the issue was to establish efficiency of the local labour markets, predominantly by the use of the matching function.

For instance, Fahr and Sunde (2002) show that inefficiencies in the labour market are determined by the composition of the labour market with respect to the age and education structure, as well as the current labour market conditions as indicated by labour market tightness. Disaggregation by region delivers a heterogeneous picture of the efficiency of the matching process but the authors consider the disaggregation across occupations to be more policy relevant than considering different regions. Nevertheless, the same authors (Fahr and Sunde, 2006) further investigate regional dependencies in job creation by applying stochastic frontier analysis and show that search intensity or competition among firms as indicated by labour market tightness significantly increases matching efficiency as does search intensity and competition among job seekers measured by the level of local unemployment. In addition, they present novel evidence on the complex interactions between spatial contingencies among regional labour markets since matching efficiency decreases with spatial autocorrelation in hiring, implying indirect evidence for crowding externalities (Fahr and Sunde, 2006).

Furthermore, Jeruzalsky and Tyrowicz (2009) try to determine the efficiency of matching on a regional level in Poland. They showed that matching abilities are driven only by demand fluctuations while other variables, like unemployment structure across time and regions, ALMPs coverage, and local labour office capacities, remain mostly insignificant. Additionally, Tyrowicz and Wojcik (2009) showed that the unemployment rates across regions in Poland were stabile over the period between 1999 and 2008, i.e. no convergence expect of the convergence of clubs for high unemployment regions. However, they demonstrated that whenever job prospects worsen in general throughout the country more deprived regions are hit harder.

Destefanis and Fonseca (2007) used a matching theory approach with stochastic frontier estimation to assess the impact that the so-called 1997 Treu Act (which greatly fostered the development of temporary work in Italy) on the Italian labour market. They prove the existence of large efficiency differences between the South and the rest of the country where Treu Act had positive impact on the matching efficiency in the North (mainly for skilled labour), but had a negative impact on the matching efficiency of unskilled labour in the South. They interpret this finding in terms of a ladder effect, i.e. the need to focus on the skill mismatch in the Southern labour market both from the demand side and from the supply side (Destefanis and Fonseca, 2007).

Several additional works focus more on the active labour market policies and their impact on a regional level. For instance, Altavilla and Caroleo (2009), using data for Italy, show how active labour market policies settled at national level generate asymmetric effects when regions have different economic structures. The work by Hujer et al. (2002) analyse macroeconomic effects of the ALMP using regional level data and find positive effects of vocational training and job creation schemes on the labour market situation for West Germany, whereas the results for East Germany do not allow profound statements. Dmitrijeva and Hazans (2007) estimate the impact of ALMP programmes on outflows from unemployment in Latvia and find positive and significant effect of training programmes on outflows from unemployment to employment indicating also that hiring process is mainly driven by a stock of unemployed at the beginning of the month and flow of vacancies during the month[2].

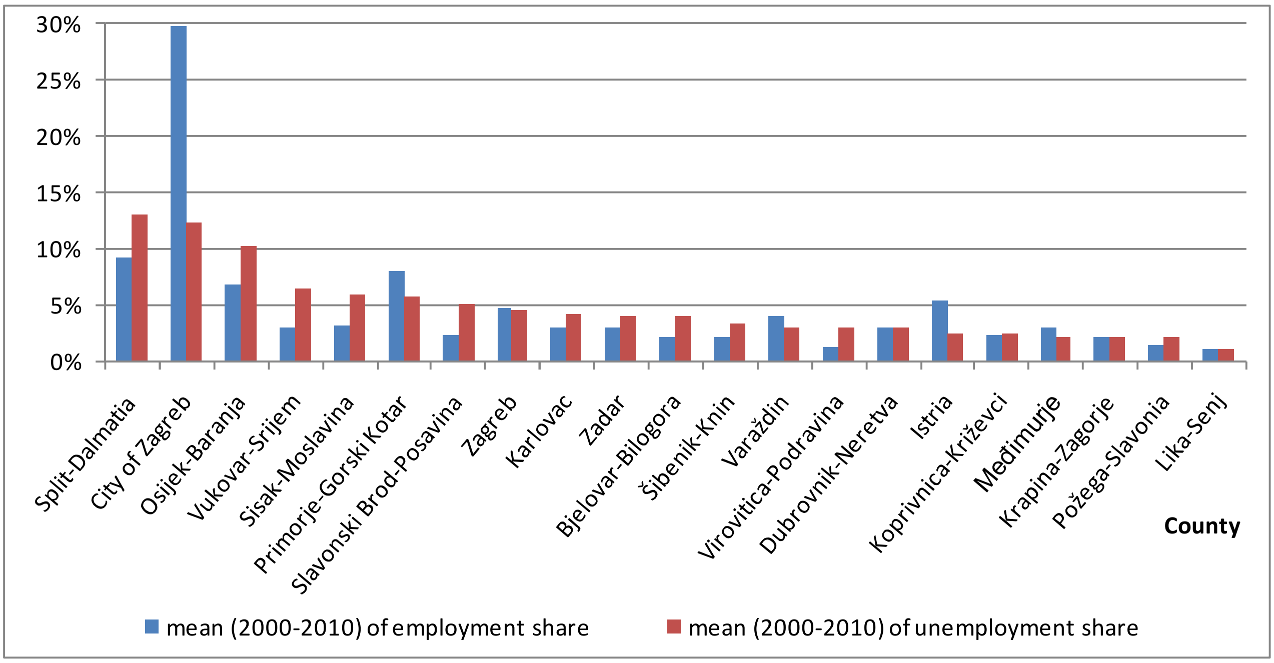
The existing literature indicates regional labour market disparities in Croatia also. Puljiz and Maleković (2007), for instance, state how in the period 2000-2005 regional differences in unemployment rates are increasing, with the absence of any convergence. Botrić (2004) empirically tests the existing differences on a NUTS2[3] level in Croatia and shows substantial differences between Croatian regions regarding unemployment. Furthermore, using county-level (NUTS3) data from LFS in the period 2000-2005, she demonstrates quite visible differences in regional labour market indicators, implying the underdeveloped equilibrating mechanisms in the Croatian labour market (Botrić, 2007). In addition, Obadić (2006a; 2006b), when explaining the problem of structural unemployment for selected transition countries finds that biggest differences in the movement of regional mismatch among the observed countries are persistent in Croatia.

Figure 1 confirms the existence of regional disparities in Croatia by examining the shares of each region's (county's) employment and unemployment in total (national) employment and

[2] The so-called *stock-flow matching* (Dmitrijeva and Hazans, 2007).
[3] Proposed NUTS2 level at that time included five different regions: Northern Croatia; Central Croatia; Eastern Croatia; Western Croatia and Southern Croatia.

unemployment. Evidently, in some of the counties the share in national employment is much larger than the share in total unemployment (City of Zagreb or Istria county, for instance) while in others the share in total unemployment is much larger than the share in employment (Split-Dalmatia or Vukovar-Srijem county, for example). One way to deal with these issues is via the actions of the Croatian Employment Service, especially its local offices.

Figure 1. Regional shares in total employment and unemployment



Source: Author's calculation based on CBS and CES.

2.2. Croatian Employment Service

Typically, public employment services are responsible for all aspects of employment service provision – registering the unemployed, paying unemployment benefits to those who are entitled, giving advice, guidance and counselling to jobseekers, and delivery of active labour market programs (Kuddo, 2009). Actually, one of the main aims of public employment services should be to match as efficiently as possible unemployed workers and open job positions. The Croatian Employment Service (CES) operates on these postulates as well.

The Croatian Employment Service is defined as a public institution aimed at resolving employment and unemployment related issues in their broadest sense. Its priority functions are:

- job mediation;
- vocational guidance;

- provision of financial support to unemployed persons[4];
- training for employment; and
- employment preparation.

In its work CES operates on two main levels: Central Office and Regional Offices. Central Office is responsible for the design and implementation of national employment policy, i.e., it creates a unique methodology for a professional and operational implementation of the procedures from the field of the CES activities. On the other hand, 22 Regional Offices[5] perform professional and work activities from the CES priority functions, as well as provide support for them via monitoring and analysing of (un)employment trends in their counties. The main task of Regional Offices is to identify the needs of their county and implement their activities in line with those specificities. The Central Office provides guidelines for the work in the Regional Offices through its logistical support from all the aforementioned activities.

CES functions as an off-budget beneficiary, which means that its financial operations are based on the funds from the state budget. Its activities are mainly financed from the contributions on the gross wage, but from other sources as well. These other sources include revenues from the help from abroad to co-finance EU projects, as well as income support and donations from domestic entities to finance expenditures for job fairs. The largest share in total expenditures is represented by expenditures for rights during unemployment (approximately 70-80 percent of total expenditures in 2008-2010 period). As of 2006 the financing of active employment programs is also included in total CES expenditures. These expenses comprise approximately 8% of total expenditures of the Service, while material and financial expenses are only 3% of total expenditure of the CES. Lately, increasingly significant share of total expenditures have projects co-financed from EU pre-accession programs.

However, the effectiveness of employment offices varies by regions. For instance, some offices are much more effective in collecting information on job vacancies and in matching the unemployed with jobs than others. As stated in Kuddo (2009), public policies to combat unemployment largely depend on the capacity of relevant institutions. The vacancy penetration ratio (Figure 2) approximates the capacity of regional employment office to collect information on job vacancies. Such capacity is important because it determines the effectiveness of job intermediation services provided by employment offices (WB, 2010). The vacancy penetration ratio less than one suggests that some of the unemployed have found jobs on their own while ratio higher than one means that some of the available vacancies cannot be filled in (possibly due to skills or regional mismatch). Figure 2 indicates that this ratio (effectiveness of regional employment offices) has decreased in the crisis. Still, a given

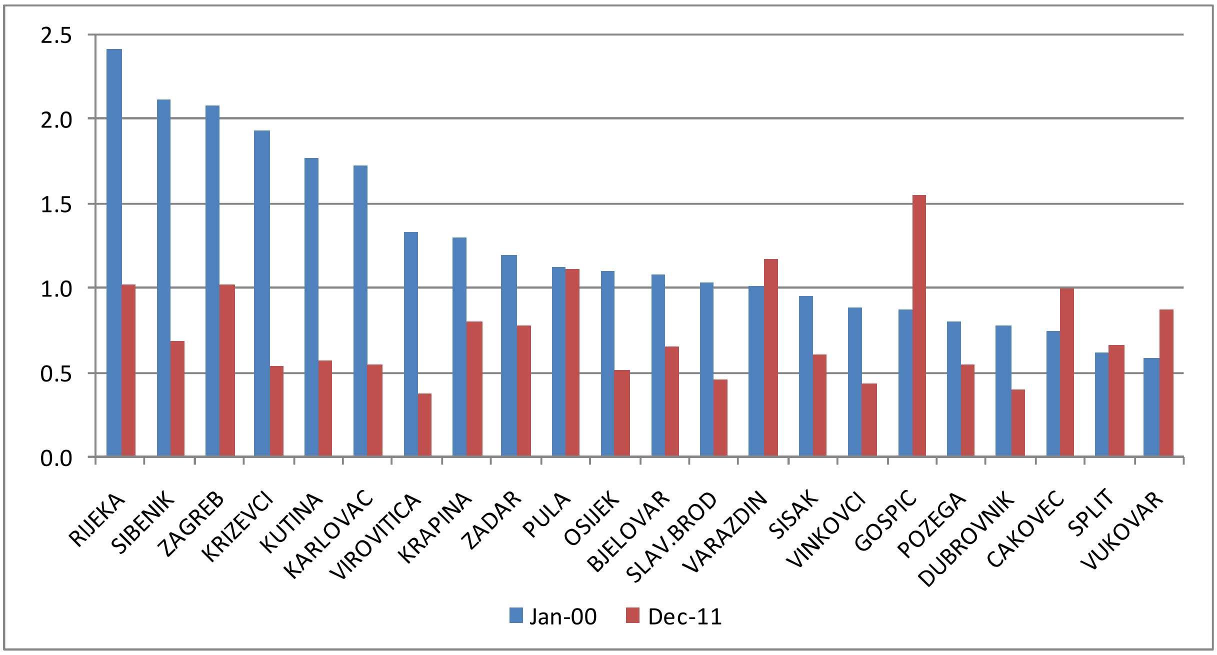
[4] According to the *Law on mediation of employment and entitlements during unemployment* (OG 80/08), unemployed people are entitled to: financial benefits; income support and compensation of training expenses; a lump-sum income support payment and travel and moving expenses compensation; and pension insurance.

[5] One office in each county, with two offices in two counties: Sisak-Moslavina and Vukovar-Srijem, and Zagreb county and the City of Zagreb placed together in one regional office (see Table A3 in Appendix 1). Furthermore, within Regional Offices there are 96 Local Offices and the CES priority aims and functions are achieved by their presence and activities throughout the entire country.

employment office can be effective in collecting vacancy information but less effective in matching the unemployed with vacancies.

On the other hand, high unemployment/vacancies ratio (Figure A2 in Appendix 2) has important policy implications too. Besides indicating that the problem probably lies in the demand deficiency, it also negatively affects the effectiveness of employment services, such as job search assistance and job brokerage (WB, 2010). Matching high number of unemployed with low number of jobs is difficult and costly, while the effect is bound to be limited. Hence, the returns to job matching services are sharply diminishing when the unemployment/vacancies ratio goes up (as in the time of the crisis). Under such conditions the main policy challenge is to enhance job opportunities by supporting job creation (WB, 2010).

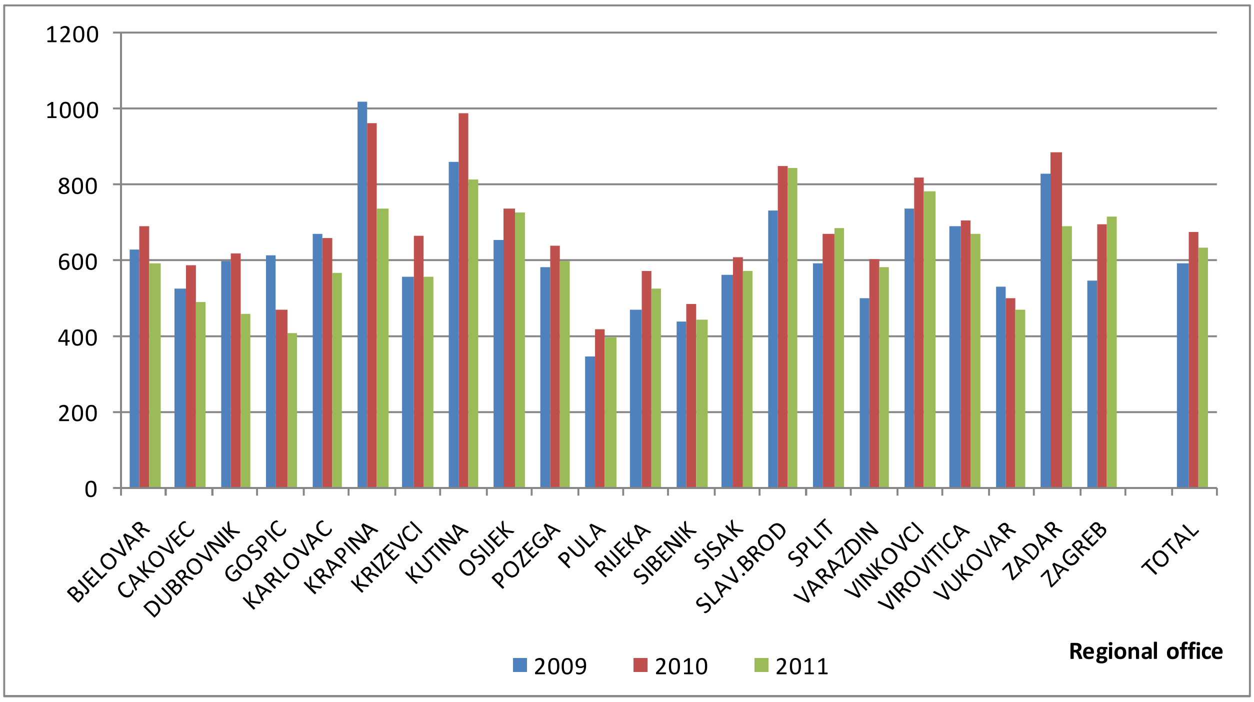
Figure 2. Effectiveness of regional employment offices (vacancy penetration ratio)



Notes: vacancy penetration ratio (V/M) - the ratio of number of vacancies collected by the employment office to the total number of available job vacancies. The total number of vacancies is not known, but it can be approximated by the number of the unemployed who were placed to jobs (M).
Source: Author's calculation based on CES data.

Figure 3 presents another indicator of regional employment office capacity – the number of job counsellors, i.e. the ratio of the number of unemployed per one job counsellor. Evidently, there are high variations between regions which indicates different capacity of the employment offices. This is further confirmed by examining the outflow rate (M/U), i.e. hiring probability by regions (Figure A4 in Appendix 2).

Figure 3. Number of registered unemployed persons per one job counsellor by regional office (2009-2011)



Source: Author's calculation based on CES data.

As far as the Active Labor Market Programs in Croatia are concerned, they include measures like:

- hiring subsidy;
- training for a known employer;
- training for an unknown employer;
- public works; and
- support for business start-ups.

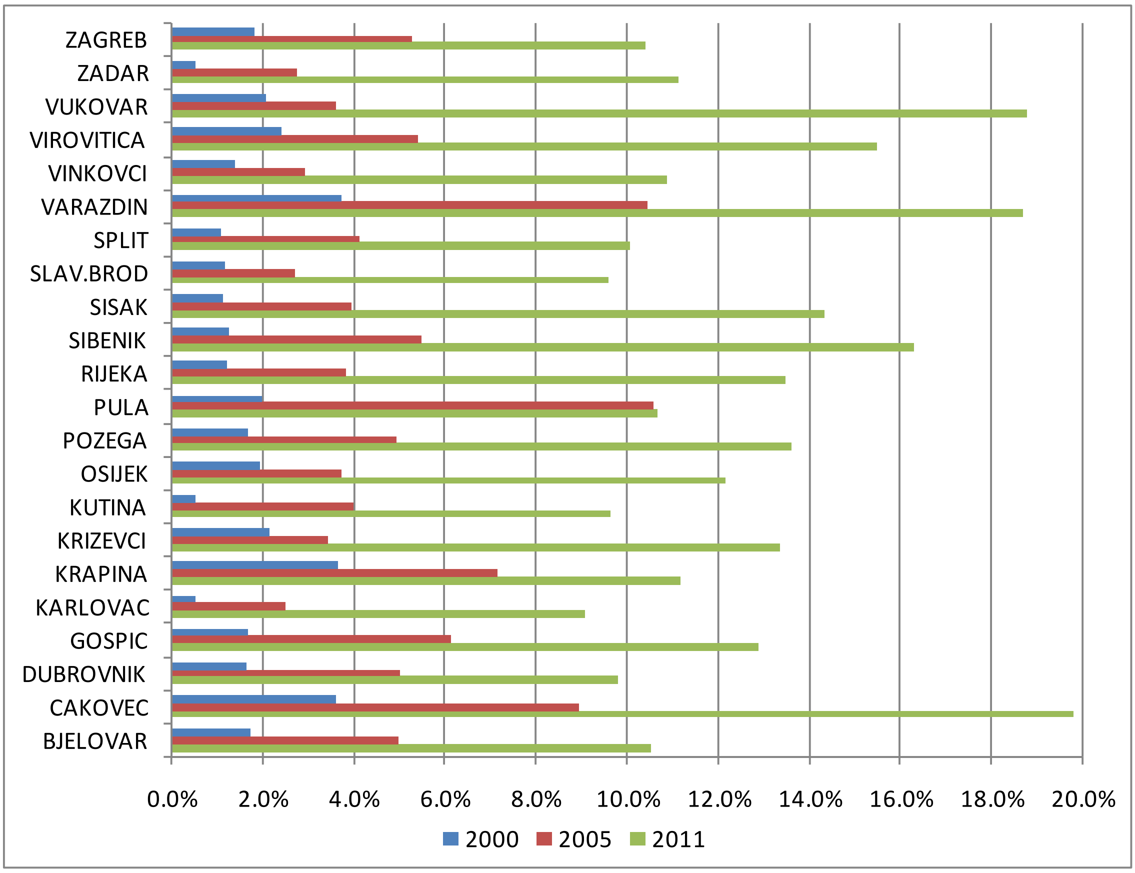
Hagen (2003) as well as Dmitrijeva and Hazans (2007) argue that raising the efficiency of matching process is usually regarded as the main aim of ALMPs, and can be reached by adjusting human capital of job seekers to the requirements of the labour market (important in transition economies) and by increasing search intensity (capacity) of the participants. Nevertheless, budget constraints are limiting the prospects of implementing active labour market measures with real impact which, together with enormous staff caseload in most of the regions (Figure 3), limits the scope of ALMP measures (Kuddo, 2009).

