Iva Tomić

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

Studeni . November 2012

Radni materijali EIZ-a . EIZ Working Papers

eiz ekonomski institut, zagreb

Br . No EIZ-WP-1204

Radni materijali EIZ-a
EIZ Working Papers
EIZ-WP-1204

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

Iva Tomić
Research Assistant
The Institute of Economics, Zagreb
Trg J. F. Kennedyja 7
10000 Zagreb, Croatia
T. 385 1 2362 244
F. 385 1 2335 165
E. itomic@eizg.hr

www.eizg.hr

Zagreb, November 2012

IZDAVAČ / PUBLISHER:
Ekonomski institut, Zagreb / The Institute of Economics, Zagreb
Trg J. F. Kennedyja 7
10000 Zagreb
Croatia
T. 385 1 2362 200
F. 385 1 2335 165
E. eizagreb@eizg.hr
www.eizg.hr

ZA IZDAVAČA / FOR THE PUBLISHER:
Sandra Švaljek, ravnateljica / director

Tiskano u 80 primjeraka
Printed in 80 copies

ISSN 1846-4238
e-ISSN 1847-7844

Contents

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

Abstract:
This paper investigates the efficiency of the matching process in Croatian labour market by estimating matching function by panel stochastic frontier estimation on a regional level using Croatian Employment Service data over the 2000-2011 period. Results suggest that the efficiency is rising over time, with great variations across regions. In order to explore these variations, structural characteristics of the labour market together with some policy variables are included into the second-stage estimation. Among structural variables the proportion of agricultural and high-skilled workers have the most important positive effect on matching efficiency, while the local unemployment rate and the share of low-skilled and workers without any experience among job-seekers have the most important negative effect. As far as policy variables are concerned, both ALMPs and the number of high-skilled employees in regional employment offices positively affect matching efficiency. Additionally, when regional income *per capita* is included into the model it shows positive impact on matching efficiency, indicating that demand fluctuations also affect the matching process. In order to get consistent estimates, panel stochastic frontier model transformation is applied. Preliminary results show that there is no major difference in estimated mean technical efficiency coefficients in comparison to the original panel stochastic frontier model.

Keywords: matching function, stochastic frontier, regional employment offices, efficiency, Croatia
JEL classification: C33, J64, J69, P3

Učinkovitost procesa sparivanja: uloga područnih ureda Hrvatskog zavoda za zapošljavanje

Sažetak:
U radu se istražuje učinkovitost procesa sparivanja na hrvatskom tržištu rada putem ocjene funkcije sparivanja. Funkcija je ocijenjena metodom panel stohastičke granice na regionalnim podacima HZZ-a tijekom razdoblja 2000.-2011. Rezultati pokazuju kako učinkovitost raste tijekom vremena, s velikim varijacijama među regijama. Kako bi se istražile te varijacije u drugoj fazi ocjene modela uključene su strukturne karakteristike tržišta rada zajedno s nekim varijablama koje bi trebale predstavljati mjere politike. Među strukturnim varijablama najvažniji pozitivan učinak na učinkovitost sparivanja ima udio poljoprivrednih i visoko kvalificiranih radnika, dok najveći negativan utjecaj imaju regionalna stopa nezaposlenosti te udio nisko kvalificiranih radnika i onih bez iskustva na tržištu rada. Što se tiče mjera politike – i aktivne politike na tržištu rada kao i broj visoko kvalificiranih zaposlenika u područnim uredima za zapošljavanje pozitivno utječu na učinkovitost procesa sparivanja. Nadalje, kada se u model uključi regionalni dohodak po stanovniku - on također pokazuje pozitivan utjecaj na učinkovitost sparivanja što govori da fluktuacije na strani potražnje također utječu na proces sparivanja. Kako bi dobili konzistentnu ocjenu modela, ocijenjen je i transformirani model panel stohastičke granice. Preliminarni rezultati pokazuju da ne postoji velika razlika u prosječnom tehničkom koeficijentu učinkovitosti sparivanja u odnosu na izvorni panel model stohastičke granice.

Ključne riječi: funkcija sparivanja, stohastička granica, područni uredi zavoda za zapošljavanje, učinkovitost, Hrvatska
JEL klasifikacija: C33, J64, J69, P3

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 were 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; Jeruzalski and Tyrowicz, 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. 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 crisis 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 the unemployed to search for a job actively and inefficient labour market in terms of matching the unemployed job-seekers and vacant jobs, or on the labour demand side, with insufficient demand for labour as the main culprit for high unemployment. Kuddo (2009) as well as Brown and Koettl (2012), on the other hand, stress the importance of the capacity of relevant institutions. Hence, the right form of institutions (intermediaries) in the Croatian labour market is needed now more than ever.

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. 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 Service is centralised in a way that financial structure and main policies are brought at the central level, the implementation of the policy is locally specific. Thus, the aim of the paper is to investigate the role played by employment offices in increasing

[1] Earlier version of this paper was presented at the 18th Dubrovnik Economic Conference, Young Economist Seminar section. I am grateful to my discussants, Professor Laurence Ball and Professor Randall Filer, for their valuable comments. My gratitude also goes to 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 me access to their data.

successful matching of vacancies and the unemployed in Croatia while controlling for different regional (both structural and policy) characteristics of the labour markets. In this respect, the stochastic frontier approach will be used since it allows for a more detailed analysis of the determinants of regional matching (in)efficiencies.

The paper is organised into five sections. After a brief introduction, the second section presents a background for the topic in the 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. The 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 the persistence of regional unemployment 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 was concentrated in successful regions for many years; and (iii) 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. The issue was mainly to establish efficiency of the local labour markets, predominantly by the use of the matching function.

Ibourk et al. (2004) explain how the efficiency of the matching process determines the number of matches that will be observed at given input values. Additionally, Ibourk et al. (2004) and Jeruzalski and Tyrowicz (2009) explain how the efficiency can be considered 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. 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 the unemployment rate, but also of the separation rate and the rate of growth in the labour force (Destefanis and Fonseca, 2007). Munich and Svejnar (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. Given that the main issue in all these works is to estimate efficiency and being that the matching function is usually interpreted as a production function – the stochastic production frontier approach is generally used. In this way, aggregate matching efficiency becomes a stochastic function of the variables accounting for the heterogeneity of job-seekers and firms (Ibourk et al., 2004). The authors also explain main advantages of this method in comparison to traditional fixed-effects model and conclude that "the stochastic frontier approach introduces powerful tools to measure the efficiency of production activities and analyse its determinants" (Ibourk et al., 2004: 2).

In their article, Ibourk et al. (2004) use stochastic (translog) production frontier model on data for 22 French regions in the 1990-1994 period and show that aggregate matching efficiency has decreased in the observed time period with wide cross-regional differences. Among explanatory variables, which explain about 30 percent of the variations of efficiency, in addition to long-term unemployment and population density, the most important ones are the share of the young, females and immigrants in the total stock of job-seekers. Fahr and Sunde (2002), on the other hand, show that inefficiencies in German 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 across 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). Destefanis and Fonseca (2007) use a matching theory approach with stochastic frontier estimation to assess the impact of 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 a positive impact on the matching efficiency in the North (mainly for skilled labour), and 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). Furthermore, Jeruzalski and Tyrowicz (2009) try to determine the efficiency of the matching process on a regional level in Poland. They show that matching abilities are driven only by demand fluctuations while other variables, like unemployment structure across time and regions, coverage of active labour market programmes (ALMPs), and local labour office capacities, remain mostly insignificant. Additionally, Tyrowicz and Wójcik (2010) showed that the unemployment rates across regions in Poland were stable over the period between 1999 and 2008, i.e. no convergence except the convergence of clubs for high unemployment regions. However, they demonstrated that whenever job prospects worsen throughout the country, the more deprived regions are hit harder.

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. Dmitrijeva and Hazans (2007) estimate the impact of ALMPs on outflows from unemployment in Latvia and find positive and significant effect of training programmes on outflows from unemployment to employment indicating also that the hiring process is driven mainly by a stock of the unemployed at the beginning of the month and the flow of vacancies during the month.[2] However, Brown and Koettl (2012) stress the fact that ALMPs improving labour market matching have an impact only in the short run. Still, they accentuate that these measures are highly cost-effective, though not during crises (Brown and Koettl, 2012).[3]

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. 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 for bold statements. 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, limits the scope of ALMP measures (Kuddo, 2009). Brown and Koettl (2012) also stress weak public institutions as barriers to raise the effectiveness of job matching in developing countries.

The existing literature indicates regional labour market disparities in Croatia as well. Puljiz and Maleković (2007), for instance, by applying various inequality measures to regional and local units, such as coefficient of variations, Gini coefficient and Theil index, show how in the period 2000-2005 regional differences in unemployment rates increased, with the absence of any convergence. Botrić (2004) empirically tests the existing differences on a NUTS2[4] level in Croatia and shows substantial differences between Croatian regions regarding unemployment. Furthermore, using county-level (NUTS3) data from Labour Force Survey (LFS) in the period 2000-2005, she demonstrates quite visible differences in regional labour market indicators, implying the

[2] The so-called *stock-flow matching* (Dmitrijeva and Hazans, 2007).

[3] They emphasize significant effects of intensified job-search assistance for unemployed on their employment probabilities and even earnings, especially for the long-term unemployed (Brown and Koettl, 2012).

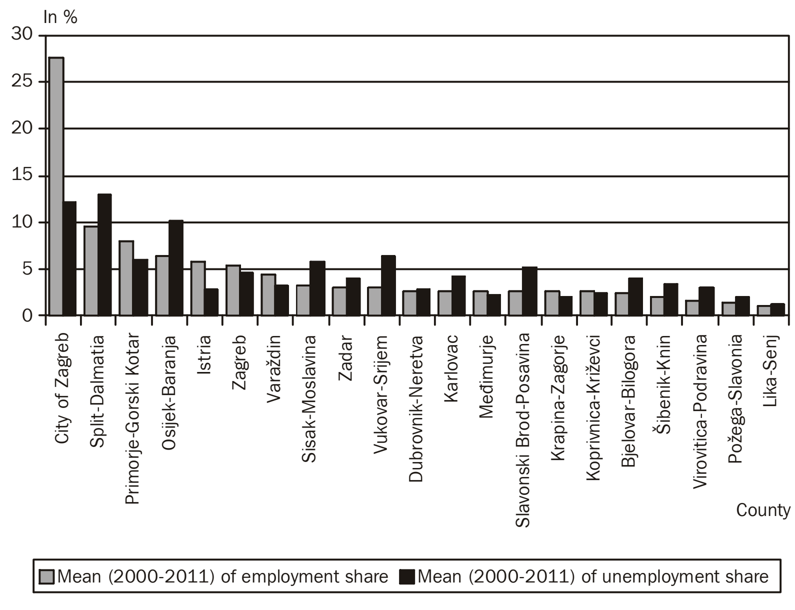
[4] Proposed NUTS2 level at that time included five different regions: Northern Croatia, Central Croatia, Eastern Croatia, Western Croatia and Southern Croatia.

underdeveloped equilibrating mechanisms in the Croatian labour market (Botrić, 2007). Furthermore, Obadić (2004), using disaggregated (translog) matching function, confirms the existence of regional mismatch in some of the Croatian counties. In addition, Obadić (2006a; 2006b), when explaining the problem of structural unemployment for selected transition countries, finds that the biggest differences in the movement of regional mismatch among the observed countries are persistent in Croatia.

2.2 Croatian Employment Service

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 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). A similar occurrence is observable with regards to regional unemployment rates (Figure A1 in Appendix 2). One way to deal with these issues is via the actions of the Croatian Employment Service, especially its regional offices.

Figure 1 **Regional Shares in Total Employment and Unemployment**



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

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 job-seekers, and delivery of active labour market programmes (Kuddo, 2009). Actually, one of the main aims of public employment services should be to match the unemployed workers with open job positions as efficiently as possible. The Croatian Employment Service operates on these postulates as well.

In its work the CES operates on two main levels:[5] Central Office and Regional Offices. Central Office is responsible for the design and implementation of the national employment policy, i.e., it creates a unique methodology for professional and operational implementation of the procedures from the field of the CES activities. On the other hand, 22 Regional Offices[6] perform professional and work activities from the CES priority functions, and provide support for them via monitoring and analysis 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 other sources are used 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 programmes is also included in total CES expenditures. These expenses comprise approximately 8 percent of total expenditures of the Service, while material and financial expenses are only 3 percent of total expenditure of the CES. Lately, an increasingly significant share of total expenditures is allocated to projects co-financed from the EU pre-accession programmes (http://www.hzz.hr).

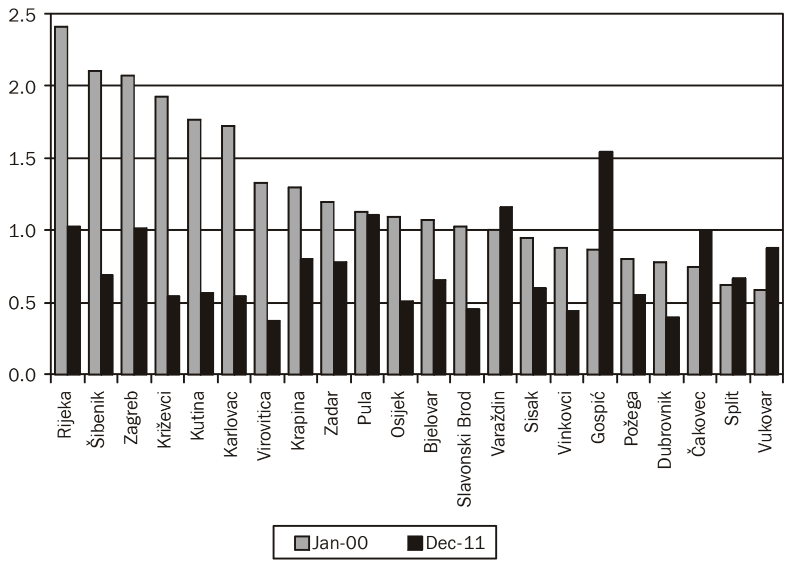
However, the effectiveness of employment offices varies by regions. For instance, some offices are much more effective than others in collecting information on job vacancies and in matching the unemployed with jobs. As stated in Kuddo (2009), in addition to (inadequate) funding, public policies to combat 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 (World Bank, 2010). Such capacity is important because it determines the effectiveness of job intermediation services provided by employment offices. 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

[5] Basic information about CES is obtained from their official web page: http://www.hzz.hr.

[6] 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 A2 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 (http://www.hzz.hr).

(effectiveness of regional employment offices) has decreased in the crisis. Still, an employment office can be effective in collecting vacancy information but less effective (or ineffective) in matching the unemployed with vacancies.

Figure 2 **Effectiveness of Regional Employment Offices (Vacancy Penetration Ratio)**



Notes: Vacancy penetration ratio (V/M) - the ratio of the 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) (World Bank, 2010).
Source: Author's calculation based on CES data.

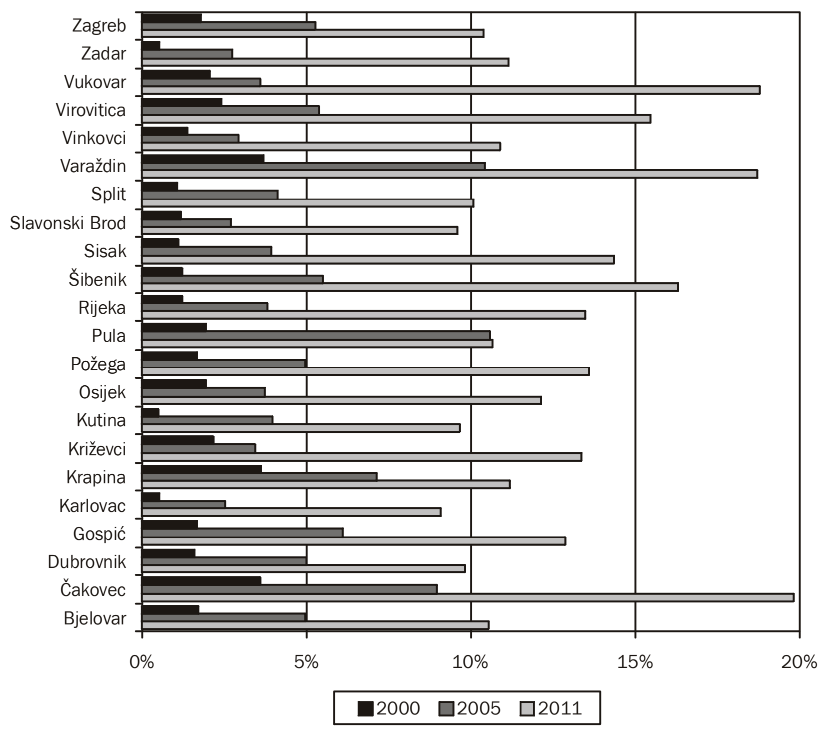
On the other hand, high unemployment/vacancies ratio (Figure A2 in Appendix 2) has important policy implications too. Besides indicating that the problem probably lies in the demand deficiency, it also negatively affects the effectiveness of employment services, such as job search assistance and job brokerage (World Bank, 2010). Matching the high number of the unemployed with the 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 (World Bank, 2010). Another indicator of regional employment office capacity is the ratio of the number of unemployed per one job counsellor (see Figure A3 in Appendix 2).[7] There are high variations between regions in this indicator which points once again to different capacities of the employment offices. This is further confirmed by examining the outflow rate (M/U), i.e. hiring probability by regions (Figures A4 and A5 in Appendix 2).

As was already mentioned, active labour market programmes, which are meant to help job-losers to find new jobs, besides poor financing (less than 10 percent of total

[7] Unfortunately, these data were not available prior to 2009.

expenditures), also have an extremely low coverage[8] (Figure 3 and Figures A6 and A7 in Appendix 2) in Croatia. The total spending on labour market programmes, both passive and active, is very low by the European standards. For instance, in 2007 Croatia spent roughly 0.4 percent of its GDP on all labour market programmes, which is substantially less than what was spent by EU countries at a similar income level, such as Hungary, Poland or Slovakia (0.6 to 1.2 percent of GDP) (World Bank, 2010).

Figure 3 **ALMP Coverage Rate Across Regional Offices**



Note: ALMP coverage rate - share of persons included in one of the active labour market programmes in total unemployment.
Source: Author's calculation based on CES data.

In the years preceding the crisis, the coverage rate for active programmes was slightly over 3 percent, and it fell to 2.5 percent in 2009 (Figure A6 in Appendix 2). However, recently, in an attempt to fight the 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 3 and Figure A6).

Nonetheless, the allocation of funds to regional employment offices, which in the end implement active labour market programmes, is mainly driven by the offices' absorption capacity while local needs, measured by the unemployment share, seem to be only a secondary factor (World Bank, 2010).[9] As it seems, regional allocation of ALMP funds is

[8] The programme coverage rate is the percentage of the unemployed who participated in any active labour market programme.

[9] Unfortunately, due to data unavailability this observation could not be confirmed in the paper.

largely historically determined and changes little in response to changing local labour market conditions. Although this capacity based allocation rule ensures that programme funds are absorbed, it may come at a cost for regions where capacity is relatively low but needs are high (World Bank, 2010). Still, evidence from the literature shows that 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 collected on a monthly basis within the NUTS3 (county) level obtained from the Croatian Employment Service over the period 2000-2011. Instead of the 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 A2 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 CES Registry (*M*). Besides these variables, the analysis also includes additional data that should affect the efficiency in the labour market. Detailed review and descriptive statistics of all the variables used in the analysis are provided in Table A1 in Appendix 1.[10]

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 as a 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 fits best the nature of the matching process. Nevertheless, the problem still exists since only a 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 extent of underreporting may differ from region to region. In the Croatian case, as of 2002 the employers are no longer legally obliged to report vacancies to the CES, while all effects of the changes in legal obligations on reporting vacancies on the labour market were no longer visible as of 2004 (CNB, 2010).[11]

[10] Additionally, these variables are explained more thoroughly in Section 4.2.

[11] This means that during some period after the legal obligation of posting vacancies at CES was abandoned there were visible effects in the labour market (including the matching process), but as of 2004 these effects vanished. Evidently, both the Croatian Employment Service and firms needed some time to adjust to a new situation.

