Impact of European Union Development Subsidies on Hungarian Regions

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Abstract

This paper is a first attempt to analyse the impacts of development support on the wellbeing of Hungarian rural areas between 2002 and 2008, employing a two stages approach. In a first step, we construct a multi-dimensional Rural Development Index measuring the overall level of regional development and quality of life in Hungarian small regions. In the second step we apply propensity score matching to evaluate the impact of the regional subsidies on the RDI. Estimations reveal two main findings. First, calculations suggest that concentration in the EU support grows as the subsidy amounts increase. Second, the robust impact assessment of Rural Development Support generates disappointing conclusions. Irrespective of support measure (total subsidy, subsidy per capita and km^2) or methodology employed, the impact is very close to zero or even negative. This finding casts serious doubts with respect to the effectiveness of development policy and long-run convergence of European regions.

Key words: EU support, impact evaluation, sub-region

1. Introduction

It is difficult to overestimate the role of Rural Development Policies (RDPs) in developed economies. 75 percent of the OECD countries' territory is classified as rural, and on average a quarter of the total population lives in these areas (OECD, 2006). In the past decades, the global economy experienced an unprecedented growth of agricultural productivity – itself a laudable process - yet despite the lavish subsidies, it lead to a fall in both agricultural employment and the weight of agriculture in national economies (at least when developed economies are considered). Whilst the agricultural output amounts to roughly 2 percent of OECD nations' GDP, the vast majority of rural land use is 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 even if only the output of rural areas is considered (OECD, 2006). Whilst the aims of EU Common Agricultural Policy (CAP) with respect to agricultural production were laid down in the 1958 Rome Treaty, and albeit with significant amendments, are applied up to present, the importance of rural development - not directly connected to production - was only recognized in the 70's. Thus the modern CAP (AGENDA 2000) shifted the support system towards an integrated rural development policy, creating the European Agricultural Model (Renting et al., 2009) with its primary aim to promote a viable and liveable rural environment rather than maximizing 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-costumes, social structures and none-the-less environment protection. The most important pre-condition of the creation/preservation of the abovementioned values is the existence of sufficient active rural population. This highlights the importance of policies aimed to slow rural to urban migration, and reverse the continuous increase of average rural inhabitants' age. The economic output of Hungarian rural areas is 50% less the national average and 3 times less than the predominantly urban output. For more details with respect to 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 economic and agricultural perspective, rural areas are also very important in terms of population, preserving the landscape tradition and none-the-less environment protection. In addition, NMS are more rural than OMS, and the income gap between rural and urban areas are more predominant in NMS than OMS. Consequently, the analysis of RDP is perhaps an even more relevant issue in these countries.

Yet despite its importance, the empirical literature with respect to the evaluation of rural development measures is rather poor. Most papers focus on the impact of agricultural policy on labour market or rural income distribution (e.g. Breustedt and Glauben, 2007; Elek et al., 2010; Esposti, 2007; Petrick and Zier, 2012; Pufahl and Weiss, 2009; Swinnen and Van Herck, 2010). A 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 included in a transparent and easy to handle fashion (from data point of view). 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 realized investments, and GDP change – see Michalek and Zarnekow 2012 for a critical review), and second, the issue of counterfactual situation, excluding the possibility of before – after comparison. Often employed naïve approaches for the impact evaluation of RDP such as simple case studies or partial indicators do not even attempt to create a counterfactual situation (Terluin and Roza, 2010). Generally, the most important drawback of partial measures is the lack of clear causality relations between partial measures and RDP (the problem to make distinction between impact of RDP and other exogenous factors). These issues may however be solved by the use of a complex Rural Development Indicator, RDI, originally proposed by Michalek and Zarnekow (2012) and counterfactual analysis. Contrary 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 2002-2008 period covering all rural development policy measures. Thus we can assess the effects of the EU rural development policy in Hungary. In the next section we detail the methodology we use, followed in section three by the discussion of data we use. Part four focuses on empirical results whilst the section five concludes.

2. Methodology

The basic idea is simple: people do move (migrate) where their quality of life is better, thus by making a decision they implicitly weight the importance of regional characteristics that define the local 'quality of life'. These characteristics and weights will then be used to derive the RDI indicator.

More specifically, the empirical methodology consists of the following steps:

1. We summarize the local data (around 130 variables) available for 3,164 administratively independent settlements into 174 small regions (a much deeper perspective than the 20 regions available under the NUTS-3 nomenclature), the subject of our analysis. Further, we employ principal component (PCA) and factor analysis to reduce the number of variables. We first test the data for the suitability of PCA using Kaiser-Meyer-Olkin measure and Bartlett's test of variable's independence, followed by rotation algorithms (Varimax), and finally, we apply Kaiser selection criteria considering only factors with Eigen values larger than one (see Afifi et al. 2004 for a practitioner's handbook on these methods).