As already mentioned, active labour market programs, which are meant to help job losers to find new jobs, besides poor financing (less than 10 percent of total expenditures), have extremely low coverage[6] (Figure 4 and Figure A5 in Appendix 2) in Croatia. The total spending on labour market programs,

[6] The program coverage rate is the percentage of the unemployed who participated in any active labour market program. It should be noted that training is provided also to the employed workers in Croatia, so the estimate of the coverage rate for the unemployed is biased upwards (WB, 2010).

both passive and active, is very low by the European standards being that Croatia spends on all labour market programs roughly 0.4 percent of GDP, which is substantially less than EU countries at a similar income level, such as Hungary, Poland or Slovakia (0.6 to 1.2 percent of GDP) (WB, 2010). In the years preceding the crisis the coverage rate for active programs was slightly over 3 percent, and it fell to 2.5 percent in 2009 (Figure A5 in Appendix 2). However, recently, in an attempt to fight impacts of the crisis on the labour market, the funds for the ALMPs somewhat increased, as well as the coverage rate for the unemployed (Figure 4).

Figure 4. ALMP coverage across regional offices (2000, 2005 & 2011)



Notes: ALMP coverage – share of persons included in one of the active labour market programs in total unemployment.
Source: Author’s calculation based on CES data.

Nonetheless, the allocation of funds to regional employment offices, which in the end implement active labour market programs, is mainly driven by the offices’ absorption capacity while local needs, measured by the unemployment share, seem to be only a secondary factor (WB, 2010). As it seems, regional allocation of ALMP funds is largely historically determined and changes little in response to the changing local labour market conditions. Although this capacity based allocation rule ensures that program funds are absorbed, it may come at a cost of regions where capacity is relatively low but needs are high (WB, 2010). Still, ALMPs are much more effective at addressing structural, rather than demand-deficient, unemployment (Kuddo, 2009).

2.3. Data

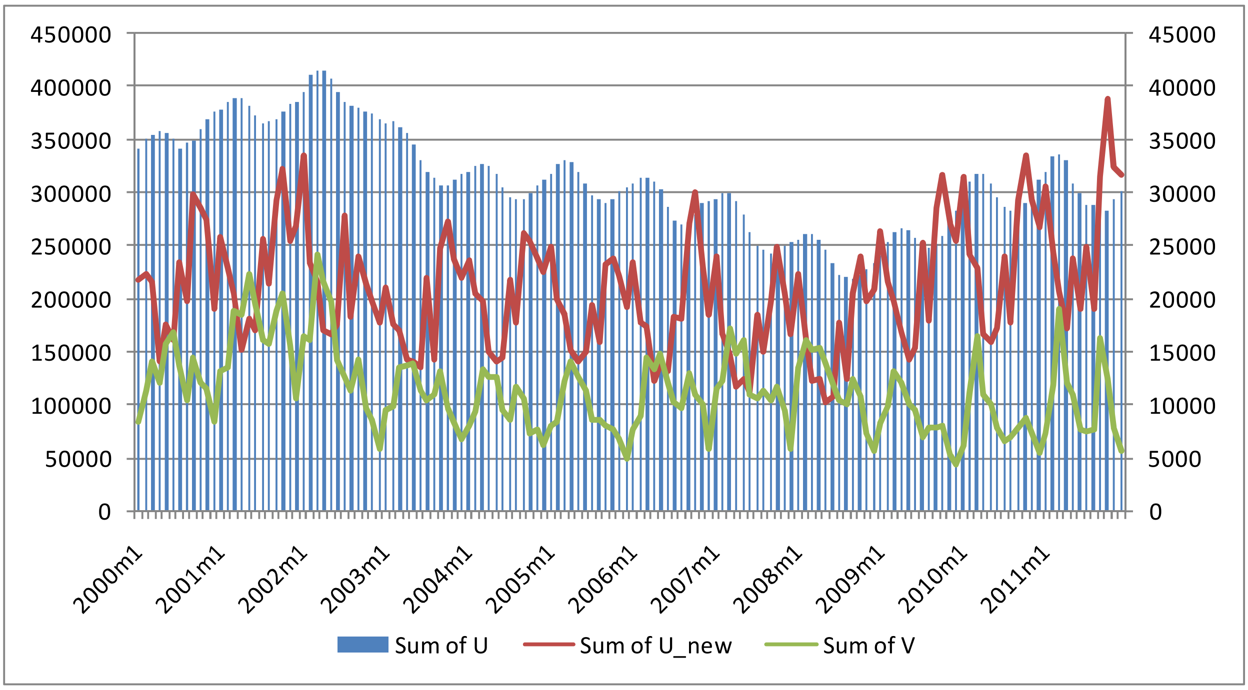
The data used for this research are regional data on a monthly basis within the NUTS3 (county) level obtained from the Croatian Employment Office over a period 2000-2011. Instead of using county-level data, for the purpose of exploring the role of employment offices, CES regional office–level data are used (see the difference in table A3 in Appendix 1). Main variables used in the analysis are: (1) the number of registered unemployed persons (U), (2) the number of reported vacancies (V), (3) the number of newly registered unemployed (U_new); and (4) the number of employed persons from the Service registry (M). Besides these variables, additional data that should affect the efficiency in the labour market are included in the analysis. Detailed review and descriptive statistics of all the variables used in the analysis are provided in Table A1 and Table A2 in Appendix 1.

However, several important points concerning the data should be stressed here. First of all, some of the variables in the analysis are 'stock' variables (as reported at the end of the (previous (t-1)) month) while other variables are 'flow' variables (during a respective (t) month). It is interesting to notice how the reported vacancies are available only as a 'flow' variable, i.e., vacancies reported by each regional office are only those vacancies posted during the respective month. However, we do not consider this to be some big obstacle, since it has been shown in a number of works (Coles and Petrongolo, 2002; Greg and Petrongolo, 2005; Dmitrijeva and Hazans, 2007; or Jeruzalski and Tyrowicz, 2009) that the dynamics between stocks of unemployed and flows of vacancies fit best the nature of the matching process. Nevertheless, the problem still exists since only relatively small portion of vacancies are registered at public employment services (Jeruzalski and Tyrowicz, 2009, Kuddo, 2009). Jeruzalski and Tyrowicz (2009) argue how vacancies are systematically underreported and cannot serve for more than a proxy of the employers need, whereas the extend of underreporting may differ from region to region. In Croatian case, as of 2002 the employers are no longer legally obliged to report vacancies to the CES, while all transitional effects of the changes in legal obligations on reporting vacancies were no longer visible as of 2004 (CNB, 2010).

Additionally, in order to get an indicator of the quality of services of local public employment offices, a number of inquiries has been sent to the Central Office concerning the number and quality (like education, position held, working tenure) of its staff on a regional level, as well as some other characteristics of each individual office (like the amount of financial resources allocated to each office, IT equipment and similar). At this point, only educational structure of the CES staff on a regional level is obtained. In addition to that, in order to evaluate the impact of ALMPs on the overall efficiency – the data concerning persons included in different programs of active labour market policies as well as the data on the amount of funds for each of the ALMP measures were tried to be obtained, but up to now only the data on the number of persons included in different programs of active labour market policies on a yearly basis are provided. Since the reporting standards with job seekers in activisation programmes and programmes themselves were defined differently across years, we use the sums of people covered by programmes in each regional labour force at each point in time (year), i.e., we consider ALMPs coverage at the end of the year.

Figure 5 shows the stocks of unemployment plus flows of unemployment and vacancies in a given period (2000m1-2011m12). Apart from the exceptionally large number of total number of unemployed, the figure shows that the number of newly registered unemployed is generally higher than the reported vacancies in the same month (also observable in Figure A2 in Appendix 2). This indicates that the problem in the Croatian labour market might be in the demand deficiency.

Figure 5. Stocks of unemployment plus flows of unemployment and vacancies - national sums



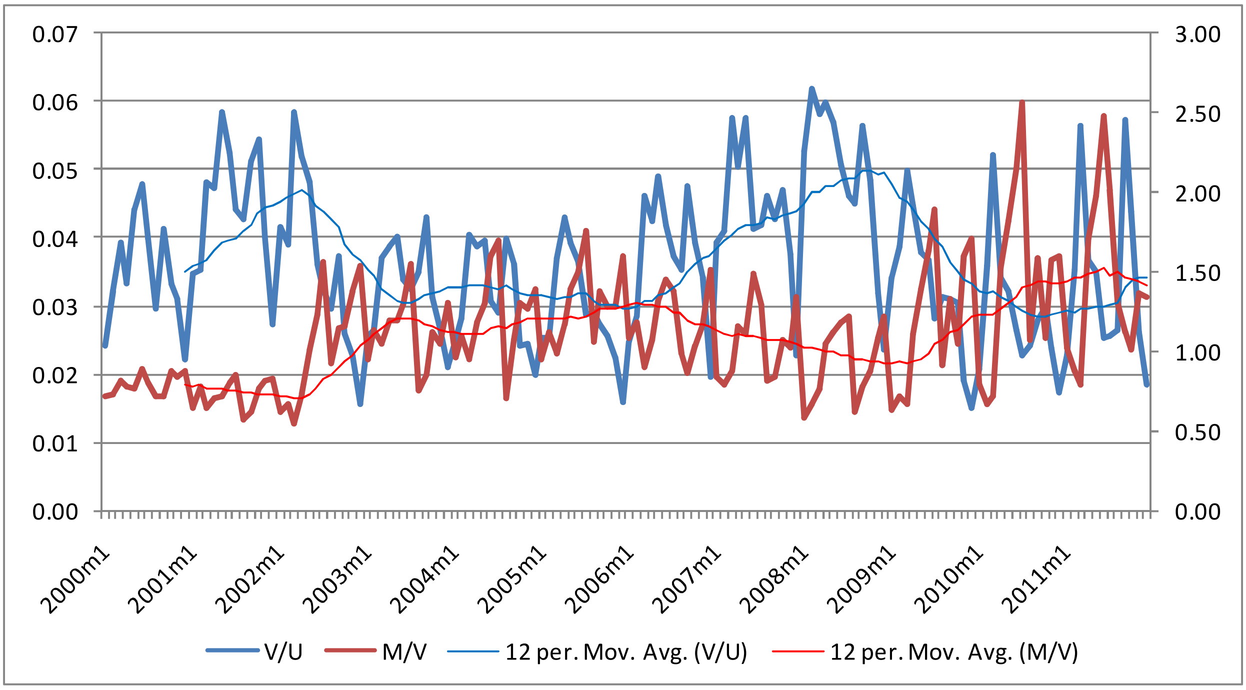
Notes: U – primary axis; U_new and V – secondary axis.
Source: CES.

On the other hand, vacancies (Figure 5) as well as vacancy ratios (Figure 6) demonstrate pretty high volatility over time. Average vacancy ratios (number of job offers per one job seeker) have ranged between 0.015 and 0.062, with the mean value of 0.036 offers per one job seeker (having in mind that this contains only the number of job offers posted at CES offices). Naturally, this property of the data may lead to many estimation problems (Jeruzalski and Tyrowicz, 2009). Among others, it seems that time trend needs to be controlled for in a non-linear way, taking into account up and down swings in the labour market outlooks. Figure 6 also demonstrates the (average) anti-cyclicality of vacancies over time opposite to the pro-cyclicality dynamics of flows to employment in relation to a number of job offers at the disposal of labour offices. Actually, the relatively high values observed at the right scale imply that indeed public employment services dispose of only a fraction of unsubsidised vacancies available in the economy[7]. In the periods of high labour demand (both cyclical and seasonal)

[7] Kuddo (2009) explains how in most of the eastern European and Central Asian countries a relatively small portion of vacancies are registered at PES. He suggests that “in order to increase vacancy notifications, PES and jobseekers themselves should be more proactive in identifying job openings and breaking into the ‘hidden job market’, be it better

considerably more unemployed find jobs than are at the disposal of local labour offices (Jeruzalski and Tyrowicz, 2009).

Figure 6. Vacancy ratio and flows from unemployment to employment (over vacancies)



Notes: V/U – primary axis; M/V – secondary axis.
Source: Author's calculation based on CES data.

3. Empirical strategy

The estimation methodology used in this paper has a foothold in the classical matching function[8]:

$$M = f(U, V) \tag{1}$$

where M is the number of jobs formed during a given time interval, U is the number of unemployed workers looking for work and V the number of vacant jobs. The matching function is assumed increasing in both its arguments, concave, and usually homogeneous of degree 1 (Petrongolo and Pissarides, 2001: 392). Dmitrijeva and Hazans (2007) explain how matching function presumes the presence of search frictions in the labour market because of information imperfections, underdevelopment of insurance markets, low labour mobility, high individual heterogeneity, high qualification mismatch, and other similar factors, i.e., how matching function reflects the efficiency of the labour market.

marketing and services to employers from PES side, to more active networking or direct employer contact from the jobseekers' side" (Kuddo, 2009: 4).

[8] See for instance, Pissarides (2000) or Petrongolo and Pissarides (2001).

The existing empirical literature, however, seldom goes beyond the basic matching function specification, despite the fact that the expanding literature has recently proposed a number of extensions, allowing for a large variety of externalities, market imperfections and particular forms of matching process (Dmitrijeva and Hazans, 2007). Most of the studies estimate a matching function in a Cobb-Douglass functional form, but there are some exceptions, of course[9]. In addition, it is often argued how the aggregation of local labour market data might result in biased estimates of the matching function (Petrongolo and Pissarides, 2001). Therefore, analysis is done on a regional level in order to capture regional disparities in both the matching process as well as in the work of local employment offices.

The matching function can be estimated using different methodological approaches. For instance, Ibourk et al. (2004), Fahr and Sunde (2002; 2006), Destefanis and Fonseca (2007), or Jeruzalsky and Tyrowicz (2009) use *stochastic frontier estimation* in order to determine the efficiency of matching process. Yet, due to possible problems with endogeneity, and, consequently, biased estimated coefficients, Munich and Svejnar (2009) and Jeruzalsky and Tyrowicz (2009) suggest rather the use of the *first difference estimation*. Dmitrijeva and Hazans (2007), on the other hand, using OLS and GLS technique, estimate the so-called *augmented matching function*, which, among the possible determinants of job matches, includes policy variables.

Evidently, the number of approaches in estimating the efficiency of the matching process is numerous. Two main techniques for evaluating matching efficiency that are usually used are stochastic frontier estimation and panel data regressions. The use of stochastic frontier approach allows a more detailed analysis of the determinants of regional matching efficiencies (Ibourk et al., 2001) while fixed effect model implies an unrealistic time-invariance assumption of the matching efficiency and it is difficult to test for the potential influence of explanatory variables on matching inefficiencies (Ibourk et al., 2004). Yet, the transformed panel stochastic frontier model, as suggested by Wang and Ho (2010), deals with this problem quite successfully. Thus, in order to explore its efficiency on a regional level, in this paper stochastic frontier approach will be used, as well as its modified version – basic-form first-difference panel stochastic frontier model.

3.1. Stochastic frontier estimation

Stochastic frontier estimation stems from estimating the production function. The basic idea behind stochastic frontier model is in estimating the efficiency of the production process where the main assumption is that each firm potentially produces less than it might due to some degree of inefficiency[10] i.e.:

[9] See, for instance, Ibourk et al. (2004).

[10] Firstly proposed in the works by Aigner, Lowell, and Schmidt (1977) and Meeusen and van den Broeck (1977). Batesse and Coelli (1993: 1) nicely explain how the stochastic frontier production function postulates the existence of technical inefficiencies of production of firms involved in producing a particular output: “For a given combination of input levels, it

$$y_{it} = f(x_{it}, \beta)\xi_{it} \tag{2}$$

where ξ_{it} is the level of efficiency for firm *i* at time *t*; and ξ_{it} must be in the interval (0; 1]. If $\xi_{it} = 1$, the firm is achieving the optimal output with the technology embodied in the production function $f(x_{it}, \beta)$. When $\xi_{it} < 1$, the firm is not making the most of the inputs x_{it} given the technology of the production function $f(x_{it}, \beta)$. Because the output is assumed to be strictly positive (i.e., $q_{it}>0$), the degree of technical efficiency is assumed to be strictly positive as well (i.e., $\xi_{it} > 0$).

However, output is also assumed to be subject to random shocks, meaning that:

$$y_{it} = f(x_{it}, \beta)\xi_{it} \exp(\upsilon_{it}) \tag{3}$$

or, in logarithm form:

$$\ln(y_{it}) = \ln\{f(x_{it}, \beta)\} + \ln(\xi_{it}) + \upsilon_{it} \tag{4}$$

Assuming that there are *k* inputs and that the production function is linear in logs, defining $u_{it} = -\ln(\xi_{it})$ yields:

$$\ln(y_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(x_{jit}) + \upsilon_{it} - u_{it} \tag{5}$$

Because u_{it} is subtracted from $\ln(y_{it})$, restricting $u_{it} \geq 0$ implies that $0 < \xi_{it} \leq 1$, as specified above. Additionally, in equation (2) υ_{it} represents the idiosyncratic error ($\upsilon_{it} \sim \mathrm{N}(0, \sigma_{\mathrm{v}}^2)$), while much of the literature has been devoted on deriving estimators for different specifications of the random inefficiency term that constitutes the only panel-specific effect, u_{it}.