Additionally, in order to get an indicator of the quality of services of regional 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). Unfortunately, only educational structure of the CES staff on a regional level has been obtained. In addition to that, in order to evaluate the impact of ALMPs on the overall efficiency we tried to obtain the data concerning persons included in different programmes of active labour market policies (as well as the data on the amount of funds for each of the ALMP measures). However, data provided on a monthly basis included only the number of new participants included in different programmes of active labour market policies, while the data on the exact number of persons included in ALMPs were unavailable.[12] Since these figures were too low (or inexistent) in the majority of the months for most of the counties (see Figure A7 in Appendix 2) this variable was not used in the empirical exercise. In the end, the data on the number of persons included in different programmes of active labour market policies on a yearly basis are provided and used in empirical analysis as a proxy for the policy variable determining the efficiency of the matching process.[13]

Figure 4 shows the stocks of unemployment plus flows of unemployment and vacancies in a given period (2000m1-2011m12). Apart from the exceptionally large 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.

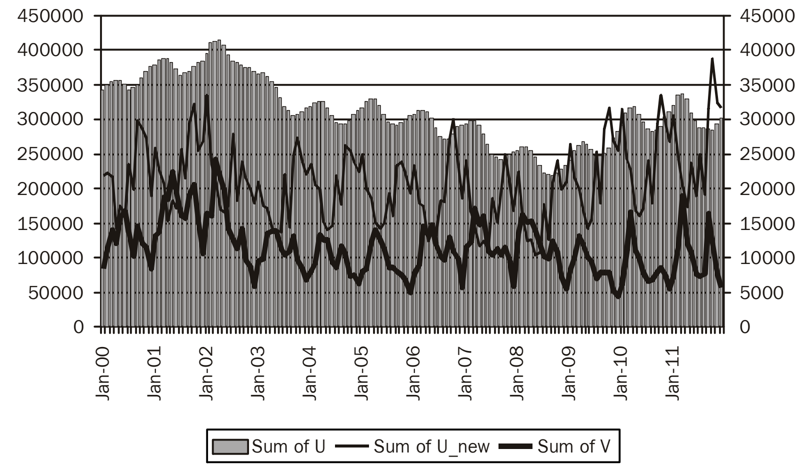
On the other hand, vacancies (Figure 4) as well as vacancy ratios (Figure 5) demonstrate pretty high volatility over time. Average vacancy ratios (number of job offers per one job-seeker) have ranged between 0.015 and 0.062, with the mean value of 0.036 offers per one job-seeker (having in mind that 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 the time trend needs to be controlled for in a non-linear way, taking into account the up and down swings in the labour market outlooks. Figure 5 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 disposal in the labour offices. Actually, relatively high values observed at the right scale, imply that indeed public employment services

[12] These data were available only after 2002.

[13] 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 office at each point in time (year), i.e., we consider ALMPs coverage at the end of the year.

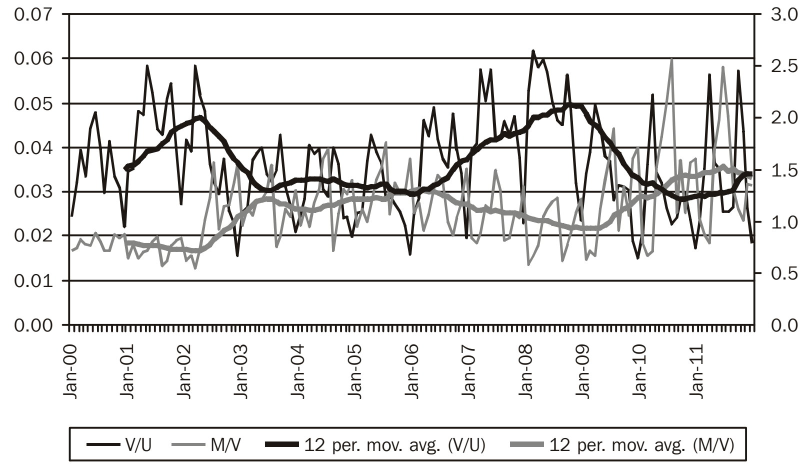
dispose of only a fraction of unsubsidised vacancies available in the economy.[14] In the periods of high labour demand (both cyclical and seasonal) considerably more of the unemployed find jobs than are at the disposal of local labour offices (Jeruzalski and Tyrowicz, 2009).

Figure 4 **Stocks of Unemployment Plus Flows of Unemployment and Vacancies - National Sums**



Notes: U - left scale; U_new and V - right scale.
Source: CES.

Figure 5 **Vacancy Ratio and Flows From Unemployment to Employment (Over Vacancies)**



Notes: V/U - left scale; M/V - right scale.
Source: Author's calculation based on CES data.

[14] Kuddo (2009) explains how in most of the Eastern European and Central Asian countries a relatively small portion of vacancies are registered at public employment service (PES). He suggests that "in order to increase vacancy notifications, PES and job-seekers themselves should be more proactive in identifying job openings and breaking into the 'hidden job market', be it better marketing and services to employers from PES side to more active networking or direct employer contact from the job-seekers' side" (Kuddo, 2009: 4).

3 Empirical Strategy

The estimation methodology used in this paper has a foothold in the classical matching function:[15]

$$M = f(U,V), \quad (1)$$

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 can be estimated using different methodological approaches.[16] 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-Douglas functional form, but there are some exceptions, of course.[17] 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, an analysis is usually carried out on a regional or occupational level. In this paper, in order to capture regional disparities in both the matching process as well as in the work of local employment offices, the estimation is performed on a regional level.

Two main techniques for evaluating matching efficiency on a regional (occupational/industrial) level that are usually used are stochastic frontier estimation and panel data regressions. However, while the 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 (in)efficiencies, the use of stochastic frontier approach allows a more detailed analysis of the determinants of regional matching efficiencies (Ibourk et al., 2004). Thus, in order to explore the efficiency on a regional level, stochastic frontier approach will be used in this paper, as well as its modified version – transformed basic-form panel stochastic frontier model.

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

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

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

3.1 Stochastic Frontier Estimation

Stochastic frontier estimation stems from the estimation of the production function. The basic idea behind the 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,[18] i.e.:

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

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 (y_{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,[19] meaning that:

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

where $\exp(\upsilon_{it})$ represents a stochastic component that describes random shocks affecting the production process.

In logarithmic 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.

---

[18] First proposed in the works by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). Battese 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 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."

[19] These shocks are not directly attributable to the producer or the underlying technology. They may come as a consequence of uncontrollable phenomena like weather changes, economic adversities and similar. Even though each producer is facing a different shock, the assumption is that the shocks are random and they are described by a common distribution.

Additionally, in Equation (5) υ_{it} represents the idiosyncratic error (υ_{it}~N(0,σ_υ^2)), while much of the literature has been devoted to deriving estimators for different specifications of the random inefficiency term that constitutes the only panel-specific effect, u_{it}.

For example, Aigner, Lovell, and Schmidt (1977) assume that u_{it} has half standard normal distribution. However, this assumption presumes that (in)efficiency is time-invariant. Batesse and Coelli (1995), on the other hand, assume that non-negative technical inefficiency effects are a function of time and firm-specific variables 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).

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 shocks 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 a 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 the one 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 specific labour markets: Ibourk et al. (2004) for France, Fahr and Sunde (2002; 2006) for Germany, Destefanis and Fonseca (2007) for Italy, and Jeruzalski and Tyrowicz (2009) for Poland.

For instance, Ibourk et al. (2004) explain how the matching process can be compared to the production process, where (in)efficiency of the matching process (ξ_{it}) corresponds to total factor productivity, i.e., it 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,[20] and say that in labour markets exhibiting high levels of matching efficiency, but low productivity, the objective for the policy-maker should be to increase the productivity.

The model in this paper is mostly based on Ibourk et al. (2004)[21] and Jeruzalski and Tyrowicz (2009) where the total number of matches is a function of the 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 the unemployed is relaxed by varying the individual search intensities.[22] Thus, we use a non-stochastic model where different groups of job-seekers can have different search intensities:

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

[20] They explain the productivity in terms of the stocks of job-seekers and vacant positions in relation to creating new employment. For example, if the elasticity of new matches with respect to these determinants is high in a certain region, these stocks exhibit a high matching productivity. However, if at the same time inefficiencies are high, an increase in the stocks would lead to fewer new matches than is technically feasible. In such an environment, policies that aim at reducing the inefficiencies would be advisable. On the other hand, finding high efficiency estimates given the stocks of unemployed and vacancies as inputs indicates that creating a vacancy or increasing the available labour force in the respective region would lead to additional job creation with high probability (Fahr and Sunde, 2002: 3).

[21] 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 it is predominant in the empirical literature.

[22] 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 the 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 the trained directly in the stochastic frontier estimation (instead of two stage approach) they risk endogeneity consequences (Jeruzalski and Tyrowicz, 2009).

where c^j represents deviations from the average search intensity, so that negative values are characteristic for less than the 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 the heterogeneity.

Rearranging Equation (9), one obtains:

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

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

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

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

Following Battese and Coelli (1995), the assumption is that the effects of heterogeneity that affect search intensity have direct impact on the matching efficiency (and not on the matching process itself), i.e., that they are included in term z_{it} in the following equation:

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

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)):

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

Furthermore, Ibourk et al. (2004) also emphasize how the unemployed workers who enter special training programmes (ALMPs) are not included in the unemployment variable, u_{it-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:

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

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 and thus they follow the approach commenced by Ibourk et al. (2004), incorporating the ALMPs effects to determine the technical efficiency scores, but not the matching process itself.[23] 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 the efficiency of the matching function comes from the fact that the data from Croatian Employment Service do not observe job-to-job flows.[24] However, this is a frequent problem in this type of research. Consequently, the estimation of the matching efficiency of a particular office (as opposed to whole regional labour markets) rests upon the vacancies that are filled exclusively from the category of the unemployed.

3.3 Model 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 the first difference approach to the estimation of the matching function, i.e.:

$$\Delta m_{it} = \beta_1 \Delta u_{it-1} + \beta_2 \Delta v_{it-1} + \Delta \varepsilon_{it}. \tag{15}$$

In addition, they 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 (Munich and Svejnar, 2009). However, Jeruzalski and Tyrowicz (2009) argue

[23] 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, the situation in the labour market worsens the 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.

[24] Additionally, due to data limitation, the interregional migration is also neglected.

that this approach does not allow capturing the relation between local conditions and the matching performance which is the main aim of this research.

Some of these issues, primarily those concerning stochastic frontier estimation, are further explored in works by Greene (2005a; 2005b) and Wang and Ho (2010). Greene (2005a) argues that the 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. Even though the first limitation is generally solved by Batesse and Coelli (1995), the second problem remains in most of the empirical works. For instance, Wang and Ho (2010) explain how even in the cases where time-invariant inefficiency assumption has been relaxed, the time-varying pattern of inefficiency is the same for all individuals. Greene (2005a; 2005b) proposes some extension of both fixed 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 the problem of incidental (fixed-effect) parameters.[25] Even though 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, upon 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 account both time-varying inefficiency and time-invariant individual effects. Their initial model resembles the one in Equation (5), i.e.:

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

where α_i is individual i's fixed unobservable effect; $\varepsilon_{it} = \upsilon_{it} - u_{it}$; $\upsilon_{it} \sim \mathrm{N}(0,\sigma_\upsilon^2)$; $u_{it} = h_{it} \cdot u_i^*$; $h_{it} = f(z_{it}\delta)$; and $u_i^* \sim \mathrm{N}^+(\mu,\sigma_u^2)$. Neither x_{it} nor z_{it} contains constants (intercepts) because they are not identified and u_i^* is independent of all T observations on v_{it}. Both u_i^* and v_{it} are independent of all T observations on $(x_{it}; z_{it})$.[26]

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

[25] Possible inconsistency due to the number of parameters growing with the number of firms.

[26] 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_{it} to be correlated over time for a given individual (Wang and Ho, 2010).

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

where $\Delta\varepsilon_{it} = \Delta\upsilon_{it} - \Delta u_{it}$; $\Delta\upsilon_{it} \sim \text{MN}(0,\Sigma)$; $\Delta u_{it} = \Delta h_{it} \cdot u_i^*$; and $u_i^* \sim \text{N}^+(\mu,\sigma_u^2)$. 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.[27]

In order to compute technical efficiency index, the conditional expectation estimator is used, i.e., conditional expectation of u_{it} on the vector of a differenced ε_{it}. The advantages of using this estimator are: (i) the vector $\Delta\tilde{\varepsilon}_i$ ($\Delta\tilde{\varepsilon}_i = (\Delta\varepsilon_{i2}, \Delta\varepsilon_{i3}, ..., \Delta\varepsilon_{iT})$) 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:

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

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.[28]

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. Hence, in order to get more consistent estimates we will use Wang and Ho's (2010) model transformation of the stochastic frontier estimation of the matching function.[29]

---

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

[28] Wang and Ho (2010) show that the within-transformed and first-differenced models are algebraically the same (by within-transformation, the sample mean of each panel is subtracted from every observation in the panel).

[29] Even though the 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 of the 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).

4 Estimation Results

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

4.1 Stochastic Frontier Estimation

For the estimation of a stochastic frontier we have used the time-varying decay model (Battese and Coelli, 1995).[30] Additionally, in order to control for the sizeable seasonality typically contained in these variables (see Figure 5) it is desirable to include month and year specific dummy variables as regressors in the model. Therefore, estimations include monthly dummies to control for the differentiated vacancies and job-seekers arrival rates throughout each year, and year dummies for the period when the reporting of vacancies at CES was still in effect, i.e., for the years 2000-2003. In addition, in the existing empirical work, variables are usually normalized (by the size of the labour force) in order to control for heteroscedasticity (Dur, 1999; Munich and Svejnar, 2009). However, since the size of the labour force in Croatia varied substantially during the observed period and being that the data about labour force on a regional level are not available,[31] 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 conducted (and presented) on the whole sample, as well as on the sample excluding the biggest region (which belongs to Zagreb regional office).[32] Besides, in the analysis estimating the determinants of matching efficiency – the variable indicating population density is included in order to control for the 'size' of the respective labour market. Finally, as explained previously, the estimations include both stocks and flows of unemployed and only flows of vacancies.

Results from the stochastic frontier estimation are reported in Table 1 (for the unrestricted estimation) and Table 2 (for the restricted estimation indicating constant returns to scale). Since the variables are in logarithms, the estimations actually represent elasticities.

[30] 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.

[31] For instance, until 2002, data on the persons employed in entities with less than ten employees were not included in total employment data at county level, while up to 2004, data on the persons employed in the police and military were not included in total employment data at county level. What's more, data on the size of the labour force on a regional level are published only once a year, indicating the situation on 31 March (see Figure A1 in Appendix 2).

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

Table 1 **Stochastic Frontier Unrestricted Estimation**								
	Total sample				**Zagreb region excluded**			
Variables	**Stocks of u**	**Flows of u**	**Both**	**Sum**	**Stocks of u**	**Flows of u**	**Both**	**Sum**
u	0.761***		0.911***		0.773***		0.924***	
	(0.023)		(0.028)		(0.021)		(0.029)	
v	0.241***	0.262***	0.233***	0.248***	0.242***	0.260***	0.235***	0.250***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)
u_new		0.026	-0.166***			0.019	-0.155***	
		(0.021)	(0.019)			(0.021)	(0.019)	
u_sum				0.741***				0.765***
				(0.020)				(0.021)
Monthly dummies	YES	YES	YES	YES	YES	YES	YES	YES
Annual dummies	YES	YES	YES	YES	YES	YES	YES	YES
Returns to scale	CRS	DRS	CRS	CRS	CRS	DRS	CRS	CRS
Constant	-2.598***	4.952***	-2.713***	-2.564***	-2.721***	7.245	-2.923***	-2.817***
	(0.191)	(0.217)	(0.192)	(0.171)	(0.180)	(6.556)	(0.209)	(0.187)
Mean technical efficiency	0.762	0.384	0.691	0.805	0.762	0.038	0.692	0.805
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.0003)	(0.002)	(0.002)
Wald χ^2	7470.74***	4625.79***	7548.41***	7779.14***	7685.43***	4693.50***	7395.96***	7563.52***
γ	0.104	0.762	0.150	0.075	0.086	0.716	0.155	0.077
	(0.038)	(0.065)	(0.045)	(0.030)	(0.032)	(0.065)	(0.049)	(0.033)
η	0.005***	0.0004***	0.005***	0.007***	0.007***	0.0001	0.005***	0.007***
	(0.001)	(0.0002)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.001)
Log likelihood	76.710	-263.551	114.912	42.030	89.924	-230.525	127.090	60.848
No. of observations	3168	3168	3168	3168	3024	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 the 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 statistically significant, detailed results available upon request. Variables are in logarithms, lagged when necessary. Standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.*

As is evident from Table 1, there is a larger weight of job-seekers in the matching process than is that of the posted vacancies. This result is not unusual, since in most of the empirical work the number of unemployed tends to affect hiring more than the number of posted vacancies (for instance, Ibourk et al., 2004; Fahr and Sunde, 2006; Jeruzalski and Tyrowicz, 2009).[33] What is more, only the stock of the unemployed positively affects the process of matching, while the newly registered unemployed decrease the matching capacity. This is 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. Additionally, in the case of summing the two variables for the unemployed, the coefficient for the number of vacancies slightly increases while the result for the total number of unemployed (*u + u_new*) is as expected.

[33] Petrongolo and Pissarides (2001) indicate how the regression that omits on-the-job search will give too low an estimate of the effect of vacancies on matchings (too high of unemployment).

As discussed earlier, the size of the region could have an impact on the matching process. That is why we present the estimates using the sample without the biggest region – Zagreb. However, by excluding the largest region, we do not get results much different from the ones with the 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.

Furthermore, in order to test for the (in)existence of the constant returns to scale in the model, the Wald test of coefficient restrictions was conducted, where null hypothesis is equal to $\beta_u + \beta_v = 1$; $\beta_u + \beta_v + \beta_{u\_new} = 1$; or $\beta_{u\_sum} + \beta_v = 1$. The results are provided in Table 1 on the basis of the test statistics. Specifications with only stocks of the 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 (where $\beta_u + \beta_v = 1$; $\beta_u + \beta_v + \beta_{u\_new} = 1$; and $\beta_{u\_sum} + \beta_v = 1$) 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 the sample without the Zagreb regional office data.

