Regional Studies

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/cres20

Regional impacts of the EU Rural Development Programme: Poland's food processing sector

Jerzy Michalek, Pavel Ciaian & Federica Di Marcantonio

To cite this article: Jerzy Michalek, Pavel Ciaian & Federica Di Marcantonio (2020) Regional impacts of the EU Rural Development Programme: Poland's food processing sector, Regional Studies, 54:10, 1389-1401, DOI: 10.1080/00343404.2019.1708306

To link to this article: https://doi.org/10.1080/00343404.2019.1708306

REGIONAL STUDIES
2020, VOL. 54, NO. 10, 1389–1401
https://doi.org/10.1080/00343404.2019.1708306

Routledge Taylor & Francis Group
Regional Studies Association

OPEN ACCESS Check for updates

Regional impacts of the EU Rural Development Programme: Poland's food processing sector

Jerzy Michalek[a], Pavel Ciaian[b] and Federica Di Marcantonio[c]

ABSTRACT
The paper illustrates the application of the regional quasi-experimental estimation approach to estimate impacts of the Rural Development Programme (RDP) on the performance of the food processing sector in Poland. It brings several advantages compared with estimations based on firm data by capturing the RDP effects on non-supported firms and measures targeting overall development of rural areas; it provides a more accurate aggregate regional policy impacts; and it partially addresses the bias caused by general equilibrium effects. The application of the approach to Polish regional data shows that the RDP impacts structural change and employment in the food processing sector in Poland.

KEYWORDS
rural development; quasi-experimental estimation; food processing

JEL Q18, R58
HISTORY Received 26 March 2019; in revised form 14 December 2019

INTRODUCTION

The Rural Development Programme (RDP) is one of the main support instrument within the European Union's Common Agricultural Policy (CAP) accounting for around one-quarter of the total CAP budget. The RDP aims to promote the development of rural areas of the EU in order to address a wide range of economic, environmental and social challenges (European Network for Rural Development (ENRD), 2015a, 2019; European Commission, 2013, 2019).

A key question related to the public support in general, and to the RDP in particular, is the extent to which the support actually promotes the achievement of the policy objectives. To answer this question, there is a growing body of literature attempting to estimate empirically the impact of the RDP support. However, the assessment of the impact of the RDP is often driven by data availability, the type of the RDP measure analysed, the geographical coverage and the econometric approach. For instance, studies usually use survey (micro-) data to estimate the RDP effects. Still, surveys are not always representative for regional or member state (MS) population which limits the possibility to extrapolate the estimated results to obtain the overall aggregate regional or MS-level RDP impacts. For example, the Farm Accountancy Data Network (FADN) is commonly used to estimate the RDP effects (e.g., Arata & Sckokai, 2016; Olper, Raimondi, Cavicchioli, & Vigani, 2014; Salvioni & Sciulli, 2018) due to its harmonization across MS and availability across a longer time horizon (Castaño, Blanco, & Martinez, 2019). However, the FADN has some specificities that might affect the estimations. For example, it is representative only for commercial farms (non-commercial or small farms are not sampled); beneficiaries of CAP payments (i.e., farms) are in general underrepresented; and certain sectors (particularly smaller ones) could be either under- or overrepresented depending on the region or MS (e.g., sugar beet) (European Court of Auditors (ECA), 2016; Louhichi et al., 2018).[1] Other survey-based RDP studies suffer from similar problems. For example, Medonos, Ratinger, Hruška, and Špička (2012) and Michalek, Ciaian, and Pokrivcak (2018) use survey data that include only large farms to estimate the effects of the farm investment support

CONTACT
[a] jmichalek@gmx.de
Independent researcher, Kiel, Germany.
[b] **(Corresponding author)** pavel.ciaian@ec.europa.eu
Joint Research Centre (JRC), European Commission, Seville, Spain.
[c] federica.di-marcantonio@ec.europa.eu
Joint Research Centre (JRC), European Commission, Seville, Spain.
Supplemental data for this article can be accessed at https://doi.org/10.1080/00343404.2019.1708306

in Czechia and the support for producer organizations in Slovakia, respectively. Similarly, Kirchweger, Kantelhardt, and Leisch (2015) use voluntary bookkeeping farm data and exclude farms with small support levels to investigate the impacts of farm investment support in Austria.

The wide range of measures encompassed within the RDP further complicates the empirical analyses since each measure might lead to different effects. For example, the RDP implemented in the programming period 2007–13 included measures split in four thematic axes, and each included between five and 13 measures. Usually most studies investigate the impact of individual RDP measures (e.g., Arata & Sckokai, 2016; Bartova & Hurnakova, 2016; Kirchweger et al., 2015; Kirchweger & Kantelhardt, 2015; Medonos et al., 2012; Michalek, Ciaian, & Kancs, 2016; Michalek et al., 2018). Few studies focus on the combined RDP measures or total RDP support (e.g., Bakucs, Ferto, & Benedek, 2019; Salvioni & Sciulli, 2018).

When looking at the specific RDP measures, the most commonly analysed in the literature is the farm investment support (e.g., Bartova & Hurnakova, 2016; Desjeux, Dupraz, Latruffe, Maigne, & Cahuzac, 2014; Garrone, 2019; Kirchweger et al., 2015; Kirchweger & Kantelhardt, 2015; Medonos et al., 2012; Michalek et al., 2016; Olper et al., 2014; Petrick & Zier, 2011). Relatively wide importance is also given to the agri-environmental measure (e.g., Arata & Sckokai, 2016; Desjeux et al., 2014; Garrone, 2019; Kuhfuss & Subervie, 2018; Olper et al., 2014; Petrick & Zier, 2011; Pufahl & Weiss, 2009; Udagawa, Hodge, & Reader, 2014). Other measures are either seldom analysed or still unexamined. Almost all studies investigate the impact of the RDP on the performance of farmers or the agricultural sector. This is expected given that the main target of the RDP is the farming sector. Only a few studies focus on the rural development impacts beyond agricultural (farm) sector such as on regional well-being, quality of life or vitality of rural areas (Bakucs et al., 2019; Mack, Fîntîneru, & Kohler, 2018; Michalek, 2012b).