For example, Aigner, Lowell, and Schmidt (1977) assume that u_{it} has half standard normal distribution. Batesse and Coelli (1995), on the other hand, assume that non-negative technical inefficiency effects are a function of firm-specific variables and time and that they are independently distributed as truncations of normal distributions with constant variance, but with means which are a linear function of observable variables, i.e.:

$$u_{it} = z_{it}\delta + \omega_{it} \tag{6}$$

where ω_{it} is defined by the non-negative truncation of the normal distribution with zero mean and variance, σ_{ω}^2, such that the point of truncation is $-z_{it}\delta$, i.e., $\omega_{it} \geq -z_{it}\delta$. Consequently, u_{it} is a non-negative truncation of the normal distribution with N ($Z_{it}\delta$, σ_u^2).

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is assumed that the realized production of a firm is bounded above by the sum of a parametric function of known inputs, involving unknown parameters, and a random error, associated with measurement error of the level of production or other factors, such as the effects of weather, strikes, damaged product, etc. The greater the amount by which the realized production falls short of this stochastic frontier production, the greater the level of technical inefficiency."

Fahr and Sunde (2002) further explain how u_{it} can vary over time, i.e.

$$u_{it} = \exp^{-\eta(t-T_i)} u_i \tag{7}$$

where T_i is the last period in the *ith* panel, η is an unknown (decay) parameter to be estimated, and the u_i's are assumed to be iid non-negative truncations of the normal distribution with mean μ and variance σ_u^2: $u \sim \mathrm{N}^+(\mu, \sigma_u^2)$; the non-negative effects u_i decrease, remain constant, or increase over time, if η>0, η=0 or η<0, respectively. u_i and v_{it} are distributed independently of each other and the covariates in the model.

The method of maximum likelihood is proposed for simultaneous estimation of the parameters of the stochastic frontier and the model for the technical inefficiency effects, while the likelihood function is expressed in terms of the variance parameters (Batesse and Coelli, 1995). Total variance of the process of matching which is not explained by the exogenous stocks is denoted as σ_s^2 ($\sigma_S^2 = \sigma_\upsilon^2 + \sigma_u{}^2$), and the share of this total variance accounted for by the variance of the inefficiency effect is γ *(*$\gamma \equiv \sigma_u{}^2 / \sigma_S^2$*)*, where γ actually measures the importance of inefficiency for the given model specification (Fahr and Sunde, 2002).

Thus, the technical efficiency of the matching process is based on its conditional expectation, given the model assumptions:

$$TE_{it} = \exp(-u_{it}) = \exp(-z_{it}\delta - \omega_{it}) \tag{8}$$

3.2. Applying stochastic frontier estimation to the matching function

The same approach as described above can be applied to labour market, i.e. to the process of matching between workers who seek for a job and firms that look for workers. In this case the output is the number of matches/hires while inputs are the number of unemployed workers looking for work and the number of vacant jobs (equation (1)). The application of this type of estimation to the labour market was first introduced by Warren (1991) while recently the model has been applied in a number of works estimating the efficiency of the matching process on a specific labour markets: Ibourk et al. (2004) for France; Fahr and Sunde (2002; 2006) for Germany; Destefanis and Fonseca (2007) for Italy; and Jeruzalsky and Tyrowicz (2009) for Poland.

For instance, Ibourk et al. (2004) explain how matching process can be compared to production process, where (in)efficiency of the matching process (ξ_{it}) corresponds to total factor productivity, i.e. determines the number of matches that will be observed at given input values. On the other hand, Fahr and Sunde (2002) differentiate between productivity and efficiency in the matching function, and say that in labour markets exhibiting high levels of matching efficiency, but low productivity, the objective for the policymaker should be to increase the productivity.

The model in this paper is mostly based on Ibourk et al. (2004)[11] and Jeruzalsky and Tyrowicz (2009) where the total number of matches is a function of total number of job vacancies and job seekers, plus a set of variables representing the share of each group *j* in total unemployment. Namely, it is explained how policy relevant variables can be introduced into the model if the assumption about the homogeneity of unemployed is relaxed by varying the individual search intensities[12]. Thus, we use a non-stochastic model where different groups of job-seekers can have different search intensities:

$$M_{i,t} = E_{i,t} V_{i,t-1}^{\beta_1} \left(\sum_j (1+c^j) U_{i,t-1}^j\right)^{\beta_2} \tag{9}$$

where c^j represents deviations from average search intensity, so that negative values are characteristic for less than average search effort. If all groups had identical search intensity, then c^j would be equal to 0 for each *j* and we would be back to the standard model without heterogeneity.

Rearranging equation (9), one obtains:

$$M_{i,t} = E_{i,t} V_{i,t-1}^{\beta_1} \left(U_{i,t-1} + \sum_j c^j U_{i,t-1}^j\right)^{\beta_2} = E_{i,t} V_{i,t-1}^{\beta_1} U_{i,t-1}^{\beta_2} \left(1 + \sum_j c^j \frac{U_{i,t-1}^j}{U_{i,t-1}}\right)^{\beta_2} \tag{10}$$

Taking logs of equation (10) and assuming the term in between brackets is close to 1, we get:

$$m_{i,t} \approx e_{i,t} + \beta_1 v_{i,t-1} + \beta_2 u_{i,t-1} + \sum_j \delta_j \frac{U_{i,t-1}^j}{U_{i,t-1}} \tag{11}$$

where small letters indicate log of the variables and $\delta_j = \beta_2 c^j$. A similar development could be made with respect to job vacancies.

Indeed, the efficiency can be considered as a product of two factors: (i) the rate at which job-seekers and employers meet (search intensity) and (ii) the probability that a contact leads to a successful match (Ibourk et al., 2004; Jeruzalski and Tyrowicz, 2009). Destefanis and Fonseca (2007) explain similarly that the efficiency term is influenced by the search intensity of firms and workers, by the effectiveness of search channels, and by the labour mismatch across micro markets defined over areas, industries, or skills. They also argue how empirical measures of efficiency will reflect the evolution not only of u_{it}, but also of the separation rate and the rate of growth in the labour force. Munich and Svejnar (2009)

[11] Even though in the first version of the paper Ibourk et al. (2001) used the Cobb- Douglas function specification, in the version from 2004 they used the translog production frontier model explaining how by using a restrictive functional form like Cobb-Douglas one may bias the estimate of the return to scale parameter (Ibourk et al., 2004). However, we stick to the Cobb-Douglas functional form because that is predominant in the empirical literature.

[12] Dmitrijeva and Hazans (2007) also suggest that policy relevant variables can be introduced into the model if the assumption about the homogeneity of unemployed is relaxed by varying the individual search intensities. They do that by assuming that unemployed who have completed some kind of training programme have higher search intensities than their non-trained peers, ceteris paribus. However, they neglect problems of adverse selection and reverse causality, and by taking the share of trained directly in the stochastic frontier estimation (instead of two stage approach) they risk endogeneity consequences (Jeruzalsky and Tyrowicz, 2009).

state how the inefficiency may emerge by inadequate labour market institutions leading to decreasing search effort, skills depreciation, rising reservation wage of the unemployed, or geographical or skill mismatch.

Following Battese and Coelli (1995), the assumption is that heterogeneity effects that affect search intensity have direct impact on the matching efficiency, i.e. that they are included in term z_{it} in the following equation:

$$m_{i,t} = \left[\alpha + \beta_1 v_{i,t-1} + \beta_2 u_{i,t-1} + \upsilon_{it}\right] + \left[z_{it}\delta + \omega_{it}\right] \tag{12}$$

where ω_{it} is defined by the truncation of the normal distribution with zero mean and variance, σ_{ω}^2. Additionally, this model may be augmented to distinguish between the stocks and the flows (of both vacancies and unemployed), as advocated by Coles and Petrongolo (2002), Greg and Petrongolo (2005), Dmitrijeva and Hazans (2007) as well as Jeruzalski and Tyrowicz (2009).

Efficiency coefficient is obtained by computing conditional estimates (as in equation (8)):

$$\hat{e}_{i,t} = E\left[e^{Z_{i,t}\hat{\delta}+\hat{\omega}_{i,t}} \mid M, V, U, Z\right] \tag{13}$$

Furthermore, Ibourk et al. (2004) also emphasize how unemployed works who enter special training programs (ALMPs) are not included in the unemployment variable, $u_{i,t-1}$, which could further decrease matching efficiency in the labour market, i.e. if the special employment programmes are in effect targeted on workers with lower employment prospects, removing them from the market will increase the observed matching efficiency:

$$m_{i,t} \approx e_{i,t} + \beta_1 v_{i,t-1} + \beta_2 u_{i,t-1} + \sum_j \delta_j \frac{U_{i,t-1}^j}{U_{i,t-1}} + \varphi \frac{S_{i,t-1}^j}{U_{i,t-1}} \tag{14}$$

where S_{t-1}^j represents the number of unemployed workers of group *j* who enter a special training programme and are withdrawn from the official unemployment statistics and $\varphi = \beta_2 \phi$ where $\phi \equiv -\sum_j \left(S_{t-1}^j / S_{t-1}\right) c^j$, i.e., the weighted search intensity of unemployed withdrawn from the market and entering special training programmes.

Jeruzalski and Tyrowicz (2009) emphasize that although by construction ALMPs and other variables should not be simultaneously correlated, endogeneity might occur in the form of the statistical phenomenon[13] and thus they follow the approach commenced by Ibourk et al. (2004), incorporating the

[13] Dmitrijeva and Hazans (2007) explain how using expenditure on ALMPs or the number of current participants in ALMPs in the model leads to the problem of endogeneity because, if, for instance, situation in the labour market worsens the

ALMPs effects to determine the technical efficiency scores, but not the matching process itself. Therefore, in this paper the used model assumes that different groups of job seekers may exhibit different search intensities, either due to the individual characteristics (e.g., age, education) or because of ALMPs.

Possible shortcoming of the estimation of efficiency of the matching function comes from the fact that data from Croatian employment office do not observe job-to-job flows. However, this is a frequent problem in this type of research. Consequently, the estimation of the matching efficiency of particular office (as opposed to whole regional labour markets) rests upon the vacancies that are filled exclusively from the category of unemployed.

3.3. First difference transformation

Munich and Svejnar (2009) argue that the explanatory variables in the matching function (unemployment and vacancies) are predetermined by previous matching processes through the flow identities. Thus, in order to obtain consistent estimates they suggest that one needs to apply first difference approach to estimation of the matching function, i.e.:

$$\Delta m_{i,t} = \beta_1 \Delta u_{i,t-1} + \beta_2 \Delta v_{i,t-1} + \Delta \varepsilon_{i,t} \qquad (15)$$

In addition, they (Munich and Svejnar, 2009) also suggest that further lags of Δu_t will be uncorrelated with $\Delta \varepsilon_t$ which they use as an argument in favour of the instrumental variables as a method of estimation. However, Jeruzalski and Tyrowicz (2009) argue that this approach does not allow to capture the relation between local conditions and the matching performance which is the main aim of this research.

Some of these issues are further explored in works by Greene (2005a, 2005b) and Wang and Ho (2010). Greene (2005a) argues how traditional panel stochastic frontier estimation approach has two main shortcomings: (i) it usually assumes that (technical) inefficiency is time invariant and (ii) it forces any time invariant cross unit heterogeneity into one term that is being used to capture the inefficiency, i.e., it does not distinguish between unobserved individual heterogeneity and inefficiency. Moreover, Wang and Ho (2010) explain how even in the cases where time-invariant inefficiency assumption has been relaxed (Battese and Coelli, 1995) the time-varying pattern of inefficiency is the same for all individuals. Greene (2005a; 2005b) proposes some extension of both the fixed effects and random effects estimator of the stochastic frontier models that should deal with these issues.

Wang and Ho (2010), on the other hand, argue that Greene's (2005a, 2005b) 'true fixed-effect stochastic frontier model' may be biased by incidental (fixed-effect) parameters problem. Even though

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expenditures may rise, which may lead to selection bias. However, they argue that when units are regions and not individuals the selection issue is less of a problem.

Greene (2005a, 2005b) showed that the incidental parameters problem does not cause bias to the slope coefficients, the estimation problem arises in the error variance estimation, which the inefficiency of the stochastic frontier is actually based on. Hence, Wang and Ho (2010) present a solution to the problem in a form of first-difference and within-transformation that can be analytically performed on the model to remove the fixed individual effects, and thus the estimator becomes immune to the incidental parameters problem. Namely, they remove the fixed individual effects prior to the estimation by simple transformations, thus taking into an account both time-varying inefficiency and time-invariant individual effects. Their initial model resembles to the one in equation (5), i.e.:

$$y_{i,t} = \alpha_i + x_{i,t}\beta + \varepsilon_{i,t} \tag{16}$$

where α_i is individual *i's* fixed unobservable effect; $\varepsilon_{i,t} = \upsilon_{i,t} - u_{i,t}$; $\upsilon_{i,t} \sim \mathrm{N}(0,\sigma_\upsilon^2)$; $u_{i,t} = h_{i,t} \cdot u_i^*$; $h_{i,t} = f(z_{i,t}\delta)$; and $u_i^* \sim \mathrm{N}^+(\mu,\sigma_u^2)$. Neither $x_{i,t}$ nor $z_{i,t}$ contains constants (intercepts) because they are not identified and u_i* is independent of all T observations on $v_{i,t}$, and both u_i* and v_{it} are independent of all T observations on ($x_{i,t}$; $z_{i,t}$)[14].

Fixed individual effect α_i can be removed from the model by first-differencing it:

$$\Delta y_{i,t} = \Delta x_{i,t}\beta + \Delta\varepsilon_{i,t} \tag{17}$$

where $\Delta\varepsilon_{i,t} = \Delta\upsilon_{i,t} - \Delta u_{i,t}$; $\Delta\upsilon_{i,t} \sim \mathrm{MN}(0,\Sigma)$; $\Delta u_{i,t} = \Delta h_{i,t} \cdot u_i^*$; and $u_i^* \sim \mathrm{N}^+(\mu,\sigma_u^2)$. The truncated normal distribution of u_i* is not affected by the transformation. This key aspect of the model leads to a tractable likelihood function[15].

In order to compute technical efficiency index the conditional expectation estimator is used, i.e. conditional expectation of $u_{i,t}$ on the vector of differenced $\varepsilon_{i,t}$. The advantages of using this estimator are: (i) the vector $\Delta\tilde{\varepsilon}_i$ ($\Delta\tilde{\varepsilon}_i = (\Delta\varepsilon_{i2}, \Delta\varepsilon_{i3}, \ldots, \Delta\varepsilon_{iT})$) contains all the information of individual *i* in the sample, and (ii) the estimator depends on $\hat{\beta}$ (for which the variance is of order 1/((N-1)/T)) but not $\hat{\alpha}_i$ (for which the variance order is 1/T). The derivation of the equation looks like the following:

$$E(u_{i,t} \mid \Delta\tilde{\varepsilon}_i) = h_{i,t}\left[\mu_* + \frac{\phi\left(\frac{\mu_*}{\sigma_*}\right)\sigma_*}{\Phi\left(\frac{\mu_*}{\sigma_*}\right)}\right] \tag{18}$$

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[14] The model exhibits the so-called "scaling property" that is, conditional on z_{it}, the one-sided error term equals a scaling function h_{it} multiplied by a one-sided error distributed independently of z_{it}. With this property, the shape of the underlying distribution of inefficiency is the same for all individuals, but the scale of the distribution is stretched or shrunk by observation-specific factors z_{it}. The time-invariant specification of u_i*allows the inefficiency $u_{i,t}$ to be correlated over time for a given individual (Wang and Ho, 2010).

[15] For details, please see Wang and Ho (2010).

which is evaluated at $\Delta\tilde{\varepsilon}_i = \Delta\hat{\tilde{\varepsilon}}_i$ and where $\mu_* = \dfrac{\mu/\sigma_u^2 - \Delta\tilde{\varepsilon}_i'\Sigma^{-1}\Delta\tilde{h}_i}{\Delta\tilde{h}_i'\Sigma^{-1}\Delta\tilde{h}_i + 1/\sigma_u^2}$; $\sigma_*^2 = \dfrac{1}{\Delta\tilde{h}_i'\Sigma^{-1}\Delta\tilde{h}_i + 1/\sigma_u^2}$; $\Delta\tilde{\varepsilon}_i = \Delta\tilde{y}_i - \Delta\tilde{x}_i\beta$; and Φ is the cumulative density function of a standard normal distribution.

Although the individual effects α_i's are not estimated in the model, their values can be recovered after the model's other parameters are estimated by the transformed model proposed above. A *T*-consistent estimator of α_i may be obtained by solving the first-order condition for α_i from the untransformed log-likelihood function of the model assuming all other parameters are known.

Furthermore, even though two-stage estimation procedure is justified on the grounds of problems with endogeneity (Jeruzalski and Tyrowicz, 2009), Batesse and Coelli (1995), Wang and Schmidt (2002) as well as Ibourk et al. (2004) argue in favour of the one-stage instead two-stage stochastic frontier estimation. Ibourk et al. (2004) state how the two-stage procedure used to this end typically implies the loss of a large amount of information and degrees of freedom. Furthermore, Battese and Coelli (1995) explain how even if a second stage regression can be performed, it is in contradiction with the identically distributed inefficiency assumption (first stage). Thus, in order to get more consistent (unbiased) estimates we will use Wang and Ho's (2010) first-difference transformation on (one-stage) stochastic frontier model estimation of the matching function.

4. Estimation results

In this part the estimation results are presented. First, the results from the first stage of stochastic frontier model (expression (12)) are shown while subsequently the results from the second stage are given, i.e., the estimation of the panel regression for the estimated technical efficiency coefficients (expression (13)) from the first step. In the third part, the results from the estimation of the basic-form transformed panel stochastic frontier model are provided.

4.1. Stochastic frontier estimations

For the estimation of stochastic frontier we have used time-varying decay model (Battese and Coelli, 1995). This means that the inefficiency term is modelled as a truncated-normal random variable multiplied by a specific function of time; the idiosyncratic error term is assumed to have normal distribution, while the random inefficiency term constitutes the only panel-specific effect. Additionally, in order to control for the sizeable seasonality typically contained in the unemployment flows it is desirable to include month and year specific dummy variables as regressors in the model. Therefore, estimations include monthly dummies to control for differentiated vacancies and job seekers arrival rates throughout each year[16]. Additionally, in the existing empirical works variables are

[16] Year dummies are included for the period when the reporting of vacancies at CES was still in effect, i.e., for the years 2000-2003.

usually normalized (by the size of the labour force) in order to control for heteroscedasticity (Munich and Svejnar, 2009; Dur, 1999). However, since the size of the labour force in Croatia varied a lot during the observed period, in this paper we do not normalize the data by the size of the workforce because it could negatively affect the statistical properties of the model. Still, the analysis is done (and presented) for the whole sample, as well as for the sample excluding the biggest region (belonging to Zagreb regional office)[17]. Finally, as explained previously, the estimations will include both stocks and flows of unemployed and only flows of vacancies.

Results are reported in Table 1. Since the variables are taken in logarithms, the estimations actually represent elasticities.