2. We estimate the migration function in order to derive the weights (β_k in eq.1) needed for the complex RDI indicator:

$$mp_{it}= \alpha_0+ \beta_k F_{ikt}+v_i+\varepsilon_{it}, \quad (1)$$

where α_0 is a constant, mp_{it} is the net migration into region i, normalised by the total population of the region i, F_{ikt} the value of factor k in region i, at time t – originating from step 1. and ε_{it} is the region specific residual, with the usual white noise properties.

Given the panel nature of data, and the strict underlying assumptions of panel models, a variety of models will be estimated using specification and diagnostic tests in order to select the 'best' model (see e.g. the handbook of Baltagi, 2008).

3. We may now estimate the RDI index which takes the following form:

$$RDI_i=h(\beta_k,Z_k^i)=\sum_k \beta_k * Z_k^i, \quad \text{where} \quad (2)$$

RDI_i – Rural Development Index in region i, Z_k^i the i region's k measurable characteristics, β_k the weights for each k characteristic, specific for region i, and time t resulting from the estimation of the migration function (1).

Thus the RDI is a complex indicator based on regional characteristics of Z_k^i, weighted by the estimated coefficients of the migration function, β_k. Weights represent the 'relative social value' of regional characteristics Z_k^i which are heuristically used by those making a decision to stay or move from the region as measures for 'quality of life'

4. Once the unbiased RDI is calculated, we are in position to actually analyse the impact of RDP's on sub-regions. Whilst in standard policy analysis settings, the sample-average treatment effects cannot be calculated because we only observe one of the two possible outcomes for each individual (or sub-region in our case), this issue is solved by the RDI allowing the creation of the counterfactual. Following the insights of impact analysis literature we can thus adopt the counterfactual framework developed by Rosenbaum and Rubin (1983). We employ propensity score matching (PSM) to predict the probability of subsidised sub-region on the basis of observed covariates for both subsidised and non-

subsidised sub-regions. The method balances the observed covariates between the subsidised and non-subsidised region based on similarity of their predicted probabilities of being subsidised regions. The aim of PSM matching is to find a comparison group of subsidised regions from a sample of non-subsidised sub-regions that is closest (in terms of observed characteristics) to the sample of subsidised sub-regions.

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

$$ATT = E(Y_1 - Y_0|D = 1) = E[(Y_1|D = 1) - (Y_0|D = 1)] \tag{3}$$

Similarly we can derive estimators of the Average Treatment effect on Controls (ATC) and the overall average treatment effect (ATE).

To solve the evaluator's classing problems the matching approach reproduces the treatment group among the non-treated by pairing each program participant with members of the non-treated group, controlling for observable characteristics. Estimating the treatment effects based on the 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. A second condition is that the Average Treatment Effect for the Treated (ATT) 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 more comprehensive discussion of the econometric theory behind this methodology we refer the reader to Imbens and Wooldridge (2009) and Guo and Fraser (2010). However, the PSM has several limitations. First, PSM requires extensive data sets on large samples of units – less of an issue for this paper since we use a large panel -, and even when those are available, a lack of common support between the treatment or enrolled group and the pool of nonparticipants may appear. Second, the assumption that no selection bias has occurred arising from unobserved characteristics is very strong, and more of a problem, it cannot be tested.

Having data on subsidised and non-subsidised sub regions over time can also help in accounting for some unobserved selection bias, by combining PSM and Difference-in Differences estimator (conditional DID estimator). The conditional DID estimator (e.g. Smith and Todd, 2005) is highly applicable in case the outcome data on programme participants (i.e. subsidised sub-regions) and nonparticipants (non-subsidised sub-regions) is available both 'before' and 'after' periods (2002 and 2008, respectively). In our study, the PSM-DID measures the impact of the subsidies by using the differences in selected outcome indicator (ATE or ATT) between subsidised (D=1) and non-subsidised sub regions (D=0) in the before-after situations. The main advantage of the PSM-DID estimator is that it can relax the unconfoundedness assumption. The PSM-DID estimator also allows for quantile differences, that is assessing the effects of subsidies at different points of the outcome variable's (RDI scores) distributions. It means that we can compare individuals across both groups and time according to their quantile[1].

[1] See Athey and Imbens (2006) and Imbens and Wooldridge (2008) for an overview on the quantile PSM-DID method.