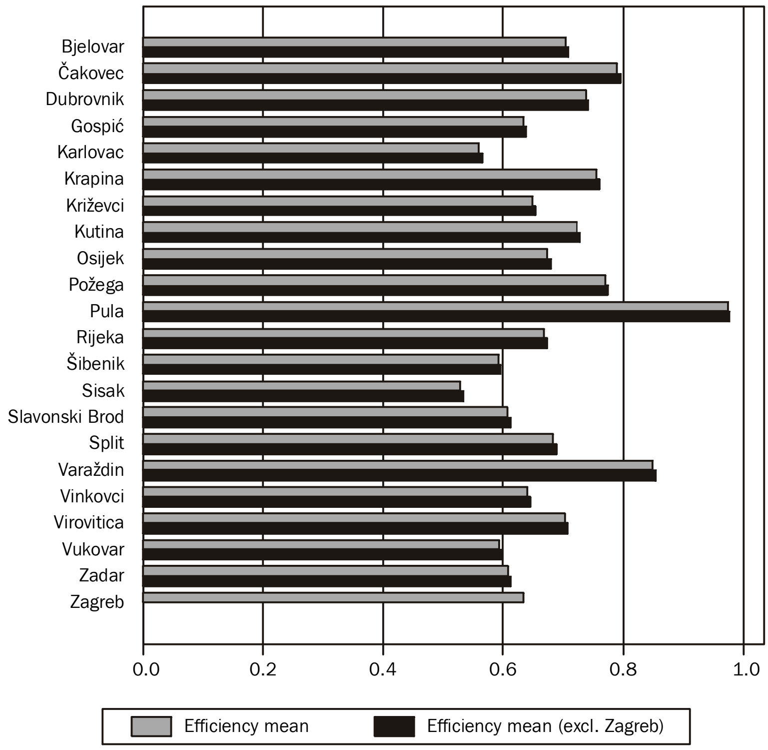
Table 2 **Stochastic Frontier Restricted Estimation**

	Total sample			**Zagreb region excluded**		
Variables	**Stocks of u**	**Both**	**Sum**	**Stocks of u**	**Both**	**Sum**
u	0.759***	0.928***		0.760***	0.921***	
	(0.010)	(0.022)		(0.010)	(0.022)	
v	0.241***	0.235***	0.249***	0.240***	0.235***	0.249***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
u_new		-0.163***			-0.155***	
		(0.019)			(0.019)	
u_sum			0.751***			0.751***
			(0.010)			(0.010)
Monthly dummies	YES	YES	YES	YES	YES	YES
Annual dummies	YES	YES	YES	YES	YES	YES
Constant	-2.577***	-2.890***	-2.664***	-2.600***	-2.888***	-2.680***
	(0.037)	(0.054)	(0.037)	(0.037)	(0.054)	(0.037)
Mean technical efficiency	0.763	0.685	0.801	0.765	0.693	0.807
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wald χ^2	9057.41***	9259.30***	9024.01***	9001.19***	5767.96***	8935.95***
γ	0.102	0.158	0.080	0.083	0.154	0.073
	(0.036)	(0.047)	(0.031)	(0.031)	(0.048)	(0.030)
η	0.006***	0.005***	0.006***	0.007***	0.005***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log likelihood	76.704	114.464	41.855	89.682	127.075	60.562
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 the 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 statistically significant, detailed results available upon request. Variables are in logarithms, lagged when necessary. Standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.*

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 (the unemployed and vacancies). Nevertheless, there are great variations across regions/regional offices (Figure 6).[34] For instance, regional office Pula exhibits almost 100 percent efficiency,[35] while regional office Sisak is 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 6 **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 7 and Figure A10 in Appendix 3).[36] Even though this result goes hand-

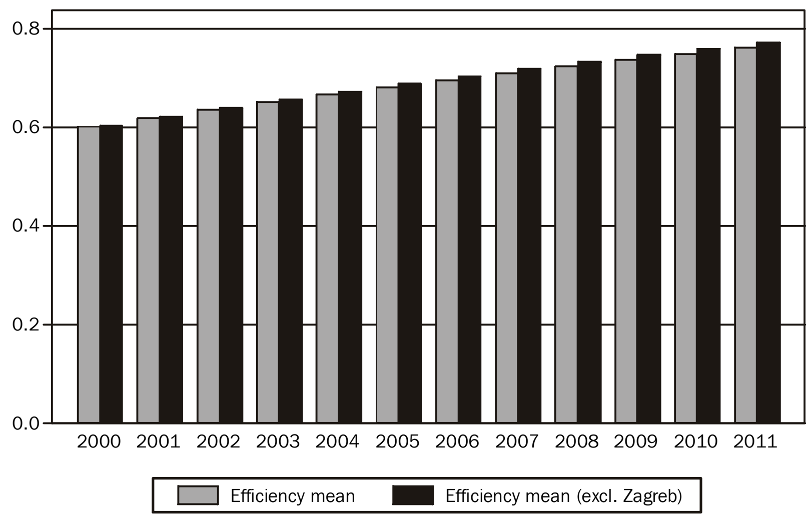
[34] In both Figure 6 and Figure 7 efficiency estimates from the (restricted) specification with both stocks and flows of the unemployed (column 2 in Table 2) are presented.

[35] This result looks a bit unusual, but it only indicates that in Istria (covered by the Pula regional office) almost all available vacancies are filled from the category of registered unemployed in a respective month. This result also points to a highly dynamic labour market in the county of Istria. This is also confirmed by the low unemployment rates (see Figure 1 and Figure A1 in Appendix 2) in this county.

[36] On top of that, if we exclude Zagreb region, the efficiency coefficient estimates stay almost the same.

in-hand with some other empirical results (for instance, Šergo, Poropat and Gržinić, 2009) this outcome is somewhat puzzling. Fahr and Sunde (2002), for instance, explain that increasing efficiency over time may be interpreted as the agents in the market learning how to find appropriate partners in order to form matches. Šergo, Poropat and Gržinić (2009) clarify their finding in a similar way, explaining how rising efficiency in Croatian labour market since the war and the de-industrialization shocks in the '90s is connected with the capitalist framework of private employers. Namely, they describe how the responsiveness of the labour market depends not only on the willingness of the unemployed to fill jobs but also on the responsiveness of employers to fill vacancies with workers. Since our model refers to a somewhat later period (2000-2011), this can only serve as partial explanation. However, one has to remember that as of 2002 only a fraction of vacancies is posted at the CES while the number of the unemployed was constantly declining up to 2009 (start of the recession), which also had influence on the increasing matching efficiency. Other factors will be explained in the following section.

Figure 7 **Mean Technical Efficiency Over the Years (With and Without Zagreb Region)**



Source: Author's calculation based on CES data.

4.2 Covariates of Technical Efficiency

Following Jeruzalski and Tyrowicz (2009), in this section we present the estimation results for the covariates of technical efficiency scores.[37] In this way, the characteristics of a local labour market are approached by the means of proxies. Namely, some local

[37] Although the regression construct specifies causality direction from the right-hand-side variables to the left-hand-side one - we are only trying to establish if there is a link between some control factors and the individual efficiency scores (Jeruzalski and Tyrowicz, 2009). In addition, it can be argued that both the unemployment and the vacancies affect the value of (in)efficiency, and that variables that serve as determinants of the (in)efficiency may directly affect the matching process. However, following the standard procedure from the literature (Warren, 1991; Batesse and Coelli, 1995; Fahr and Sunde, 2002; 2006; Ibourk et al., 2004; Destefanis and Fonseca, 2007 or Jeruzalski and Tyrowicz, 2009) it is assumed that the variables that affect matching (in)efficiency do not directly impact the matching process. Possible endogeneity of vacancies and unemployment will be discussed later on in the paper.

markets may be more dynamic than others, while some may be populated by the more difficult groups of the unemployed. To account for this differentiation, following Ibourk et al. (2004), Destefanis and Fonseca (2007) and Jeruzalski and Tyrowicz (2009), we have used the following measures:

- Labour market structure (Figure A9 in Appendix 2):
  - vacancy ratio (*v/u*): measure of labour market tightness
  - regional unemployment rate (*reg_unrate*)
  - ratio of employed to delisted (*m/delisted*)
  - share of females in total unemployment (*u_female*) and in total flows to employment (*m_female*)
  - share of the young (*u_<24y*) in the pool of the unemployed
  - share of the long-term unemployed in the pool of the unemployed (*u_12m+*)
  - share of workers without experience in the pool of the unemployed (*u_w/o experience*)
  - share of workers previously employed in the primary sector of economic activity in the pool of the unemployed (*u_primary_sector*)
  - share of unemployed persons receiving unemployment benefits in the pool of the unemployed (*u_benefits*)
  - share of the no or low-skilled unemployed among the jobless (*u_low skilled*)
  - share of the high-skilled unemployed among the jobless (*u_high skilled*)
- ALMPs coverage rate (*u_almp_coverage*)
- Number of the highly skilled employed at the respective CES regional office per one unemployed (*CES_high skilled*)
- Net income *per capita* in a specific region/county (*net income_pc*)
- Size of the labour market measured by the population density (*pop_density*)

In addition, linear and quadratic trends are included to control for the country-wide labour market fluctuations, while monthly and annual dummies are introduced in order to control for large seasonal fluctuations.

Different variables 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 the search intensity of firms and competition among firms for applicants (Fahr and Sunde, 2006), but it can also be a good measure of the cycle (Petrongolo and Pissarides, 2001). Level of local unemployment (regional unemployment rate), on the other hand, can be a good measure of the search intensity and competition among job-seekers. The 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 demonstrates higher adaptability (search intensity), while the 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 the long-term unemployed may capture both business cycle effects and more structural difficulties (such as skills mismatch) (Ibourk et al., 2004) while share of the unemployed receiving unemployment benefits should affect the willingness to accept the job (via reservation wage). Furthermore, share of females in total unemployment as well as the share of long-term unemployed may indicate ranking effects while the share of unemployed in agriculture (primary sector) may indicate some firm effects (Destefanis and Fonseca, 2007).

As discussed earlier, ALMPs coverage rate (*u_almp_coverage*) is constructed as the number of individuals in any treatment over the pool of the unemployed in a respective region at the year end. This variable is important because it should affect different search intensities and thus influence the matching efficiency. Moreover, the number of the 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 (see Figure A3 in Appendix 2), the number of highly skilled CES employees per one unemployed will serve this purpose. In order to somehow control for the demand fluctuations, net income *per capita* on a regional level is used here. Some other variables, like investments or consumption, could probably serve a better purpose in this respect, but due to data unavailability on a region/county level we stick to net income *per capita*.[38]

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, i.e., population density serves as a proxy for the size of social networks and the transmission of information. Munich and Svejnar (2009), on the other hand, indicate that not controlling for the district size may lead to biased coefficients unless the function exhibits constant returns to scale (omitted variable problem) which leads to the spurious scale effect. In our specification, we follow Ibourk et al. (2004) and use population density as covariate of technical efficiency.

Results of these estimations are reported in Table 3.[39] There are five different model specifications. First, only the 'labour market structure' variables (Figure A9 in Appendix 2) are used. Then, ALMPs coverage rate variable is added to the model specification, while in the third specification the number of highly skilled CES employees per one unemployed (proxy of CES regional office capacity) is included. Specification four adds a measure of 'demand fluctuation', i.e., net income *per capita*, while specification five additionally includes time trend, measure of the region's size (population density), and monthly and annual dummies.[40]

[38] For instance, Mian and Sufi (2012) explain how negative demand shocks affected employment levels during the recent recession in the U.S. and use household balance sheets, i.e., debt-to-income ratio of the households, in this respect. They conclude that 65 percent of the lost jobs in the 2007-2009 time period is due to the decline in aggregate demand driven by household balance sheet shocks (Mian and Sufi, 2012).

[39] In this case, the efficiency estimates from the (restricted) specification with both stocks and flows of the unemployed (column 2 in Table 2) are used.

[40] Figure A11 in Appendix 3 shows correlations between the efficiency coefficient and a set of explanatory variables.

Table 3 **Determinants of Technical Efficiency**					
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
v/u	0.0001	0.00003	-0.00004	-0.0006***	0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
reg_unrate	-0.0197***	-0.0249***	-0.0166***	0.0041*	-0.0457***
	(0.0018)	(0.0021)	(0.0020)	(0.0023)	(0.0038)
m/delisted	-0.0006***	-0.0008***	-0.0008***	-0.0006***	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
m_female	-0.0009**	-0.0011**	-0.0011**	-0.0014***	0.0009*
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
u_female	0.0331***	0.0374***	0.0301***	0.0402	-0.0191***
	(0.0064)	(0.0076)	(0.0071)	(0.0069)	(0.0068)
u_<24y	-0.0027	-0.0024	0.0107***	0.0134***	0.0349***
	(0.0023)	(0.0026)	(0.0027)	(0.0026)	(0.0029)
u_12m+	0.0018	0.0008	-0.0051*	-0.0011	0.0029
	(0.0027)	(0.0032)	(0.0031)	(0.0030)	(0.0029)
u_w/o_experience	-0.0313***	-0.0367***	-0.0397***	-0.032***	-0.0368***
	(0.0022)	(0.0026)	(0.0024)	(0.0025)	(0.0028)
u_primary_sector	0.0020**	0.0041***	0.0057***	0.0056**	0.0105***
	(0.0010)	(0.0012)	(0.0011)	(0.0008)	(0.0010)
u_benefits	0.0009	0.0017	0.0027*	0.0013	0.0086***
	(0.0014)	(0.0017)	(0.0016)	(0.0016)	(0.0015)
u_low skilled	-0.0395***	-0.0412***	-0.0373***	-0.0371***	-0.0063**
	(0.0030)	(0.0035)	(0.0034)	(0.0033)	(0.0032)
u_high skilled	0.0121***	0.0137***	0.0113***	0.0092***	0.0019
	(0.0014)	(0.0016)	(0.0015)	(0.0015)	(0.0017)
u_almp coverage		0.0008**	0.0006**	0.0005*	0.0023***
		(0.0003)	(0.0003)	(0.0003)	(0.0006)
CES_high skilled			0.0316***	0.0297***	0.0301***
			(0.0021)	(0.0020)	(0.0020)
net income_pc				0.0638***	0.0359***
				(0.0037)	(0.0079)
Time trend					0.0012***
					(0.0001)
Squared time trend					-2.79e^{-06}***
					(4.73e^{-07})
pop_density					0.0311***
					(0.0019)
Monthly dummies					YES
Annual dummies					YES
Constant	0.5983***	0.6038***	0.8179***	0.2256***	0.2933***
	(0.0108)	(0.0127)	(0.0186)	(0.0399)	(0.07689)
Wald χ^2	1098.45***	1350.13***	1598.98***	2290.03***	8095.08***
No. of observations	3168	3168	3168	3168	3168

*Notes: Dependent variable: estimates of the technical efficiency from the stochastic frontier as reported in Table 2 (column 2). Monthly and annual dummies are statistically 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.*

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 number of the unemployed) or ALMPs coverage (Jeruzalski and Tyrowicz, 2009). The estimated coefficients in Table 3 only partially confirm these expectations. Namely, some of the covariates are not significant and for some that are significant, the sign of the relationship is not clear. However, as explained earlier, we are only trying to establish if there is a link between some control factors and the individual efficiency scores, not their causality.

As far as structural variables are concerned, none of the estimated coefficients seems to be large enough to explain variations in the technical efficiency coefficient. Vacancy ratio as well as the share of the long-term unemployed proved to be insignificant in almost all of the model specifications[41] while the share of those receiving unemployment benefits and share of the young 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 suggests that the relationship between them and the matching efficiency is spurious.

Taking all this into account, we can see that only regional unemployment rate,[42] share of workers without experience, and share of low-skilled workers have unvarying negative and significant impact on technical efficiency, while the share of workers previously employed in the primary sector and share of high-skilled workers have significant and positive effect[43] on the coefficient of technical efficiency. These results, except perhaps for the share of agricultural workers, are quite intuitive and expected.

Unexpected results come (where significant) from the share of females in both the unemployed and the outflows from unemployment. Namely, larger percentage of females in the pool of the 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) a higher share of females in the unemployed positively affects efficiency estimates while female share in outflows from unemployment has a negative effect. Still, in the last model specification, where all the variables are included, these two covariates have an '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 (although insignificant), while later it becomes positive (as expected).

Relationship between the share of persons receiving unemployment benefits and technical efficiency coefficient is another unexpected result. Namely, this variable

[41] This is somehow surprising being that in some other empirical explorations (such as Fahr and Sunde, 2006) these variables proved to be important in explaining technical (in)efficiency of the matching process on a regional level.

[42] Except in the fourth model specification.

[43] Except in the last model specification for high-skilled workers.

positively affects matching efficiency (although is mostly insignificant). 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, since the amount of the benefits on a monthly basis is on average pretty low (Rutkowski, 2003; Tomić and Domadenik, 2012) it does not have a great impact on the reservation wage increase, i.e., on lowering the matching efficiency. Positive effect probably comes from the fact that these people represent the recently unemployed (period of receiving benefits is also limited) with a higher search intensity.

The ALMPs coverage rate has a positive and significant effect on the matching efficiency.[44] This suggests that programmes are effectively targeted on the unemployed workers with below average matching efficiencies (Ibourk et al., 2004).[45] However, the value of the estimated coefficient is too small to have any real impact on the matching efficiency. The number of highly skilled CES employees per one unemployed, on the other hand, is positive and somewhat larger, suggesting that the regional employment service office capacity positively affects matching efficiency.

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 the efficiency of a local labour office. Thus, in the last two model specifications net income *per capita* in a respective county is added into the estimation. As expected, this coefficient is significant and positive indicating that 'demand fluctuations' have an impact on the matching efficiency as well. Time trend has a positive impact (visible in Figure 7 and Figure A10 in Appendix 3), as well as population density (last model specification). As Jeruzalski and Tyrowicz (2009) argue, a large part of the observed heterogeneity will be an interaction of time and unit characteristics.

4.3 Stochastic Frontier Estimation by 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 the time trend and two variables indicating labour market structure[46] as constraints for the technical efficiency as well as additional variable that should stand as a proxy for demand fluctuation (*net income_pc*).[47]

[44] Via their effect on the composition of the stock of job-seekers.

[45] Additionally, this variable should also indicate the quality of the allocation of resources as well as staff quality of regional employment offices being that they are responsible for the selection of unemployed persons who participate in the programme.

[46] One that should affect efficiency positively (share of high-skilled workers) and one that should have a negative impact on efficiency (share of low-skilled workers).

[47] The model, by its construction, does not allow the inclusion of the constant as well as individual-specific and time-invariant, i.e., dummy variables, into the equation.

As the results indicate, model transformation did not significantly change the estimations of the coefficients for the stock and flow of the unemployed (*u and u_new*) and flow of vacancies (*v*) in comparison with the 'regular' stochastic frontier estimation (Table 1 and Table 2). However, efficiency covariates are somewhat changed from the ones in earlier estimation (Table 3).

Table 4 **Stochastic Frontier Estimation by Model Transformation**

	Total sample			
	Stocks of u	**Flows of u**	**Both**	**Sum**
Frontier				
u_tr	0.726***		0.918***	
	(0.048)		(0.046)	
v_tr	0.382***	0.365***	0.325***	0.396***
	(0.013)	(0.013)	(0.013)	(0.013)
u_new_tr		-0.278***	-0.370***	
		(0.019)	(0.019)	
u_sum_tr				0.583***
				(0.050)
Constraints				
u_low skilled	0.368	0.521	0.262	0.545
	(0.398)	(1.100)	(0.254)	(0.511)
u_high skilled	0.198	-0.077	-0.208	0.301
	(0.243)	(0.626)	(0.163)	(0.322)
net income_pc	-0.375	-1.360	0.911**	-0.655
	(0.588)	(1.367)	(0.447)	(0.746)
Time trend	-0.018***	-0.033***	-0.018***	-0.020***
	(0.005)	(0.010)	(0.004)	(0.006)
c_υ	-2.190***	-2.184***	-2.306***	-2.162***
	(0.025)	(0.025)	(0.025)	(0.025)
c_u	5.697	23.838	-20.507**	11.996
	(12.150)	(28.984)	(8.690)	(15.701)
Mean technical efficiency $\left[E(\exp(-u_{it}) \mid \Theta)\right]$	0.848	0.956	0.760	0.881
	(0.122)	(0.080)	(0.132)	(0.112)
Wald χ^2	1217.11***	1221.61***	1729.66***	1097.10***
Log likelihood	-1035.93	-1046.36	-857.84	-1079.16
No. of observations	3146	3146	3146	3146

Notes: Dependent variable: first difference of log of monthly flows to employment out of unemployment (d_m). $\Theta = \Delta\widetilde{\varepsilon}_i$; $c_\upsilon = \ln(\sigma_\upsilon^2)$; $c_u = \ln(\sigma_u^2)$. *Variables are in logarithms, lagged when necessary. Standard errors (except for technical efficiency where standard deviation is reported) reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.*

Namely, variables representing labour market structure (share of low and high-skilled workers) are insignificant and of the sign opposite than the one expected in most of the model specifications. Variable representing demand fluctuations – regional net income *per capita* – is also insignificant, except in the model specification with both stock and flow of the unemployed where it has an (expected) positive impact on the matching efficiency.

Linear time trend is negative and significant in all the model specifications. This result indicates lowering efficiency over time, which was also the case in Jeruzalski and Tyrowicz's (2009) first-difference estimation of the matching function. However, when looking at the estimated technical efficiency coefficients over the years one can observe the rise in the mean technical efficiency coefficient over time.

As far as the estimates of the technical efficiency coefficient are concerned – a transformed model gives somewhat higher efficiency coefficients. As was already mentioned, mean technical efficiency coefficient is rising over time – similarly as in the case of the original model estimates (Figure 7) while variation across regions is somewhat different than in the original panel stochastic frontier estimation (Figure 6). 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.

5 Conclusions

This paper explores the efficiency in the labour market by estimating the matching function on a regional level in Croatia. Since 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 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 – transformed panel stochastic frontier model.