Table 1. Stochastic frontier unrestricted estimation

	Total sample			Zagreb region excluded		
Variables	**Stocks of u**	**Flows of u**	**Both**	**Stocks of u**	**Flows of u**	**Both**
u	0.761*** (0.023)		0.911*** (0.028)	0.773*** (0.021)		0.924*** (0.029)
v	0.241*** (0.010)	0.262*** (0.011)	0.233*** (0.010)	0.242*** (0.010)	0.260*** (0.012)	0.235*** (0.010)
u_new		0.026 (0.021)	-0.166*** (0.019)		0.019 (0.021)	-0.155*** (0.019)
Monthly dummies	YES	YES	YES	YES	YES	YES
Annual dummies	YES	YES	YES	YES	YES	YES
Returns to scale	CRS	DRS	CRS	CRS	DRS	CRS
constant	-2.598*** (0.191)	4.952*** (0.217)	-2.713*** (0.192)	-2.721*** (0.180)	7.245 (6.556)	-2.923*** (0.209)
Mean technical efficiency	0.762	0.384	0.691	0.762	0.038	0.692
Wald χ^2	7470.74***	4625.79***	7548.41***	7685.43***	4693.50***	7395.96***
γ	0.104*** (0.038)	0.762*** (0.065)	0.150*** (0.045)	0.086*** (0.032)	0.716*** (0.065)	0.155*** (0.049)
η	0.005*** (0.001)	0.0004*** (0.0002)	0.005*** (0.001)	0.007*** (0.001)	0.0001 (0.0003)	0.005*** (0.001)
Log likelihood	76.710	-263.551	114.912	89.924	-230.525	127.090
No. of observations	3168	3168	3168	3024	3024	3024

Notes: Dependent variable: log of monthly flows to employment out of unemployment (m). γ represents the share of total variance accounted for by the variance of the inefficiency effect ($\gamma \equiv \sigma_u^2 / \sigma_S^2$) while η comes from time-varying decay model ($u_{it} = \exp^{-\eta(t-T_i)} u_i$), where the non-negative effects u_i decrease, remain constant, or increase over time, if $\eta>0$, $\eta=0$ or $\eta<0$, respectively. Monthly and annual dummies are statically significant, detailed results available upon request. Variables taken in logarithms, lagged when necessary. Standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

As evident from the Table 1, there is a larger weight of job seekers in the matching process than of the posted vacancies. This result is not unusual since in most of the empirical works the number of

[17] Larger labour markets are usually characterised by larger flows, including outflows to employment without any support from the public employment services (Jeruzalski and Tyrowicz, 2009).

unemployed tends to affect hirings more than the number of posted vacancies (for instance, Fahr and Sunde, 2006; Jeruzalski and Tyrowicz, 2009). What's more, only the stock of the unemployed affects positively the process of matching, while the newly registered unemployed decrease the matching capacity. This is also in congruence with some other empirical results (Jeruzalski and Tyrowicz, 2009). Nonetheless, in this case adding the flow variable in the model actually increases the impact of the stock variable.

As discussed earlier, size of the region could have an impact on the matching process. That's why we present the estimates using the sample without the biggest region – Zagreb (see Figure 1). However, by excluding this largest region, we do not get much different results from the ones with data from the entire sample. That is why we will use the estimates of technical efficiency coefficients from the estimation for the whole sample in the rest of the paper.

Table 2. Stochastic frontier restricted estimation

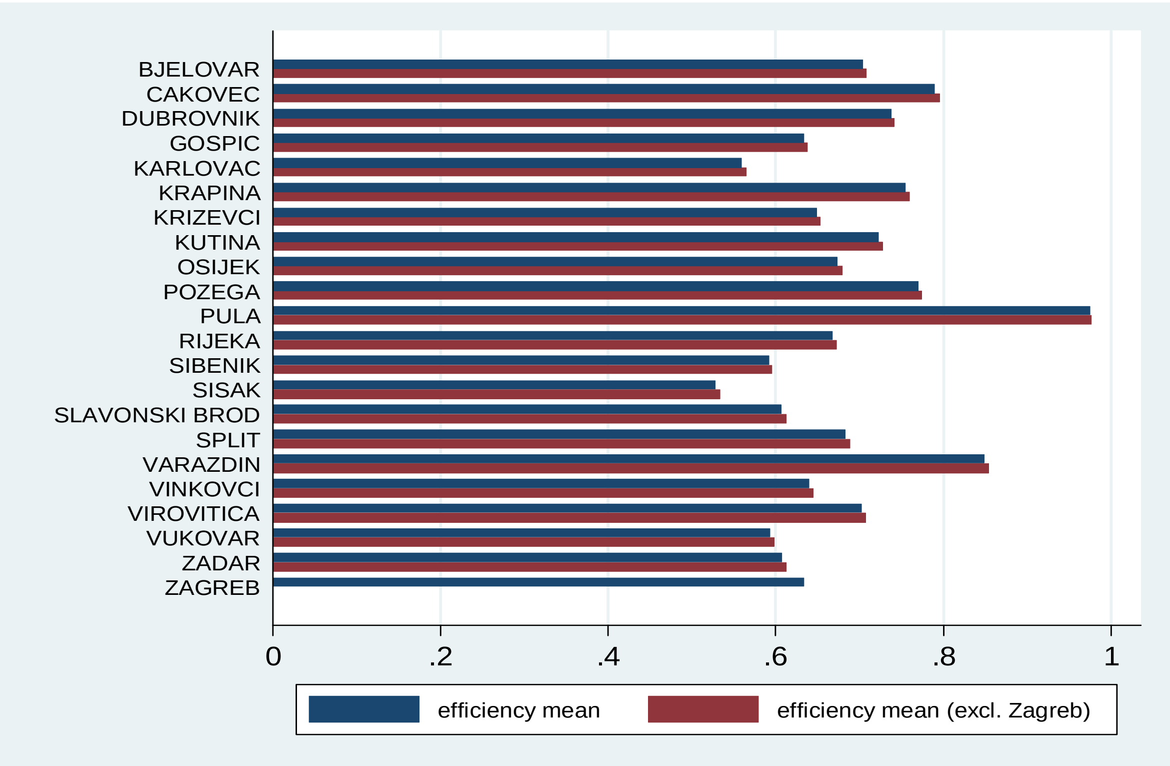
	Total sample		**Zagreb region excluded**	
Variables	**Stocks of u**	**Both**	**Stocks of u**	**Both**
u	0.759*** (0.010)	0.928*** (0.022)	0.760*** (0.010)	0.921*** (0.022)
v	0.241*** (0.010)	0.235*** (0.010)	0.240*** (0.010)	0.235*** (0.010)
u_new		-0.163*** (0.019)		-0.155*** (0.019)
Monthly dummies	YES	YES	YES	YES
Annual dummies	YES	YES	YES	YES
constant	-2.577*** (0.037)	-2.890*** (0.054)	-2.600*** (0.037)	-2.888*** (0.054)
Mean technical efficiency	0.763	0.685	0.765	0.693
Wald χ^2	9057.41***	9259.30***	9001.19***	5767.96***
γ	0.102*** (0.036)	0.158*** (0.047)	0.083*** (0.031)	0.154*** (0.048)
η	0.006*** (0.001)	0.005*** (0.001)	0.007*** (0.001)	0.005*** (0.001)
Log likelihood	76.704	114.464	89.682	127.075
No. of observations	3168	3168	3024	3024

Notes: Dependent variable: log of monthly flows to employment out of unemployment (m). γ represents the share of total variance accounted for by the variance of the inefficiency effect ($\gamma \equiv \sigma_u^2 / \sigma_S^2$) while η comes from time-varying decay model ($u_{it} = \exp^{-\eta(t-T_i)} u_i$), where the non-negative effects u_i decrease, remain constant, or increase over time, if η>0, η=0 or η<0, respectively. Monthly and annual dummies are statically significant, detailed results available upon request. Variables taken in logarithms, lagged when necessary. Standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Furthermore, specifications with only stocks of unemployed and with both stocks and flows in Table 1 indicate that the model exhibits constant returns to scale. Therefore, in Table 2 the results from the restricted estimation ($\beta_u + \beta_v = 1$ or $\beta_u + \beta_v + \beta_{u\_new} = 1$) are presented. As expected, there is no significant difference between these estimations and those presented in Table 1, including both total sample as well as sample without the Zagreb regional office data. The same hols for the estimated technical efficiency coefficients.

However, the main aim of this estimation was to establish the degree of (in)efficiency of the matching process. Interestingly, adding the newly registered unemployed to the model specification diminishes matching efficiency. Mean values from Table 1 suggest that the matching (hiring) process is on average 25-30 percent inefficient given the inputs (unemployed and vacancies). Nevertheless, there are great variations across regions/regional offices (Figure 7)[18]. For instance, regional office Pula exhibits almost 100 percent efficiency, while regional office Sisak in approximately 50 percent efficient in matching unemployed workers with available jobs. This variability of estimated technical efficiency coefficients across regions guarantees sufficient variation to perform the second stage analysis (Jeruzalski and Tyrowicz, 2009).

Figure 7. Mean technical efficiency across regional offices (with and without Zagreb region)



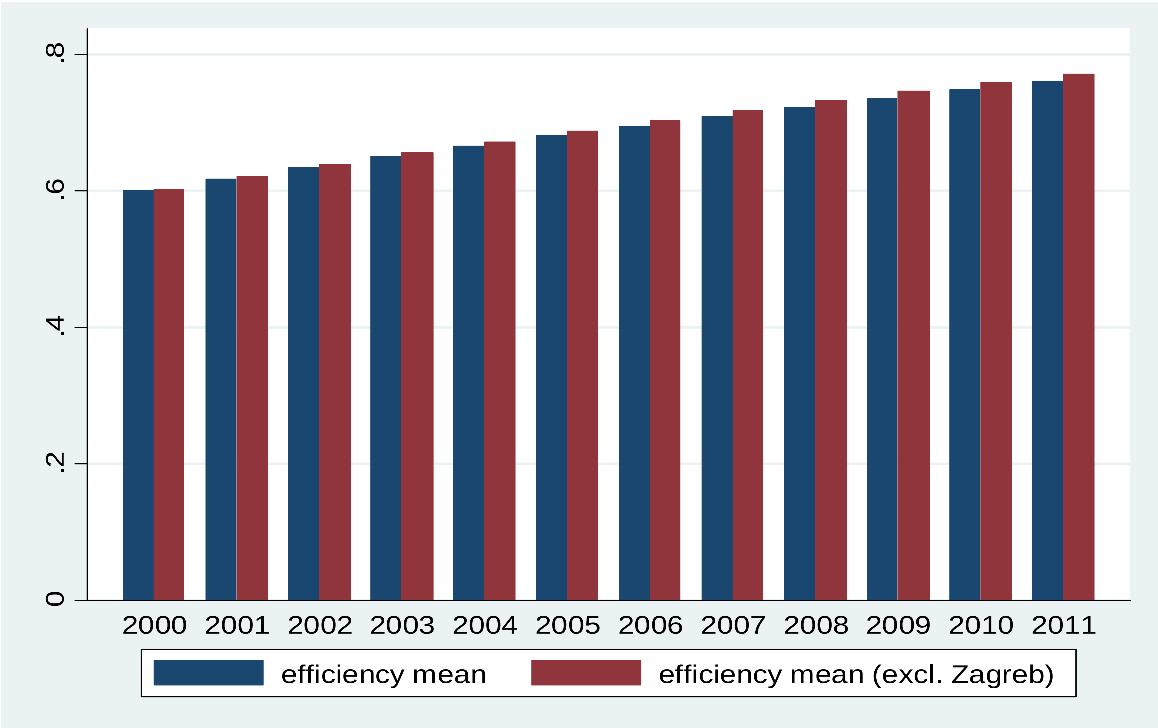
Source: Author's calculation based on CES data.

Nevertheless, all regional offices show a rise in the matching efficiency in the period 2000-2011 (Figure 8 and Figure A7 in Appendix 3). This result goes hand-in-hand with some other empirical

[18] In both Figure 7 and Figure 8 efficiency estimates from the (restricted) specification with both stocks and flows of the unemployed (column 3 in Table 2) are presented.

results (for instance, Sergo, Poropat and Gržinić, 2009)[19]. On top of that, if we exclude Zagreb region, the efficiency coefficient estimates stay almost the same.

Figure 8. Mean technical efficiency over years (with and without Zagreb region)



Source: Author's calculation based on CES data.

4.2. Covariates of technical efficiency

Following Jeruzalsky and Tyrowicz (2009), in this part we present the estimation results for the covariates of technical efficiency scores[20]. In this way, the characteristics of a local labour market are approached by the means of proxies. Namely, some local markets may be more dynamic than others, while some may be populated by more difficult unemployed than others. To account for this differentiation, following Ibourk et al. (2004), Destefanis and Fonseca (2007) and Jeruzalski and Tyrowicz (2009), we have used the next measures:

- Labour market structure (Figure A7 in Appendix 2):
    - Vacancy ratio (v/u). Measure of labour market tightness.

[19] Increasing efficiency over time may be interpreted as learning of the agents in the market how to find appropriate partners in order to form matches (Fahr and Sunde, 2002).

[20] Although, the regression construct specifies causality direction from the RHS variables to the LHS one - we are only trying to establish if there is a link between some control factors and the individual efficiency scores (Jeruzalsky and Tyrowicz, 2009).

    - Share of females in total unemployment (u_female) and in total flows to employment (m_female).
    - Ratio of employed to delisted (m/delisted).
    - Share of youth (u_<24y) in the pool of unemployed.
    - Share of long-term unemployed in the pool of unemployed (u_12m+).
    - Share of workers without experience in the pool of unemployed (u_w/o experience).
    - Share of workers previously employed in the primary sector of economic activity in the pool of unemployed (u_primary_sector).
    - Share of unemployed persons receiving unemployment benefits in the pool of unemployed (u_benefits).
    - Share of no or low skilled unemployed among jobless (u_low skilled).
    - Share of high skilled unemployed among jobless (u_high skilled).
- ALMPs coverage (u_almp_coverage).
- Number of highly skilled employed at the respective CES regional office per one unemployed (CES_high skilled).
- Size of the labour market measured by the population density (pop_density).

In addition, linear and quadratic trends are included to control for country wide labour market fluctuations.

Different measures included in 'labour market structure' may reflect different search intensities, willingness to accept received job offers and/or firms' attitudes (Ibourk et al., 2004). For instance, labour market tightness represents search intensity of firms and competition among firms for applicants (Fahr and Sunde, 2006) and it can be a good measure of the cycle (Petrongolo and Pissarides, 2001). Namely, share of females in both unemployment and in total flows to employment corresponds to the diversity of job creation and destruction in particular labour markets; youth usually demonstrate higher adaptability (search intensity), while low skilled unemployed typically represent lower value to the employers, which may constitute an obstacle in smooth unemployment-to-employment transitions (Jeruzalski and Tyrowicz, 2009). Additionally, share of long-term unemployed may capture both business cycle effects and more structural difficulties (such as skills mismatch) (Ibourk, et al., 2004) while share of unemployed receiving unemployment benefits should affect the willingness to accept the job (reservation wage). Furthermore, share of females in total unemployment as well as share of long-term unemployed may indicate ranking effects while share of unemployed in agriculture (primary sector) may indicate some firm effects (Destefanis and Fonseca, 2007).

As discussed earlier, ALMPs coverage (u_almp_coverage) is constructed as a number of individuals in any treatment over the pool of unemployed in a respective district at the year end. This variable is important because it should affect different search intensities and thus influence the matching efficiency. Additionally, the number of highly skilled employed at the respective CES regional office per one unemployed (CES_high skilled) should serve as a proxy of regional labour office capacity. Even though the number of job counsellors or even job brokers (Jeruzalski and Tyrowicz, 2009) would be a better measure, due to unavailability of the data, the number of highly skilled CES employees per one unemployed will serve this purpose.

As argued by Ibourk et al. (2004) as well as Munich and Svejnar (2009) the size of the respective labour market is important for a number of reasons. Ibourk et al. (2004), for instance, use population density which is meant to capture effects coming from the density of economic activities and the probability that a contact is established between the right employer and employee. Munich and Svejnar (2009), on the other hand, indicate how without controlling for the district size may lead to biased coefficients unless the function exhibits constant returns to scale (omitted variable problem) which leads to spurious scale effect. In our specification, we follow Ibourk et al. (2004) and use population density as well as squared population density as covariates of technical efficiency.

Results of these estimations are reported in Table 3[21]. There are six different model specifications. First, only the 'labour market structure' variables are used. Then, ALMPs coverage variable is added to the model specification, while in the third specification the number of highly skilled CES employees per one unemployed is included. Specification four to six subsequently include time trend, measure of the region's size (population density), and monthly and annual dummies[22].

The capacity of the public employment services to match employers with the job seekers may be negatively affected by some structural characteristics, but it is supposed to be positively affected by some policy variables, like number of PES employees (per no of unemployed) or ALMPs coverage (Jeruzalski and Tyrowicz, 2009). The estimated coefficients in Table 3 only partially confirm these expectations. Namely, even though most of the covariates are statistically significant and of expected sign, the obtained estimations are generally too low to bring any major conclusions about their intercorrelation with technical efficiency coefficients.

As far as structural variables are concerned, none of the estimated coefficients is large enough to explain variations in technical efficiency. Vacancy ratio proved to be insignificant in all of the model specifications while share of females in both unemployment and employment, ratio of employed to delisted, and share of long-term unemployed is significant in some specifications while in others is insignificant.

Besides that, depending on the model specification, some of the covariates change their sign which suggest that the relationship between them and matching efficiency is spurious. Taking all this into an account, we can see that only share of workers without experience and share of low skilled workers have unvarying negative and significant impact on technical efficiency, while share of workers previously employed in the primary sector and share of high skilled workers have significant and

[21] In this case, the efficiency estimates from the (restricted) specification with both stocks and flows of the unemployed (column 3 in Table 2) are used.
[22] Figure A8 in Apendix 3 shows correlations between the efficiency coefficient and a set of explanatory variables.

positive effect on the coefficients of technical efficiency. These results, except perhaps for the share of agricultural workers, are quite intuitive and expected.

