Success or Waste of Taxpayer Money? Impact Assessment of Rural Development Programs in Hungary

Abstract

The effectiveness of support directed to less developed regions is a timely question halfway through the 2014-2020 programming period. This paper describes an analysis of the impact of development support on the wellbeing of Hungarian LAU1 regions between 2008 and 2013. The aim is to measure the overall impact of all of the Rural Development Funds, covering all measures within the program. Three indices of local wellbeing are used: the multi-dimensional, local-variables-based Rural Development Index which measures the overall level of regional development. Furthermore, two simple, migration-based indices are used, as proxies for perceived quality of life. Propensity score matching and difference-in-difference estimation techniques are employed to evaluate the impact of subsidies. Irrespective of the way the amount of support is calculated, or the measure of local wellbeing or methodology employed, the impact is generally not significant, or even negative. This casts doubt on the effectiveness of Rural Development Policy.

Keywords: Regional Development Funds, Impact assessment, LAU1 regions, Propensity Score Matching, Difference in difference

Introduction

It is difficult to overestimate the role of Regional Development Policies (RDPs) in developed economies. Seventy-five percent of the territory of OECD countries is classified as rural, and on average a quarter of the total population live in these areas (OECD, 2006). In the past decades, the global economy has experienced unprecedented growth in agricultural productivity – itself a laudable outcome – yet, despite lavish subsidies, this has led to a fall in both agricultural employment and the importance of agriculture to national economies (at least when developed economies are considered). Whilst agricultural output amounts to roughly 2 percent of OECD nations' GDP, the vast majority of rural land is used for agricultural purposes (e.g. 96 percent in the EU25, including forests). However, in the EU25 only 13 percent of rural labour is employed in agriculture – the OECD average is 10 percent, producing a gross value-added of only 6 percent (OECD, 2006). Whilst the aims of EU Common Agricultural Policy (CAP) with respect to agricultural production were laid down in the 1958 Treaty of Rome, and, albeit with significant amendments, have been applied until now, the importance of rural and indeed regional development – i.e. that not directly connected to production – was only recognized in the 1970s. Thus the modern CAP (AGENDA 2000) shifted the support system towards a more integrated rural development policy, creating the European Agricultural Model (Renting et al., 2009) whose primary aim is to promote a viable and liveable rural environment rather than maximize agricultural output (for further discussion, see for example 'The new rural paradigm: policies and governance', OECD 2006). It was a key revelation that, besides production, a nation's agriculture contributes to the creation or preservation of a number of important values such as landscape, traditions-customs, social structures and environmental protection. The most important pre-condition of the creation/preservation of the abovementioned values is the existence of a sufficiently large active rural population. This highlights the importance of policies designed to slow rural-to-urban migration, and reverse the continual increase in the average age of rural inhabitants. The economic output of Hungarian rural areas is 50 percent less than the national average, and three times less than that of the predominantly urban output (for more detail about sectoral and regional differences in the EU and OECD countries, see for example, Bollman et al. (2005), Copus et al. (2006), or Terluin et al. (2011)). To sum up, besides the economic and agricultural perspective, rural areas are also very important in terms of population, preserving landscape traditions and environmental protection. In addition, New Member States (NMS) are more rural than Old Member States (OMS), and the income gap between rural and urban areas is more predominant in NMS than OMS. Within the European Union (EU), Hungary is one of the biggest beneficiaries of Rural Development Program (RDP) payments – at least when per capita transfers are considered. In the 2007 – 2013 programming period, EUR 3.8 billion was spent, whilst for the 2014 – 2020 period EUR 4.2 billion (of which EUR 740 million in the form of national co-funding) is earmarked for this purpose. The question that naturally arises is: do these substantial transfers make a difference? The European Commission's mandatory ex-ante, mid-term and ex-post program evaluations – based on monitoring a set of (partial) indicators and qualitative assessment – fail to provide an answer because of the need for uniformity and comparability across Member States. On the other hand, academic research with respect to the evaluation of RDP measures is rather scanty. Most papers focus on the impact of agricultural policy on labour markets or rural income distribution (e.g. Olper at al. 2014; Breustedt and Glauben, 2007; Elek et al., 2010; Esposti, 2007; Petrick and Zier, 2012; Swinnen and Van Herck, 2010) or focus on the farm level (e.g. the impact of RDP investment support, Medonos et al. 2012, or Pufahl and Weiss, 2009 on the evaluation of farm programs). One possible reason for the scarcity of relevant literature is that the policy evaluation or impact assessment of RDP is a rather complicated issue since complex notions are hard to quantify, whilst all relevant aspects of the impact should be captured in a transparent and easy-to-handle fashion. There are two key issues here: first, the problem of applying partial indicators (such as number of projects supported, area supported, change in employment, value of investments realized, and GDP change – see Michalek and Zarnekow

2012 for a critical review); and second, the existence of a counterfactual situation which excludes the possibility of making a before-and-after comparison. Moreover, GDP data is not available at a disaggregated level, thus the analyst is basically left with unemployment levels/rates or taxes. The often employed naïve approaches to the impact evaluation of RDP such as simple case studies or partial indicators do not even attempt to address the counterfactual situation (Terluin and Roza, 2010). Generally, the most important drawback of partial measures is the lack of clear causality between partial measures and RDP (the problem of making a distinction between the impact of RDP and other exogenous factors). These issues may, however, be solved by use of a complex Rural Development Indicator, RDI, originally proposed by Michalek and Zarnekow (2012) and counterfactual analysis. We follow this approach, and construct an 'objective' Quality of life (QoL) index, complemented by two 'subjective', internal-migration-based QoL indices, along with the idea that, regardless of objectively computed local development scores, people tend to migrate when the perceived QoL is higher. In contrast to Michalek (2012), who investigates only the impact of the SAPARD programmes in Poland and in Slovakia between 2002 and 2005, we focus on the 2008-2013 period which covers all regional development policy measures and try to answer the following simple question: have the significant amount of Rural Development funds that have been distributed had any measurable impact? The rest of the paper is organised as follows: in the next section we detail the methodology and data we use. In Part Four, we focus on empirical results. The paper is concluded in Section Five.