Geographical coverage also plays an important role when assessing the effects of the RDP supports because the implementation details of each specific RDP measure (e.g., eligibility criteria, size of the support) could vary between MS (ENRD, 2015a). Given this variation in the RDP implementation, a more desirable approach would be to perform an estimation for each regional unit separately. Studies usually perform estimates for either a specific EU region (e.g., Michalek et al., 2016) or an MS (e.g., Arata & Sckokai, 2016; Bakucs et al., 2019; Bartova & Hurnakova, 2016; Kirchweger et al., 2015; Kirchweger & Kantelhardt, 2015; Medonos et al., 2012; Michalek et al., 2018; Salvioni & Sciulli, 2018). However, this choice is apparently driven by data availability rather than by implementation of the studied RDP measures. Also, some studies combine different MS or EU regions together (e.g., Garrone, 2019; Olper et al., 2014).

From an econometric point of view, quasi-experimental estimation approaches dominate the literature in analysing the RDP effects. The most commonly applied quasi-experimental method is the (binary and, to a lesser extent, generalized) propensity-score matching (PSM) (e.g., Arata & Sckokai, 2016; Bakucs et al., 2019; Bartova & Hurnakova, 2016; Kirchweger et al., 2015; Kirchweger & Kantelhardt, 2015; Kuhfuss & Subervie, 2018; Medonos et al., 2012; Michalek, 2012a, 2012b; Michalek, Ciaian, & Kancs, 2014; Michalek et al., 2018; Salvioni & Sciulli, 2018; Udagawa et al., 2014).[2] The key challenge of quasi-experimental approaches is the construction of an appropriate counterfactual situation (i.e., a situation without the RDP support) in order to serve as a comparison point with the situation when the RDP is applied (Bakucs et al., 2019; Castaño et al., 2019). Some studies also apply spatial econometrics or dynamic panel econometric approaches to estimate the impacts of the RDP (e.g., Bakucs et al., 2019; Desjeux et al., 2014; Garrone, 2019; Olper et al., 2014; Petrick & Zier, 2011). In general, these econometric approaches can exploit variation in the RDP support intensity to estimate its effects. However, they estimate marginal effects of the support as compared with the quasi-experimental methods that attempt to identify the average treatment effect.

The objective of the present paper is to illustrate the application of the regional quasi-experimental estimation approach to estimate the regional impacts of the support on the performance of the food processing sector. Although the estimation of the RDP impacts based on micro-data is usually the preferred method (Castaño et al., 2019), the application of the regional approach might be more desirable in several situations such as when the aim is to estimate the overall (broader) regional effects of the RDP support, when there are important intraregional general equilibrium effects, in the case of support that targets the overall development of rural areas (e.g., public infrastructure) or in cases when the micro-data are not available. We apply the regional approach for Poland using panel data for 314 Nomenclature of Statistical Units 4 (NUTS-4).[3] By combining quasi-experimental approach with NUTS-4 data, we can address the shortcomings usually pertinent to the analysis of regional policy impacts at a more aggregated level such as at NUTS-2 where it is often more difficult to match supported with non-supported regions in order to make statistically sensible comparisons of mean outcomes (e.g., Mitze, Paloyo, & Alecke, 2012). Furthermore, if policy support is provided to all regions, yet with various intensity levels, it is statistically advantageous and methodologically desirable to consider a higher number of regions and to analyse policy impacts by applying methodological approaches which can account for such specificity (e.g., generalized PSM).

We use the RDP implemented in the programming period 2007–13 in Poland to illustrate the application of the regional quasi-experimental approach. We consider the RDP measure M123, which was targeted towards the food processing sector (referred to as 'food processing support', or FP-RDP) as well as the total RDP support (T-RDP). We analyse the RDP effects on the performance of the food processing sector using three impact indicators: the number of food processing firms, the number of exiting food processing firms and the employment in the food processing sector. The first two indicators aim to capture the structural change in the food processing sector. The third indicator measures the contribution of the RDP to employment creation, which is an important policy priority of the RDP (European Commission, 2006). To our knowledge, this is the first paper to apply a quasi-experimental regional approach to investigate the impacts of the RDP on the performance of the food processing sector.

We apply binary quasi-experimental evaluation methodology to estimate the impact of the FP-RDP. For the T-RDP, we employ the generalized propensity score (GPS) approach in order to address the problem of unavailability of the counterfactual non-supported regions. Further, the application of the GPS allows one to estimate how the effects of the T-RDP vary with the size (intensity) of the support.

Although this paper is an application for the RDP, it has also relevance for the evaluation of other type of regional development programmes in general and EU regional policies in particular, which are one of the most researched policies in the literature. The quasi-experimental estimation approaches are relatively commonly used in the literature to estimate the impact of regional development programmes on a variety of issues such as on growth and employment, poverty reduction, regional convergence, social inclusion or environmental performance (e.g., Kancs & Siliverstovs, 2016; Winters & Rubio, 2010). Alongside quasi-experimental estimation approaches, several other tools are also applied such as cross-sectional and panel data regression analyses (Rodríguez-Pose & Fratesi, 2004), regression discontinuity design methods (Becker, Egger, & von Ehrlich, 2010; Crescenzi & Giua, 2018), spatial econometric techniques (De Dominicis, 2014; Maynou, Saez, Kyriacou, & Bacaria, 2014) and non-parametric estimations (Coppola & Destefanis, 2015). The regional development programmes (similar as RDPs) often include support for non-productive activities or broader development issues that aim to deliver infrastructure and services for economic actors and affect multiple sectors and economic agents (firms, households). Important aspects of the regional development programmes is that often the key policy target is the development of specific regions and their economic convergence to other more developed regions. Further, the regional development policies might induce important interregional general equilibrium effects (Piattoni & Polverari, 2016). These factors give preference for the application of the regional approach compared with using micro-data as it might better identify the policy impacts, especially when the regional policy focuses on the development and convergence of regions (Hagen & Mohl, 2009).