3. Data

To derive the RDI we use a Central Statistical Office regional database provided by Databank of Centre for Economic and Regional Studies of Hungarian Academy of Sciences. We employ 132 variables covering various fields of quality of life including demographics (15 variables), health services (9), business units (2), tourism and catering (9), retail sector (24) transport (7), community infrastructure (14), environment (4), culture (2), unemployment (4), education (16), social protection (17) personal income tax (3), number of houses (5), number of villages (1). In order to provide more comprehensiveness of dimensions of well-being we cannot take into account unequal number of indicators per dimensions[2]. Data for the EU development funds is from the Information Systems of National Regional Development. We use both value data of EU funds and number of projects funded by the EU. We use three subsidy indicators: total support per sub-region, support per km^2, and support per capita.

The descriptive statistics of the total (years 2002-2008) development subsidies, presented in Table 1, emphasise an uneven distribution of funds.

Table 1 Descriptive statistics of subsidies

	N	mean	SD	Minimum	Maximum
support (mil. HUF)	1218	2253	18021	0	505647
Number of projects	1218	88	171	2	3686
support/project (mil. HUF)	1218	23	40	0	541
support/capita (thousands. HUF)	1218	29	39	0	661
support/km^2 (mil. HUF)	1218	4	34	0	963

Source: Own calculations

[2] The paper of Fertő and Varga (2014) focuses exclusively on the computation of RDI in the Hungarian sub-region context.

The average value of support per sub-region amounts to HUF 2,2 billion, but there are sub-regions with no support at all (minimum value 0) whilst the maximum value of support per project was HUF 541 million. The uneven distribution is also reflected by the extremely high standard deviation. The picture is nuanced by the last two rows of Table 1 (the per capita and per square km subsidy) where the inequality of distribution is less prominent.

Table 2 presents the yearly averages of support variables. Note the post EU accession (2004) non-monotonic increase of the average development funds. Somewhat surprisingly, the number of projects supported continuously decreases after 2004, resulting in a dynamic expansion of subsidy per project averages. The support/km^2 increased five folds, whilst the support per capita roughly doubled between start and end period (an otherwise expected outcome – i.e. the distribution of funds is more likely to follow the sub-regions total population rather than area surface).

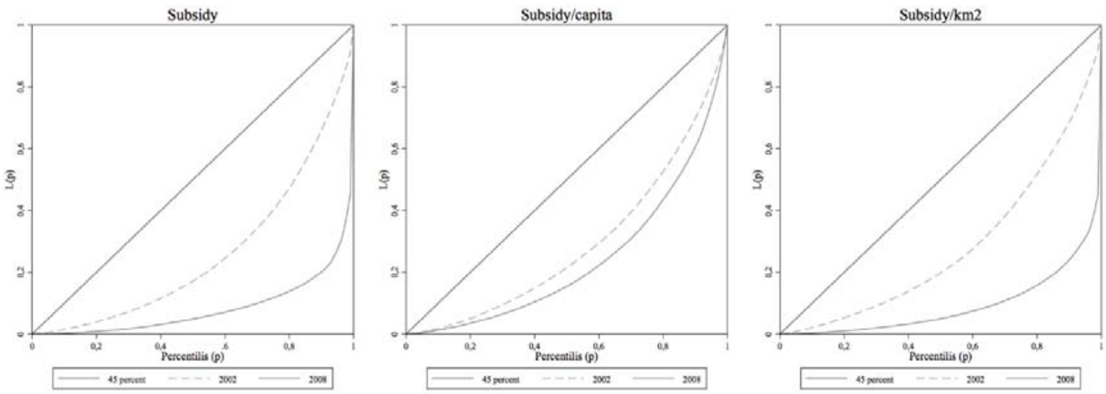
Table 2 Average values of subsidies and supported projects per sub-regions, 2002-2008

	Support Mil. HUF	No. of projects	support/project Mil. HUF	support/capita Tho. HUF	support/km^2 Mil. HUF
2002	1028	135	8	23	2.0
2003	997	110	9	22	1.8
2004	116	134	9	19	2.2
2005	2852	91	31	51	5.4
2006	177	58	30	30	3.4
2007	2328	38	61	7	4.4
2008	5668	46	124	49	10.6
total	15769	613	272	201	29.8

Source: Own calculations

The Lorenz curves (Figure 1.) reinforce our prior beliefs with respect to increasing subsidy concentration experienced between 2002 and 2008. The most prominent increase is recorded for total subsidies received and for the per square km support indicators, whilst the lowest for the per capita support. The higher concentration ratio in 2008 is evident from the graph.