Data and methodology

Hungary, covering an area of 93,000 km^2 and with an approximate population of 9.8 million, has been a Central European EU member state since 2004. The country has three NUTS 2 regions, and 20 NUTS 3 ones (19 counties plus the capital city, Budapest). On a Local Administrative Unit level (LAU1, formerly NUTS4) there are 174 small regions, composed of 3,164 administratively independent settlements. We were in a position to employ a highly disaggregated dataset of yearly data with respect to these administratively independent settlements, which we believe contributes to the unique nature of this research. The T-STAR database of the Hungarian Central Statistical Office was obtained from the CERS-HAS databank (http://adatbank.krtk.mta.hu/adatbazisok___tstar). This source of data is designed for use in spatial studies and consists of several hundred variables relating to demographics, public health, education, pollution, unemployment, social care, economic entities, infrastructure, commerce and hospitality, tourism, culture, housing stock, municipal aid, municipal budgets, agriculture and personal income tax. These variables are available for the 2007-2013 period for all 3,166 administratively independent Hungarian settlements. An internal migration database was provided by the Hungarian Central Statistical Office. Data about development funds for the period 2008-2013 was taken from the Information Systems of National Regional Development. Using total payments per locality, we created three subsidy indicators: total support, support per km^2, and support per capita in LAU1 regions.

Our empirical strategy consisted of three steps:

1. First, we composed a local, 'objective' development indicator based on the wealth of variables available in the T-STAR database. There are several potential approaches to this. The most prominent methods are factor/principal component analysis (i.e. 'let the data choose') and the construction of an indicator based on selected variables. Factor and Principal Component Analysis have been used by Michalek and Zarnekow (2012) to evaluate the SAPARD programme in Poland and Slovakia. In the Hungarian context, the research of Lukovics and Kovács (2008) and Lukovics (2009) uses factor and PCA analysis and employs the same TSTAR dataset as used in this paper to compute regional competitiveness indices. Further, Fertő et al. (paper under revision) employs similar techniques to derive the dominant factors responsible for regional development levels for the period 2002-2008. Since factor analysis also requires a great deal of manual – and one may argue subjective – selection between a large number of variables in order to avoid (amongst other things) multicollinearity and matrix singularity issues, whilst the factors themselves are hard to characterise, we chose the second approach; i.e. the construction of an RDI index by selecting variables. Moreover, to ensure the future policy applicability of our results, we applied an improved version of the methodology the Hungarian Government uses to target less developed localities (Hungarian Official Journal - Gov. Order. No. 105/2015. IV. 23.) Thus, we created four groups of variables, each describing specific aspects of local development and quality of life, as follows:

- Group 1: Social and demographic conditions (e.g. mortality rate, birth rate, migration, nursery - kindergarten - schools per appropriate age group, migration, etc.)

- Group 2: Habitation and living conditions (e.g. houses built as percentage of existing stock, number of cars per 1000 habitants, taxes paid per capita, etc.)

- Group 3: Local economy and employment (e.g. businesses per 1000 habitants, various measures of unemployment such as total, per level of education, long-term, etc.)

- Group 4: Infrastructure and environment (e.g. houses connected to a centralised sewage system from total number of houses, natural gas, electricity, running water usage normalised with either population or housing stock, services provided by local government, distance in minutes to LAU1 centre, etc.).

Each individual local variable that enters one of the groups was scaled according to the following eq. 1:

$$var_{i,j,norm} = \frac{var_{i,j} - \min(var_{i,j})}{max(var_{i,j}) - \min(var_{i,j})} * 100 \tag{1}$$

The weighted sum of four Groups 1 - 4 resulted in an 'objective' quality of living indicator we denote as rdi.

Group indicators are the arithmetic average of composed scaled variables (variables with negative impact such as mortality, unemployment, travel time entered with a negative sign). Once the locality-specific group variables were calculated, the data was aggregated[1] to 174 small regions, corresponding to the Hungarian LAU1 (formerly NUTS4) regions. The database was then merged with the National Regional Development data to form a balanced panel of 174 regions and 6 years.

2. Second, we calculated the region- and year-specific net migration variable and relative net migration variables:

net_migr = (inmigr – outmigr) (2)

rel_migr = (inmigr-outmigr)/pop (3)

as proxy variables for 'subjective' quality of living in a given region. These in turn were also merged with the National Regional Development database.

3. Once the 'objective' and 'subjective' indices were calculated, we were in a position to actually analyse the impact of RDPs on LAU1 regions. Whilst in standard policy analysis settings, the sample-average treatment effects cannot be calculated because only one of the two possible outcomes for each individual (or region in our case) can be observed, this issue was solved by the RDI which allowed for the creation of the counterfactual. Following the insights from impact analysis literature, we thus adopted the counterfactual framework developed by Rosenbaum and Rubin (1983). We employed propensity score matching (PSM) to predict the probability of a region being subsidised on the basis of observed covariates for both subsidised and non-subsidised regions. The method balances the observed covariates between the subsidised and non-subsidised regions based on the similarity between the predicted probability of their being selected as subsidised regions. The aim of PSM matching is to find a comparison group of subsidised regions from a sample of non-subsidised regions that is closest (in terms of observed characteristics) to the sample of subsidised regions. More

[1] One could argue that the inclusion of Budapest and county seat cities (19 in total) could induce an upward bias. However, a simple mean comparison test of LAU1 subsidies with and without the major cities did not reveal substantial differences. Further, a dummy variable controls for LAU1 regions with county seats.

specifically, sub-regions are selected into treatment and non-treatment groups that have similar potential outcomes (*rdi*, *relative* and *net migration* scores). We employed a matching estimation technique to identify the treatment effects. More specifically, sub-regions selected into treatment and non-treatment groups had the potential outcomes (TE scores) Y_0, Y_1 in both states (subsidised or not subsidised) D=0,1: those in which outcomes were observed ($E[Y_1|D=1]$, $E[Y_0|D=0]$), and those in which outcomes were not observed ($E[Y_1|D=0]$, $E[Y_0|D=1]$), respectively. The most common evaluation parameter of interest is the Average Treatment Effect on the Treated (ATT), defined in eq. 4 as:

$$ATT = E(Y_1 - Y_0|D = 1) = E[Y_1|D = 1) - (Y_0|D = 1)] \tag{4}$$

Estimating the treatment effects based on Propensity Score Matching (PSM) requires two assumptions. First, the Conditional Independence Assumption (CIA), which states that for a given set of covariates participation is independent of potential outcomes. The second condition is that the Average Treatment Effect for the treated is only defined within the region of common support. This assumption ensures that treatment observations have comparison observations 'nearby' in the propensity score distribution. For a more comprehensive discussion of the econometric theory behind this methodology, we refer the reader to Imbens and Wooldridge (2009) and Guo and Fraser (2010).