METHODOLOGICAL CHALLENGES FOR IDENTIFYING THE RDP EFFECTS

The estimation of the RDP effects implies encountering several methodological challenges given the complex nature of the RDP support and wide variety of agents that can receive it (Castaño et al., 2019; Michalek, 2012a, 2012b).[4] With a specific focus on the food processing sector,[5] the RDP support may affect the performance of this sector in at least six different ways:[6]

- Effect I: through a *direct effect* of the measures specifically targeting food processing sector (i.e., FP-RDP) on the *supported food processing firms*.
- Effect II: through an *indirect effect* of other RDP measures (e.g., targeting agricultural farms) on the *supported food processing firms*.
- Effect III: through an *indirect effect* of other RDP measures on the *non-supported food processing firms*.
- Effect IV: through *specific mea*sure*s* targeting the *overall development of rural areas on supported and non-supported food processing firms*, such as support for public infrastructure, basic services or village renewal.
- Effect V: through the *general equilibrium* (spillover) *effect* of (all types of) the RDP support on the performance *non-supported food processing firms* and *non-food processing sector* (e.g., technology and capital suppliers, construction sector).
- Effect VI: through the *interaction effect between RDP measures* (i.e., the simultaneous effect of two or more independent RDP measures interacting with each other) on *supported and non-supported food processing firms*.

The performance of the food processing sector is affected through Effect I because it allocates subsidies directly to food processing firms, namely by the FP-RDP in the programming period 2007–13. The FP-RDP affects the supported firms either by improving the performance of the existing ones or facilitating the entrance of new (supported) firms. Given that in Poland the FP-RDP is granted in the form of capital subsidy, it is expected to facilitate on-firm investments on supported firms which can be translated into an improvement in their performance, particularly when firms have constrained access to credit (Brandsma, Kancs, & Ciaian, 2013; Michalek et al., 2016). Further, the impact of the FP-RDP might be reflected by reducing the capital cost that is expected to induce the substitution of capital for labour, and thus supported firms might become more capital intensive (Daly, Gorman, Lenjosek, MacNevin, & Phiriyapreunt, 1993).

Effects II and III imply that the RDP could have an indirect effect on the supported and non-supported food processing firms through secondary impacts of other RDP measures not directly targeting food processing firms but the primary agricultural production (farmers) (e.g., support for fostering innovation or quality schemes in agriculture, producer groups). These measures are expected to affect competition level and transaction and coordination costs among players in the chain by impacting vertical and horizontal integration in the agri-food sector (Dwyer, 2013; Michalek et al., 2018). These indirect effects may cause either positive effects (e.g., farmers' participation in the food quality schemes) or negative impacts (e.g., the RDP support for producers' groups) on the food processing sector depending on the type of RDP measure.

In the case of Effect IV, the RDP support for rural infrastructure and social services may reduce transaction costs and facilitate trade integration of rural areas and enable food processing firms' accessing inputs from rural areas or respond to new types of demand (e.g., agri-tourism) (Bakucs et al., 2019; Basile, Castellani, & Zanfei, 2008; Michalek, 2012b). Effect V – the general equilibrium effect – implies that the non-supported food processing firms might be affected either (1) indirectly (positively or negatively) by the RDP through competitive pressure, technological spillover effects or imitations or (2) through increase in factor prices (e.g., cost of labour, loan interest rate) and by crowding-out investment on non-supported firms both of which might adversely affect non-supported firms (Bronzini & De Blasio, 2006; Michalek et al., 2016).

Finally, the impact of the total RDP support or the combination of different measures on the performance food processing firms reflects the interactions between the RDP measures (Effect VI). Different measures can have complementary effects on each other and hence reinforcing the RDP effects on the performance of the food processing firms or alternatively it might fully or partially offset each other implying small RDP effects.

This complex nature of the possible effects of the RDP on the food processing sector poses several methodological challenges for their empirical identification. Indeed while some effect can be directly estimated with standard methodology, others require a more sophisticated approaches (Castaño et al., 2019; Fucilli, 2009; Michalek, 2012a, 2012b). For example, under the stable unit treatment value assumption (SUTVA), that is, an assumption of the lack of general equilibrium effects, Effect I can be estimated straightforwardly using quasi-experimental evaluation methodologies (e.g., PSM) based on firm-level data sets. However, micro-data for the food processing sector are often not collected or not easily available; owing to the privacy, they are generally not accessible to researchers. Most of the studies available in the literature investigate RDP effects on farmers for which micro-data are more accessible (e.g., Arata & Sckokai, 2016; Kirchweger et al., 2015; Medonos et al., 2012; Salvioni & Sciulli, 2018).

However, even if the individual firm panel data for food processing firms would be available about participants and non-participants in the RDP support, it might not be possible to identify the unbiased RDP impacts on the food processing firms (Effect I) because of the confounding general equilibrium effect of the RDP on non-supported firms (Effect V) (e.g., De Castris & Pellegrini, 2016).

The indirect effects of other RDP support measures on the food processing firms (Effects II and III) can be controlled in the quasi-experimental evaluation methodologies if these measures (their intensity levels) are used as explanatory variables in matching supported firms and the unsupported control firms. The interaction effect of RDP measures (Effect VI) is implicitly captured in the quasi-experimental evaluation methodologies when the total RDP support or the combination of different measures is considered in the estimations.