Main results point to a 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. Model specification that includes both stocks (at the end of the previous month) and flows (newly registered) of the 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 the unemployed suggests that the model exhibits decreasing returns to scale. In addition, flows of the unemployed included in the model, unlike in some other empirical analyses, increase positive impact of stocks.

The main aim of the analysis – the efficiency of the matching process – proved to be rising over time with significant regional variations. On average, the 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 a set of covariates that should affect it. Namely, it is assumed that the policy relevant variables can be introduced into the original model if the assumption about the homogeneity of the 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 programmes or employment service staff capacity.

As far as the labour market structure variables are concerned, the obtained results suggest that the regional unemployment rate and the shares of workers without experience and low-skilled workers in the pool of the unemployed have the highest negative impact on the matching efficiency while the shares of primary sector and high-skilled workers in the pool of total unemployed have the highest positive impact in the respective regional labour market.

Policy variables, on the other hand, have a mostly positive impact on the matching efficiency. Nevertheless, the CES was reluctant to provide the data on financial resources devoted to each of its regional offices (or any financial data for that matter), as well as more detailed data about its staff, equipment and similar, which would be very helpful in determining the quality of services provided by the regional employment offices. Hence, the quality of the regional employment offices' services is proxied by the number of highly skilled employed at the respective CES regional office per one unemployed as well as by the ALMP coverage rate which should indicate the quality of the allocation of resources as well as staff quality (they determine who participates in the programme) - both which have a positive impact on the efficiency of the matching process.

Namely, the results suggest that the ALMP coverage rate has a positive impact on the efficiency of the matching process, but the size of the estimated coefficient is too small for us to come to any strong conclusions. However, the number of highly skilled CES employees per one unemployed indicates a stronger significant positive impact in all the model specifications. This suggests that the CES regional office staff caseload is important for the explanation of the variation in the matching efficiency. Yet, one has to bear in mind that the CES office staff capacity variable depends not only on the number of employees per one office, but even more on the number of unemployed persons in a respective region.

Net income *per capita*, as an indicator of the demand fluctuations, also proved to have a positive impact on the matching efficiency. Thus, it seems that demand fluctuations remain one of the main causes of matching (in)efficiency in Croatia. It is 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, it seems that 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 account when implementing new policies and allocating funds to CES regional offices. However, due to data limitation, this could not be further explored in this paper.

Then again, classic panel stochastic frontier estimation of the matching function has some problems, including possible endogeneity of independent variables. In order to get more consistent estimates, transformation of the original panel stochastic frontier model is applied. Nevertheless, preliminary results from the basic-form transformation model show that there is no significant difference in estimated mean technical efficiency coefficients in comparison to the original panel stochastic frontier model. Still, this result should be taken with caution since it included only a couple of variables possibly affecting matching efficiency.

This paper 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 the registered unemployed job-seekers and posted vacancies. Methodological approach used here upgrades the standard estimation of the matching function by combining regional data on vacancies and the 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 the estimation of the basic-form 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.

Appendix 1 – Data Description

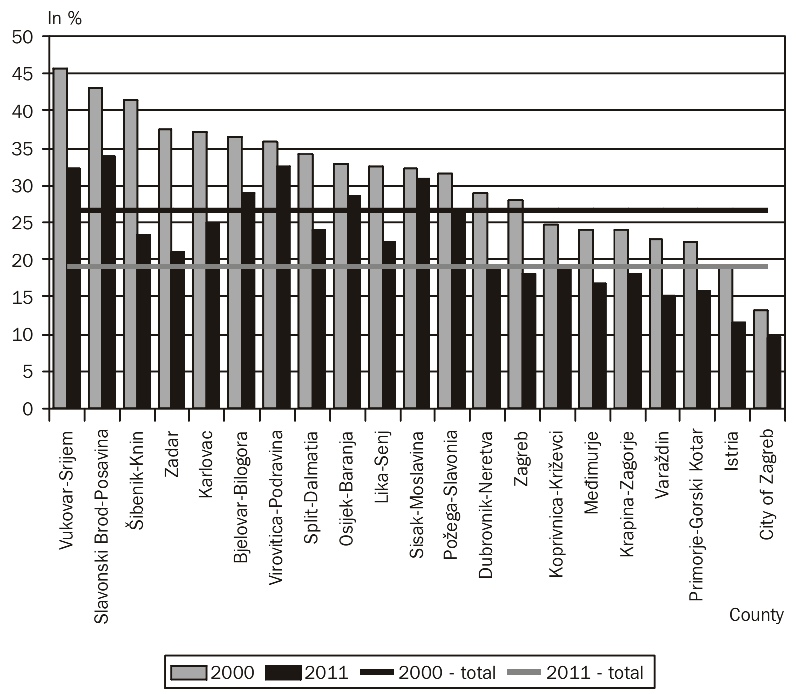
Table A1 **Data Description**						
Variable	**Description**	**Type***	**Period**	**Source**	**Mean**	**Std. Dev.**
M	Number of employed persons from the CES Registry during the month	Flow	Monthly	CES	538.838	498.130
U	Number of registered unemployed persons at the end of the previous (t-1) month	Stock	Monthly	CES	14174.79	12536.88
V	Posted vacancies during the month	Flow	Monthly	CES	514.403	595.357
U_new	Number of newly registered unemployed during the month	Flow	Monthly	CES	954.800	899.247
U_sum	Sum of the no. of unemp. at the end of the previous month and the no. of newly registered unemp. during the month	Stock + flow	Monthly	CES	15129.59	13338.36
V/U	Vacancy ratio (measure of labour market tightness)	Flow over stock	Monthly	CES	0.039	0.030
Reg_unrate	Regional unemployment rate (per counties) on 31 March each year	Stock	Yearly	CBS	0.244	0.088
M/delisted	Ratio of employed to delisted from the Registry for other reasons	Flow	Monthly	CES	0.898	1.319
M_female	Share of females in total flows to employment	Flow	Monthly	CES	0.528	0.085
U_female	Share of females in total unemployment	Stock	Monthly	CES	0.566	0.047
U_<24y	Share of youth (≤24 years) in total unemployment	Stock	Monthly	CES	0.215	0.056
U_12m+	Share of long-term unemployed (12 months or more) in total unemployment	Stock	Monthly	CES	0.547	0.079
U_w/o_experience	Share of persons without experience in total unemployment	Stock	Monthly	CES	0.221	0.066
U_primary_sector	Share of those previously employed in primary sector of economic activity in total unemployment	Stock	Monthly	CES	0.039	0.026
U_benefits	Share of unemployed persons receiving unemployment benefits in total unemployment	Stock	Monthly	CES	0.235	0.086
U_low skilled	Share of low-skilled (no schooling and uncompleted basic school + basic school) persons in total unemployment	Stock	Monthly	CES	0.349	0.077
U_high skilled	Share of high-skilled (non-university college + university and postgraduate degrees) persons in total unemployment	Stock	Monthly	CES	0.060	0.033
U_almp coverage	Share of persons in active labour market programmes in total number of unemployed in each regional office at the year end	Stock	Yearly	CES	0.049	0.041
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	0.003	0.001
Net income_pc	Net income p/c in a specific county	Stock	Yearly	MFIN/TA	18043.24	4986.01
Pop_density	Population density per km^2	Stock	Yearly	CBS	81.663	59.082

Notes: * - flow variable - *during the month;* stock variable - *end of the previous (t-1) month or end of the year.*

Table A2 **Distribution of Regional Offices**			
NUTS2	**County (NUTS3)**	**Regional office**	
Northwest Croatia	City of Zagreb	Zagreb	ZG
	Zagreb		
	Krapina-Zagorje	Krapina	KR
	Varaždin	Varaždin	VZ
	Koprivnica-Križevci	Križevci	KZ
	Međimurje	Čakovec	CK
Central and Eastern (Pannonian) Croatia	Bjelovar-Bilogora	Bjelovar	BJ
	Virovitica-Podravina	Virovitica	VT
	Požega-Slavonia	Požega	PZ
	Slavonski Brod-Posavina	Slavonski Brod	SB
	Osijek-Baranja	Osijek	OS
	Vukovar-Srijem	Vukovar	VU
		Vinkovci	VK
	Karlovac	Karlovac	KA
	Sisak-Moslavina	Sisak	SK
		Kutina	KT
Adriatic Croatia	Primorje-Gorski Kotar	Rijeka	RI
	Lika-Senj	Gospić	GS
	Zadar	Zadar	ZD
	Šibenik-Knin	Šibenik	SI
	Split-Dalmatia	Split	ST
	Istria	Pula	PU
	Dubrovnik-Neretva	Dubrovnik	DU

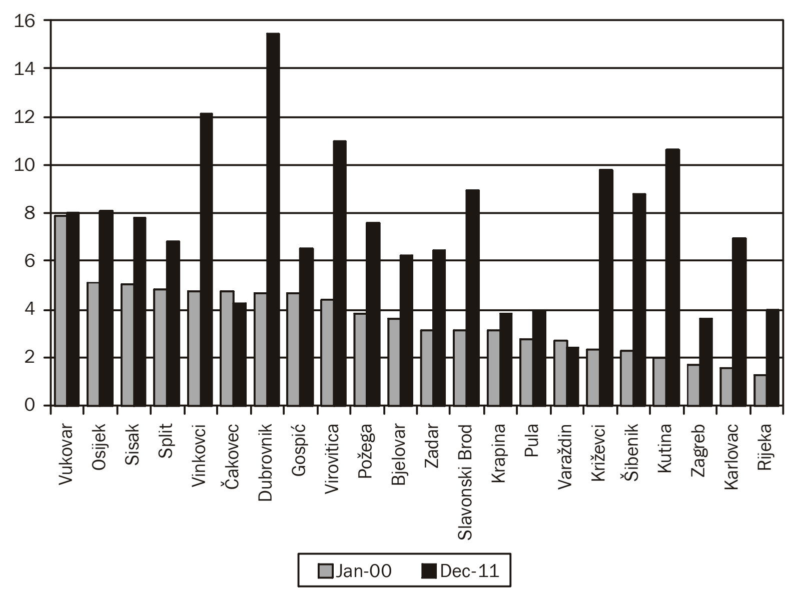
Appendix 2 – Additional Charts

Figure A1 **Regional Unemployment Rates**



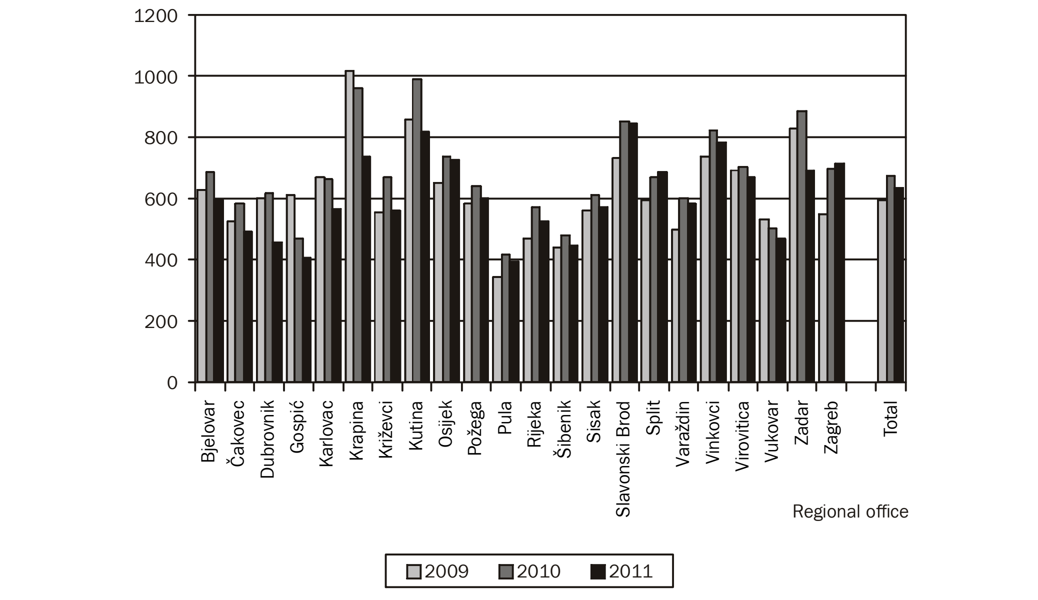
Note: Data relating to 31 March each year.
Source: CBS.

Figure A2 **Newly Registered Unemployed to Newly Registered Vacancies (U-new/V)**



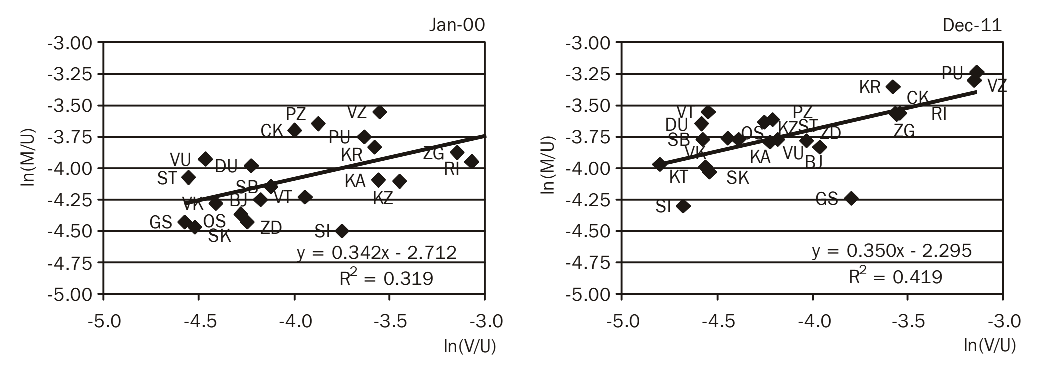
Source: Author's calculation based on CES data.

Figure A3 **Number of Registered Unemployed Persons per One Job Counsellor by Regional Office (2009-2011)**



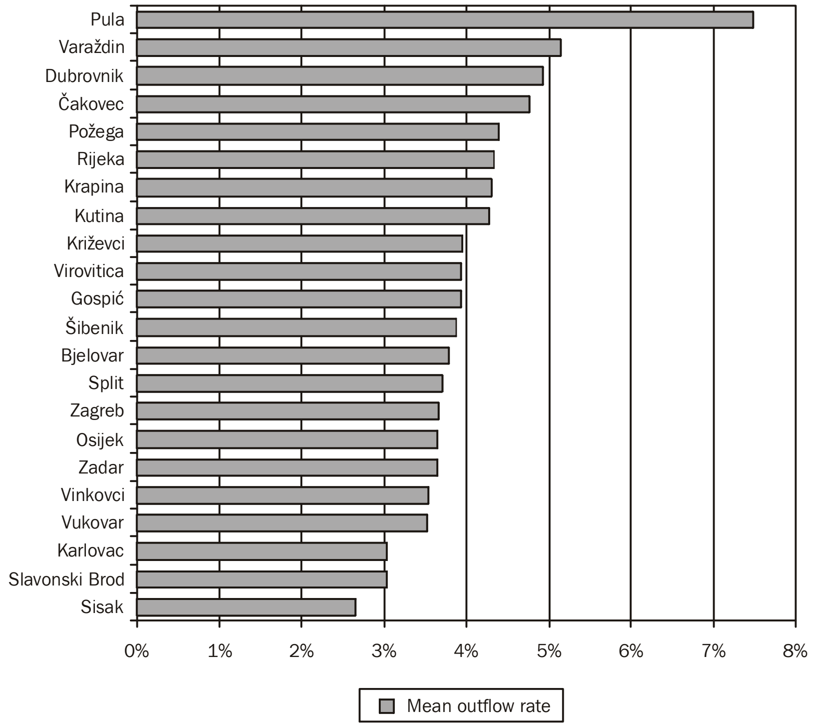
Source: Author's calculation based on CES data.

Figure A4 **Vacancy Ratio and Hiring Probabilities Across Regions – 2000m1 (left) and 2011m12 (right)**



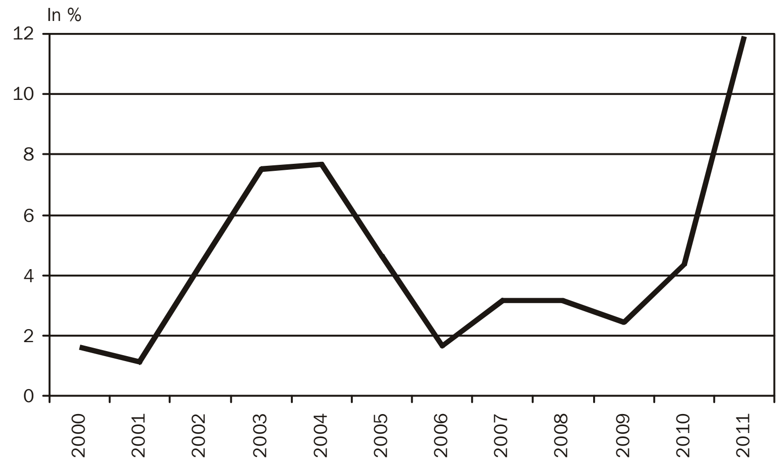
Notes: M/U - hiring probability (outflow rate); V/U - vacancy ratio.
Source: Author's calculation based on CES data.

Figure A5 **Mean Outflow Rate by Regional Office (2000m1-2011m12)**



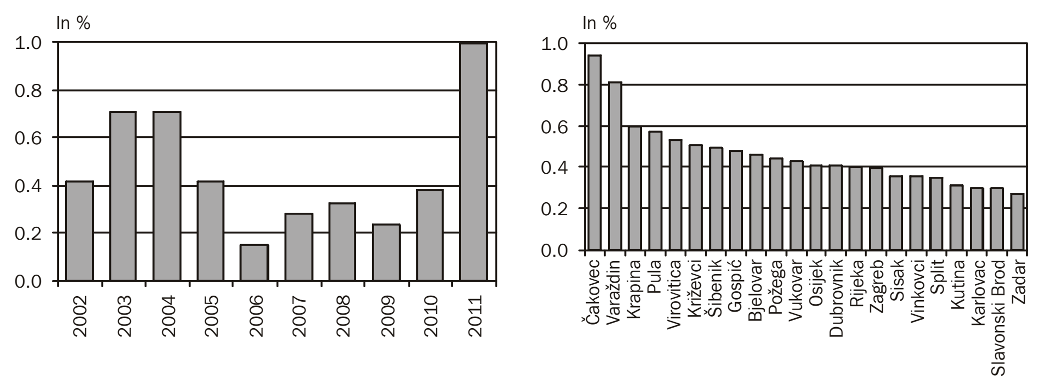
Note: Outflow rate - M/U.
Source: Author's calculation based on CES data.

Figure A6 **ALMP Coverage Rate Over the Years (2000-2011)**



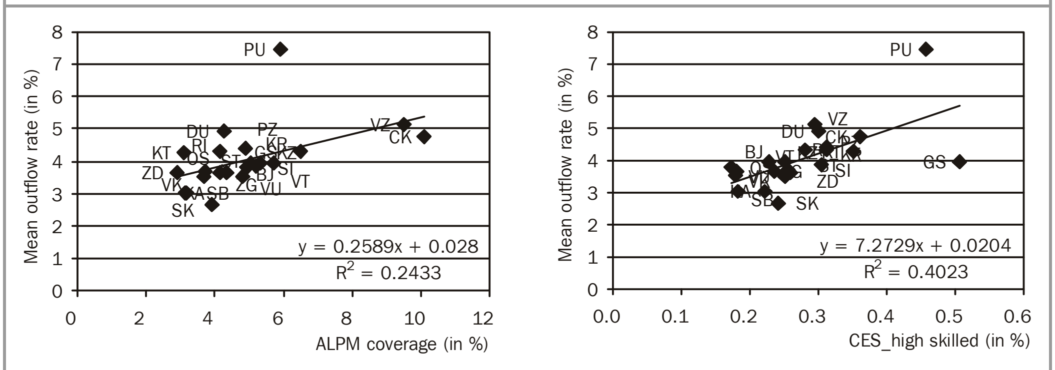
Note: ALMP coverage rate - the share of persons included in one of the active labour market programmes in total unemployment.
Source: Author's calculation based on CES data.