The descriptive statistics for the development subsidies (years 2008-2013, total per region, per capita and per square km) presented in Table 1 emphasise the uneven distribution of funds. The average value of support per LAU1 region amounts to HUF 780 Million[2], but there are sub-regions with very low levels of support, whilst in some regions the maximum value of support reached HUF 7.1 billion. This uneven distribution is also reflected in the extremely high standard deviations. The negative minimum numbers in the table are due to two regions that had to repay RDP funds. The picture is made more nuanced by the last two rows in Table 1 (per capita and per square km subsidy) in which the inequality of distribution is less prominent.

Table 1. Descriptive statistics for subsidies for the period 2008–2013

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
T. subsidy (th. HUF*)	1,044	780185.1	814366.4	-36435	7111930
Subsidy/cap (th. HUF)	1,044	19.707	17.077	-2.106	126.25
Subsidy/km² (th. HUF)	1,044	1386.61	1209.213	-95.581	13203.6

Source: Authors' calculations, nominal prices. * EUR 1= HUF 307 (as of 25.05.2017).

[2] At the time of research, 1 EUR was equivalent to approximately HUF 307.

Figure A2 in the Annex depicts the box plot graphs of total, per capita and per km^2 subsidies; here we focus on the yearly averages of all subsidy variables (Table 2).

Table 2. Yearly averages of subsidy variables (2008 – 2013)

Year	T. Subsidy (th. HUF*)	Subsidy/cap (th. HUF)	Subsidy/km^2 (th. HUF)
2008	415932.6	741.4727	10.42477
2009	**896959.9**	**1582.969**	**21.80959**
2010	*344121.3*	*611.1701*	*8.787789*
2011	916278.1	1632.067	23.27737
2012	1010492	1804.834	25.74464
2013	1097327	1947.158	28.20319

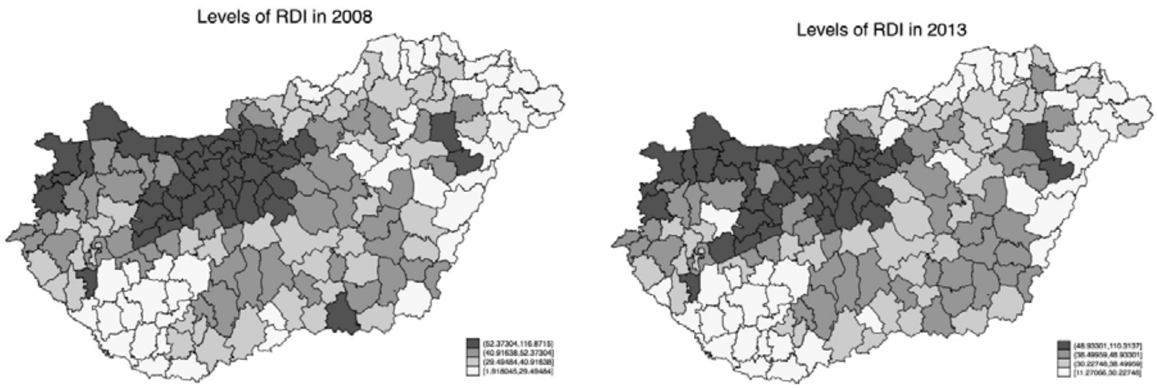
Source: Authors' calculations, nominal prices. * EUR 1= HUF 307 (as of 25.05.2017).

The interesting numbers are the average subsidy paid in 2009 and 2010. National elections were held in 2010, thus in 2009 both payments were sped up (see the doubled mean) by the Government – which ultimately lost the election. The newly elected Government in 2010 completely reorganized the system and agency of payments, thus the means of subsidy variables for 2010 are almost three times lower than those of previous and earlier years.

Results and discussion

Inspection of the ten highest and lowest RDI indices confirm what seems intuitive; i.e. RDI is lowest in the North-East, East, and South-West of Hungary (e.g. the Ozdi, Berettyóújfalúi, and Fehérgyarmati regions) whilst the high RDI regions are clustered around the capital, Budapest (e.g. Gödöllői, Ráckevei, Dunakeszi, and Budapest regions) and in the North-West. The RDIs display high correlation indices across the timespan, suggesting the stability of development rankings over the years. Regional objective RDI levels for the beginning and end of the period under examination are presented in Figure 1A. Regions are coded from highest ranking (darkest shade) to lowest (lightest shade). Results also confirm our intuition: LAU1 regions in the East/North-East and South-West (bordering Romania, Ukraine, Slovakia and Serbia/Croatia respectively) are less developed, whilst the centre of Hungary, and the West and North-West (bordering Austria, Slovakia, and to some extent, Slovenia) are the most developed. Inspection of the graphs does not reveal the major changes which took place between the start and end of the programming period, albeit some regions changed their status.

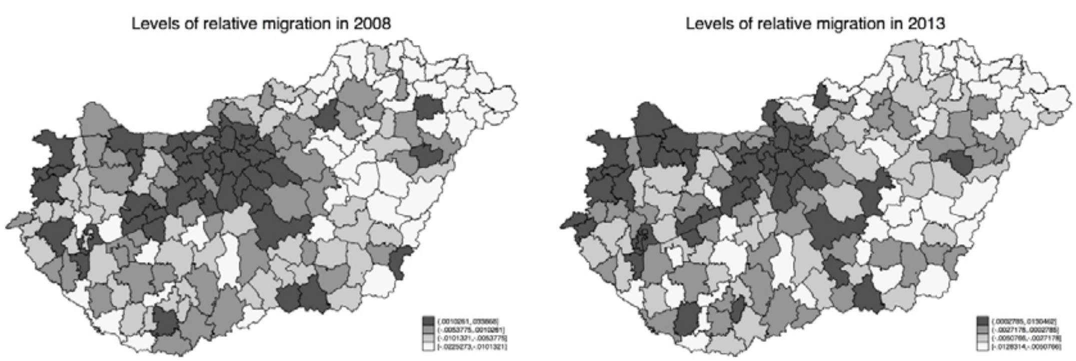
Figure 1A. Levels of regional (LAU1) development in 2008 and 2013 based on RDI



Source: Authors' calculations, using spmap (Stata)