Regarding the RDP measures targeting the overall development of rural areas (Effect IV), their impacts cannot be identified using individual firm data because beneficiaries of these measures are usually not firms but public authorities who invest this support in public services (e.g., rural roads, child daycare facilities).

Considering all the aforementioned methodological challenges, the estimation of the effects of the RDP support on the food processing sector using individual micro-data might therefore be a complex task and an alternative methodological approach might need to be applied to address them.

THE REGIONAL QUASI-EXPERIMENTAL METHODOLOGICAL APPROACH

Although the estimation of the RDP impacts based on micro-data is the usually preferred approach (Castaño et al., 2019), the data on relevant socioeconomic aspects of rural development including those linked to the development of food processing at a regional or various administrative levels in individual MS can be exploited as an alternative solution to address the above methodological challenges.

The advantage of the regional approach is that it can address the problem related to the bias caused by the general equilibrium effect of the RDP on non-supported firms (Effect V) and the identification of the impacts of the RDP measures targeting overall development of rural areas (Effect IV).

Overall, the regional approach estimates the combined net intraregional effects of the RDP support reflecting the direct effect on the supported processing firms (Effect I) and the general equilibrium effect on the non-supported firms (Effect V). That is, the estimated net regional effect of the RDP encompasses impacts such as the productivity and profitability improvement of supported firms (Effect I), the competitive pressure between supported and non-supported firms, and the technological spillover effects or imitation on non-supported food processing firms (Effect V).[7] Although the regional approach corrects for the intraregional general equilibrium effects, it still suffers from the bias resulted from the interregional general equilibrium effect of the impacts of the RDP when the support allocated in one region impacts the performance of non-supported food processing firms from other regions.

Further, the regional approach can capture more accurately the impact of the measures targeted on the overall development of rural areas on the food processing sector (Effect IV) because, among others, it can compare the performance of the food processing sector between the supported regions and the non-supported control regions. The estimation approach based on micro-data usually cannot identify impacts of these type of measures because supported and non-supported firms cannot be identified as usually all firms in a given region are impacted by Effect IV.

A further advantage of the regional approach is that it can estimate the aggregate regional RDP impacts of the support on the performance of the food processing sector.

In contrast, the estimates based on the micro-survey data might lead to biased aggregate regional effects if sample is not representative.

As with any approach based on micro-data, also in the case of the regional approach it is desirable that it is applied at the programming area level containing a sample of regions at lower administrative units within the programming area (e.g., NUTS-4 or -5). This is because MS have certain regulatory flexibility in implementing the RDP which allows them to design instruments tailored to the specific needs of rural regions. This implies that the RDP implementation usually vary across programming areas (e.g., in terms of eligibility criteria, sectors supported) (European Commission, 2017). If the approach is applied at a higher level than the programming area (e.g., across several MS), then the estimated RDP effects will be affected by the differences in the RDP implementation across regions because each area might imply differential impacts depending on the implementation details (e.g., the impacts will likely differ for the support granted for the adoption of new technology as compared with the support targeting improvement of environment). That is, the estimates will provide the average RDP effect over the different programming areas which cannot be generalized to a specific area. One way to circumvent this problem in quasi-experimental estimation approaches is to use dichotomous control variables capturing the specific implementation characteristics of the RDP across regions when matching different types of regions. This approach will ensure that when applying the regional approach for several programming areas or at the EU level, the RDP effects are derived by comparing regions that have similar implementation of the RDP.

Further, as with any approach, the overall sample size must be sufficiently large in order to be able to identify econometrically the RDP effects. To obtain a larger sample size with the regional approach a straightforward strategy could be to assess the impact of the RDP at a programming area level containing a sample at a lower administrative level such as NUTS-3, -4 or -5. However, there is trade-off between the choice of regional level and to what extent the general equilibrium effect is controlled for in estimations. The lower the administrative level used in estimations, the greater is the likelihood that the estimated impacts are biased due to the presence of the interregional general equilibrium effects. However, in the case of the RDP, it is likely that the general equilibrium effects occur primarily at a local level such as through local imitations or impacting the price of immobile assets (e.g., land prices). In general, the share of the RDP support is low in the total economy;[8] hence, it is expected to have an insignificant economy-wide or interregional effects such as on labour wages level or credit costs (interest rate).

DATA AND VARIABLES

To illustrate the advantages of the regional approach, we use regional panel data for Poland at the NUTS-4 (powiat) level for the period 2006–16. The data are available from the Regional Data Bank published by the Polish Statistical Office. Of the total 379 NUTS-4 regions in Poland, 314 regions (rural NUTS-4) are included in the analysis (i.e., approximately 83% of all NUTS-4 regions). The remaining 65 regions are excluded because they represent urban areas.

The NUTS-4 panel data set contains approximately 120 variables capturing all relevant rural development dimensions, that is, economic, social, environmental, infrastructural, demographic, etc. The data also include information about the level of support for individual RDP measures (including for FP-RDP) and the allocation of other public support (e.g., Structural Funds). Additionally, data contain several indicators that can be used to measure the performance of the food processing sector.

In total we consider 63 potential socioeconomic variables as control covariates (before the RDP support implementation, i.e., 2006)[9] that can be used in the matching in the quasi-experimental design to address the selection bias in the allocation of the RDP support.[10] Given that in the analysed period regions also received other support than that under the RDP (or FP-RDP), we include in the set of control variables a covariate that reflects the level of other RDP support (in the case of the FP-RDP) and non-RDP support (e.g., Structural Funds, other CAP subsidies, etc.) (for both the FP-RDP and T-RDP). This variable is calculated as a cumulated amount of total public support (including from Structural Funds and both from EU and national sources) received by an individual NUTS-4 region over the period 2007–15 minus the support obtained from the RDP (i.e., minus the FP-RDP for the FP-RDP estimations and minus the T-RDP for the T-RDP estimations).