Figure A7 **Mean Share of the New Entrants into Active Labour Market Programmes in Total Number of Unemployed Over Years (left) and Across Regional Offices (right)**



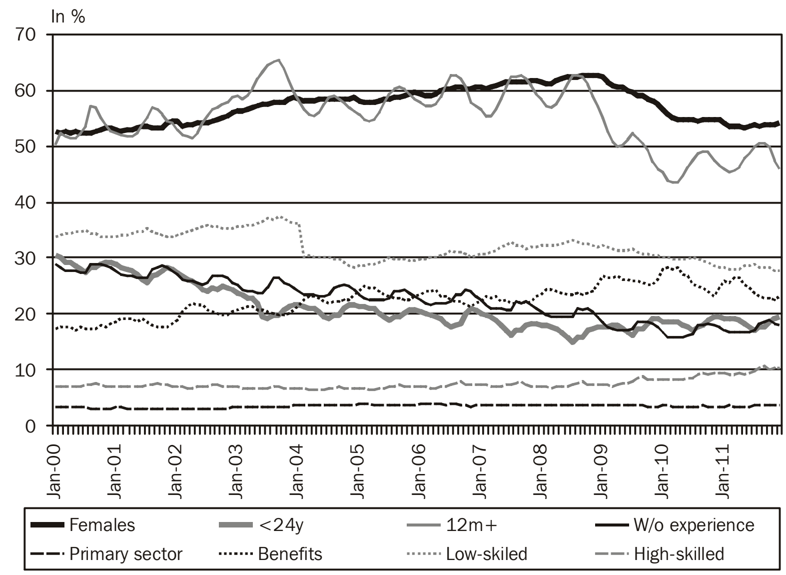
Source: Author's calculation based on CES data.

Figure A8 **Mean Outflow Rate and Number of Highly Skilled CES Employees per Number of the Unemployed (left) and ALMP Coverage Rate (right)**



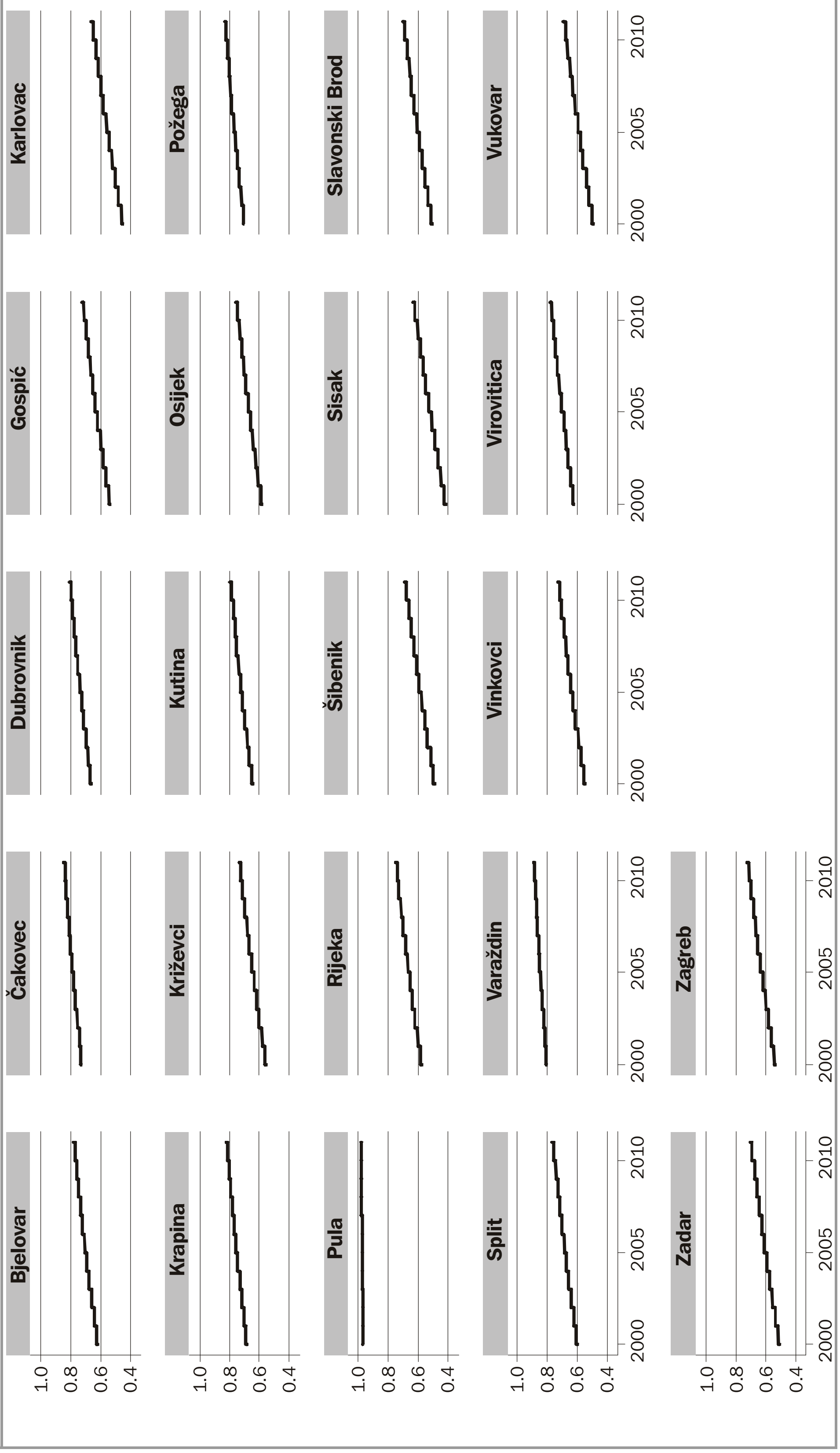
Notes: M/U - hiring probability (outflow rate); ALMP coverage rate - the share of persons included in one of the active labour market programmes in total unemployment; CES_high skilled - number of highly skilled employed at respective CES office over the number of registered unemployed.
Source: Author's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

Figure A9 **Unemployed Workers Main Characteristics (2000m1-2011m12)**



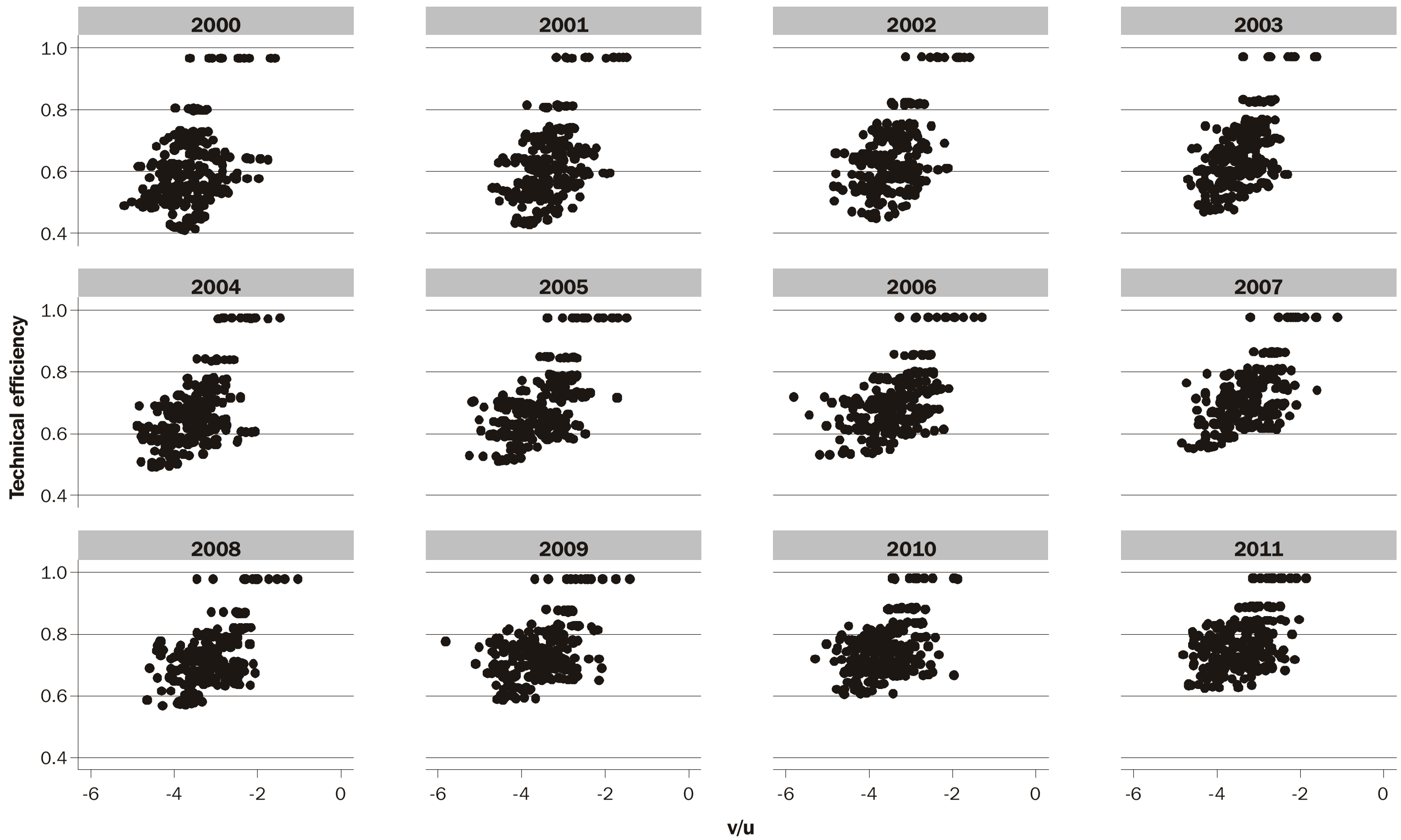
Source: CES.

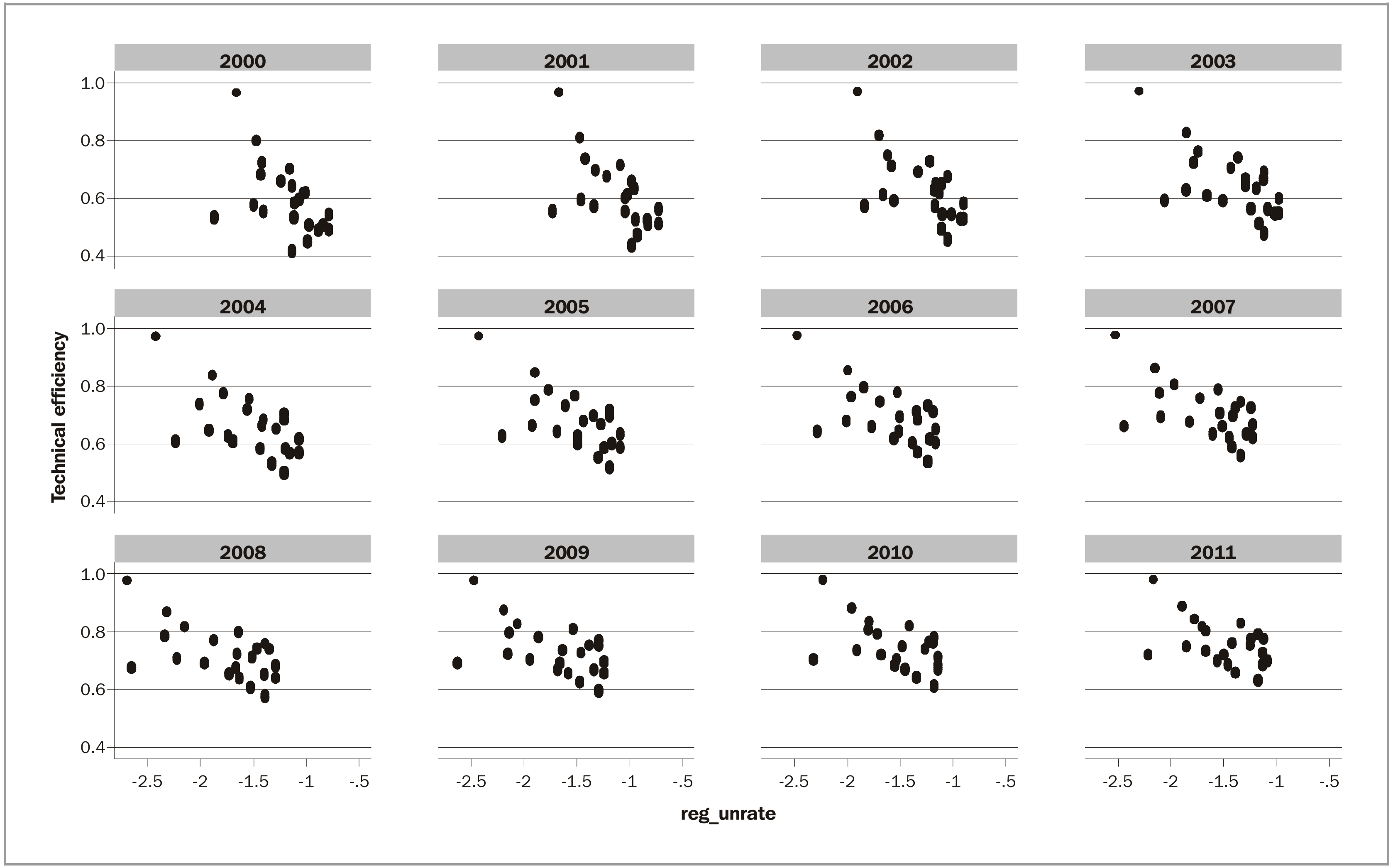
Figure A10 **Technical Efficiency Across Regional Offices Over the Years**



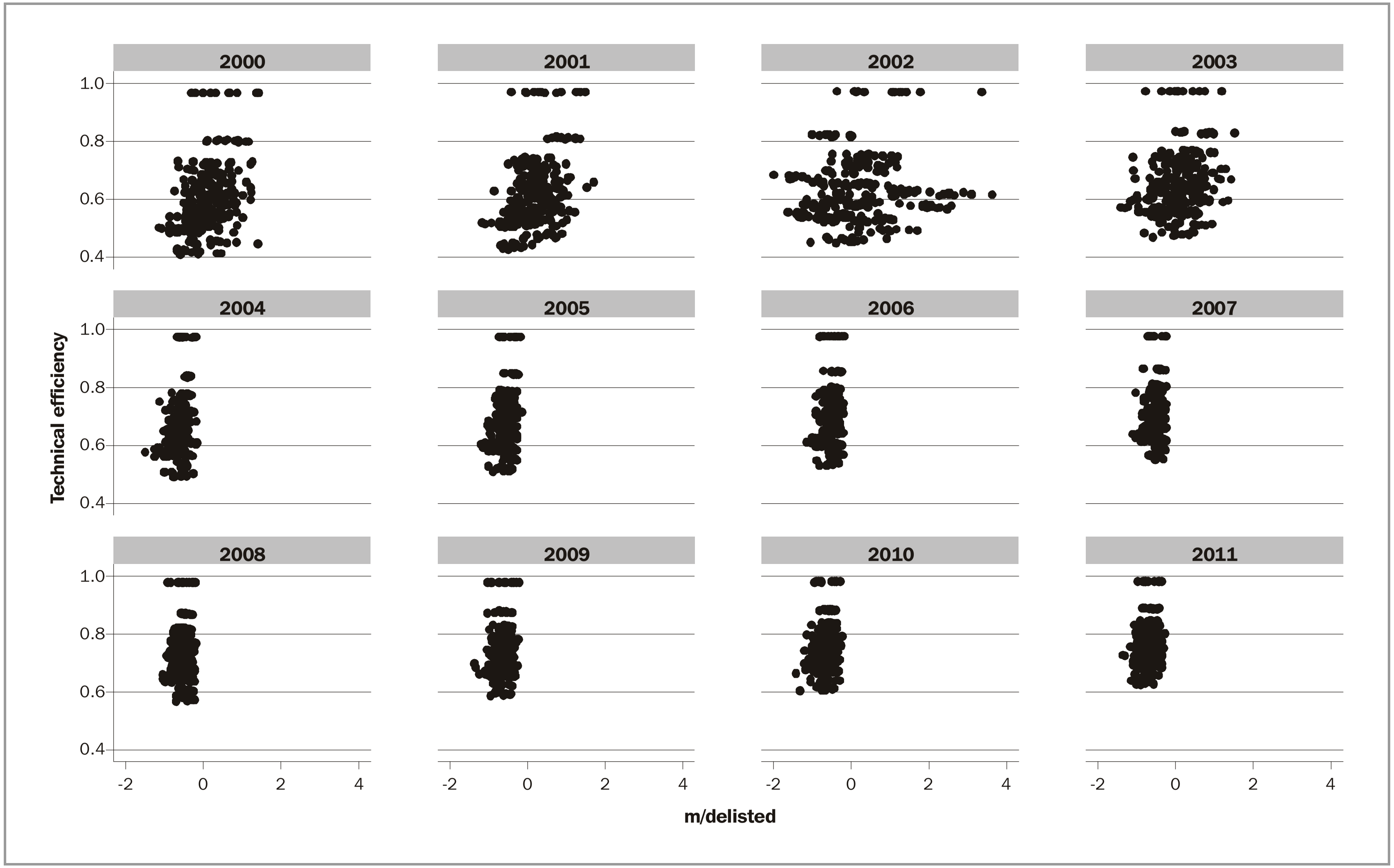
Source: Author's calculation based on CES data.