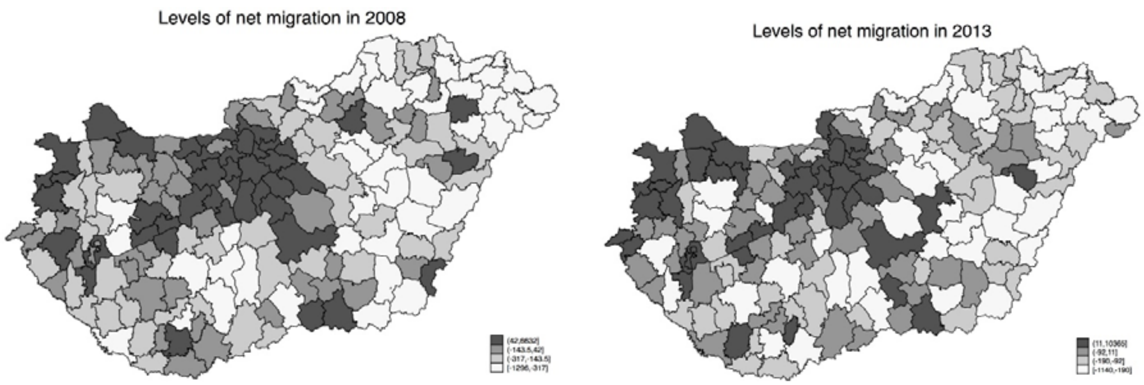
Figures 1B and 1C complement the picture of the development of Hungarian regions. Figure 1B depicts the internal migration flow relative to the size of local, LAU1, and population, whilst 1C accounts only for net migration flows. The argument for using both relative and net migration is that the government, faced with the depopulation of areas, may choose to target these, irrespective of the planned objective level of development. Further, whilst relative migration is more often used, persistent outmigration from the North, North-East and South decreases the denominator in eq. 3, thus in the long run these connected yet different concepts may diverge.

Figure 1B. Levels of regional (LAU1) development in 2008 and 2013 based on Relative Migration



Source: Authors' calculations, using spmap (Stata)

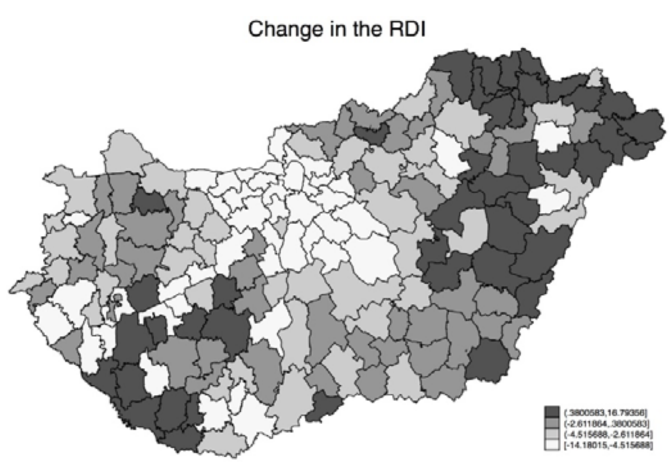
Figure 1C. Levels of regional (LAU1) development in 2008 and 2013 based on Net Migration



Source: Authors' calculations, using spmap (Stata)

As expected, the maps in figures 1A, 1B and 1C are quite similar, yet the correlation indices between indicators emphasise non-trivial differences (see the correlation in Table A1 in the Annex). Thus, impact analysis should provide more robust results with all three QoL indicators. To analyse the changes in the objective RDI throughout the timespan, Figure 2A shows the change in objective RDI between 2008 and 2013. As expected from a policy point of view, the largest changes (darkest shade) are indeed concentrated in the less-developed regions, and the least in already developed Central and Western Hungary (lightest shade). Thus, it appears from an objective point of view that some convergence between Hungarian regions is happening.

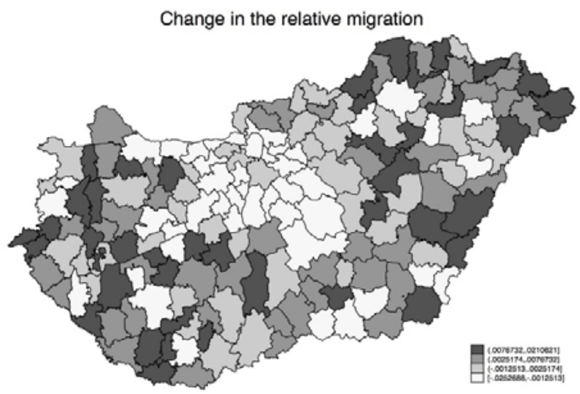
Figure 2A. Change in regional (LAU1) levels of development between 2008 and 2013



Source: Authors' calculations, using spmap (Stata)

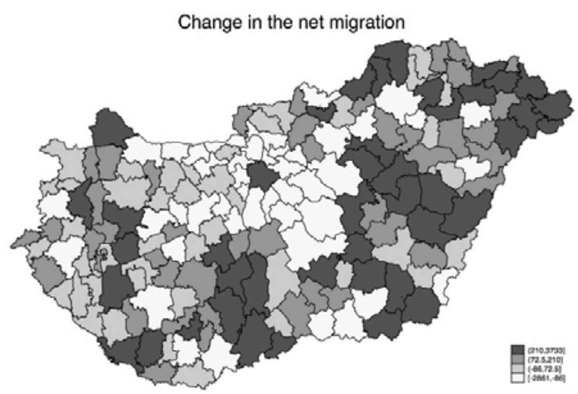
Thus the graphical evidence suggests that less-favoured regions increased their relative levels of development more (on average) than already developed regions; this should be in line with policy aims. The situation, however, is less positive if we look at the change between relative migration (Figure 2B) and net migration (Figure 2C) between 2013 and 2008. The maps emphasise that development policy did not put a halt to outmigration from the poorest Hungarian regions; indeed, the rate accelerated between 2008 and 2013.

Figure 2B. Change in regional (LAU1) relative migration between 2008 and 2013



Source: Authors’ calculations, using spmap (Stata)

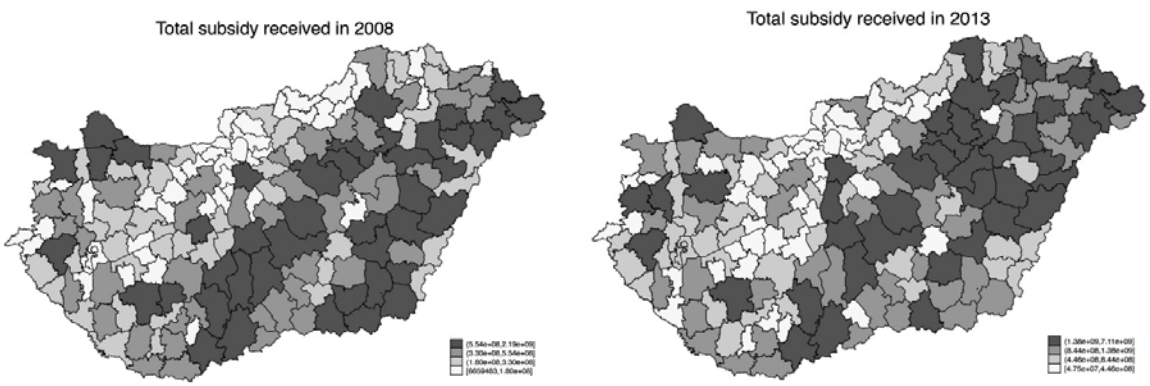
Figure 2C. Change in regional (LAU1) net migration between 2008 and 2013