An important factor determining the applicability of the quasi-experimental approach (in particular, in the binary treatment) is the structure of the data regarding the support, for example, the ratio of supported to non-supported regions. Of the total 314 regions used in this paper, 270 (86%) received FP-RDP support, whereas only 44 regions (14%) were unsupported by this measure. In the case of T-RDP support, all (314) regions were supported. The comparison of the mean of covariates in the FP-RDP supported and non-supported regions for the pre-support period (i.e., 2006) is shown in Table G1 in Appendix G in the supplemental data online.

We use three outcome indicators to assess the impact of the RDP on the performance of the food processing sector calculated as the difference between the period after the implementation and the period before the implementation of the RDP:

- A change (difference) in the average number of food processing firms between 2009 and 2016.
- The number of exiting food processing firms expressed as a cumulative number of exiting firms between 2009 and 2016.[11]
- A change (difference) of employment in food processing firms between 2006 and 2013.

The number of food processing firms measures growth of firms (and the sector) as a whole, while the number of exiting firms (bankruptcies) captures the intensity (dynamics) of the structural change occurring in the food processing sector in Poland. For example, a positive growth in the total number of firms combined with a high firm exit rate indicates a larger structural change as compared with a situation when the increase in the total number of firms is the same, but the firm exit rate is lower. The former case also implies a higher entry rate of new firms as compared with the latter. The change (difference) of employment in food processing firms is a key socioeconomic indicator reflected in RDP priorities (European Commission, 2006).

The period considered for the numbers of food processing firms and exiting firms does not exactly match the programming before and after the implementation of the RDP (i.e., 2007–13). This difference is determined by the data availability at regional level which is the case for 2009 and 2016 for these two impact indicators. That is, the estimations are expected to capture the RDP impacts for the time period considered, that is, the change in the number of food processing firms and the number of exiting firms over the period 2009–16. The availability of the start year 2009 instead of 2006 is not expected to have a significant implications for the estimations given that the RDP takes considerable time until it is launched and supported projects are approved (i.e., due to the preparation of the national and regional RDP plans by MS followed by the launch of the calls for projects and selection of the successful projects from the eligible applicants). The use of 2016 as the last year instead of 2013 implies that we capture longer term effects of the RDP on the number of food processing firms and the exiting firms. In contrast, the estimated effects for the employment impact variable are rather short-term in nature given that 2013 is used as the last year in our analyses.

ESTIMATION APPROACH

We employ the binary treatment framework to estimate the FP-RDP effects, whereas for the T-RDP, we apply GPS. This choice is made for the reason to apply the most suitable procedures given the data characteristics as well as to illustrate the advantages of both approaches. In the case of the FP-RDP support, the data contain non-treated regions so they allow the use of a binary approach. The GPS is applied for the T-RDP support due to the unavailability of the counterfactual non-supported regions. Further, the application of GPS allows one to estimate how the T-RDP effects vary with the size of the support.

Binary treatment framework

We analyse the impact of the FP-RDP support on the performance of the food processing sector as measured by the average treatment on the treated (ATT), a widely applied method in the literature for quasi-experimental evaluation of policies (e.g., Abebaw & Haile, 2013; Démurger & Wan, 2012; Michalek et al., 2016; Nilsson, 2017). In this approach the causal effect of the support is the difference between the potential outcome with the RDP support (treated regions) and the potential outcome without the support (untreated regions). For treated regions, the expected value of the potential outcome without the support is not directly observed. In most non-experimental settings the estimation of the causal effect of a programme is based on regions without support as a control group. However, as explained above, this may result in a selection bias, because the RDP support allocation is non-random (Heckman, 1997; Heckman & Robb, 1985; Smith & Todd, 2004). To address the selection bias, we apply the ATT conditional on the probability distribution of observed covariates. We apply the combination of matching and difference-in-differences (DID) method. DID combined with the matching algorithms was implemented in order to remove time-invariant systematic differences (fixed effects) between supported and non-supported regions which might affect impact indicators.

We test three matching algorithms – Mahalanobis distance matching (MDM), PSM and coarsened exact matching (CEM) – as well as some of their combinations (e.g., CEM–PSM) and all jointly with DID (for more details on matching approaches, see also Appendix E in the supplemental data online).

Given that in our data set the number of the available control regions is smaller than the number of supported ones, this could create problems when attempting to find appropriate matches using standard PSM (Stuart, 2010) such as it may lead to a severe reduction of the number of available matches and therefore may affect negatively the external validity of the obtained results. We attempt to maximize the use of information contained in the data describing the group of possible controls (non-supported regions) in the sense that all their possible matches (with supported regions) will be taken into account by applying a modified exact MDM matching. The advantages of the modified MDM compared with a standard PSM are, among others, that full information included in the data set on possible controls is used, and it enables calculation of ATT using the largest possible set of non-supported regions as controls.

Some studies have advocated coarsened exact matching (CEM) (e.g., Iacus, King, & Porro, 2009; Wells et al., 2013). For this reason we also apply the CEM method. We apply it in two ways: (1) directly, using all control variables as described above and calculating effects of the FP-RDP by adjusting regression equation using CEM matched regions only; and (2) in association with the PSM–DID matching, where only regions matched under the CEM method (supported and non-supported) were used for the calculation of FP-RDP effects (a double matching).[12] The main advantage of CEM includes the fact that increasing balance on one variable cannot increase imbalance on another one (this may happen in PSM). Other important advantages are the easiness of its implementation, less sensitivity to measurement error and greater computational efficiency. The drawback associated with CEM matching is that it is very sensitive to the numbers of control variables and coarsened stratums (strata).