Table 3. Determinants of technical efficiency

Variables	(1)	(2)	(3)	(4)	(5)	(6)
v/u	0.0002 (0.0001)	0.0002 (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)	0.0002 (0.0001)	0.0002 (0.0002)
m/delisted	-0.0007*** (0.0002)	-0.0009*** (0.0002)	-0.0007*** (0.0002)	-0.0001 (0.0001)	-0.0001 (0.0001)	-0.0002 (0.0002)
m_female	-0.0013** (0.0005)	-0.0016*** (0.0006)	-0.0011** (0.0005)	-0.0001 (0.0004)	0.0001 (0.0004)	0.0009* (0.0005)
u_female	0.0459*** (0.0070)	0.0575*** (0.0080)	0.0329*** (0.00064)	0.0067 (0.0055)	-0.0018 (0.0053)	-0.0158** (0.0074)
u_<24y	-0.0043* (0.0025)	-0.0055* (0.0028)	0.0079*** (0.0025)	0.0159*** (0.0019)	0.0177*** (0.0020)	0.0375*** (0.0030)
u_12m+	-0.0018 (0.0030)	-0.0046 (0.0035)	-0.0077*** (0.0028)	0.0032 (0.0023)	0.0018 (0.0024)	-0.0001 (0.0031)
u_w/o_experience	-0.0330*** (0.0024)	-0.0372*** (0.0028)	-0.0330*** (0.0023)	-0.0212*** (0.0018)	-0.0202*** (0.0018)	-0.0447*** (0.0029)
u_primary_sector	0.0038*** (0.0011)	0.0061*** (0.0012)	0.0038*** (0.0010)	0.0016** (0.0008)	0.0019** (0.0008)	0.0082*** (0.0010)
u_benefits	0.0030* (0.0016)	0.0048*** (0.0018)	-0.0040*** (0.0015)	0.0042*** (0.0011)	0.0056*** (0.0011)	0.0121*** (0.0016)
u_low skilled	-0.0361*** (0.0033)	-0.0366*** (0.0037)	-0.0288*** (0.0032)	-0.0095*** (0.0024)	-0.0087*** (0.0026)	-0.0119*** (0.0033)
u_high skilled	0.0127*** (0.0015)	0.0138*** (0.0017)	0.0102*** (0.0014)	0.0105*** (0.0011)	0.0095*** (0.0012)	0.0084*** (0.0017)
u_almp coverage		0.0018*** (0.0003)	0.0009*** (0.0003)	$1.72e^{-06}$ (0.0002)	0.0001 (0.0002)	0.0033*** (0.0006)
CES_high skilled			0.0304*** (0.0019)	0.0161** (0.0015)	0.0202*** (0.0016)	0.0382*** (0.0021)
time trend				0.0014*** (0.0001)	0.0015*** (0.0001)	0.0013*** (0.0001)
squared time trend				$-1.79e^{-06}$*** ($3.77e^{-07}$)	$-2.03e^{-06}$*** ($3.89e^{-07}$)	$-2.36e^{-06}$*** ($5.25e^{-07}$)
pop_density					0.0034 (0.0089)	0.0592*** (0.0096)
squared pop_density					0.0031** (0.0012)	-0.0043*** (0.0013)
Monthly dummies						YES
Annual dummies						YES
constant	0.6444*** (0.0113)	0.6639*** (0.0132)	0.8489*** (0.0164)	0.7039*** (0.0129)	0.6614*** (0.0190)	0.6995*** (0.0233)
Wald χ^2	852.23***	1013.54***	1062.30***	7043.24***	7084.03***	6315.92***
No. of observations	3168	3168	3168	3168	3168	3168

Notes: Dependent variable: estimates of the technical efficiency from the stochastic frontier as reported in Table 2 (column 3). Monthly and annual dummies are statically significant, detailed results available upon request. Hausman specification test suggests the use of fixed effects estimator. However, after the models are checked for heteroscedasticity and autocorrelation, they are corrected by using cross-sectional time-series FGLS regression estimation. Standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Unexpected results come (where significant) from the share of females in both unemployed and outflows from unemployment. Namely, larger percentage of females in the pool of unemployed should signify less diversified labour markets, i.e., lower capacity for matching, while higher share of female outflows should signify exactly the opposite. However, in our case (in most of the specifications) higher share of females in the unemployed positively affects efficiency estimates while female share in outflows from unemployment has negative effect. Still, in the last model specification, where all variables are included, these two covariates have 'appropriate' sign. Another 'inconsistency' comes with the young (<24) job-seekers where in the first two model specifications the sign for this covariate is negative, while later it becomes positive (as expected).

Relationship between the share of persons receiving unemployment benefits among the unemployed and technical efficiency coefficients is another unexpected result. Namely, this variable positively (except in one model specification) affects matching efficiency. Being that it should affect the willingness to accept a job via increase in the reservation wage of the job-seeker, one would expect that the higher the share of unemployment benefit receivers the lower the matching efficiency in a respective market. However, being that the amount of the benefits on a monthly basis is on average pretty low (Rutkowski, 2003; Tomić and Domadenik, 2012) it does not have some greater impact on the reservation wage increase, i.e. on lowering the matching efficiency. Positive effect probably comes from the fact that these people represent recently unemployed (period of receiving benefits is also limited) who have higher search intensity.

Looking at the ALMPs coverage – it has positive and significant effect in most of the specifications. However, the value of the estimated coefficient is too small to have any real impact on the matching efficiency. Number of highly skilled CES employees per one unemployed, on the other hand, is positive and somewhat larger, but still not large enough. Time trend has positive impact (visible in Figure 8 and Figure A7 in Appendix 3), as well as population density. As Jeruzalski and Tyrowicz (2009) argue, large part of the observed heterogeneity will be an interaction of time and unit characteristics. Since one should expect that units react differently to country-wide shocks, the response in the labour market may owe a lot to the local response to shock apart from efficiency of a local labour office.

4.3. Stochastic frontier estimation by first-difference model transformation

Table 4 contains estimation results from the transformed panel stochastic frontier model as suggested in Wang and Ho (2010). At this point, only the basic-form of the model is estimated - using merely time variables as constraints for the technical efficiency.

As the results indicate, first difference transformation did not change much the estimations of the coefficients for the stock and flow (u and u_new) of the unemployed and flow of vacancies (v) in comparison with the 'regular' stochastic frontier estimation (Table 1 and Table 2). However, efficiency covariates (time trend and squared time trend) are somewhat changed from the earlier estimation (Table 3). Namely, linear time trend is significant only in the final model specification (both stocks and flows of the unemployed), but this time it is negative, suggesting lowering efficiency over time. This was also the case in Jeruzalski and Tyrowicz's (2009) difference-in-difference estimation of the matching function. As far as the estimates of the sole technical efficiency coefficient are concerned - first difference model transformation gives somewhat higher efficiency coefficients. However, this is only the basic-form model, while for stronger conclusions other variables (potentially) affecting the efficiency need to be included in the estimation.

Table 4. First-difference stochastic frontier estimation

	Total sample		
	Stocks of u	**Flows of u**	**Both**
Frontier			
d_u	0.789*** (0.054)		0.926*** (0.049)
d_v	0.391*** (0.013)	0.358*** (0.014)	0.322*** (0.013)
d_u_new		-0.292*** (0.019)	-0.357*** (0.019)
Annual dummies	YES	YES	YES
Constraints			
time trend	0.016 (0.012)	0.016 (0.014)	-0.011* (0.006)
squared time trend	-0.001*** (0.0002)	-0.001*** (0.0003)	0.00001 (0.00002)
c_{υ}	-2.199*** (0.025)	-2.205*** (0.025)	-2.302*** (0.025)
c_u	-3.895*** (0.445)	-2.627*** (0.608)	-2.682*** (0.641)
Mean technical efficiency $\left[E(\exp(-u_{i,t}) \mid \Theta)\right]$	0.892 (0.145)	0.940 (0.099)	0.730 (0.119)
Wald χ^2	1240.95***	1285.77***	1789.03***
Log likelihood	-1078.195	-1074.399	-861.054
No. of observations	3146	3146	3146

Notes: Dependent variable: first difference of log of monthly flows to employment out of unemployment (d_m). $\Theta = \Delta\tilde{\varepsilon}_i$; $c_{\upsilon} = \ln(\sigma_{\upsilon}^2)$; $c_u = \ln(\sigma_u^2)$. Annual dummies are statically significant, detailed results available upon request. Variables taken in logarithms, lagged when necessary. Standard deviation reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

5. Conclusions

This paper explores the efficiency in the labour market by estimating matching function on a regional level in Croatia. Being that there are huge regional differences in both employment and unemployment levels among Croatian regions (counties), the main objective of the paper is to evaluate the efficiency levels as well as changes that may have taken place both over time and across regions. Furthermore, the role of regional employment offices is taken into account. Thus, the empirical analysis is conducted on a regional level using the regional office-level data obtained from the Croatian Employment Service (CES) on a monthly basis in the period 2000-2011. In order to do that, panel stochastic frontier model is used, as well as its modified version – basic-form first-difference panel stochastic frontier model. Namely, as the literature (Greene 2005a, 2005b; Wang and Ho, 2010) suggests, there are some unresolved issues with classic panel stochastic frontier estimation and, thus, the first-difference transformation of the original panel stochastic frontier estimation is suggested (Wang and Ho, 2010).

Main results point to larger weight of job seekers in the matching process in comparison to posted vacancies which is not unusual, especially taking into account the fact that vacancies posted at the CES offices are not all the available vacancies in the economy. However, model specification that includes both stocks (at the end of the previous month) and flows (newly registered) of unemployed as well as the one that includes only stocks points to the existence of constant returns to scale, while model specification with only flows of unemployed suggest that the model exhibits decreasing returns to scale. In addition, flows of unemployed included in the model, unlike in some other empirical analyses, increase positive impact of stocks.

In order to get consistent estimates, first-difference transformation of the original panel stochastic frontier model is applied. However, preliminary results from the basic-form first-difference transformation model show that there are no significant differences in estimated technical efficiency coefficients in comparison to the original panel stochastic frontier model.

The main aim of the analysis – the efficiency of the matching process – proved to be rising over time with significant regional variations. On average, technical efficiency of the matching process is 70-75 percent, ranging from about 50 percent in Sisak region to almost 100 percent in Istria (Pula regional office). However, adding the newly registered unemployed to the model specification diminishes matching efficiency. The variations of estimated technical efficiency coefficients across regions suggest the need for the evaluation of the second stage analysis – i.e. the regression of technical efficiency coefficients and set of covariates that should affect it.

Namely, it is assumed how policy relevant variables can be introduced into the original model if the assumption about the homogeneity of unemployed is relaxed by varying the individual search intensities. Different search intensities emerge either due to the structural characteristics of the respective labour market (e.g., age, education) or due to policy variables like active labour market programs or employment service staff capacity. However, even though most of the used 'labour market structure' variables as well as policy variables proved to be significant, none of the estimated coefficients is large enough to explain regional variation in matching efficiency. For instance, both ALMPs coverage as well as the number of highly skilled CES employees per one unemployed have positive impact on the technical efficiency, but the size of the estimated coefficient is too small to bring any strong conclusions. Similar goes for the structural characteristics of the labour market.

Thus, it seems that demand fluctuations remain as the main cause of matching (in)efficiency in Croatia. As nicely explained by Kuddo (2009: 65): “Active labour market services, in and of themselves, do not create jobs. In general, a favourable investment and business climate, and rapid economic development are key to job creation. ALMPs can only contribute to less inequality in the labour market, a reduction in long-term unemployment, and an easier filling of the existing vacancies.” Nonetheless, as explained earlier, the allocation of funds to regional employment offices is driven by the absorption capacity of the respective office based on historical records while local needs serve only as a secondary factor. And this is something that should be definitely taken into an account when implementing new policies and allocating funds to CES regional offices.

This work should contribute to the literature in several ways. First of all, it adds to the existing literature that uses stochastic frontier estimation of the matching process in order to determine its efficiency. Secondly, by estimating matching efficiency on a regional level, this paper also assesses the role of (regional) employment offices in matching of the registered unemployed job seekers and posted vacancies. Methodological approach used here upgrades standard estimation of the matching function by combining regional data on vacancies and unemployed with additional data measuring the quality of services provided by regional employment offices. This could provide valuable policy information concerning further investments in (active) labour market policies. What's more, modified panel stochastic frontier model is applied for the first time to the labour market (matching process) by estimation of the basic-form first-difference transformed panel stochastic frontier model. Namely, suggested modifications of the classic panel stochastic frontier model (Greene 2005a, 2005b; Wang and Ho, 2010) were, up to this point, applied only to financial markets or health-care sector.

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Appendices

Appendix 1 – Data Description

Table A1. Data description				
Variable	**Description**	**Type (flow/stock)**	**Period**	**Source**
m	number of employed persons from the CES Registry during the month	flow	monthly	CES
u	number of registered unemployed persons at the end of the previous (t-1) month	stock	monthly	CES
v	posted vacancies during the month	flow	monthly	CES
u_new	number of newly registered unemployed during the month	flow	monthly	CES
v/u	vacancy ratio (measure of labour market tightness)	flow over stock	monthly	CES
m/delisted	ratio of employed to delisted from the Registry for other reasons	flow	monthly	CES
m_female	share of females in total flows to employment	flow	monthly	CES
u_female	share of females in total unemployment	stock	monthly	CES
u_<24y	share of youth (≤24 years) in total unemployment	stock	monthly	CES
u_12m+	share of long-term unemployed (12 months or more) in total unemployment	stock	monthly	CES
u_w/o_experience	share of persons without experience in total unemployment	stock	monthly	CES
u_primary_sector	share of those previously employed in primary sector of economic activity in total unemployment	stock	monthly	CES
u_benefits	share of unemployed persons receiving unemployment benefits in total unemployment	stock	monthly	CES
u_low skilled	share of low-skilled (no schooling and uncompleted basic school + basic school) persons in total unemployment	stock	monthly	CES
u_high skilled	share of high-skilled (non-university college + university and postgraduate degrees) persons in total unemployment	stock	monthly	CES
u_almp coverage	share of persons in active labour market programs in total number of unemployed in each regional office at the year end	stock	yearly	CES
CES_high skilled	number of highly skilled (non-university college + university and postgraduate degrees) employed at CES over the number of registered unemployed	stock	year over month	CES
pop_density	population density per km^2	stock	10-year	CBS
Notes: *flow variable* – during the month; *stock variable* – end of the previous (t-1) month or end of the year.				

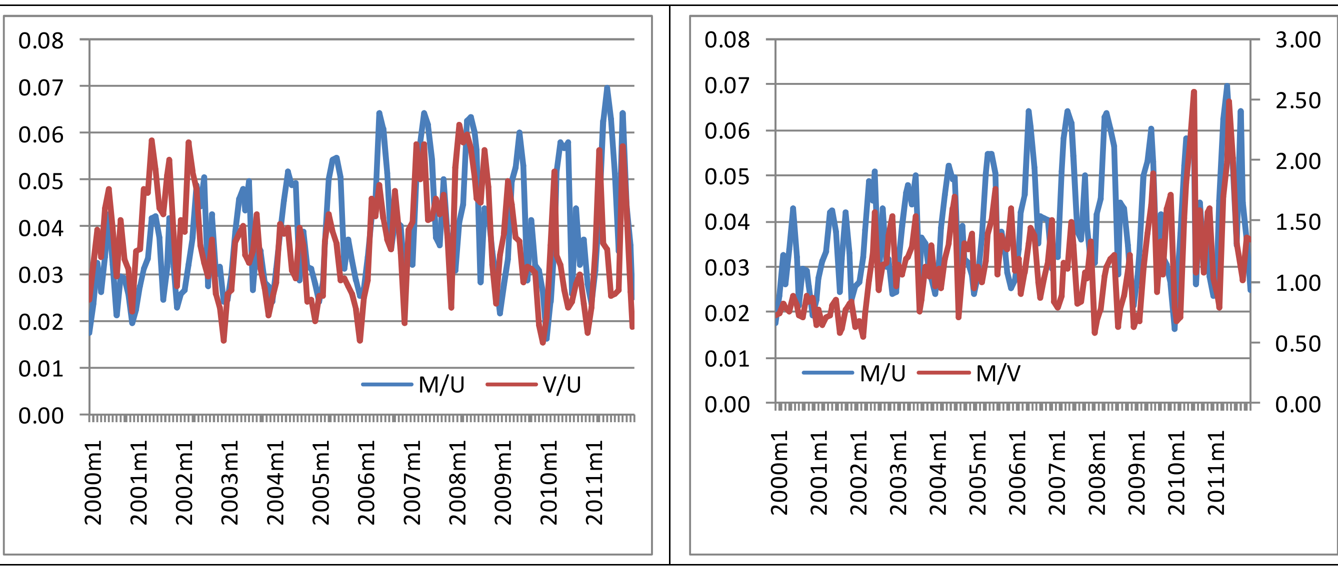
Table A2. Descriptive statistics				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
m	538.838	498.1296	28	4057
u	14174.8	12536.88	2676	75930
v	514.403	595.3572	13	5372
u_new	954.8	899.2469	91	6210
v/u	0.03944	0.0297231	0.0029	0.3608
m/delisted	0.89762	1.318973	0.134	37.8781
m_female	0.52848	0.0849477	0.237	0.781
u_female	0.56558	0.0469917	0.427	0.677
u_<24y	0.21537	0.055855	0.099	0.427
u_12m+	0.54683	0.079394	0.209	0.744
u_w/o_experience	0.2213	0.0659512	0.063	0.373
u_primary_sector	0.03883	0.0260552	0.006	0.132
u_benefits	0.23516	0.0862013	0.091	0.568
u_low skilled	0.34932	0.0768742	0.174	0.539
u_high skilled	0.05963	0.0329329	0.019	0.17
u_almp coverage	0.04926	0.041474	0.00307	0.2322
CES_high skilled	0.00279	0.0010941	0.00102	0.0086
pop_density	82.5264	58.11427	9.531	300.059
Source: Author’s calculation based on CES and CBS data.				