Source: Authors’ calculations, using spmap (Stata)

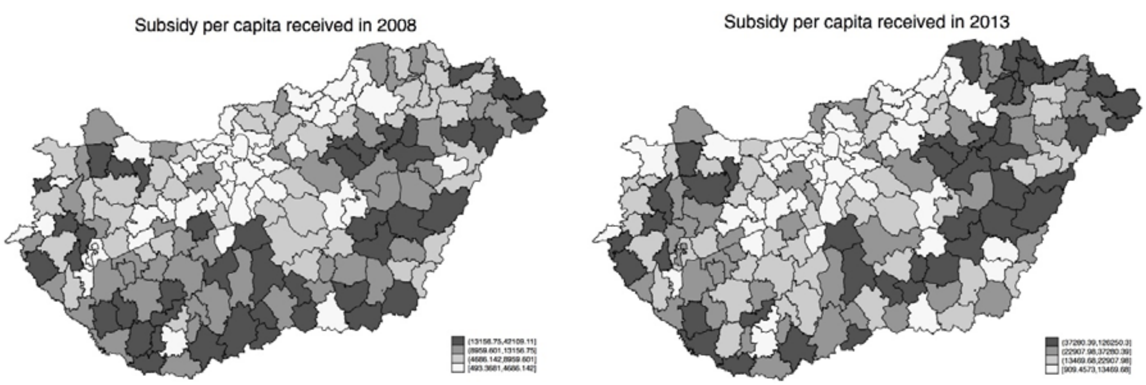
Now, turning our attention to the impact of development funds, in our analysis we specifically focus on Rural Development Subsidies, 75% of which are paid by the EU, and 25% in the form of co-financing. In the introduction to this paper we already emphasised the magnitude and importance of these payments. With respect to subsidies, Figures 3-5 depict the regional intensity of total, per capita and per square km subsidies received. The pattern of geographical distribution is less obvious compared to that illustrated on the regional development maps. It can be seen that less-developed regions benefited most from support, especially in terms of per capita or per km^2 subsidies.

Figure 3. Total subsidies received in 2008 and 2013



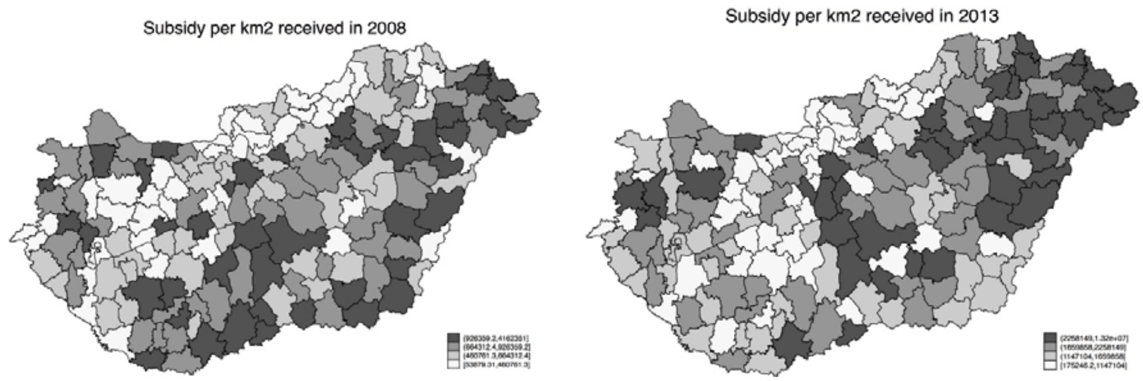
Source: Authors' calculations using spmap (Stata)

Figure 4. Per capita subsidies received in 2008 and 2013



Source: Authors' calculations using spmap (Stata)

Figure 5 Subsidies per square km received in 2008 and 2013



Source: Authors' calculations using spmap (Stata)

In line with the current literature, we analysed the impact of regional development subsidies using propensity score matching[3]. The estimated propensity score is actually the probability of participation in a program (treatment), conditioned on control variables calculated for all sub-regions. A number of matching algorithms are available for this purpose, such as nearest neighbour, radius caliper, stratification matching and kernel matching (Abadie et al. 2004, Leuven, Sianesi 2009). Whilst asymptotically all matching procedures should result in similar conclusions, small sample estimation may pose some problems. The following criteria were used to choose the appropriate matching algorithm: a) standardised bias, b) t-test, and c) common significance and pseudo R^2.

Since all sub-regions received some development support, a (necessarily subjective) rule had to be imposed to differentiate between treated and non-treated region. For robustness, in the research described in this paper for each treatment indicator dummy (i.e. total subsidy per region, per capita, and per km²) we used two definitions: areas where support intensity was higher than two-thirds of the yearly median/average subsidy (MSub and ASub, respectively) were qualified as subsidised (for the yearly distribution of treated and non-treated regions, see Table A1). In the first step, a Probit model was estimated for all three subsidy indicators (thus only the dependent variable changes). Two of the covariates controlled for the initial status of a given sub-region: level of objective quality of living (rdi_ob08), and unemployment rate (unemp08), both measured in 2008. In addition, yearly unemployment rate ($unemp_{it}$), the variables used to build the objective index (group1_n to group4_n), and finally, a dummy capturing whether the given LAU1 region is the home of the county seat were used as explanatory variables in the binary choice model. Results of the Probit estimations (see Table A2 displaying probit estimations for PSM; results of DID are available upon request) were used to

[3] We used the psmatch2 STATA routine for the estimation.

calculate the probability of participation (of being treated) of a given region in development projects. As discussed before, to create appropriate counterfactuals the PSM methodology requires careful balancing of covariates. Thus, before turning to the actual assessment of the impact of development subsidy payments upon Hungarian regions, we present balancing tests of covariates in Tables 3-5. Results emphasise that the correct matching approach was used (i.e. where the mean values of covariates were significantly different in the unmatched sample, after matching the difference in the mean was insignificant across treated and untreated sub-regions).