Thus, it was necessary to reduce the set of covariates to 15 in the estimations.[13]

Dose–response framework

Whilst the binary treatment framework permits one to assess the impact for the RDP support by exploiting the information related to the receipt of the support, it fails to account for the size (intensity) of the support. According to their specific characteristics, regions can differ in both obtaining or not the RDP supports and also in receiving lower or higher support (intensity of the treatment). We measure the intensity of the T-RDP support in terms of the total RDP amount allocated over the supported period (2007–13) among all considered 314 NUTS-4 regions in Poland.

In order to estimate the effects of various support intensity levels on the performance of the food processing sector, we apply a GPS matching and the dose–response function (Hirano & Imbens, 2004), where GPS is defined as the conditional density of the treatment (support) given the covariates and has a balancing property similar to the propensity score under the setting of binary treatment (Michalek et al., 2014). We have selected 15 covariates for GPS matching, the same as for the estimation of CEM method under the binary treatment. The empirical implementation of the GPS approach follows Hirano and Imbens (2004) and Bia and Mattei (2008).[14]

RESULTS

The impacts of food processing support: binary treatment framework

The estimated results for the FP-RDP effects on the food processing sector for all three impact indicators using the alternative matching approaches are presented in Table 1. Alongside the modified MDM and CEM–PSM–DID matching methods, we also include the standard PSM–DID for comparison purposes. Note that PSM–DID is a less efficient estimator for the data set used in this paper due to the low ratio of control to supported regions.

Overall, the signs of the estimated effects are consistent across the alternative matching approaches. However, there is some variation in the magnitude of the estimated effects. The estimated results show that the FP-RPD support contributed to the growth of the total number of food processing firms but also to the exit of firms from the food processing sector in Poland. Based on the modified MDM approach, on average the support led to an increase of the total number of food processing firms by 1.9 per supported region, which represents 513 (= 1.9 × 270 regions) firms overall in Poland. The growth of the number of food processing firms caused by the support represent 14% of the total growth observed in the studied period (i.e., 2009–16). The number of exiting food processing firms induced by the FP-RPD support represents 4.9 per supported region and 1323 firms overall in Poland. The increase in the number of firms' exits caused by the support represents 10% of the total exits observed in the studied period (Table 1). Given that the FP-RPD support led to a net increase in the total number of food processing firms, this implies that the support contributed to the creation of 6.9 (= 1.9 + 4.9) new firms per supported region (1836 overall in Poland).

The CEM method estimates a greater impact for the FP-RPD support on the number of exiting firms and a smaller impact on the total number of firms compared with the modified MDM approach. The increase in the number of the food processing firms due to the FP-RPD is positive as estimated by the CEM method, yet it is smaller than in the case of the MDM method. In the case of exiting food processing firms, the estimated effect is almost twice greater in the CEM method than in the MDM method. Indirectly, the higher firm exit due to the FP-RPD support estimated by the CEM method implies a smaller growth of the total number of firms. The remaining two methods (i.e., CEM–PSM–DID and PSM–DID) provide similar effects or are in between the modified MDM and CEM approaches (Table 1).

Overall, these results imply that the FP-RPD support contributed to structural change in the food processing sector in Poland by causing many firms to exit, but at the same time it contributed to the creation of new ones and their overall increase.

No studies in the literature estimate the impact of the RDP support on the food processing sector in general, and even less so on the structural change in the sector. Most of the studies cover the farming sector. However, even in the case of farm-focused analyses, not many studies investigate the impact of the RDP on (farm) structural change. A measure comparable with the FP-RDP but targeted on the farming sector is the on-farm RDP investment support. This is because both types of support are capital subsidies and are expected to induce similar incentives for the beneficiary sector. To our knowledge, the only study available in the literature that investigates the impact of on-farm investment support on farm structural change is Kirchweger and Kantelhardt (2015), which estimates the impact of farm investment support on structural change of farmers across different production specializations. Their results show that the on-farm investment support reduces exit rates from husbandry and stimulates farmers to enter organic farming. However, they do not estimate the exit or entry into the farming (agricultural) sector.

Although due to the FP-RDP the number of food processing firms increased, the estimates of all considered matching approaches suggest that the FP-RDP led to a reduction in the employment in the food processing sector in Poland. That is, the results show that although the FP-RDP support contributed to an increase of employment in the food processing sector in supported regions, this increase was much lower than in the comparable (matched) group of non-supported regions. The net effect of the FP-RDP on employment was therefore negative. The employment reduction effects of the FP-RDP support vary between 57.8 and 214.1 persons per supported region and between 15,606 persons and 57,807 persons overall in Poland among the alternative matching approaches.

Table 1. Estimated 'food processing support' of the Rural Development Programme (FP-RDP) effects on the food processing sector for the alternative evaluation methodologies.

	PSM–DID (65 control variables)	Modified MDM (65 control variables)	CEM–PSM–DID (15 control variables)	CEM (weighted regression with 15 control variables)
Number of food processing firms				
I. ATT–DID (per supported region)	1.94	1.90	0.26	0.32
II. ATT–DID (per country, I × 270 regions)	522.72	513.00	70.65	86.40
III. Effect of other factors (IV – II)	3098	3108	3550	3535
IV. Total effect (Poland) (2009–16)	3621	3621	3621	3621
Number of exiting food processing firms				
I. ATT–DID (per supported region)	6.27	4.90	3.97	8.45
II. ATT–DID (per country, I × 270 regions)	1692	1323	1071	2281
III. Effect of other factors (IV – II)	11,319	11,688	11,940	10,730
IV. Total effect (Poland) (2009–16)	13,011	13,011	13,011	13,011
Employment in the food processing sector				
I. ATT–DID (per supported region)	−102.04	−214.10	−168.60	−57.80
II. ATT–DID (per country, I × 270 regions)	−27,552	−57,807	−45,522	−15,606
III. Effect of other factors (IV – II)	34,162	64,417	52,132	22,216
IV. Total effect (Poland) (2013–06)	6610	6610	6610	6610

Note: ATT, average treatment on the treated; CEM, coarsened exact matching; DID, difference-in-differences; MDM, Mahalanobis distance matching; PSM, propensity-score matching.