Table A3. Distribution of regional offices

NUTS2	County (NUTS3)	Regional office
Northwest Croatia	City of Zagreb	Zagreb
	Zagreb	
	Krapina-Zagorje	Krapina
	Varazdin	Varazdin
	Koprivnica-Krizevci	Krizevci
	Medimurje	Cakovec
Central and Eastern (Pannonian) Croatia	Bjelovar-Bilogora	Bjelovar
	Virovitica-Podravina	Virovitica
	Pozega-Slavonia	Pozega
	Slavonski Brod-Posavina	Slavonski Brod
	Osijek-Baranja	Osijek
	Vukovar-Srijem	Vukovar
		Vinkovci
	Karlovac	Karlovac
	Sisak-Moslavina	Sisak
		Moslavina
Adriatic Croatia	Primorje-Gorski Kotar	Rijeka
	Lika-Senj	Gospic
	Zadar	Zadar
	Sibenik-Knin	Sibenik
	Split-Dalmatia	Split
	Istria	Pula
	Dubrovnik-Neretva	Dubrovnik

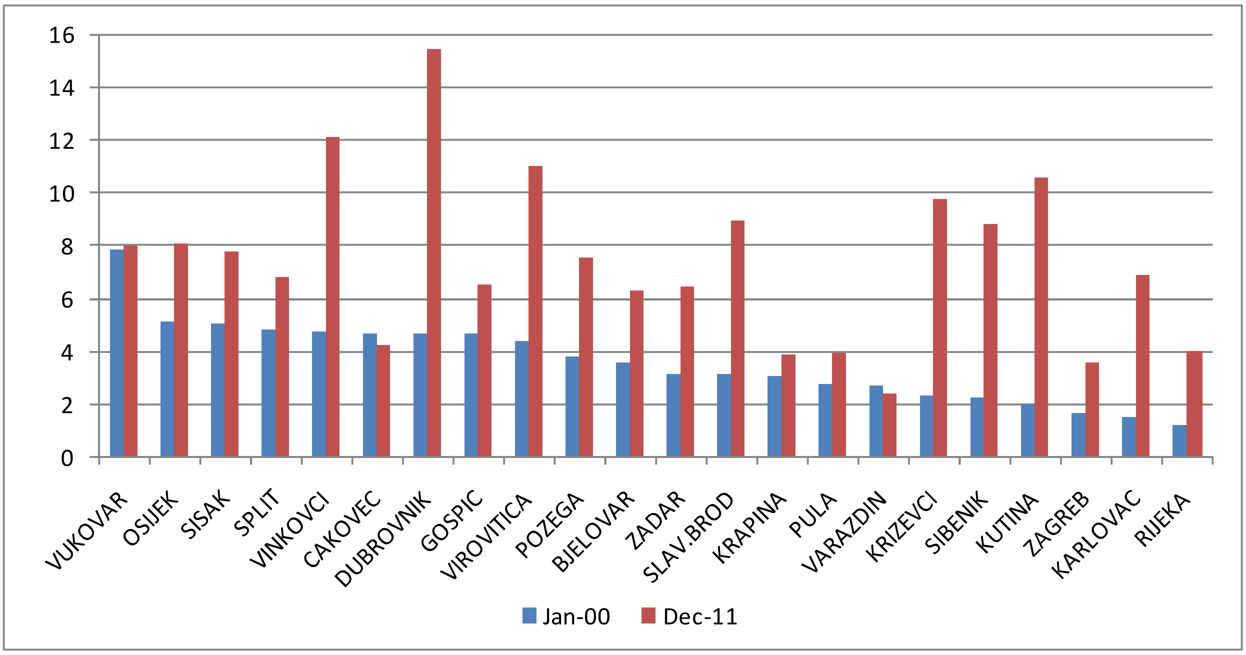
Appendix 2 – Additional charts

Figure A1. Hiring probabilities and vacancy ratio (left) and flows from unemployment to employment (over vacancies) (right) (2000m1-2011m12)



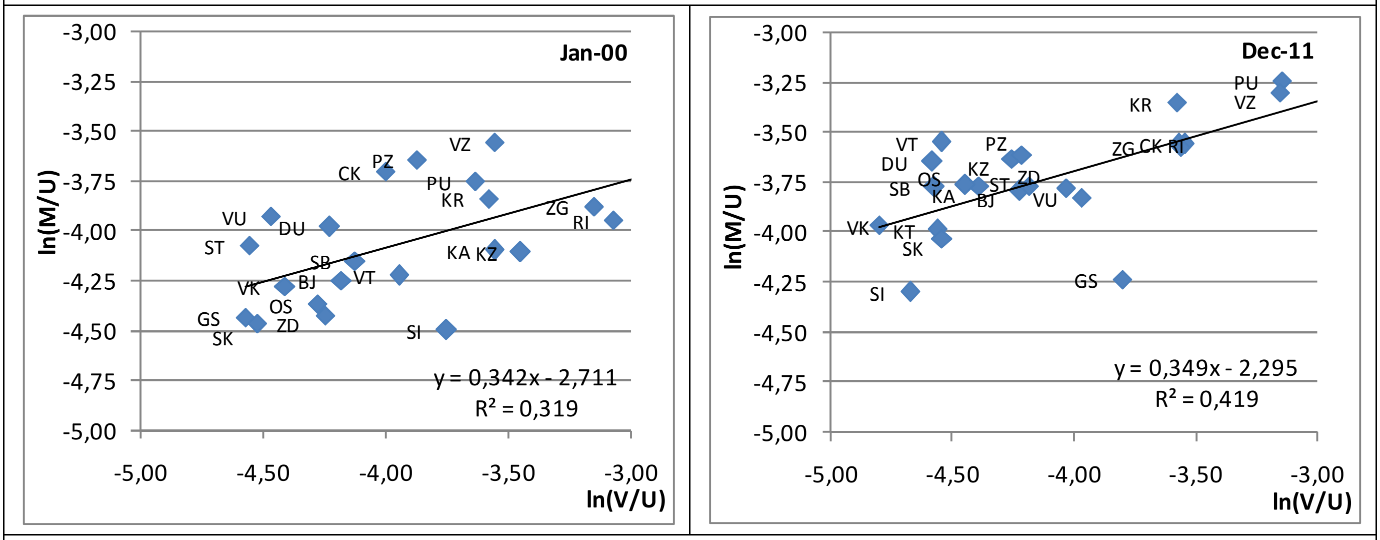
Notes: M/U – hiring probability (outflow rate) and V/U – vacancy ratio (primary axis); M/V - flows from unemployment to employment over vacancies (secondary axis).
Source: Author's calculation based on CES data.

Figure A2. Newly registered unemployed to newly registered vacancies (U-new/V)



Source: Author's calculation based on CES data.

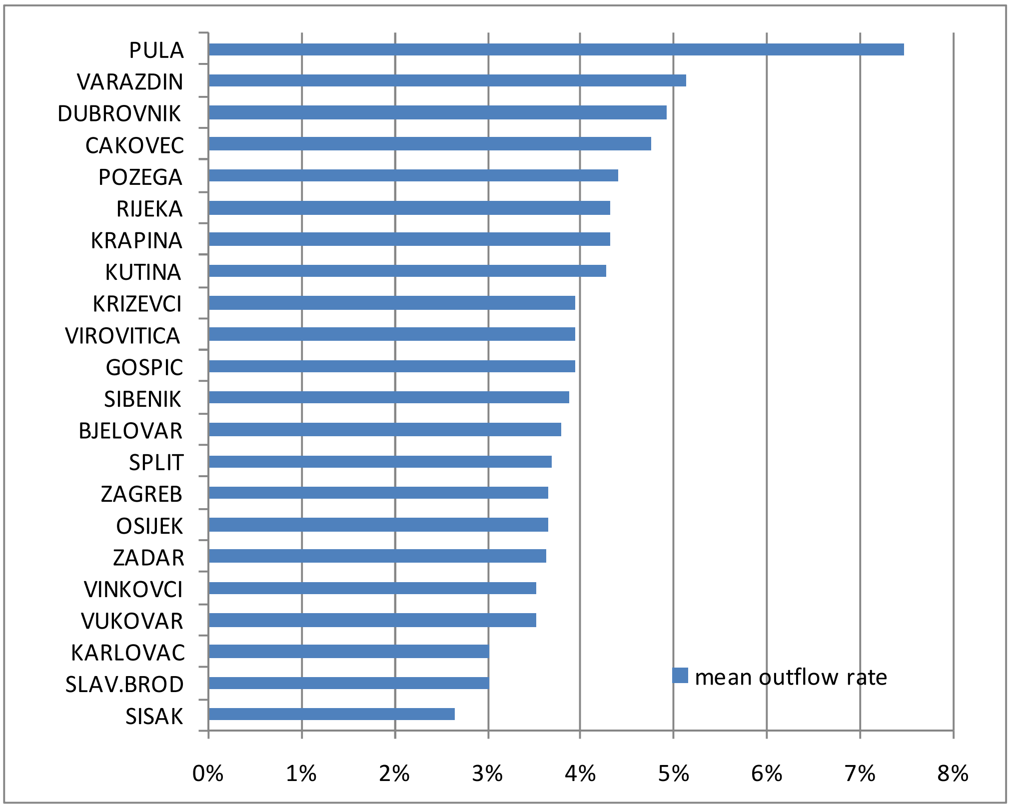
Figure A3. Vacancy ratio and hiring probabilities across regions – 2000m1 (left) and 2011m12 (right)



Notes: M/U – hiring probability (outflow rate) and V/U – vacancy ratio (primary axis).

Source: Author's calculation based on CES data.

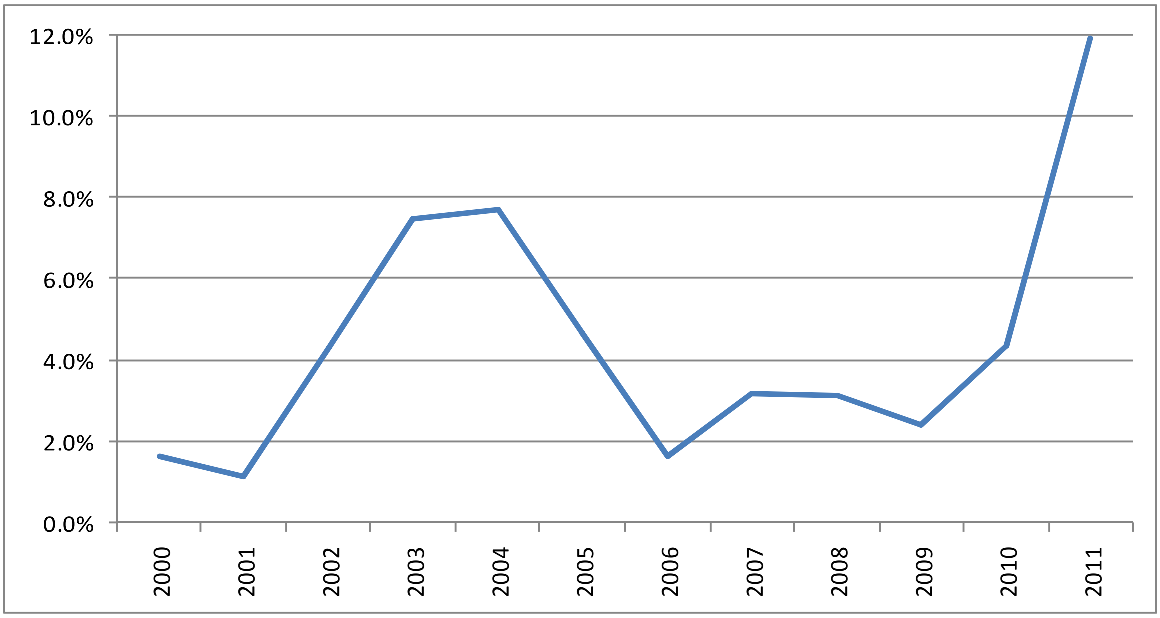
Figure A4. Mean outflow rate by regional office (2000m1-2011m12)



Notes: outflow rate – M/U.

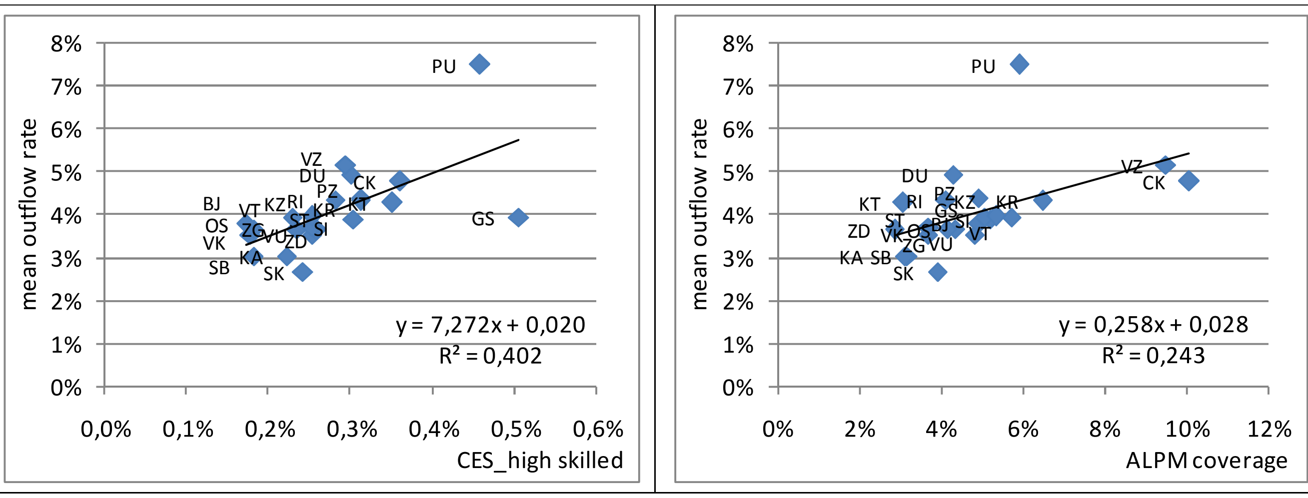
Source: Author's calculation based on CES data.

Figure A5. ALMP coverage over years (2000-2011)



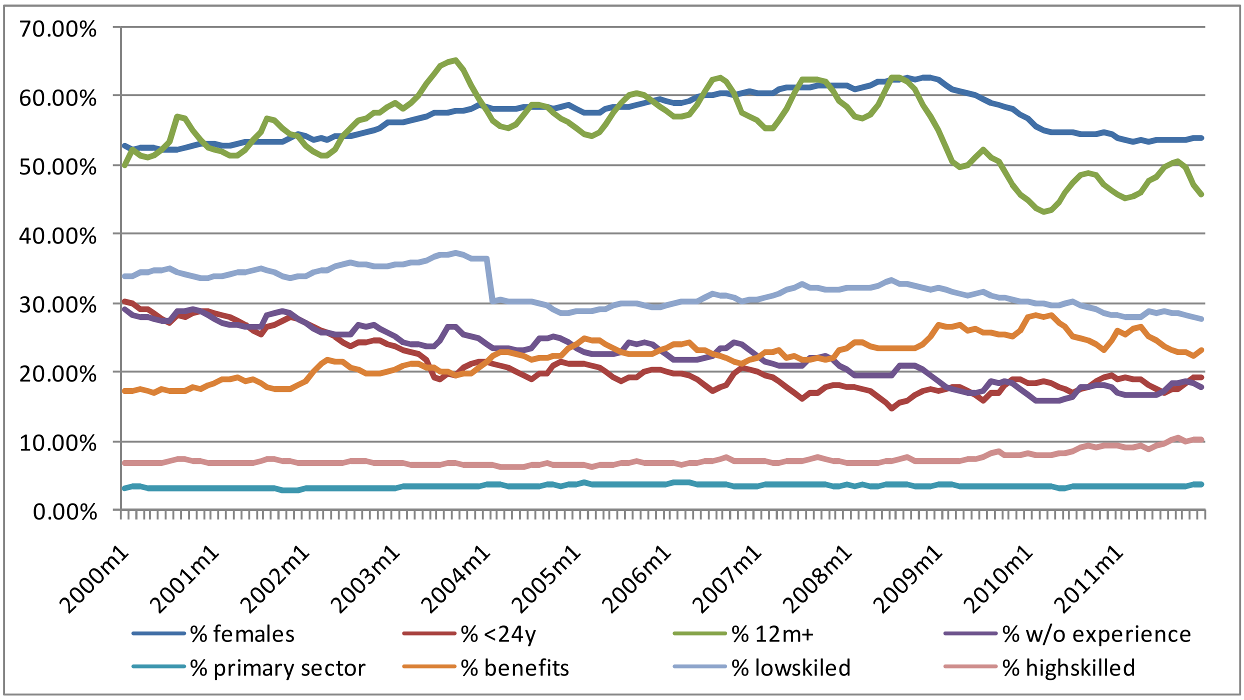
Notes: ALMP coverage – share of persons included in one of the active labour market programs in total unemployment.
Source: Author's calculation based on CES data.

Figure A6. Mean outflow rate and number of highly skilled CES employees per number of unemployed (left) and ALMP coverage (right)



Notes: M/U – hiring probability (outflow rate); ALMP coverage – share of persons included in one of the active labour market programs in total unemployment; CES_high skilled - number of highly skilled employed at respective CES office over the number of registered unemployed.
Source: Author's calculation based on CES data.

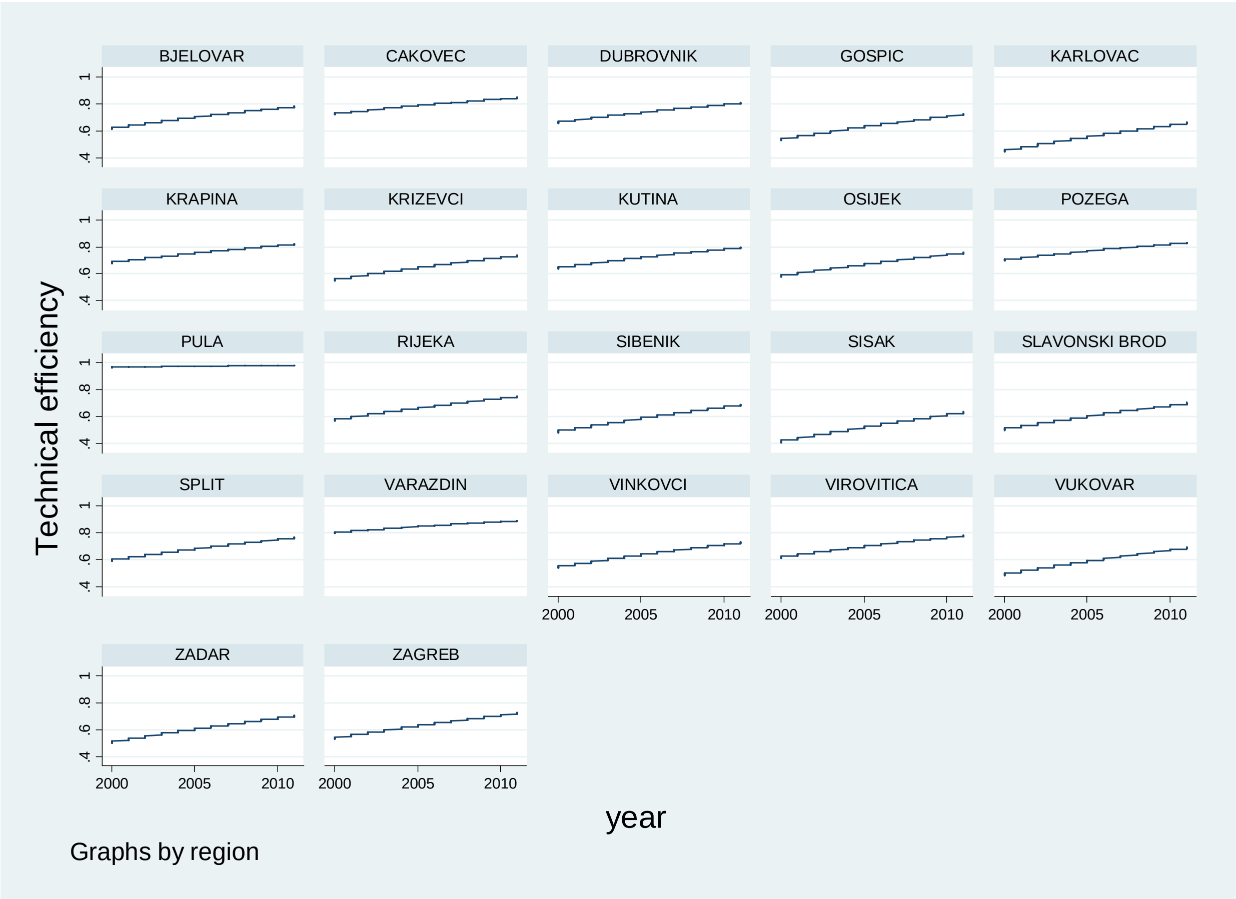
Figure A7. Unemployed workers main characteristics (2000m1-2011m12)



Source: CES.