Table 3. Balancing tests for total subsidies (common support: sub-region) in subsidised and non-subsidised sub-regions

	Sample	Mean			%reduct	t- test	
Variable	U/M	Treated	Control	%bias	|bias|	t	p>t
group1_n	U	5.196	4.767	18.6		2.600	0.009
	M	4.966	4.971	-0.2	98.8	-0.050	0.959
group2_n	U	11.476	13.924	-56.5		-8.990	0.000
	M	11.442	11.424	0.4	99.3	0.100	0.924
group3_n	U	-3.841	-2.603	-22.3		-3.310	0.001
	M	-4.128	-4.547	7.5	66.1	1.340	0.180
group4_n_i	U	24.863	28.109	-53.8		-7.880	0.000
	M	24.752	24.926	-2.9	94.6	-0.570	0.569
unemp08	U	0.011	0.010	1.7		0.250	0.804
	M	0.011	0.010	2.8	-68.6	0.500	0.616
$unemp_{it}$	U	0.070	0.058	41.6		6.170	0.000
	M	0.072	0.073	-3.5	91.5	-0.630	0.528
rdi_ob08	U	6.414	7.829	-8.2		-1.270	0.205
	M	6.409	6.209	1.2	85.9	0.240	0.814
D_county	U	0.144	0.031	40.900		5.500	0.000
	M	0.102	0.123	-7.400	81.900	-1.190	0.233

Source: Authors' calculations

Table 4. Balancing tests for subsidies per capita (common support: sub-region) in subsidised and non-subsidised sub-regions

	Sample	Mean			%reduct	t- test	
Variable	U/M	Treated	Control	%bias	|bias|	t	p>t

group1_n	U	4.835	5.559	-26.2		-4.450	0.000
	M	4.842	4.712	4.7	82	1.240	0.214
group2_n	U	10.899	15.121	-103.1		-16.970	0.000
	M	11.100	11.179	-1.9	98.1	-0.480	0.629
group3_n	U	-4.373	-1.478	-54.9		-7.980	0.000
	M	-4.479	-4.462	-0.3	99.4	-0.060	0.956
group4_n	U	24.097	29.698	-93.3		-14.580	0.000
	M	24.475	24.749	-4.6	95.1	-0.950	0.341
unemp08	U	0.012	0.007	20.3		2.830	0.005
	M	0.011	0.010	2.4	88	0.400	0.689
unemp	U	0.074	0.050	85.5		12.550	0.000
	M	0.072	0.073	-1.6	98.1	-0.280	0.780
rdi_ob08	U	5.973	8.754	-15.6		-2.510	0.012
	M	6.022	5.449	3.2	79.4	0.730	0.467
D_county	U	0.056	0.224	-49.9		-8.360	0.000
	M	0.061	0.056	1.4	97.3	0.360	0.721

Source: Authors' calculations

Table 5. Balancing tests for subsidies per square kilometre (common support: sub-region) in subsidised and non-subsidised sub-regions

	Sample	Mean			%reduct	t- test	
Variable	U/M	Treated	Control	%bias	|bias|	t	p>t
group1_n	U	5.161	4.788	16.5		2.150	0.031
	M	4.923	4.958	-1.5	90.7	-0.380	0.704
group2_n	U	11.818	13.402	-36.9		-5.410	0.000
	M	11.762	11.990	-5.3	85.6	-1.130	0.257
group3_n	U	-3.631	-2.974	-11.9		-1.670	0.096
	M	-3.870	-3.955	1.5	87.2	0.290	0.775
group4_n	U	25.449	27.043	-25.9		-3.600	0.000
	M	25.255	25.496	-3.9	84.9	-0.790	0.427
unemp08	U	0.011	0.009	9.1		1.250	0.211
	M	0.011	0.011	1.4	84.6	0.250	0.802

unemp	U	0.068	0.061	24.5		3.440	0.001
	M	0.069	0.068	3.6	85.3	0.680	0.494
rdi_ob08	U	7.059	6.270	4.8		0.670	0.501
	M	6.920	6.769	0.9	80.9	0.180	0.859
D_county	U	0.129	0.055	25.8		3.380	0.001
	M	0.095	0.122	-9.2	64.2	-1.630	0.104

Source: Authors' calculations

An important requisite of PSM methodology is an assessment of whether common support or overlap assumptions actually hold (Caliendo, Kopeining, 2005). The test is based on a comparison of the distribution of estimated propensity scores in the treated and untreated samples. This may be done using graphical approaches (kernel density functions or histograms) or by applying parametric/non-parametric statistical tests. The result of Smirnov-Kolmogorov tests suggest that we may not reject the null hypothesis of the equal distribution of the two groups at a 1% significance level. We assessed the ATT impact of development subsidies on sub-regions (see Abadie et al. 2004 for a discussion of pros and cons) using non-parametric Kernel matching with common support. Table 6 presents our main results for the objective (rdi) and subjective (rel_migr and net_migr) local development indices. We reached the same conclusion – quite unfortunate from a policy perspective – that, regardless of the outcome variable (objective or subjective), or the definition of the treatment dummy, the impact of support is not significant.

Table 6. Impact (ATT) of development subsidies on objective and subjective RDI

	MSub/tot	MSub/cap	MSub/km2
rdi	37.033	35.938	38.07
rel_migr	-0.003	-0.004	-0.003
net_migr	-92.521	-135.24	-84.212
	ASub/tot	ASub/cap	ASub/km2
rdi	37.224	35.243	38.188
rel_migr	-0.003	-0.004	-0.003
net_migr	-30.786	-139.47	-84.04

Source: Authors' calculations, Legend: *p<.1; **p<.05; *** p<.01.

Next, we present the results of PSM-DID which can help overcome hidden-bias, and generally may improve non-experimental program evaluation. Table 7 displays the results of DID for the six support dummy variables. A key issue here was how the baseline and end periods are defined. Since data exist for six years, for robustness three definitions were used. First, the two extreme years (2008 and 2013), followed by the first two and last two years, and finally, the first three and last three years.