The results based on the modified MDM and CEM–PSM–DID are the highest and rather close to each other, that is, −214 versus −169 persons per region, though in the case of the CEM–PSM–DID method, the number of originally used control variables (65) was significantly reduced (to 15 only). In contrast, the difference in the absolute magnitude of the estimated FP-RDP effect based on the modified MDM method is much larger compared with the CEM method (Table 1).

The estimated reduction of employment could be because the FP-RDP support in Poland targeted in particular new technology adoption and the modernization of the technical facilities in the food processing sector which is expected to replace labour in production process. Similar results are obtained in some studies analysing the impact of the on-farm RDP investment support. Although some studies find insignificant or positive employment effects, others bring some evidence that on-farm investment support could potentially reduce agricultural employment. For example, the estimates of Olper et al. (2014) for 150 EU regions show that the on-farm investment support exerts a positive impact on the labour outflow from agriculture potentially due to the substitution of labour by capital. In contrast, a more extensive study by Garrone (2019) for 210 EU regions, which is based on a more representative subsidy indicators, finds that the on-farm RDP investment support has no effect on the labour outflow from agriculture at the EU level (i.e., when all EU regions are pooled together in the estimations); the effect was found significant only in new MS by reducing labour outflow from agriculture in these countries, while in the old MS it was insignificant. The estimates of Bartova and Hurnakova

(2016) show that the farm investment support contributed to a decline in farm labour in large farms in Slovakia for the period 2007–13. Desjeux et al. (2014) find that farm labour in France during the period 2006–11 was not affected by the contemporaneous on-farm RDP investment support granted during the period 2006–11 only by the participation in on-farm investment support in the previous programming period. Salvioni and Sciulli (2018) find that the RDP support had no impact on farm employment but increased capital–labour intensity in farms in Italy. However, they did not estimate the effects of the RDP investment support alone but combined with other measures (i.e., on-farm farm investment support, the establishment of young farmers, and improvement in the processing and marketing of farm products) implying that other non-investment measures (i.e., the establishment of young farmers) might have offset the reduction of the employment effect of the investment subsidies. Petrick and Zier (2011) find no significant effect of the on-farm investment support in three East German states, while the investment support for processing and marketing of agricultural products was found to have a significant negative effect on agricultural employment. Finally, Kirchweger et al. (2015) find an insignificant impact of on-farm investment support on farm labour input in Austria.

The differences in the magnitude of the effects obtained for the alternative matching approaches highlight the sensitivity of the estimated effects to the applied matching methodology. We note that the standard PSM–DID appears less suitable than both the MDM and CEM because in a situation when there are more supported units than controls (as is our case), the external validity of the obtained results may be negatively affected (i.e., the obtained results are valid for only a small fraction of supported regional units). Regarding the MDM and CEM approaches, the results of the modified MDM could be considered as the first best. This is because the modified MDM approach uses full information on the possible set of controls in matching non-supported units with their matching twins and enables calculation of ATT using the largest possible set of non-supported regions as controls. In contrast, the CEM approach being sensitive to the number of control variables, size of coarsening (size of coarsened bins) and the number of coarsened strata it made necessary to reduce the set of covariates as well as to drop a relatively significant number of regions because exact matches could not be found. Indeed, the sample size is usually found in the literature to be negatively correlated with the magnitude of the estimated policy effects (Slavin & Smith, 2009). The fact that the CEM approach made it necessary to reduce both the number of regional units in the matching and the number of control variables potentially implies that, by using this approach (also in a combination with PSM–DID), the original selection bias could not be fully addressed.

The impacts of the T-RDP support: dose–response framework

The estimated T-RDP effects using the dose–response function for the three impact indicators are presented in Figures G5–G7 in Appendix G in the supplemental data online. Overall, the estimated effects depend on the size (intensity) of the support. More specifically, the results show positive effects of the T-RDP support on the number of food processing firms. According to GPS results, the T-RDP support led to an increase of the total number of food processing firms approximately between zero and 12 per supported region (i.e., up to 3768 in the whole country). However, the GPS results suggest the effectiveness of the support varied with the support intensity level. The increase in the number of food processing firms dropped with the support intensity ranging between PLN0 and PLN180 million per region from approximately 10 firms to around zero firms per supported region and thereafter increased reaching in the maximum point (at the intensity level of around PLN590 million per region) approximately 10–12 firms per supported region. A further increase of the support intensity beyond this level leads again to a decrease of the change of the number of food processing firms (see Figure G5 in Appendix G in the supplemental data online). As argued above, the T-RDP support implies various effects on the food processing sector either stimulating or constraining the sector development. Given that the T-RDP leads to an increase in the number of food processing firms, the estimates suggest that the positive T-RDP effects more than offset the negative effects.

As shown in Figure G6 in Appendix G in the supplemental data online, the T-RDP support resulted in an increase in the number of exiting food processing firms. As above, the support effect varied with its intensity level. The number of exiting firms decreased from approximately 40 firms per supported region to about 18 firms with the support intensity level ranging between PLN0 and PLN450 million per supported region and, thereafter, increased again with a higher support intensity reaching in the maximum point (at the intensity level of around PLN700 million per region) approximately 35 exiting firms per supported region.