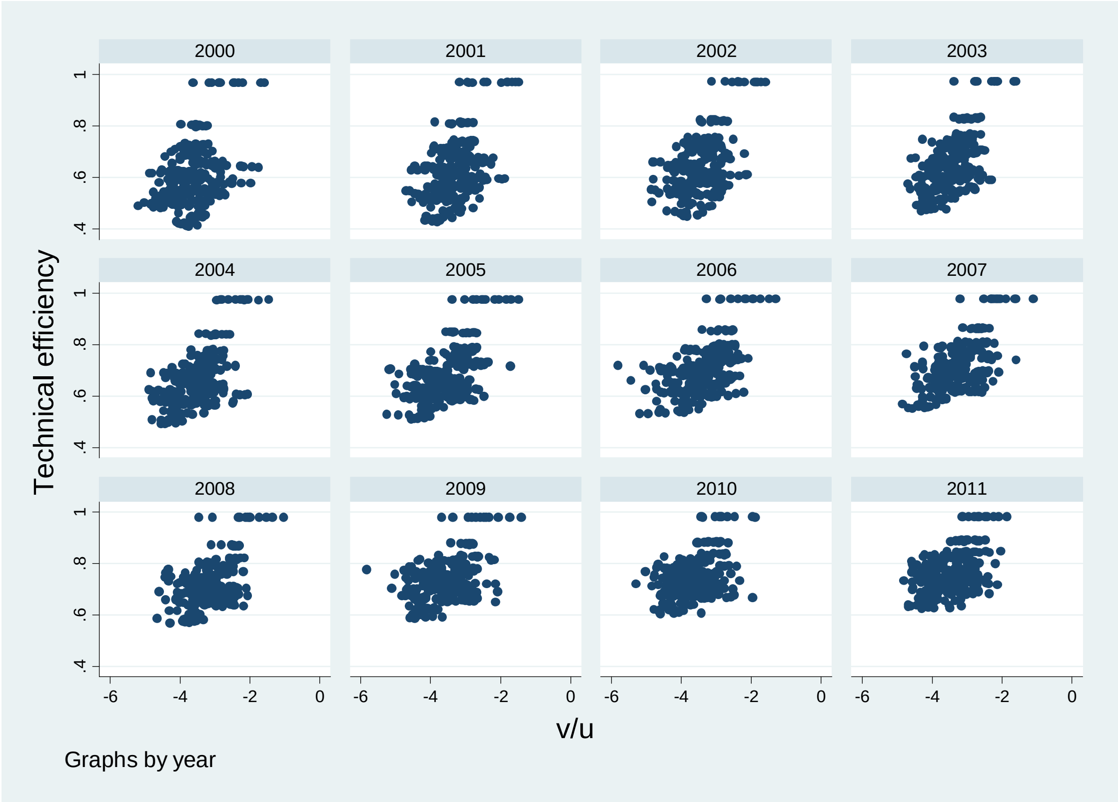
Appendix 3 – Technical efficiency

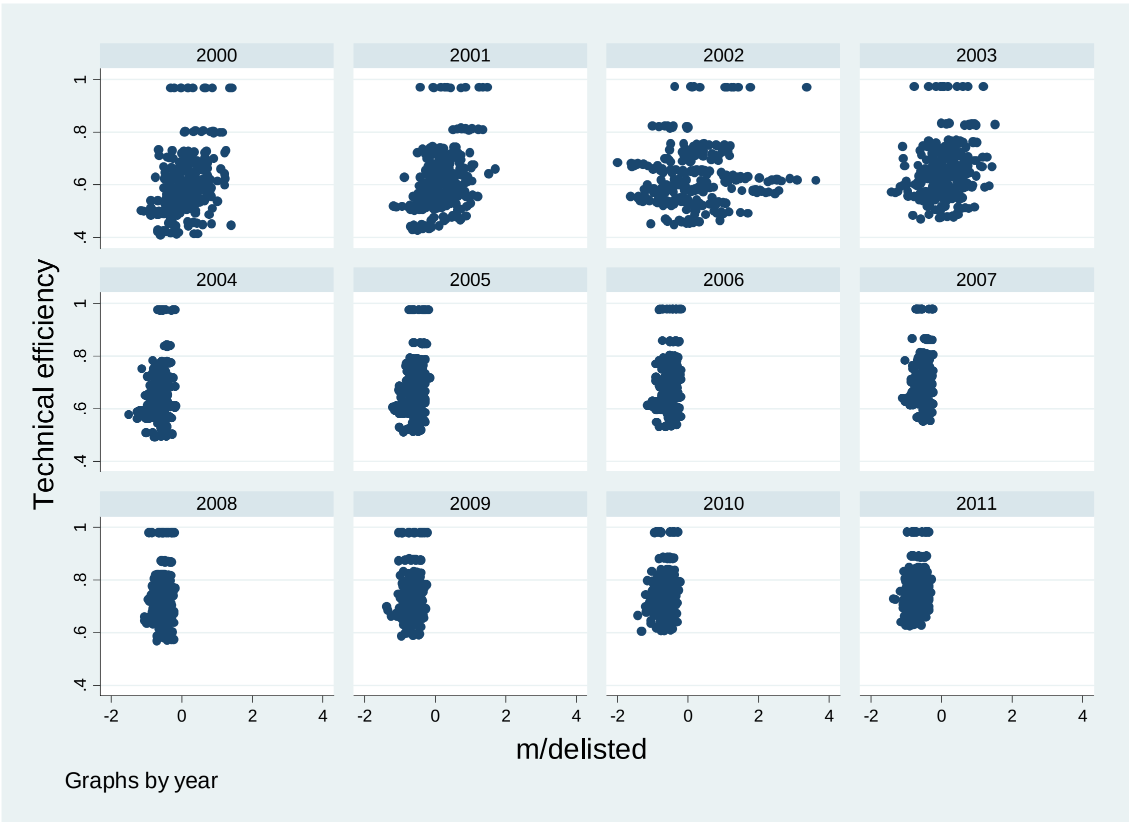
Figure A7. Technical efficiency across regional offices over years



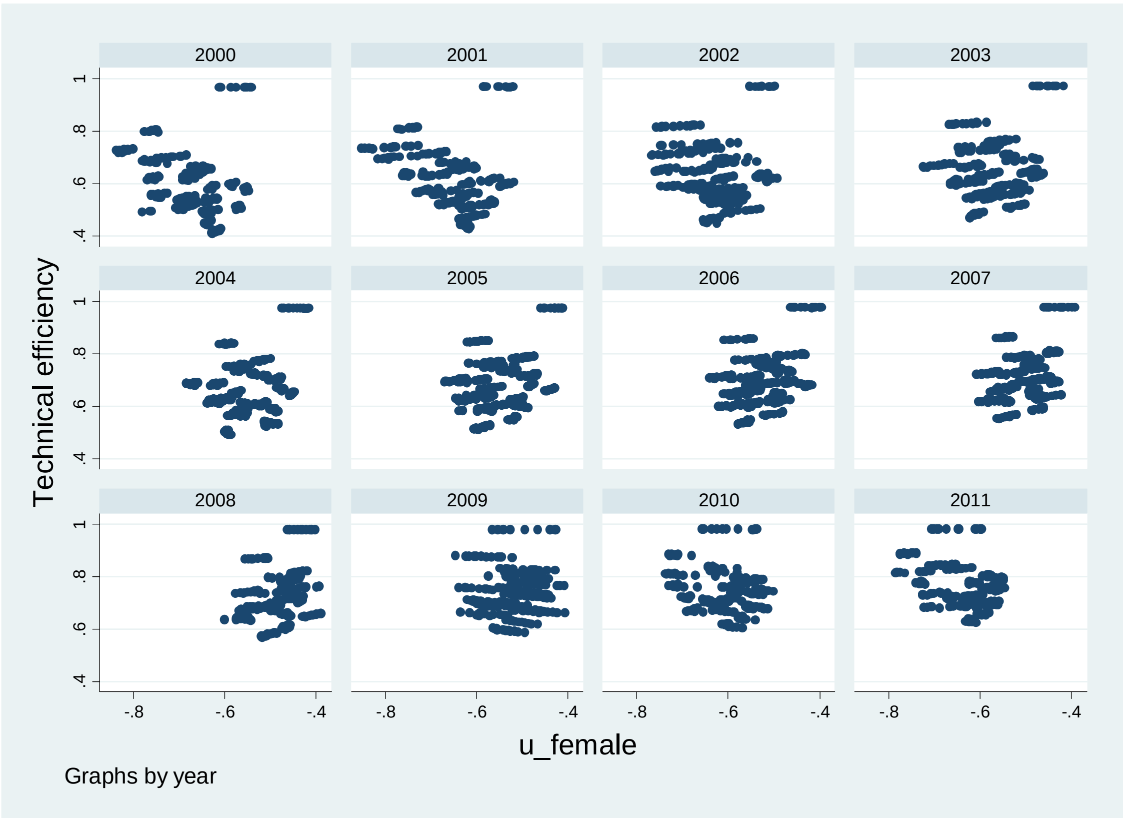
Source: Author’s calculation based on CES data.

Figure A8. Technical efficiency vs. explanatory variables

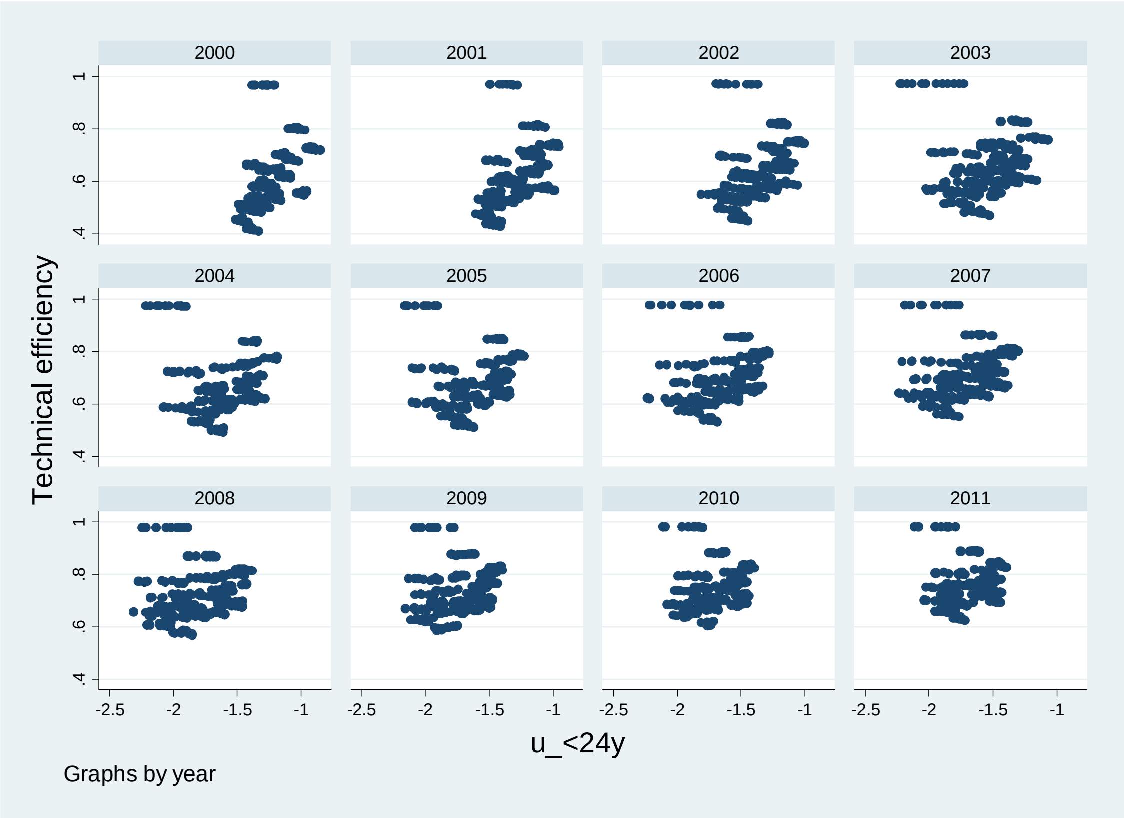


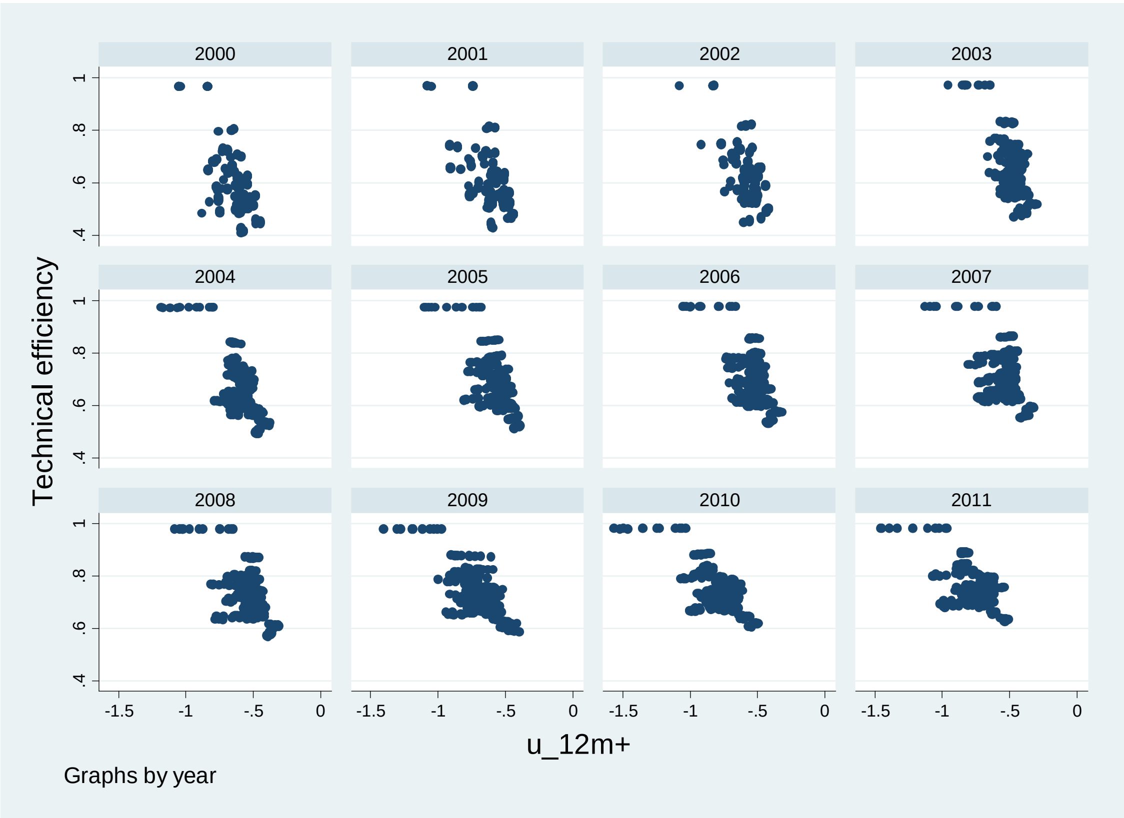


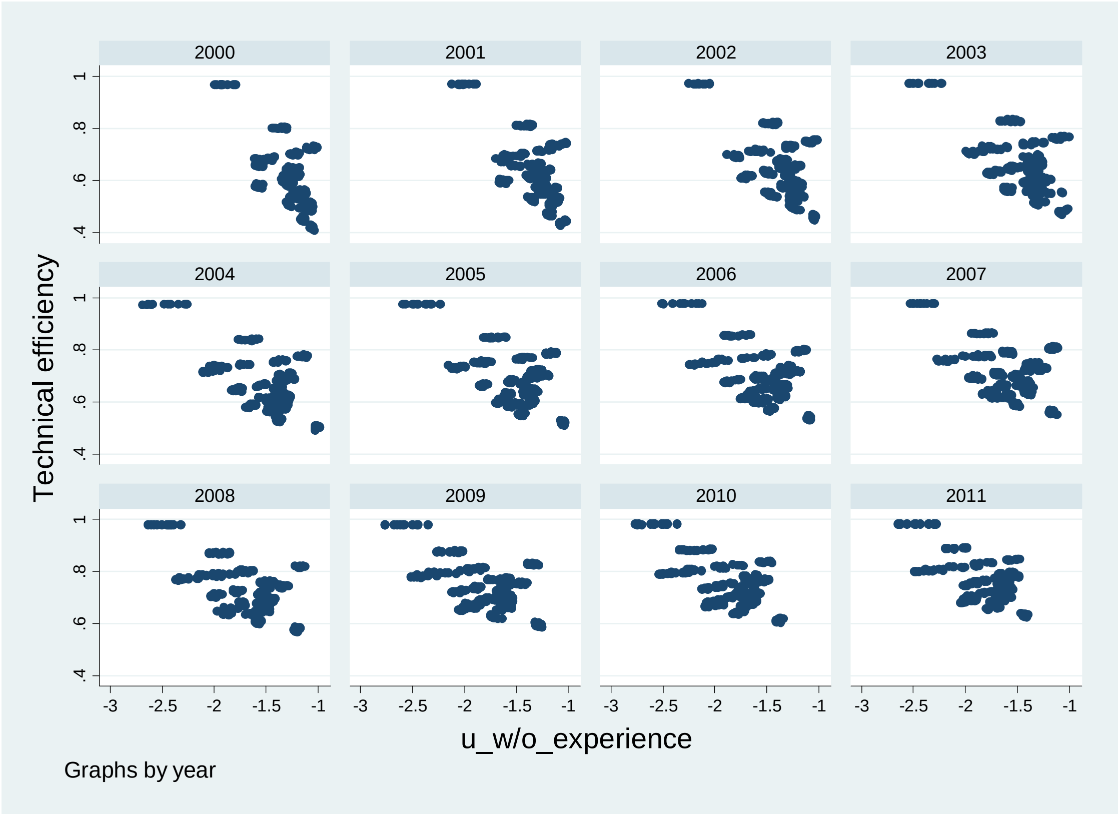
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
m_female
Graphs by year