Figure 1 Lorenz curves of the sub-regional distribution of subsidies in 2002 and 2008



Source: Own calculations

4. Results

In line with the current literature, we analyse the impact of regional development subsidies by 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 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 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 (subjective) rule must be created to differentiate between treated and non-treated region. In this paper, for each indicator (i.e.

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

subsidy per region; per capita; and per km²), sub-regions where the programme intensity was higher than 2/3 of the median were qualified as subsidised (i.e. treated). In a first step, a logit model[4] (eq. 4) is estimated for all three subsidy indicators (thus the dependent variable changes).

$$Subsidy_{it}=\alpha_0+\alpha_1 RDI2002_{it}+\alpha_2 UNEMP2002_{it}+\alpha_3 UNEMP_{it}+v_i+\varepsilon_{it} \quad (4)$$

where $Subsidy_{it}$ is dummy variable takes value one if a sub-region is identified as a subsidised one, and zero otherwise. $RDI2002_{it}$ is the 2002 level of rural development index and $UNEMP2002_{it}$ is the 2002 absolute value of unemployment - these variables control for the initial status of a given sub-region. In addition, the variable $UNEMP_{it}$ captures the current level of unemployment in the sub-region. The results of the logit estimations are used to calculate the probability of participation (of being treated) of a given sub-region in the development projects.

We present our results in three blocks. The balancing tests in the first block help to assess the appropriateness of the counterfactuals, followed by the estimation of ATT and finally, the DID results of impact assessment.

As discussed before, PSM methodology requires careful balancing of covariates, Tables 3 – 5 present test results of various matching procedures. Results emphasise the correct matching approach was used (e.g. where the mean values of covariates were significantly different in the unmatched sample, after matching the null of mean equality across treated and untreated sub-regions may generally not be rejected.

[4] Dose Response Treatment Models employing a continuous treatment variable (untreated: whose level is 0 and treated: treatment level ranging between >0 and 100%) are also available in the literature (see e.g. Hirano and Imbens 2004 or Cerulli 2014), yet require more assumptions and are technically somewhat demanding. These models resulted the same conclusions as the binary treatment variable models employed in this paper. Results are available upon request.

Table 3 Balancing tests of subsidies (common support: sub-region, biweight kernel) in subsidised and not subsidised sub-regions

		mean		% decrease		t-test	
Variable	Sample	treated	control	% bias	bias	t	p>t
RDI2002	unmatched	9.7e-05	0.0002	-4.9		-0.83	0.406
	matched	0.0001	0.0001	0.2	8.96	0.04	0.967
UNEMP2002	unmatched	363.83	154.8	22.3		3.49	0.000
	matched	175.9	147.03	3.1	86.2	1.01	0.311
$UNEMP_{it}$	unmatched	0.0066	0.0057	5.0		0.83	0.407
	matched	0.0045	0.0035	5.4	-9.0	1.32	0.186

Source: Own calculation

Table 4 Balancing tests of subsidies per capita (common support: sub-region, biweight kernel) in subsidised and not subsidised sub-regions

		mean		% decrease		t-test	
Variable	Sample	treated	control	% bias	bias	t	p>t
RDI2002	unmatched	-6.7e-05	0.0005	-23.3		-4.21	0.000
	matched	-4.9e-06	-3.3e-05	1.2	95.0	0.36	0.721
UNEMP2002	unmatched	296.48	260.12	3.5		0.60	0.550
	matched	274	262	1.1	67.5	0.25	0.804
$UNEMP_{it}$	unmatched	0.0073	0.0045	16.4		2.63	0.009
	matched	0.0062	0.0057	3.0	81.6	0.59	0.555

Source: Own calculation

Table 5 Balancing tests of subsidies per square kilometre (common support: sub-region, biweight kernel) in subsidised and not subsidised sub-regions

		mean		% decrease		t-test	
Variable	Sample	treated	control	% bias	bias	t	p>t
RDI2002	unmatched	0.0002	4.8e-05	6.7		1.9	0.276
	matched	0.0001	5.0e-05	4.3	35.9	1.1	0.311
UNEMP2002	unmatched	332.51	201.29	8.13		2.17	0.030
	matched	175.84	153.26	2.4	82.8	0.79	0.430

$UNEMP_{it}$	unmatched	0.0064	0.0061	1.7		0.29	0.770
	matched	0.0048	0.0046	1.0	45.3	0.22	0.829

Source: Own calculation

An important requisite of PSM methodology is to assessment whether the *common support* or *overlap* assumptions do hold (Caliendo, Kopeining, 2005). The test is based on the 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 result suggest we may not reject the equal distribution of the two groups null hypothesis at 1% significance level.