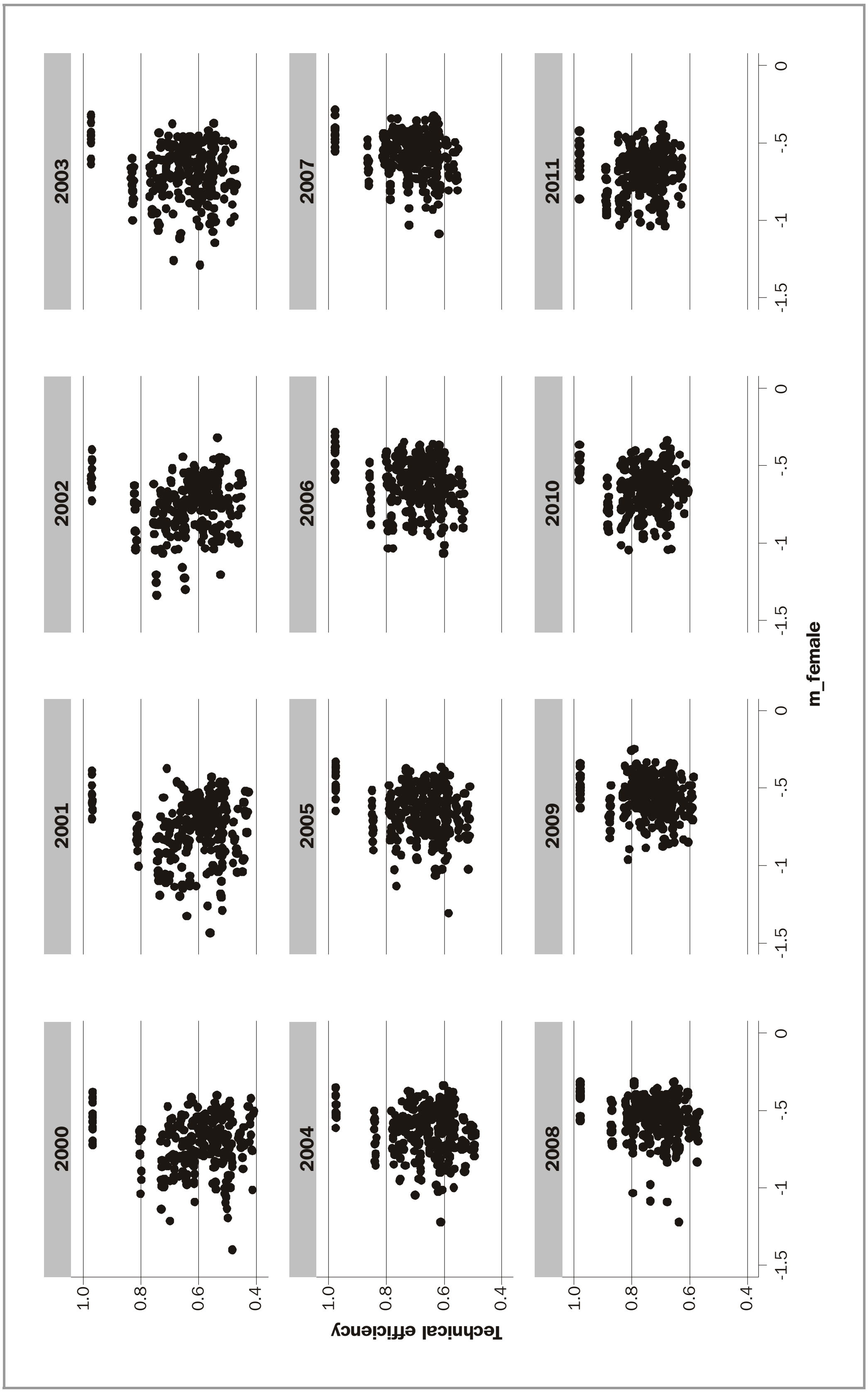
Figure A11 **Technical Efficiency vs. Explanatory Variables**

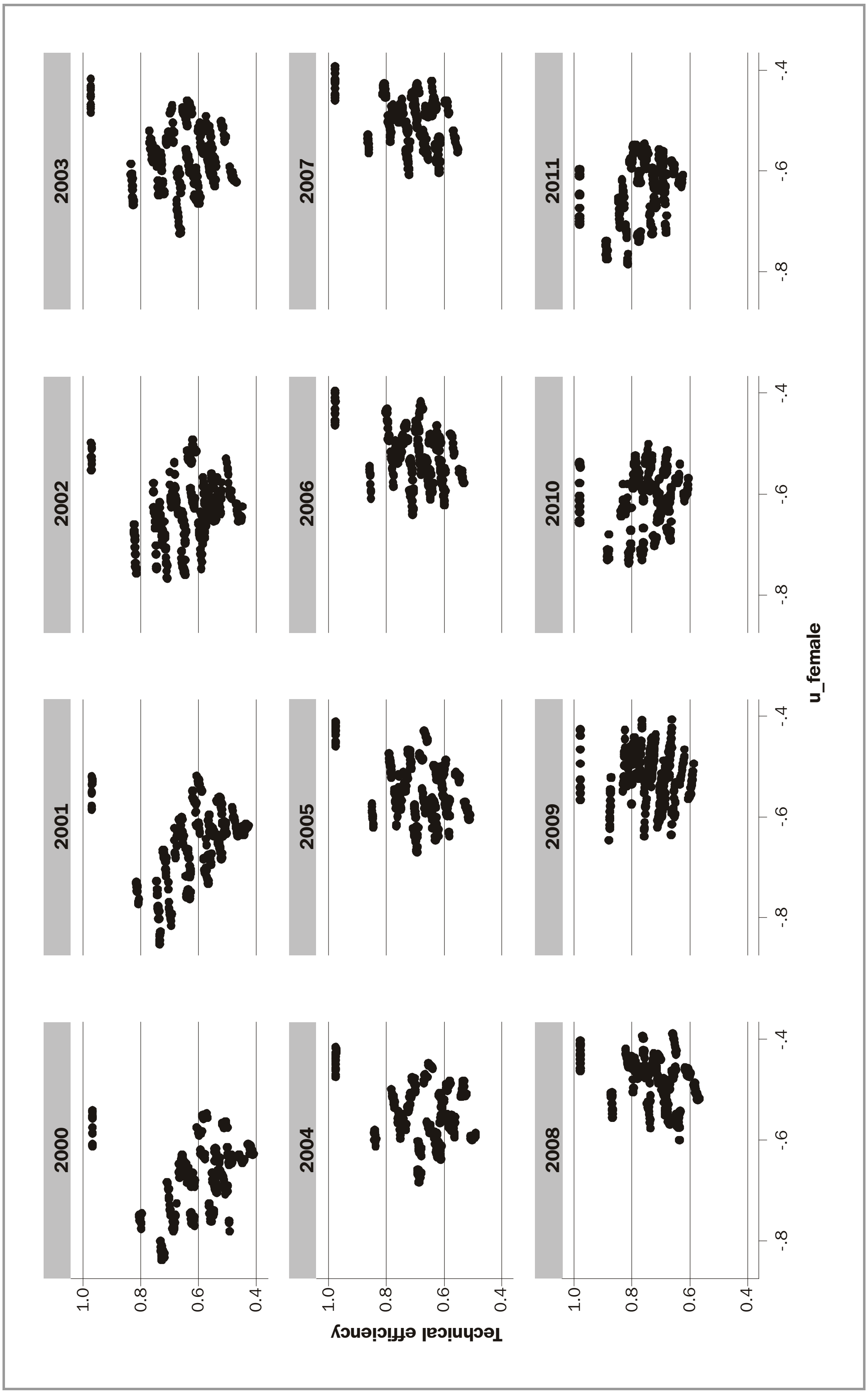


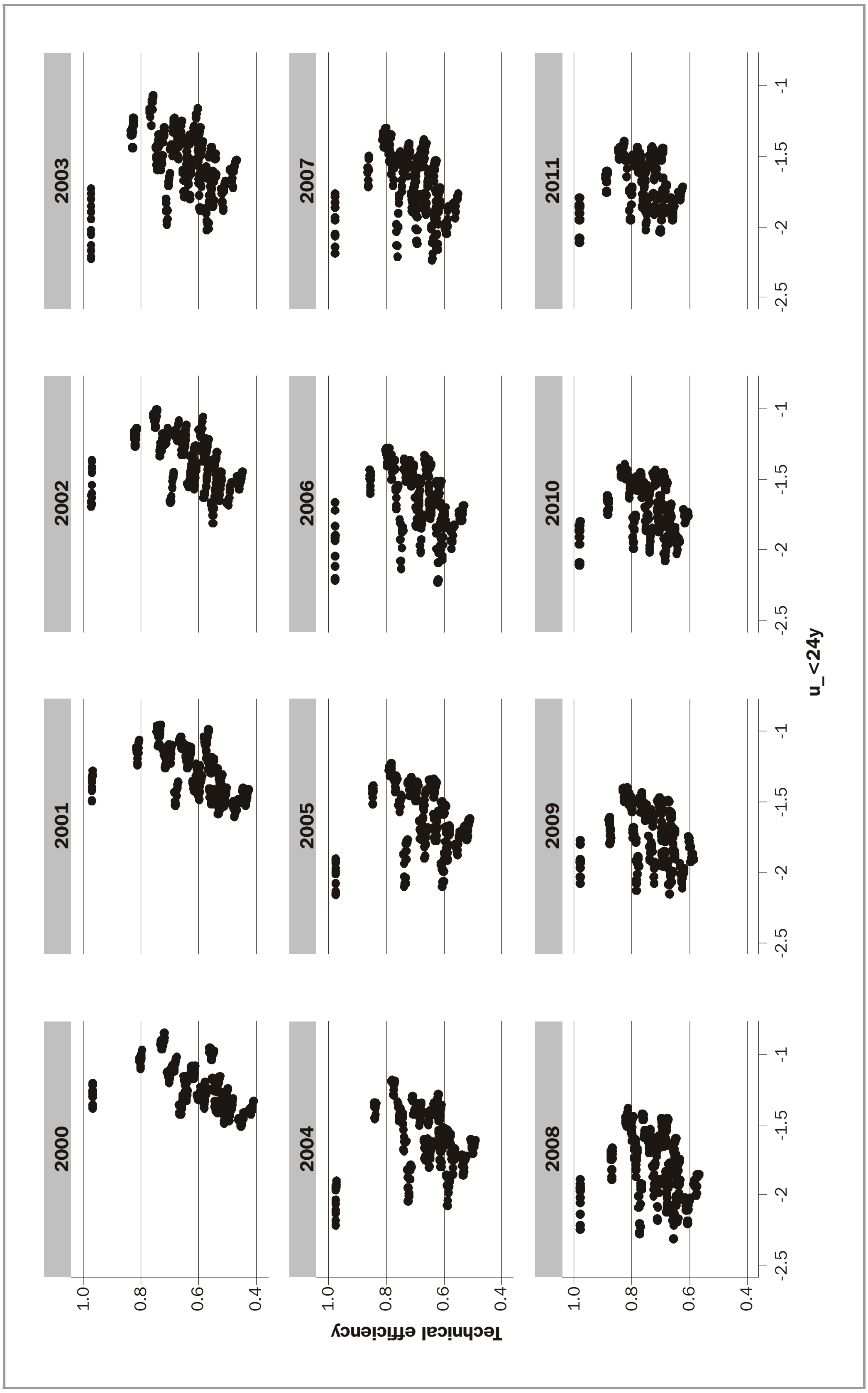


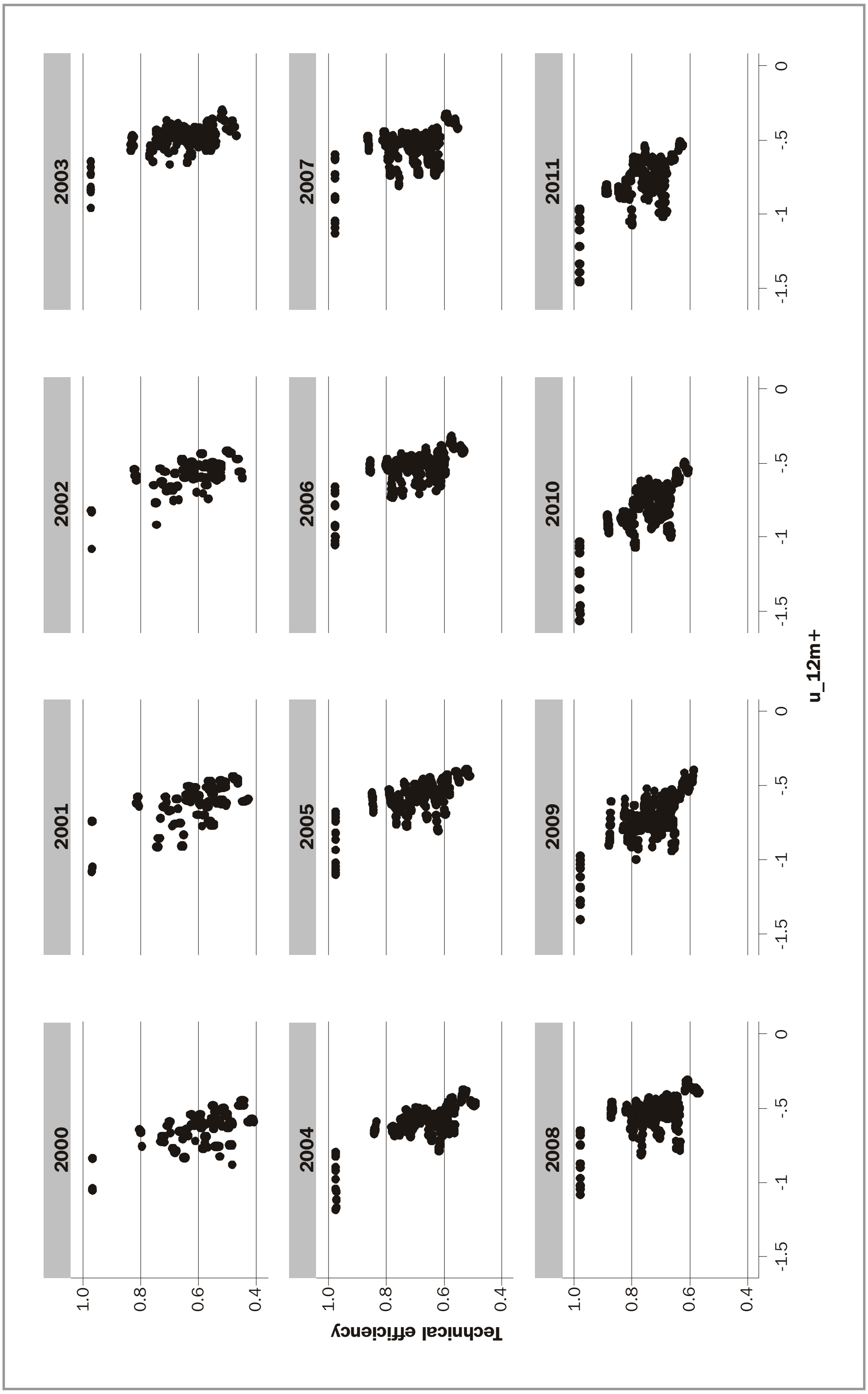
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
-2.5
-2
-1.5
-1
-.5
reg_unrate

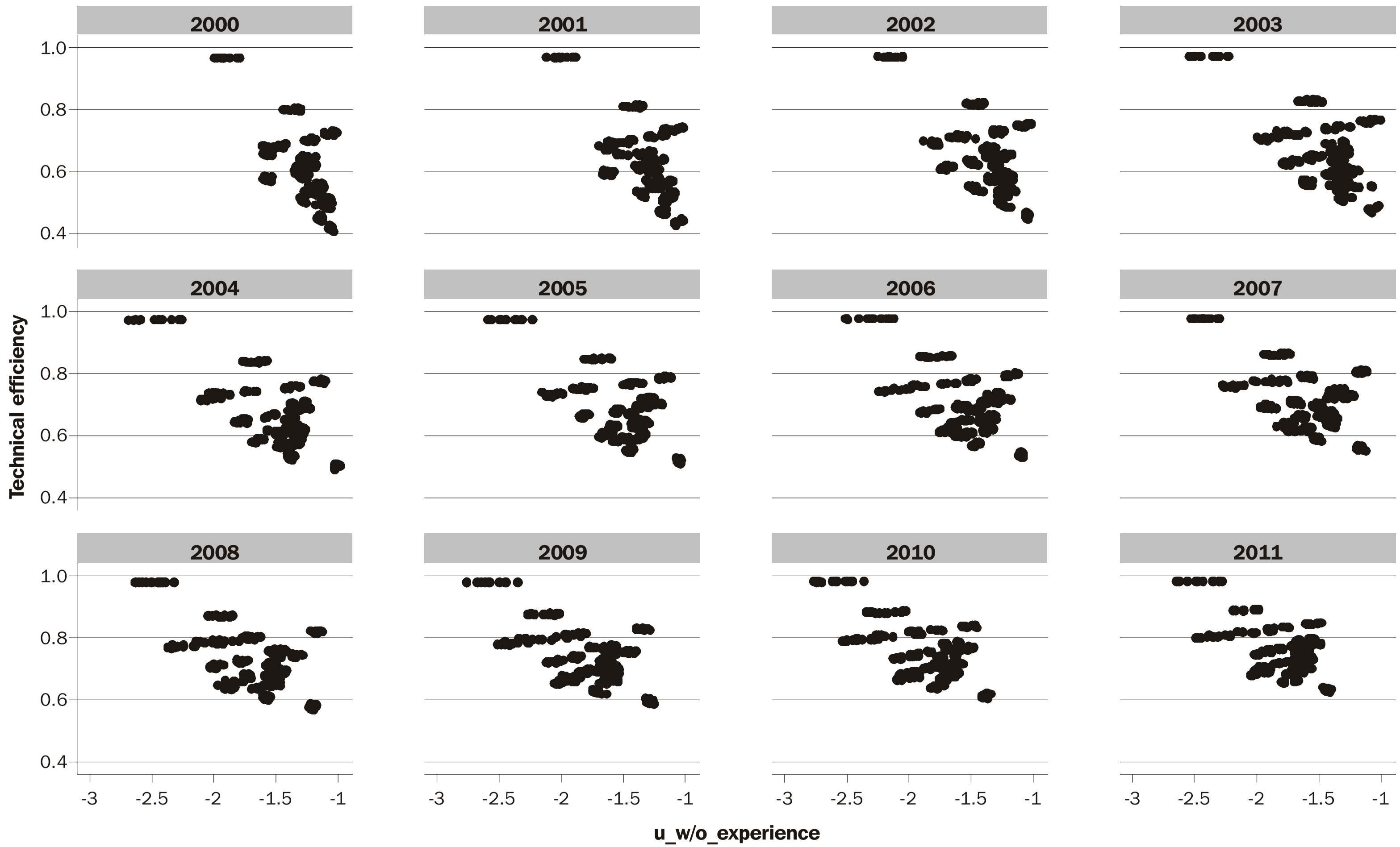

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
1.0
0.8
0.6
0.4
-2
0
2
4
Technical efficiency
m/delisted