Table 7. Diff-in-diff treatment effect (PSM-DID[1]) results for total subsidy, subsidy per cap. and subsidy per km^2 using three definitions of baseline and end periods

	MSub/tot	MSub/cap	MSub/km2	ASub/tot	ASub/cap	ASub/km2
	Baseline: 2008, End: 2013					
rdi	-3.261	-0.289	-5.469	0.186	2.443	-2.888
rel_migr	-0.002	0.001	-0.002	0.000	0.001	-0.003
net_migr	-74.52	28.85	-120.71	39.29	15.96	-167.03*
	Baseline: 2008 - 2009, End: 2012 - 2013					
rdi	-0.631	0.671	-2.215	0.717	-0.723	-2.567
rel_migr	-0.002	0.000	-0.001	-0.001	0.001	-0.002
net_migr	-36.24	-23.11	-92.30	-38.42	39.43	-113.9*
	Baseline: 2008 - 2010, End: 2011 - 2013					
rdi	-3.741*	0.527	-1.696	1.217	2.145	-0.917
rel_migr	-0.002**	0.001	-0.002**	0.000	0.001	-0.001
net_migr	-54.786	43.183	-102.92**	-53.06	23.27	-88.75**

Source: Authors' calculations. Note: [1] balancing tests are available upon request. Robust SE were used to compute significances and common support was imposed. *p<.1; **p<.05; *** p<.01.

Of the 54 diff-in-diffs estimated, only seven proved to be significant – mainly when the first three years were taken as baseline, and the last three as follow-up periods. Note, significant impacts are all negative, and generally small. That suggests a negative effect of subsidies on RDI, although these impacts are very small

PSM-DID estimates partly reinforced the findings of ATT; namely, that it is difficult to identify any positive effects of RDP funds upon regional levels of development. Regardless of the subsidy variable employed or definition of baseline–end period, most results were not significant. Even more surprisingly, where significant, the impact was negative.

Conclusions

The main contribution to the literature of this paper is its assessment of (almost) an entire programming period and focus on the overall effects of Rural Development payments at a highly disaggregated level using three QoL indicators, along with six definitions of subsidies. This analysis of sub-regions' subsidy data and econometric estimations leads to several conclusions. First, we find considerable variation in terms of the level of subsidies received by regions during the period under analysis. Second, and most importantly from a policy point of view, it is very difficult to identify any impact of European development subsidies, and not only because estimates are sensitive to the chosen supported variables. Only a few estimations revealed significant impacts, and these were negative instead of the expected positive. Due to the lack of relevant papers about the topic, it is difficult to assess these results against other research to evaluate the impact of European RDP. The exception is a paper by Michalek (2012) which assessed the impact of the SAPARD program in Slovakia. Using directly comparable methodology, Michalek (2012) also finds negligible impacts for the SAPARD RD program on Slovakian rural regions. We conclude that, irrespective of estimated coefficients, the impact of regional subsidies is negligible – a result that should raise important policy-related questions. As a consequence, further research is needed to explore the impacts and mechanisms of subsidies.

Acknowledgements: The authors are grateful to Simon Milton for his language-related contributions. Support from Global Development Network through CERGE-EI Foundation for the research project entitled "Success or Waste of Taxpayers' Money? Impact of EU Rural Development Policies upon Hungarian NUTS4" Regions is gratefully acknowledged"

References

Abadie, A., Drukker, D., Herr, J.L., Imbens, G.W. (2004). Implementing matching estimators for average treatment effects in Stata. *Stata Journal* 4, 290-311.

Afifi, A., Clark, V.A., May, S. (2004). Computer-Aided Multivariate Analysis, 4th Edition, Chapman & Hall/CRC.

Athey, S., Imbens, G. (2006) Identification and inference in nonlinear difference-in-differences models. Econometrica 74, 431-497.

Baltagi, B. H. (2008). Econometric Analysis of Panel Data. 4th edition. Wiley. New York.

Bollman, R., Terluin, I., Godeschalk, F., Post, J., (2005). Comparative analysis of leading and lagging rural regions in OECD countries in the 1980s and 1990s, 45th Congress of the European Regional Science Association (ERSA), Vrije Universiteit Amsterdam, pp. 23-27.

Breustedt, G., Glauben, T. (2007). Driving forces behind exiting from farming in Western Europe. *Journal of Agricultural Economics* 58, 115-127.

Caliendo, M., Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22, 31-72.

Copus, A., Hall, C., Barnes, A., Graham, D., Cook, P., Weingarten, P., Baum, S., Stange, H., Linder, C., Hill, A. (2006). Study on employment in rural areas (SERA). European Commission, DG Agri.

Elek, S., Fertő, I., Forgács, C. (2010). The possible effects of the CAP Reform on farm employment in Hungary. *Agricultural Economics Review* 11, 29-34.

Esposti, R. (2007). Regional growth and policies in the European Union: Does the Common Agricultural Policy have a counter-treatment effect? *American Journal of Agricultural Economics* 89, 116-134.

Guo, S., Fraser, M.W. (2010). Propensity score analysis: Statistical methods and applications. Sage Publications.

Imbens, G.M., Wooldridge, J.M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature* 47, 5-86.

Leuven, E., Sianesi, B. (2003). PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Statistical Software Components.

Lukovics, M., 2009. Measuring regional disparities on competitiveness basis. Regional competitiveness, innovation and environment. JATE Press, Szeged, 39-53.

Lukovics, M. and Kovács, P., (2008). Eljárás a területi versenyképesség mérésére. *Területi statisztika*, 48(3), 245-263.

Maddala, G.S., Kim, I.M. (1998). Unit roots, Cointegration and Structural Change. Cambridge University Press, Cambridge.

Medonos, T., Ratinger, T., Hruska, M. and Spicka, J. (2012) The assessment of the effects of investment support measures of the Rural Development Programmes: the case of the Czech Republic. *Agris on-line Papers in Economics and Informatics* 4.4 : 35.

Michalek, J., (2012). Counterfactual impact evaluation of EU rural development programmes-Propensity Score Matching methodology applied to selected EU Member States. Volume 2: A regional approach. Institute for Prospective and Technological Studies, Joint Research Centre.

Michalek, J., Zarnekow, N. (2012). Application of the rural development index to analysis of rural regions in Poland and Slovakia. *Social indicators research* 105, 1-37.

OECD (2006). The new rural paradigm: Policies and Governance. Organisation for Economic Co-operation and Development, Paris.

Olper, A., Raimondi, V., Cavicchioli, D. and Vigani, M., (2014). Do CAP payments reduce farm labour migration? A panel data analysis across EU regions. European Review of Agricultural Economics, 41(5), 843-873.

Petrick, M., Zier, P. (2012). Common Agricultural Policy effects on dynamic labour use in agriculture. *Food policy* 37, 671-678.

Pufahl, A., Weiss, C.R. (2009) Evaluating the effects of farm programmes: results from propensity score matching. European Review of Agricultural Economics 36, 79-101.

Renting, H., Rossing, W., Groot, J., Van der Ploeg, J., Laurent, C., Perraud, D., Stobbelaar, D.J., Van Ittersum, M. (2009). Exploring multifunctional agriculture. A review of conceptual approaches and prospects for an integrative transitional framework. *Journal of Environmental management* 90, S112-S123.