We assess the ATT impact of development subsidies on sub-regions using two approaches (see Abadie et al. 2004 for a discussion of pros and cons). First (ATT in table 6) a non-parametric Kernel matching (using bootstrapped z values) and second (SATT in table 6), nearest neighbour matching – allowing bias adjustment and heteroscedasticity robust variance estimation – are employed[5].

Table 6 presents our main results obtained with the abovementioned approaches. We reach the same – quite unfortunate from policy point of view– conclusion of extremely low, close to zero impact of subsidies on the sub-regions. The overall subsidy, and the per km^2 subsidy received seems to have a small positive impact (yet for the former this is significant only when bootstrap methods and 10% significance level is used. The per square km subsidy is significantly (small) positive with both methods. Contrary, when the per capita subsidy indicator is used, we obtain negative effects, regardless of estimation procedure.

[5] We apply STATA nnmatch program developed by Abadie et al 2004.

Table 6 Impact (ATT) of development subsidies

ATT	Coef.	SD	z	P>z
Subsidy*	0.0005	0.0003	1.67	0.095
Subsidy per capita	-0.0015	0.0003	-4.63	0.000
Subsidy per km^2*	0.00012	0.0003	3.69	0.000
SATT				
Subsidy	0.0004	0.0003	1.49	0.137
Subsidy per capita	-0.0013	0.0003	-4.07	0.000
Subsidy per km^2	0.0001	0.0003	3.52	0.000

Source: Own calculations; Note: *bootstraped z statistic (200 replications)

Next, we present the PSM-DID results – that can overcome the hidden-bias, and generally may improve non-experimental program evaluation. Tables 7 – 9 display results of DID and Quantile DID for the three support variables[6].

Table 7 PSM-DID and Quantile PSM-DID results for total subsidy

		Baseline period	End period	Diff in Diff
RDI	mean	-0.001	0.002	0.003
Std.Error		0.001	0.002	0.002
RDI	Q90	-0.004	0.007	0.011*
Std.Error		0.003	0.005	0.006

Source: Own calculations. Note: only the mean and quantiles with statistically significant results are shown. *,**,*** denote 10, 5 and 1% significance levels respectively.

Table 8 PSM-DID and Quantile PSM-DID results subsidy per capita

		Baseline period	End period	Diff in Diff
RDI	mean	-0.000	0.003	0.003**
Std.Error		0.001	0.001	0.001
RDI	Q70	-0.000	0.004	0.005***
Std.Error		0.001	0.002	0.002
RDI	Q90	-0.000	0.007	0.006**
Std.Error		0.001	0.003	0.003

Source: Own calculations. Note: only the mean and quantiles with statistically significant results are shown. *,**,*** denote 10, 5 and 1% significance levels respectively.

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[6] The STATA module diff by Villa (2011) is used for estimations.

Table 9 PSM-DID and Quantile PSM-DID results for subsidy per km^2

		Baseline period	End period	Diff in Diff
RDI	mean	-0.001	0.002	0.003*
Std.Error		0.001	0.002	0.002
RDI	Q90	-0.008	0.007	0.015***
Std.Error		0.002	0.003	0.003

Source: Own calculations. Note: only the mean and quantiles with statistically significant results are shown. *,**,*** denote 10, 5 and 1% significance levels respectively.

PSM-DID estimates reinforce the ATT findings, namely, that it is difficult to find any positive effect of RDP funds upon the sub-regions' level of development. Regardless of subsidy variable employed, results for most quantiles are not significant. For the total subsidy (table 7) only results for the Q90 quantile are significant – yet close to 0. For subsidy per capita and per km^2 the mean and upper quantile results are significant, but with an impact effect close to zero.

5. Conclusions

The analysis of sub-regions subsidy data and econometric estimations reveal several main findings. First, calculations suggest that EU subsidies concentrate on already well supported regions. Second, we find considerable variation in terms of the level of subsidies during the period analysed. Finally and most importantly form policy point of view, our results imply that it is very difficult to identify any impacts of European development subsidies, and not only because estimations are highly sensitive on have the chosen support variables. The significance of identified effects is rather low and its direction can be both positive and negative but always very close to zero. With the lack of relevant papers in the field, it is difficult to assess our results against other research evaluating the impact of European RDP. The exception is the paper by Michalek (2012) assessing the impact of SAPARD program in Slovakia. With a directly comparable methodology, Michalek (2012) also concludes negligible impacts of 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 questions. As a consequence, further research is needed to explore impacts mechanisms of subsidies.

Acknowledgements: Authors gratefully acknowledge 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".

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