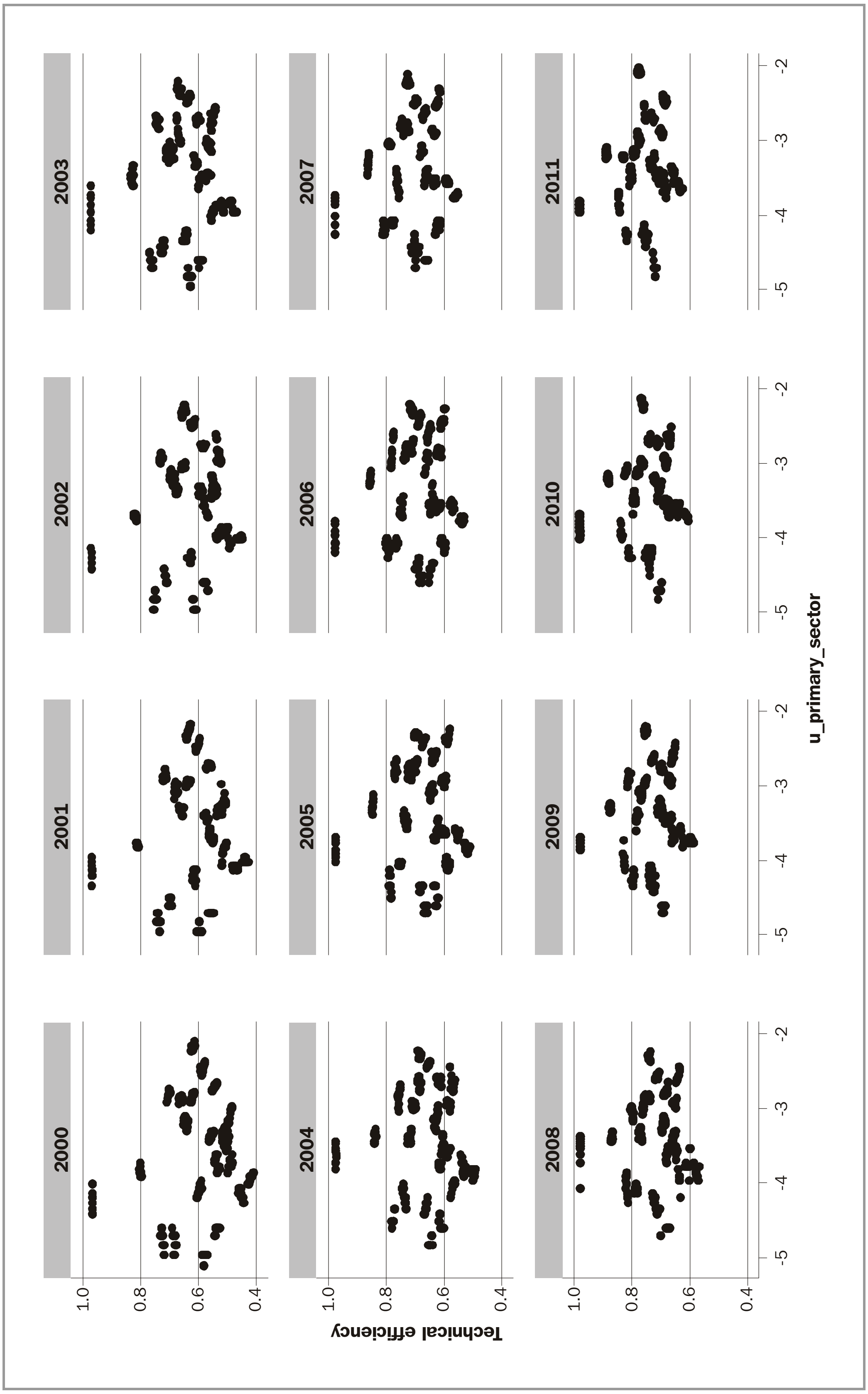

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
m_female

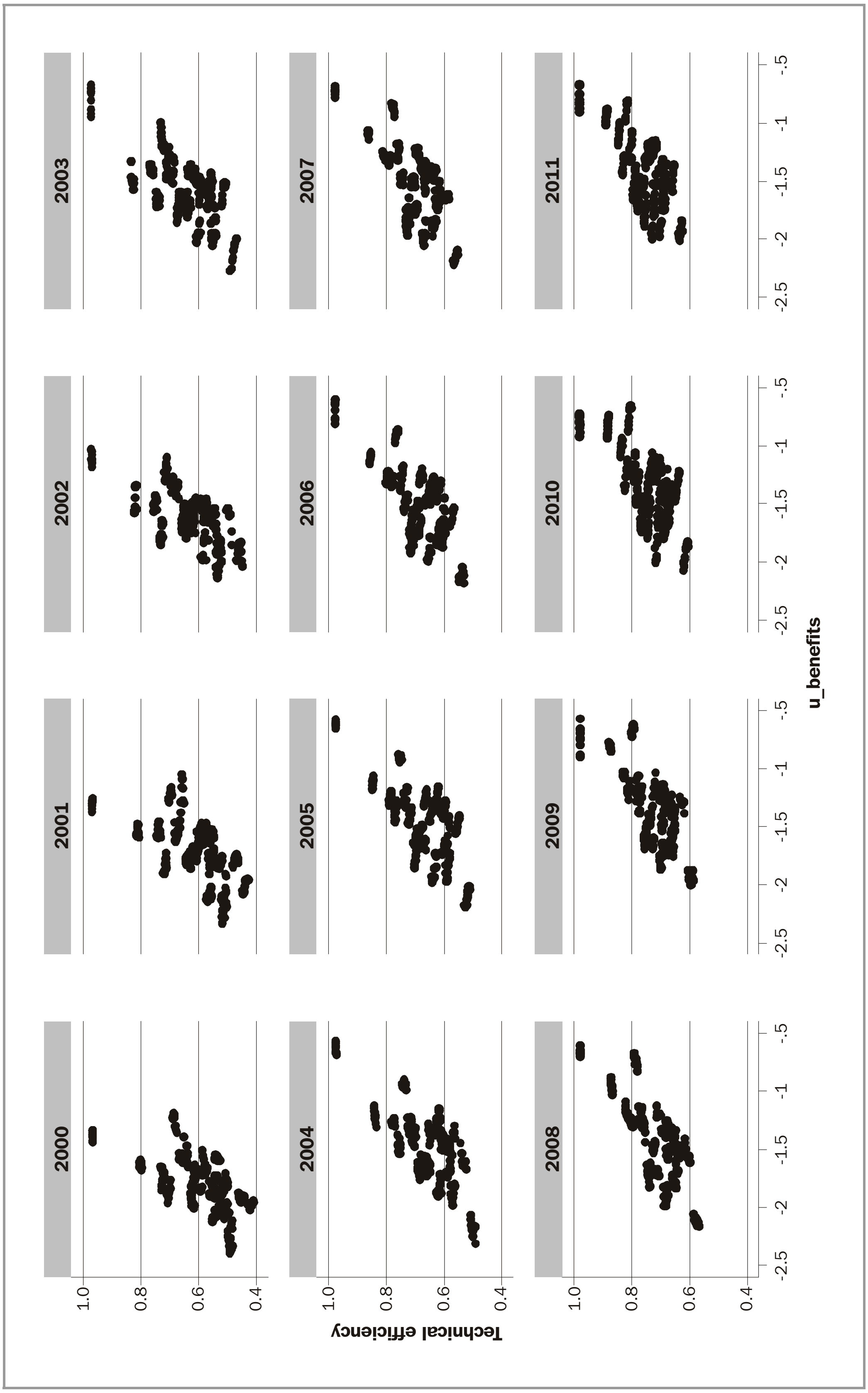

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
u_female
-.8
-.6
-.4

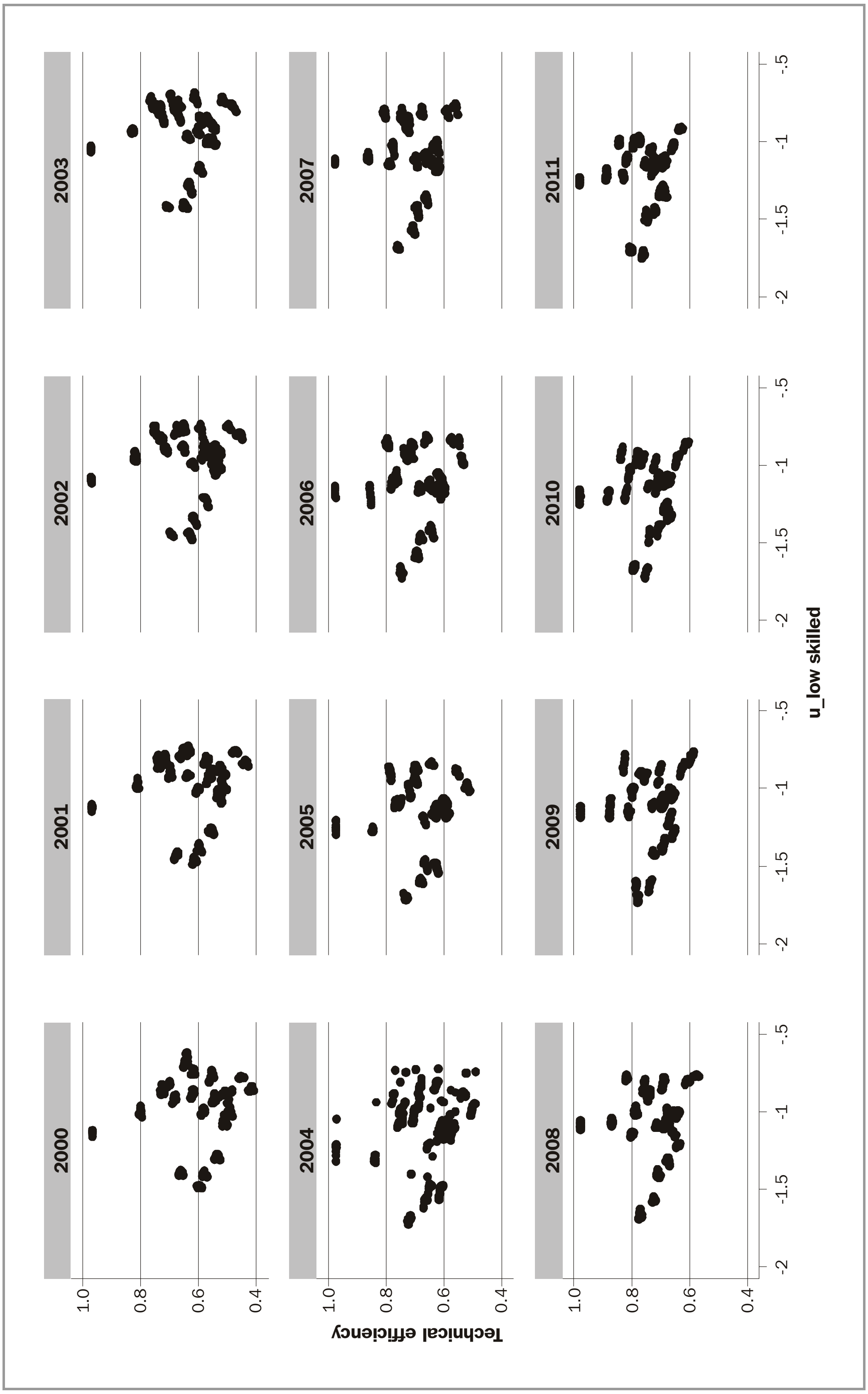

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
-2.5
-2
-1.5
-1
u_<24y

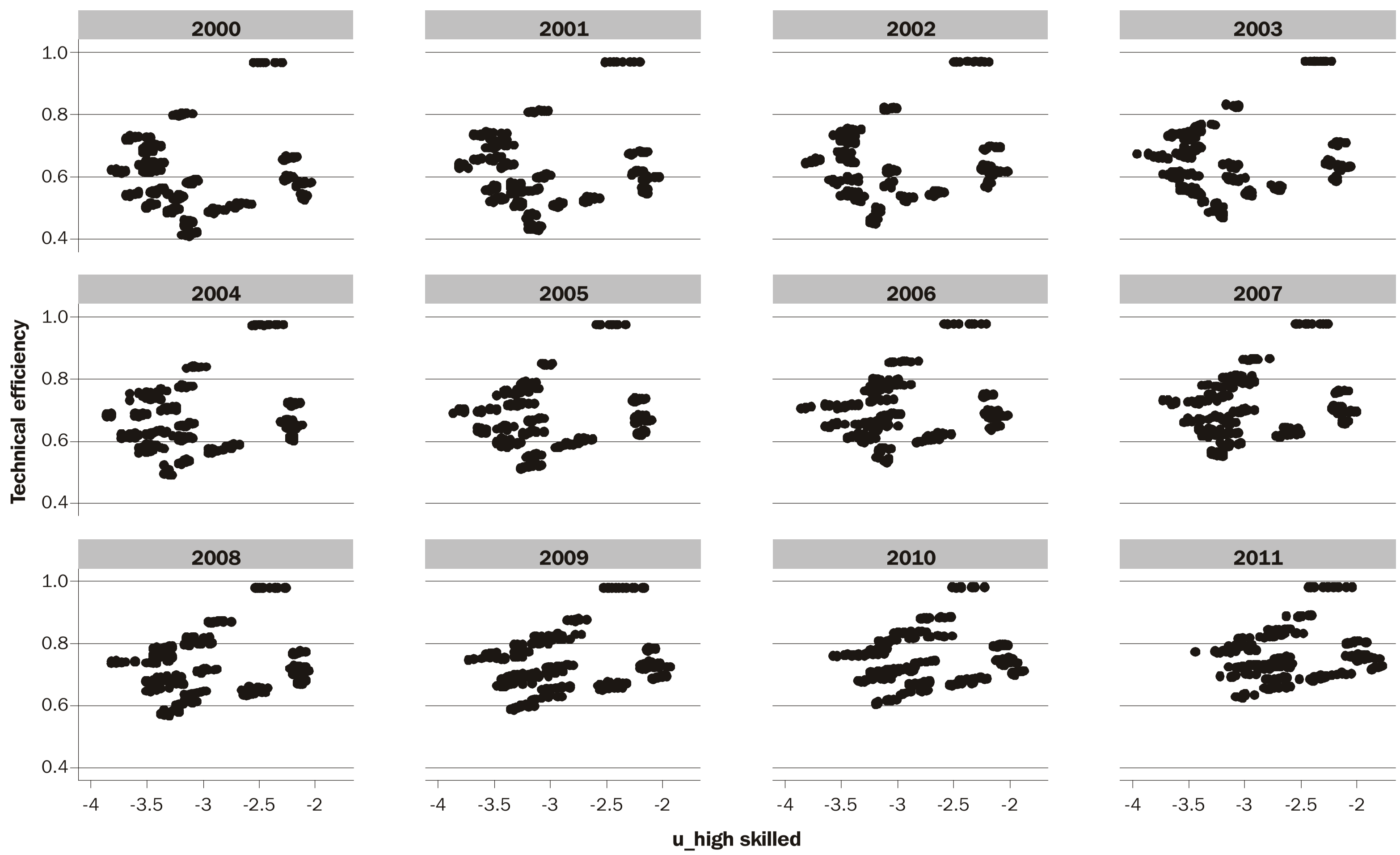

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
-1.5
-1
-.5
0
u_12m+

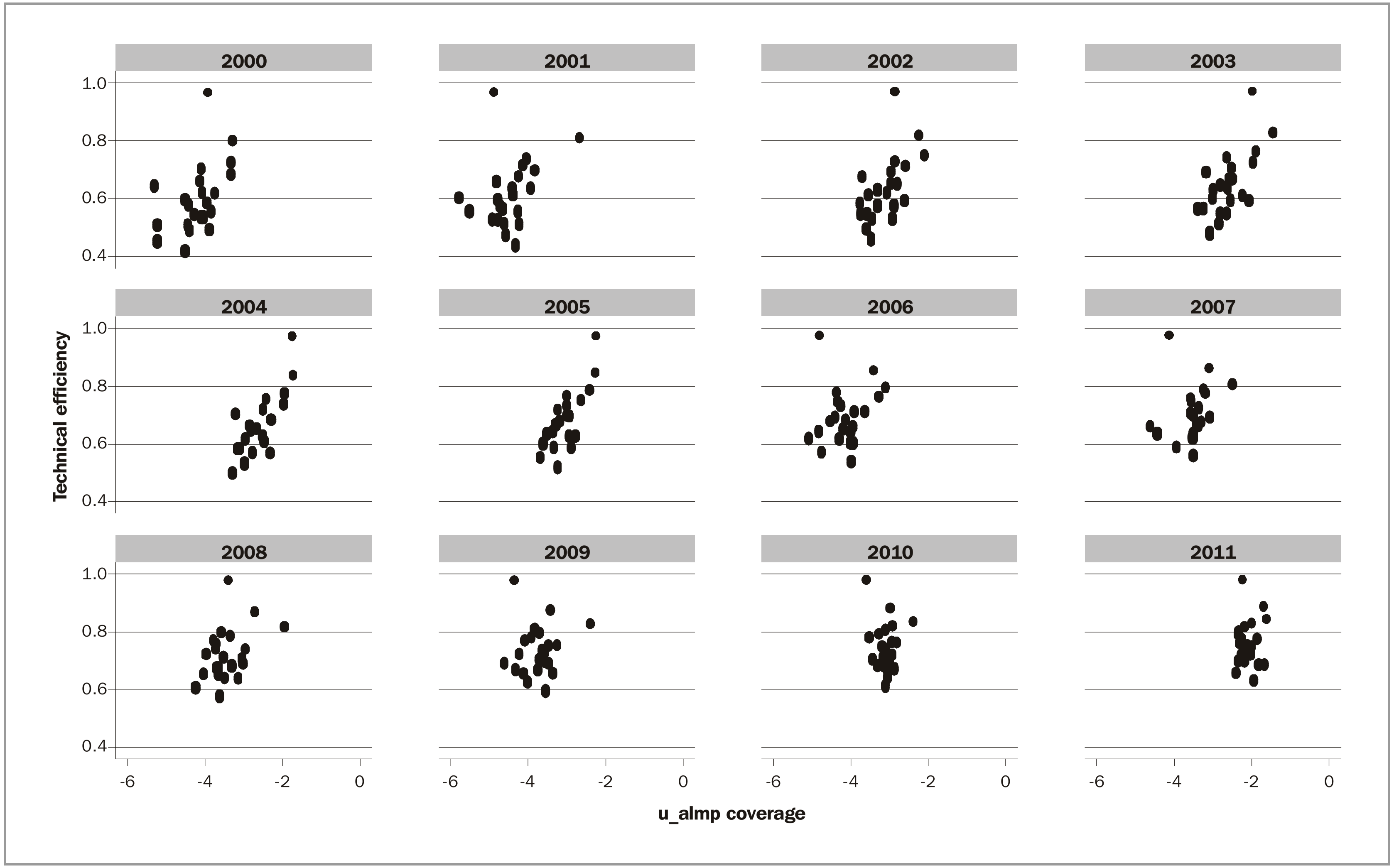

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
-3
-2.5
-2
-1.5
-1
u_w/o_experience

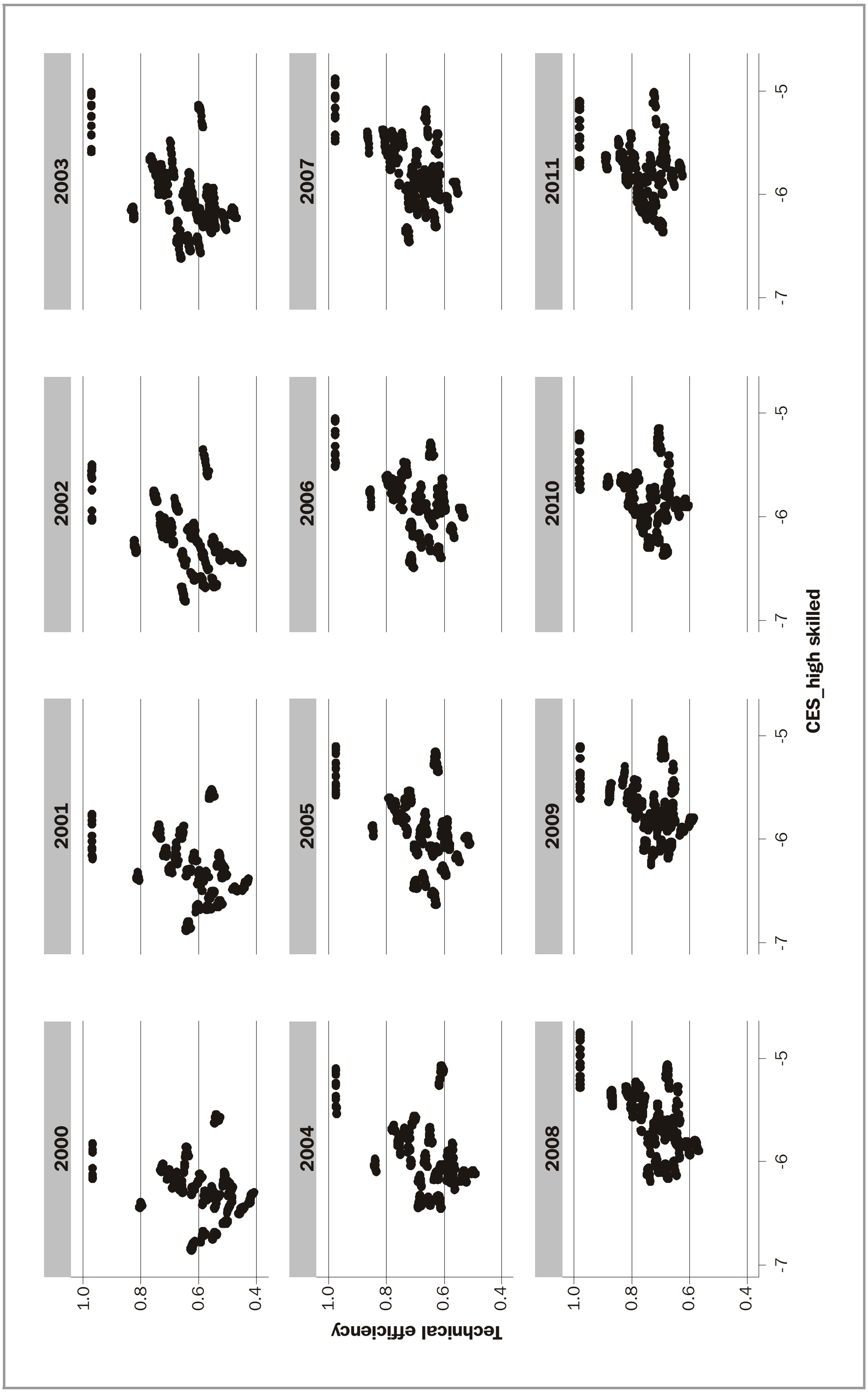

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
u_primary_sector
1.0
0.8
0.6
0.4
-5
-4
-3
-2