2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
u_female
Graphs by year


2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
u_<24y
Graphs by year


2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
u_12m+
Graphs by year



2000
2001
2002
2003
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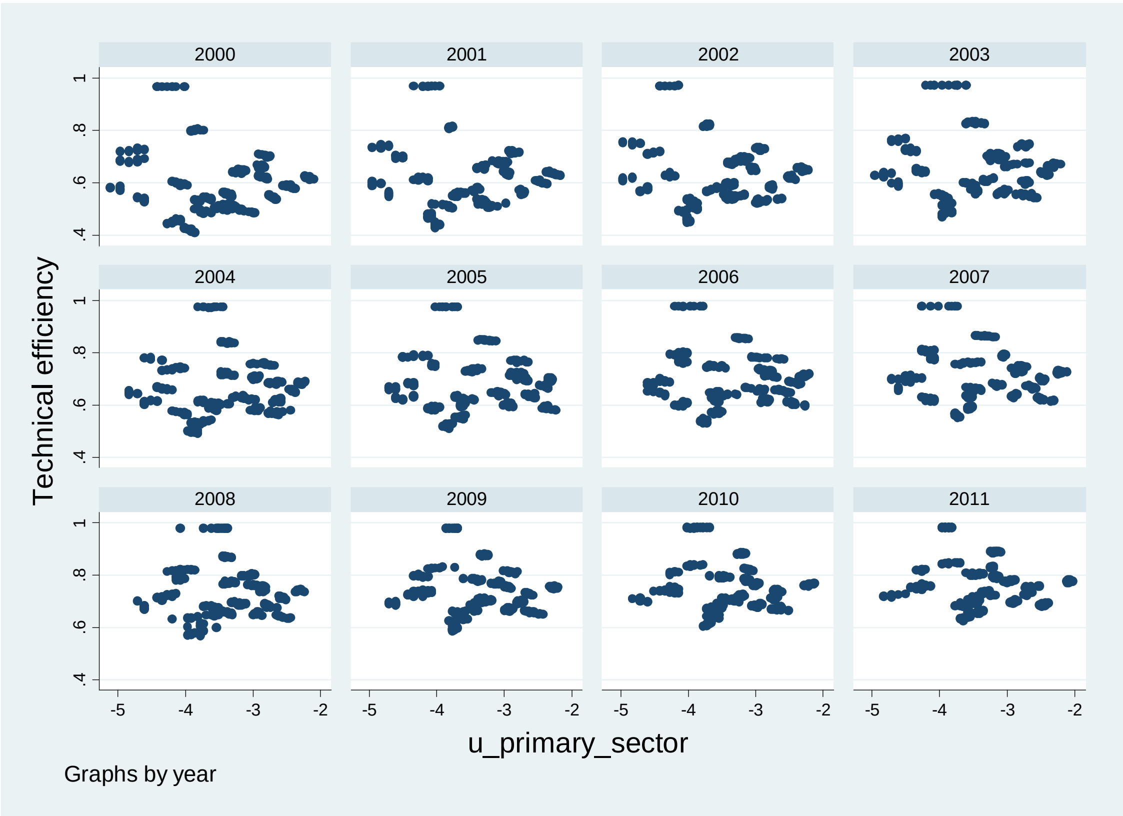
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
.4
.6
.8
1
-3
-2.5
-2
-1.5
-1
u_w/o_experience
Graphs by year



2000
2001
2002
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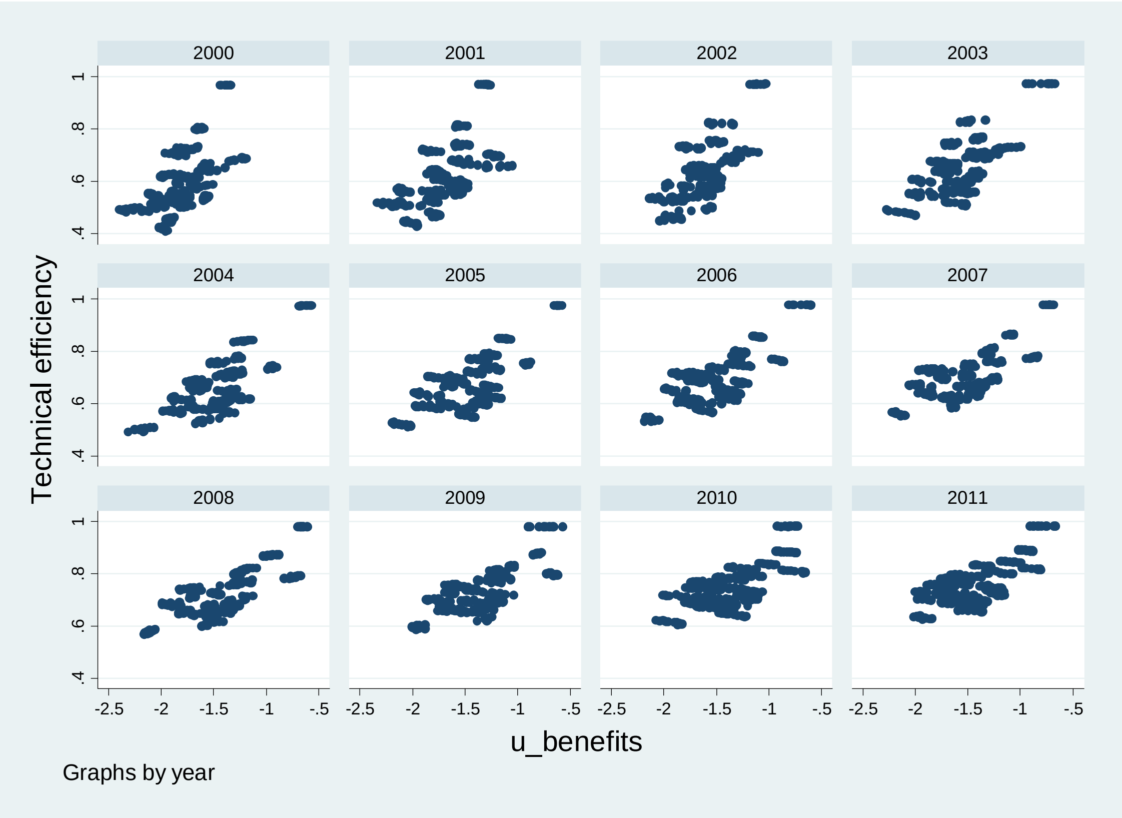
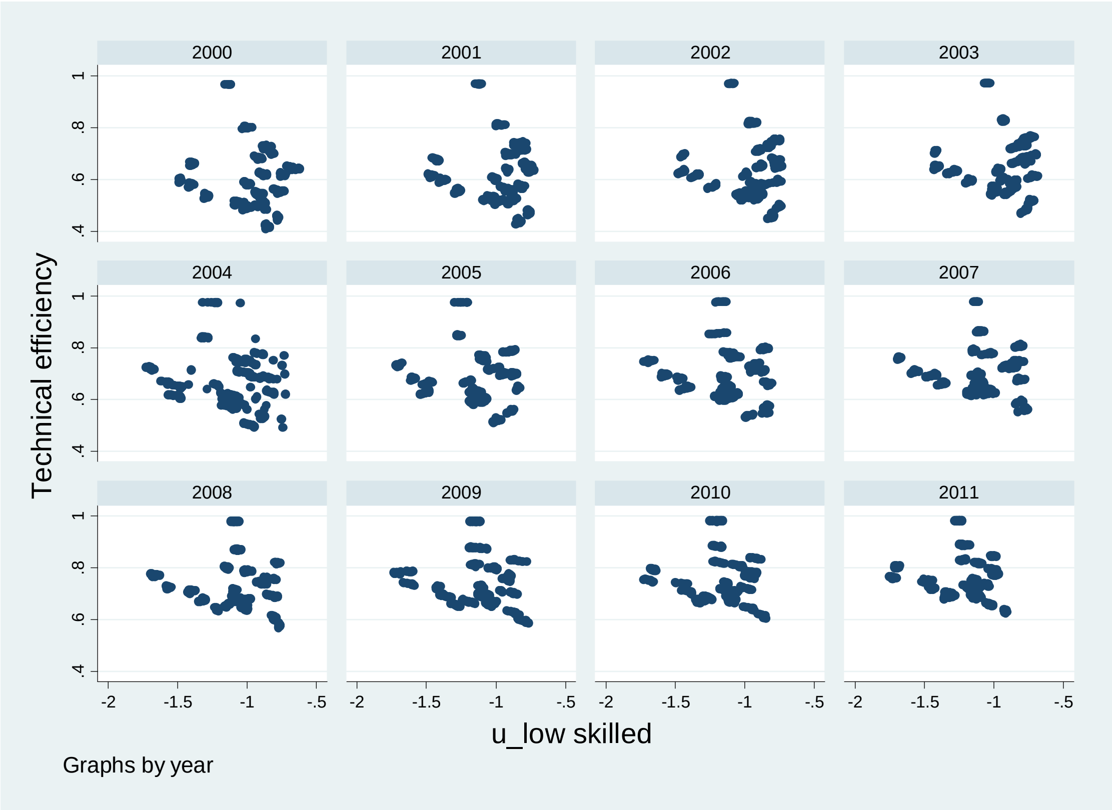
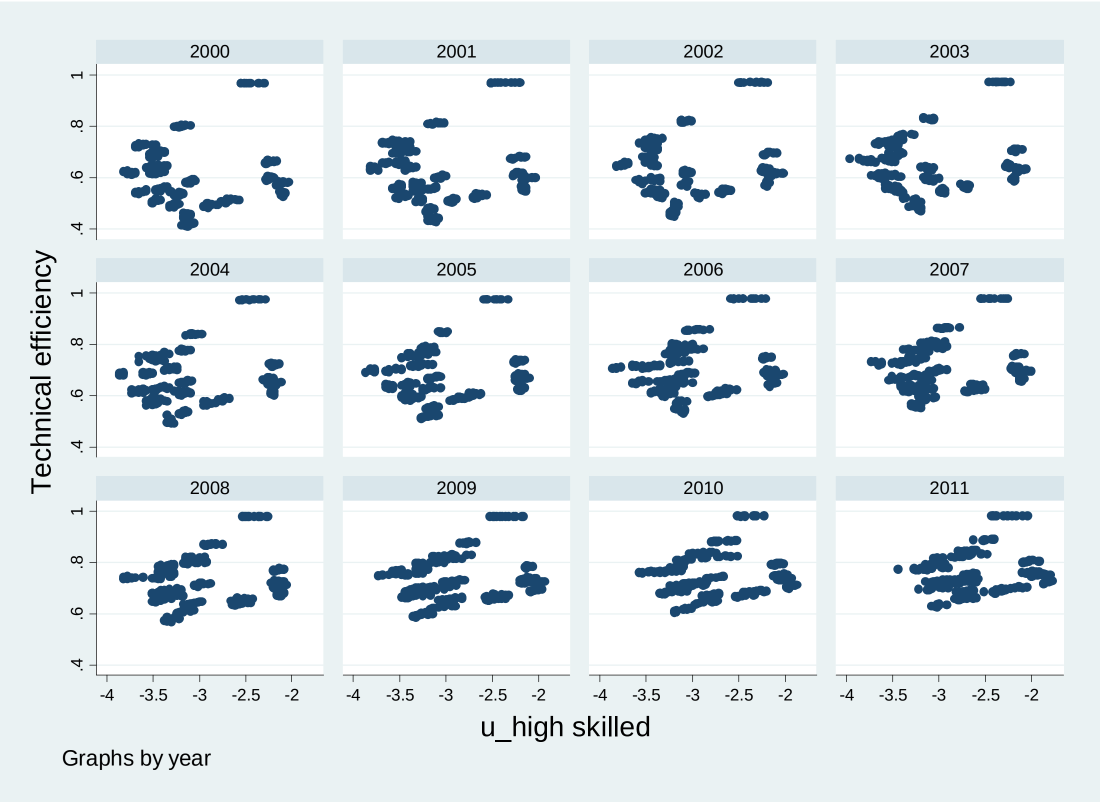
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
.4
.6
.8
1
-5
-4
-3
-2
u_primary_sector
Graphs by year



2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
u_benefits
Graphs by year



2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
u_low skilled
Graphs by year


2000
2001
2002
2003
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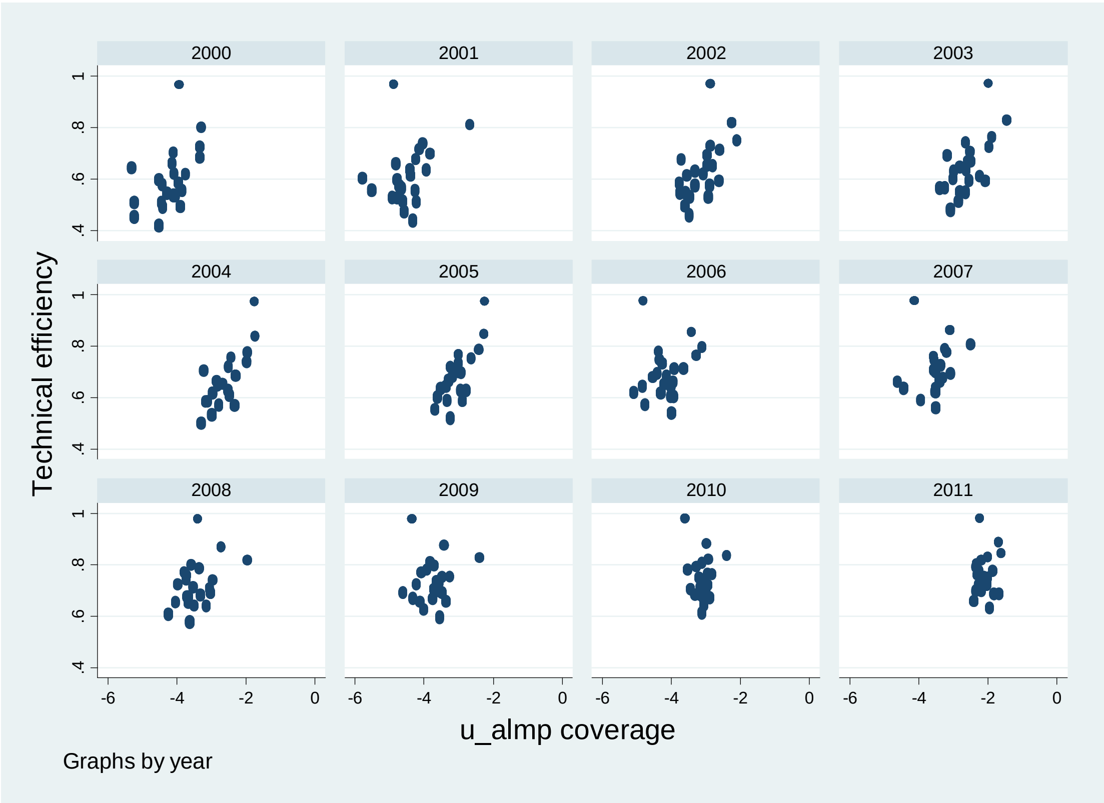
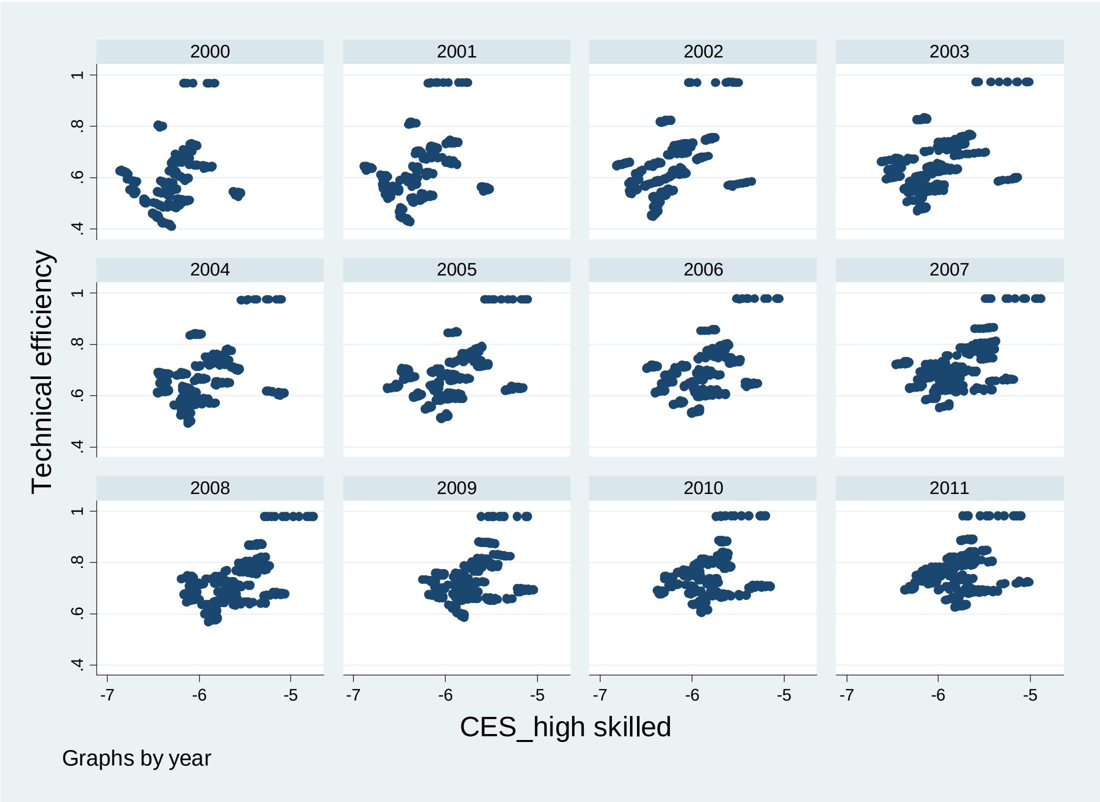
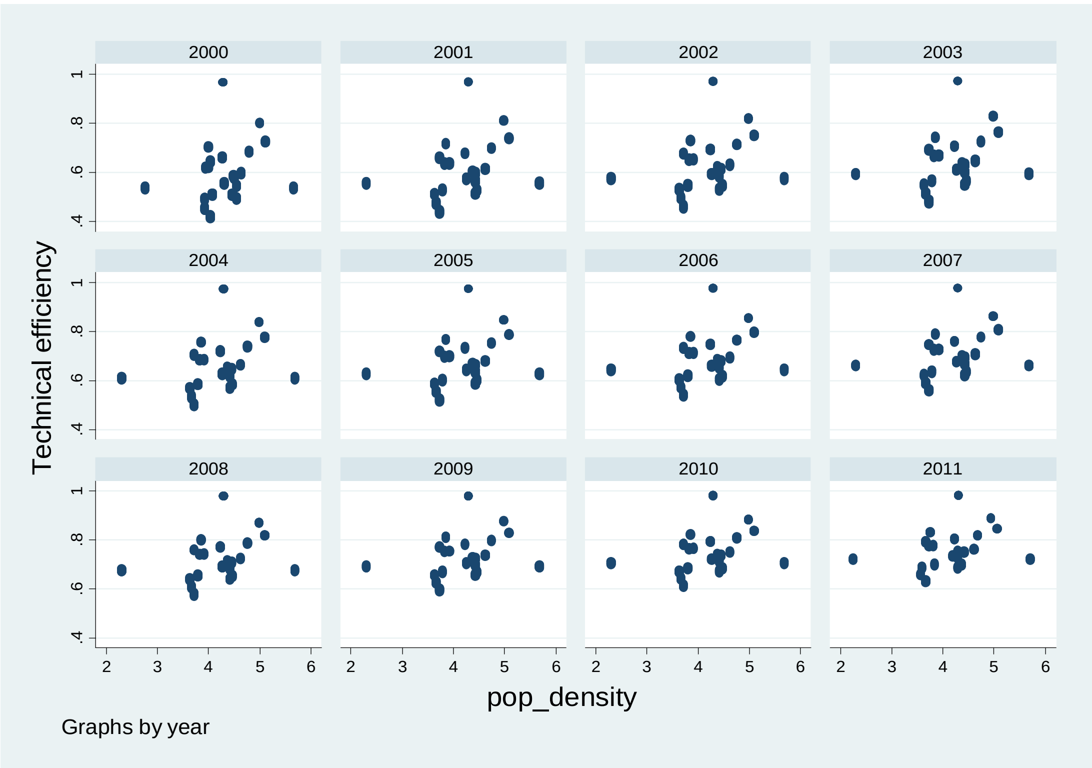
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
u_high skilled
Graphs by year


2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
u_almp coverage
Graphs by year





Notes: Explanatory variables are in logarithm form.
Source: Author’s calculations based on CES data.