Rosenbaum, P.R., Rubin, D.B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrica* 70, 41-55.

Sianesi, B. (2004) An evaluation of the Swedish system of active labor market programs in the 1990s. Review of Economics and Statistics 86, 133-155.

Smith, J.A., Todd, P.E. (2005) Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics* 125, 305-353.

Swinnen, J., Van Herck, K. (2010). Compensation payments in EU Agriculture. Trade Adjustment Costs in Developing Countries: Impacts, Determinants and Policy Responses, London: Centre For Economic Policy Research and Washington, DC: The World Bank, 361-381.

Terluin, I., Strijker, D., Munch, W., (2011). Economic dynamics in rural regions, in: Oskam, A., Meester, G., Silvis, H. (Eds.), EU policy for agriculture, food and rural areas. Wageningen Academic Publishers, Wageningen, pp. 317-332.

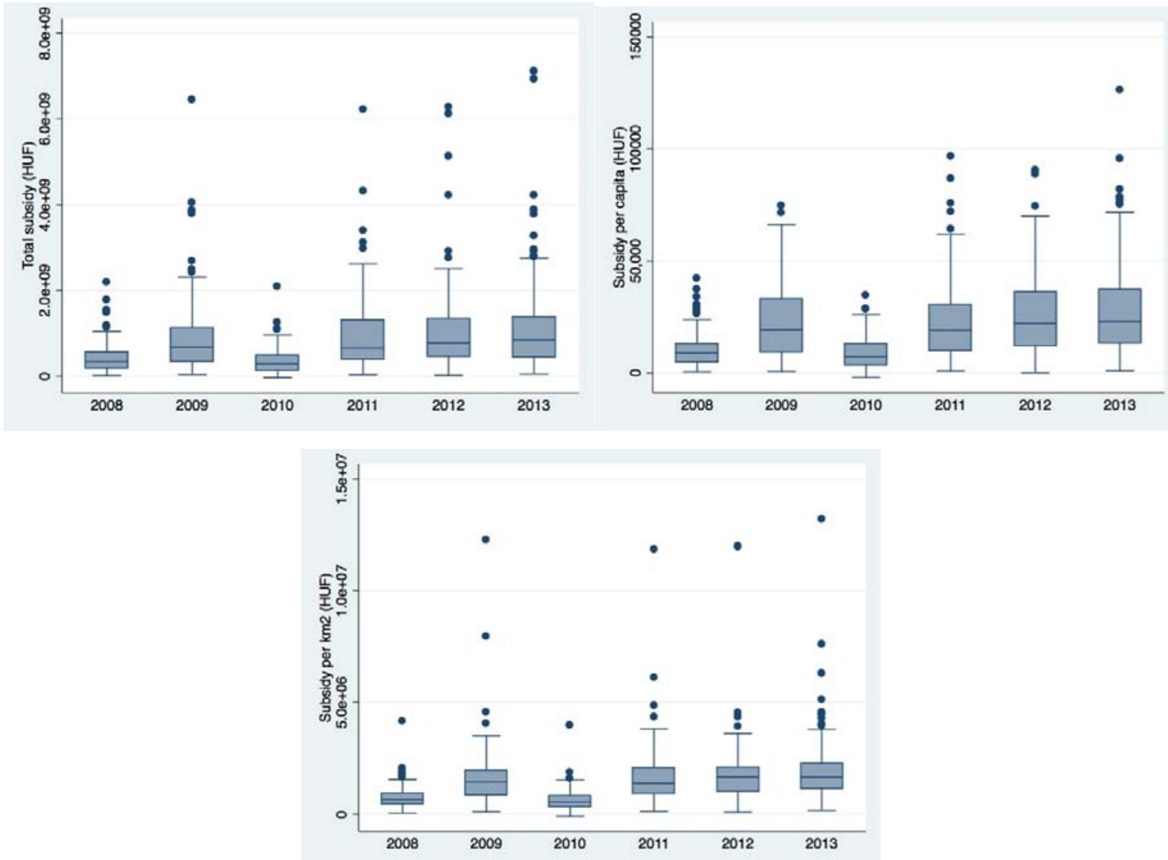
Terluin, I.J., Roza, P. (2010). *Evaluation methods for rural development policy*. LEI Wageningen UR.

Tocco, B., Davidova, S., Bailey, A., (2012). *Commonalities and Differences in Labour Market Developments and Constraints in Different EU Regions.*

Villa, J.M. (2011). DIFF: Stata module to perform Differences in Differences estimation. Statistical Software Components.

Annex

Figure A1. Box plot of yearly subsidies (total, per capita and per km^2) received (Hungarian Forint)



Source: Authors' calculations

Table A1. Correlation between local development variables

	rdi	rel_migr	net_migr
rdi	1		
rel_migr	0.6339	1	
net_migr	0.5432	0.4619	1

Source: Authors' calculations

Table A2. Number of LAU1 regions supported per year

Subsidy dummy	On/off support	2008	2009	2010	2011	2012	2013
	0	92	46	103	40	31	31
	1	82	128	71	134	143	143
	0	77	77	74	81	72	79
	1	97	97	100	93	102	95
	0	97	47	110	45	39	33
	1	77	127	64	129	135	141
	0	64	64	71	65	63	67
	1	110	110	103	109	111	107
	0	96	32	110	23	15	15
	1	78	142	64	151	159	159
	0	51	55	53	64	54	57117
	1	123	119	121	110	120	

Source: Authors' calculations

Table A2. Probit regression results for the RDI variable

Covariates	Dsubsidy	P>z	Dsubsidy_cap	P>z	Dsubsidy_km2	P>z
group1_n	0.119	0.000	-0.020	0.400	0.074	0.002
group2_n	-0.091	0.000	-0.129	0.000	-0.063	0.000
group3_n	0.082	0.000	0.123	0.000	0.054	0.001
group4_n	-0.061	0.000	-0.048	0.000	-0.022	0.028
unemp08	-0.408	0.860	6.438	0.034	0.608	0.796

unemp	10.401	0.001	19.558	0.000	7.672	0.016
rdi_ob08	0.007	0.064	0.002	0.722	0.007	0.059
D_county	1.406	0.000	-0.520	0.000	0.769	0.000
_cons	2.085	0.000	2.611	0.000	1.198	0.001
No. obs.		1044.000		1044.000		1044.000
LR chi2(8)		218.880		344.580		81.350
Prob > chi2		0.000		0.000		0.000
Pseudo R2		0.170		0.265		0.068

Source: Authors' calculations