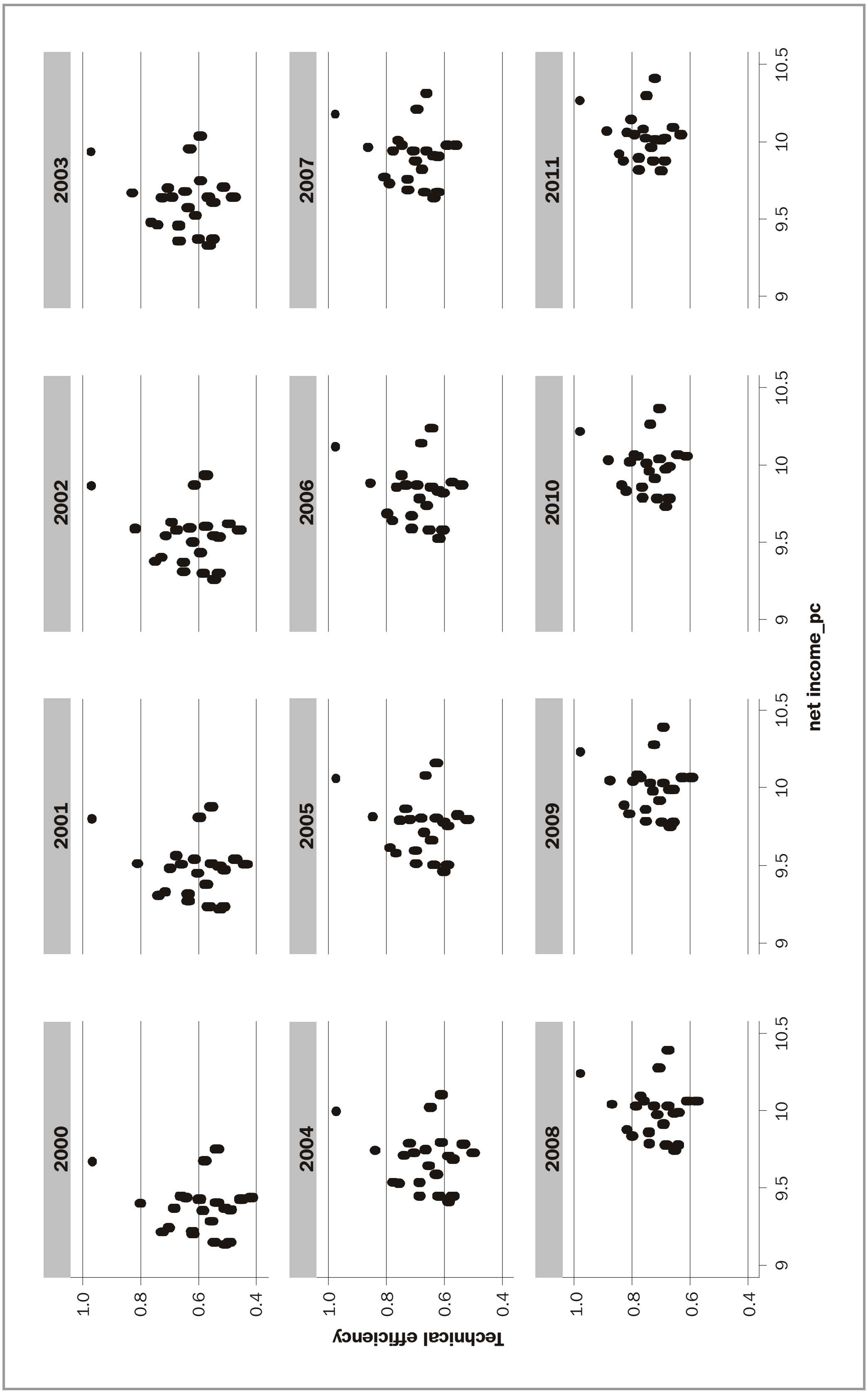

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
u_benefits
-2.5
-2
-1.5
-1
-.5


2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
u_low skilled
-2
-1.5
-1
-.5

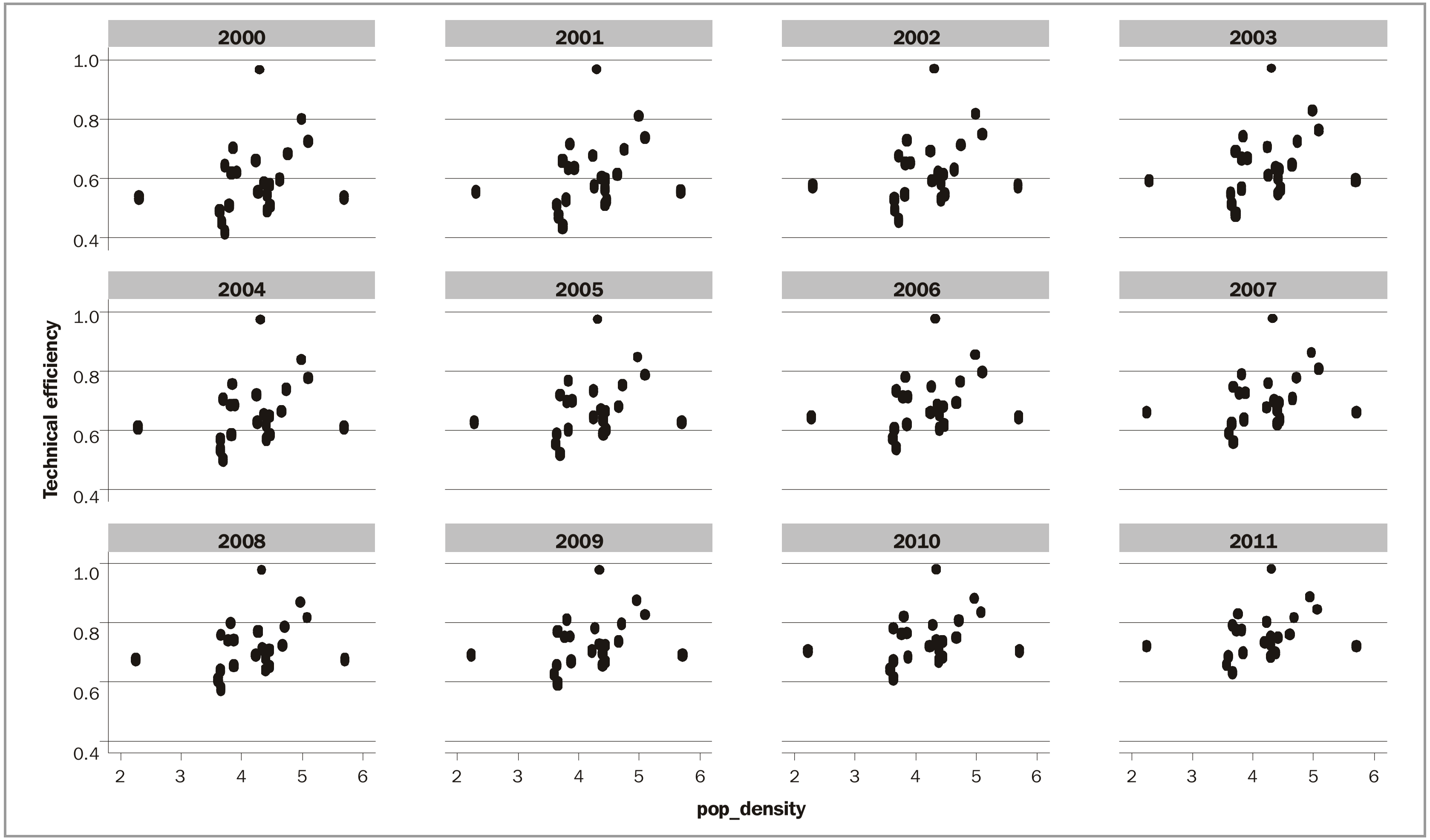

2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
1.0
0.8
0.6
0.4
Technical efficiency
-4
-3.5
-3
-2.5
-2
u_high skilled


2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
-6
-4
-2
0
u_almp coverage


2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
CES_high skilled
-7
-6
-5



2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
Technical efficiency
1.0
0.8
0.6
0.4
9
9.5
10
10.5
net income_pc



Note: Explanatory variables are in logarithmic form.
Source: Author's calculations based on CES data.

References

Aigner, Dennis, C. A. Knox Lovell and Peter Schmidt, 1977, "Formulation and estimation of stochastic frontier production function models", *Journal of Econometrics*, 6(1), pp. 21-37.

Altavilla, Carlo and Floro E. Caroleo, 2009, "Unintended Effects of National-based Active Labour Market Policies", IZA Discussion Papers, No. 4045, Bonn: Das Institut zur Zukunft der Arbeit, http://ftp.iza.org/dp4045.pdf.

Autor, David H., 2008, "The Economics of Labor Market Intermediation: An Analytic Framework", NBER Working Paper Series, No. 14348, Cambridge, MA: National Bureau of Economic Research, http://www.nber.org/papers/w14348.pdf.

Battese, George E. and Tim J. Coelli, 1993, "A stochastic frontier production function incorporating a model for technical inefficiency effects", University of New England Working Papers, No. 69, Armidale: University of New England, https://www.une.edu.au /bepp/working-papers/econometrics/emetwp69.pdf.

Battese, George E. and Tim J. Coelli, 1995, "A model for technical inefficiency effects in a stochastic frontier production function for panel data", *Empirical Economics*, 20(2), pp. 325-332.

Boeri, Tito and Jan van Ours, 2008, *The Economics of Imperfect Labour Markets*, Princeton, NJ: Princeton University Press.

Botrić, Valerija, 2004, "Regional Aspects of Unemployment in Croatia", *Croatian Economic Survey*, 6(1), pp. 77-95.

Botrić, Valerija, 2007, "Regional Labour Market Differences in Croatia: Evidence from the 2000-2005 Labour Force Survey Data", *Privredna kretanja i ekonomska politika*, 17(113), pp. 26-51.

Brown, Alessio J. G. and Johannes Koettl, 2012, "Active Labor Market Programs: Employment Gain of Fiscal Drain?", IZA Discussion Papers, No. 6880, Bonn: Das Institut zur Zukunft der Arbeit, http://ftp.iza.org/dp6880.pdf.

Calmfors, Lars, 1994, "Active labour market policy and unemployment – a framework for the analysis of crucial design features", *OECD Economic Studies*, No. 22, Paris: OECD, http://www.oecd.org/dataoecd/50/4/33936463.pdf.

CNB, 2010, *Bulletin*, No. 160, quarterly report, Zagreb: Croatian National Bank.

Coles, Melvyn G. and Barbara Petrongolo, 2002, "A Test Between Unemployment Theories Using Matching Data", CEPR Discussion Papers, No. 3241, London: Centre for Economic Policy Research, http://www.cepr.org/pubs/new-dps/dplist.asp?dpno=3241.

Croatian Employment Service (CES) official web page: http://www.hzz.hr.

Destefanis, Sergio and Raquel Fonseca, 2007, "Matching Efficiency and Labour Market Reform in Italy: A Macroeconometric Assessment", *Labour*, 21(1), pp. 57-84.

Dmitrijeva, Jekaterina and Mihails Hazans, 2007, "A Stock-Flow Matching Approach to Evaluation of Public Training Program in a High Unemployment Environment", *Labour*, 21(3), pp. 503-540.

Dur, Robert A.J., 1999, "Mismatch between unemployment and vacancies in the Dutch labour market", *Applied Economics*, 31(2), pp. 237-244.

Fahr, René and Uwe Sunde, 2002, "Estimations of Occupational and Regional Matching Efficiencies Using Stochastic Production Frontier Models", IZA Discussion Papers, No. 552, Bonn: Das Institut zur Zukunft der Arbeit, ftp://repec.iza.org/RePEc /Discussionpaper/dp552.pdf.

Fahr, René and Uwe Sunde, 2006, "Regional dependencies in job creation: an efficiency analysis for Western Germany", *Applied Economics*, 38(10), pp. 1193-1206.

Ferragina, Anna Maria and Francesco Pastore, 2006, "Regional Unemployment in the OST literature" in Floro E. Caroleo and Sergio Destefanis, eds., *The European Labour Market: Regional Dimensions*, pp. 33-87, Heidelberg: Physica-Verlag, Springer Company.

Greene, William, 2005a, "Fixed and Random Effects in Stochastic Frontier Models", *Journal of Productivity Analysis*, 23(1), pp. 7-32.

Greene, William, 2005b, "Reconsidering heterogeneity in panel data estimators of the stochastic frontier model", *Journal of Econometrics*, 126(2), pp. 269-303.

Greg, Paul and Barbara Petrongolo, 2005, "Stock-flow Matching and the Performance of the Labor Market", *European Economic Review*, 49(8), pp. 1987-2011.

Hagen, Tobias, 2003, "Three Approaches to the Evaluation of Active Labour Market Policy in East Germany Using Regional Data", ZEW Discussion Paper, No. 03-27, Mannheim: Zentrum für Europäische Wirtshaftsforschung, ftp://ftp.zew.de/pub/zew-docs/dp/dp0327.pdf.

Hujer, Reinhard, Uwe Blien, Marco Caliendo and Christopher Zeiss, 2002, "Macroeconometric Evaluation of Active Labour Market Policies in Germany - A

Dynamic Panel Approach Using Regional Data", IZA Discussion Papers, No. 616, Bonn: Das Institut zur Zukunft der Arbeit, ftp://repec.iza.org/RePEc/Discussionpaper /dp616.pdf.

Ibourk, Aomar, Benedicte Maillard, Sergio Perelman and Henri R. Sneessens, 2001, "The Matching Efficiency of Regional Labour Markets: A Stochastic Production Frontier Estimation, France 1990-1995", IZA Discussion Papers, No. 339, Bonn: Das Institut zur Zukunft der Arbeit, ftp://repec.iza.org/RePEc/Discussionpaper/dp339.pdf.

Ibourk, Aomar, Benedicte Maillard, Sergio Perelman and Henri R. Sneessens, 2004, "The Matching Efficiency of Regional Labour Markets: A Stochastic Production Frontier Estimation, France: 1990-1994", *Empirica*, 31(2), pp. 1-25.

Jeruzalski, Tomasz and Joanna Tyrowicz, 2009, "(In)Efficiency of Matching – The Case of A Post-transition Economy", MPRA Paper, No. 16598, http://mpra.ub.unimuenchen.de /16598/1/MPRA_paper_16598.pdf .

Kuddo, Arvo, 2009, "Employment Services and Active Labor Market Programs in Eastern European and Central Asian Countries", The World Bank SP Discussion Papers, No. 0918, Washington, DC: The World Bank, http://siteresources.worldbank.org /SOCIALPROTECTION/Resources/SP-Discussion-papers/Labor-Market-DP/0918.pdf.

Meeusen, Wim and Julien van den Broeck, 1977, "Efficiency Estimation from Cobb-Douglas Production Functions With Composed Error", *International Economic Review*, 18(2), pp. 435-444.

Mian, Atif R. and Amir Sufi, 2012, "What explains high unemployment? The aggregate demand channel", NBER Working Papers, No. 17830, Cambridge, MA: National Bureau of Economic Research, http://www.nber.org/papers/w17830.pdf?new_window=1.

Munich, Daniel and Jan Svejnar, 2009, "Unemployment and Worker-Firm Matching Theory and Evidence from East and West Europe", The World Bank Policy Research Working Paper Series, No. 4810, Washington, DC: The World Bank, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1327279.

Obadić, Alka, 2004, "Regionalna analiza učinkovitosti hrvatskog tržišta rada", *Ekonomski pregled*, 55(7-8), pp. 531-556.

Obadić, Alka, 2006a, "Theoretical and empirical framework of measuring mismatch on a labour market", *Zbornik Ekonomskog fakulteta u Rijeci*, 24(1), pp. 55-80.

Obadić, Alka, 2006b, "Influence of regional mismatch on the employment process in selected transition countries", *Ekonomski pregled*, 57(1-2), pp. 3-30.

Petrongolo, Barbara and Christopher A. Pissarides, 2001, "Looking into the Black Box: A Survey of the Matching Function", *Journal of Economic Literature*, 39(2), pp. 390-431.

Pissarides, Christopher A., 2000, *Equilibrium Unemployment Theory*, Cambridge, MA: MIT Press.

Puljiz, Jakša and Sanja Maleković, 2007, "Regional Income and Unemployment Disparities in Croatia" in Zlatan Reić and Maja Fredotović, eds., Seventh International Conference on Enterprise in Transition: Enterprise in Transition Proceedings, CD ROM, Split: Faculty of Economics, University of Split, http://bib.irb.hr/datoteka /332497.Full_Paper_Disparities.pdf.

Rutkowski, Jan, 2003, "Analiza i prijedlozi poboljšanja tržišta rada u Hrvatskoj", *Financijska teorija i praksa*, 27(4), pp. 495-513.

Šergo, Zdravko, Amorino Poropat and Jasmina Gržinić, 2009, "Croatia's Beveridge Curve and Estimation of Natural Rate of Unemployment", *Ekonomska istraživanja*, 22(3), pp. 29-47.

Tomić, Iva and Polona Domadenik, 2012, "Matching, adverse selection and labour market flows in a (post)transition setting: the case of Croatia", *Post-communist economies*, 24(1), pp. 39-72.

Tyrowicz, Joanna and Piotr Wójcik, 2010, "Active Labour Market Policies and Unemployment Convergence in Transition", *Review of Economic Analysis*, 2(1), pp. 46-72.

Wang, Hung-Jen and Chia-Wen Ho, 2010, "Estimating fixed-effect panel stochastic frontier models by model transformation", *Journal of Econometrics*, 157(2), pp. 286-296.

Wang, Hung-Jen and Peter Schmidt, 2002, "One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency levels", *Journal of Productivity Analysis*, 18(2), pp. 129-144.

Warren, Ronald S., 1991, "The Estimation of Frictional Unemployment: A Stochastic Frontier Approach", *The Review of Economics and Statistics*, 73(2), pp. 373-377.

World Bank, 2010, "Croatia: Social Impact of the Crisis and Building Resilience Report", No. 55111-HR, Washington, DC: The World Bank.

Popis objavljenih Radnih materijala EIZ-a / Previous issues in this series

2012

EIZ-WP-1203 Jelena Budak, Ivan-Damir Anić and Edo Rajh: *Public Attitudes towards Surveillance and Privacy in Western Balkans: The Case of Serbia*

EIZ-WP-1202 Valerija Botrić: *Intra-industry Trade between the European Union and Western Balkans: A Close-up*

EIZ-WP-1201 Jelena Budak and Edo Rajh: *Corruption Survey in Croatia: Survey Confidentiality and Trust in Institutions*

2011

EIZ-WP-1104 Jelena Budak and Edo Rajh: *Corruption as an Obstacle for Doing Business in the Western Balkans: A Business Sector Perspective*

EIZ-WP-1103 Alfio Cerami and Paul Stubbs: *Post-communist Welfare Capitalisms: Bringing Institutions and Political Agency Back In*

EIZ-WP-1102 Marina Tkalec: *The Dynamics of Deposit Euroization in European Post-transition Countries: Evidence from Threshold VAR*

EIZ-WP-1101 Jelena Budak, Ivan-Damir Anić and Edo Rajh: *Public Attitudes Towards Surveillance and Privacy in Croatia*

2010

EIZ-WP-1003 Marin Božić: *Pricing Options on Commodity Futures: The Role of Weather and Storage*

EIZ-WP-1002 Dubravka Jurlina Alibegović and Sunčana Slijepčević: *Performance Measurement at the Sub-national Government Level in Croatia*

EIZ-WP-1001 Petra Posedel and Maruška Vizek: *The Nonlinear House Price Adjustment Process in Developed and Transition Countries*

2009

EIZ-WP-0902 Marin Božić and Brian W. Gould: *Has Price Responsiveness of U.S. Milk Supply Decreased?*

EIZ-WP-0901 Sandra Švaljek, Maruška Vizek and Andrea Mervar: *Ciklički prilagođeni proračunski saldo: primjer Hrvatske*

2008

EIZ-WP-0802 Janez Prašnikar, Tanja Rajkovič and Maja Vehovec: *Competencies Driving Innovative Performance of Slovenian and Croatian Manufacturing Firms*

EIZ-WP-0801 Tanja Broz: *The Introduction of the Euro in Central and Eastern European Countries – Is It Economically Justifiable?*

2007

EIZ-WP-0705 Arjan Lejour, Andrea Mervar and Gerard Verweij: *The Economic Effects of Croatia's Accession to the EU*

EIZ-WP-0704 Danijel Nestić: *Differing Characteristics or Differing Rewards: What is Behind the Gender Wage Gap in Croatia?*

EIZ-WP-0703 Maruška Vizek and Tanja Broz: *Modelling Inflation in Croatia*

EIZ-WP-0702 Sonja Radas and Mario Teisl: *An Open Mind Wants More: Opinion Strength and the Desire for Genetically Modified Food Labeling Policy*

EIZ-WP-0701 Andrea Mervar and James E. Payne: *An Analysis of Foreign Tourism Demand for Croatian Destinations: Long-Run Elasticity Estimates*

ISSN 1846-4238