The GPS estimates show a positive impact of the T-RDP on employment in the food processing sector. However, the effectiveness of this support varied with the support intensity level. The employment growth due to the support decreased from around 500 persons to almost zero persons per supported region with the support intensity rising from PLN0 to PLN160 million per region. The employment growth then increased moderately with a higher support intensity reaching the maximum point (at around PLN600 million per region) of approximately 270 persons per supported region (see Figure G7 in Appendix G in the supplemental data online). These results are different to those obtained for the FP-RDP support. The difference in the employment effects between the T-RDP and the FP-RDP are because in the former case many different RDP measures are included (e.g., farm investment support, agro-environmental measures, animal welfare, farm producers groups, support for rural infrastructure and social services), implying that many of these measures impact positively the employment in the food processing sector, whereas the FP-RDP is capital subsidy which likely leads to the substitution of labour for capital.

As mentioned above, to our knowledge no available comparable studies in the literature analyse the impact of the RDP on the food processing sector. Comparing instead our estimates with the studies estimating the impact of the T-RDP support on the farming sector, for example, Olper et al. (2014) (covering 150 EU regions) find that the T-RDP tends to exert a negative impact on the labour outflow from agriculture. In contrast, a more extensive study by Garrone (2019) for 210 EU regions, which uses a more representative subsidy indicators, finds that the T-RDP has no effect on the labour outflow from agriculture when the whole EU is considered in the estimations; the effect is significant only in the subsample of the old MS by reducing labour outflow from agriculture in these countries.

CONCLUSIONS

In this paper we contribute to the literature by illustrating the application of the regional quasi-experimental estimation approach to estimate the impacts of the EU RDP support implemented in the programming period 2007–13 on the performance of the food processing sector. We apply a binary quasi-experimental evaluation methodology to estimate the impact of the FP-RDP support and the generalized PSM approach for the T-RDP. We show how the regional approach can address some limitations of other estimation approaches based on the micro-survey data. Particularly we show how the regional approach can partially address the bias caused by the general equilibrium effects of the RDP on non-supported firms, and identify the impacts of the RDP measures targeting overall development of rural areas as well as how they can deliver more accurate aggregate regional impacts for the support. We illustrate the impact of the RDP on the performance of the food processing sector using regional panel data for 314 Polish NUTS-4 regions for three impact indicators: the number of food processing firms, the number of exiting food processing firms and the employment in the food processing sector.

The estimated results for the FP-RPD show that this support contributed to some important structural change in the food processing sector in Poland by causing many firms to exit, but at the same time it contributed to the creation of new ones and their overall increase. In terms of employment, we find that the FP-RPD led to a reduction of labour in the food processing sector in Poland, likely because the support induced substitution of labour for capital. Similar results were obtained for the T-RDP support. The T-RDP caused an increase in both the total number food processing firms and the number of exiting firms. However, in contrast to the FP-RPD, the T-RDP support had a positive impact on employment in the food processing sector because the T-RDP includes many different measures, many of which impact positively the employment in the food processing sector. The GPS approach used for estimating the T-RDP effects shows that the support effects varied with its intensity level, suggesting different policy efficiency depending on its size.

The implication of our analyses for the RDP impact analyses is that the regional quasi-experimental estimation approach can provide important additional insights in bringing evidence to support policy-making in this area. This is valid not only for the RDP support but also for other (non-food or non-agricultural) types of regional development programmes. In particular, this methodology is relevant for assessing the impacts of regional programmes where there are important intraregional general equilibrium effects, for programmes targeting general economic development of regions (e.g., EU regional policy), when the objective is to estimate the overall regional effects of the programme, or when the micro-data are not available. However, the application of this approach has several important caveats that need to be taken into consideration in policy evaluations. First, the differences in the magnitude of the estimates effects obtained for the alternative binary treatment approaches highlight the need to select carefully an appropriate matching methodology also in order to evaluate the sensitivity of the estimated effects. Second, although the regional approach corrects for the intraregional general equilibrium effects – in contrast to methods based on individual data – it still does not account for the interregional general equilibrium effect of the RDP impacts. Third, the estimated results in this paper as such cannot be straightforwardly generalized to other MS/regions or to other types of development programmes (e.g., EU regional policy) because usually the implementation details of each programme are different (e.g., in terms of the eligible sectors, the eligible types of firms), and the implementation of the same programme often differs across MS/regions. Finally, while the applied estimation approach can be used for other MS/regions or other types of regional policies, the list of covariates to control for selection bias needs to be adjusted according to the specificities of a particular programme and data structure.

DISCLOSURE STATEMENT

The authors are solely responsible for the content of the paper. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

FUNDING

The authors acknowledge the financial support received from the Joint Research Centre of the European Commission, project Estimation of the Impacts of Rural Development Policies on the EU Food Processing Sector Performance and Growth [grant number D.B721202].

NOTES

1. According to ECA (2016), the share of beneficiaries of CAP direct payments (i.e., farms) not represented in FADN varies from 12% in Bulgaria to 79% in Slovakia. In the case of sugar beet, FADN underrepresents sugar

beet production by 18%, 99% and 235% compared with the total populations in Greece, Slovenia and Sweden, respectively. In contrast, in Italy, Slovakia, the UK and Spain, it is over represented by 22%, 25%, 48% and 119%, respectively (Louhichi et al., 2018). This implies that estimations based on FADN data might in some MS lead to an overestimation and in others to an underestimation of the aggregated policy impacts at the MS level depending on the bias in the representation of a given sector or farm population.

2. Recently, a novel methodological approach was proposed based on 'spatial propensity score matching' technique (De Castris & Pellegrini, 2016).

3. Empirical applications in the literature estimating policy impacts at a regional level usually use NUTS-2 data (e.g., Olper et al., 2014; Garrone, 2019); data at lower regional unit are used to a lesser extent, although their application has increased recently (e.g., Fratesi & Perucca, 2014; Desjeux et al., 2014; Bakucs et al., 2019). This choice is mainly driven by data availability. At the NUTS-2 level, most of the variables required for estimations exist. At a lower regional level (e.g., NUTS-3 or -4), detailed data are usually not available for the full set of required variables or regions, which restricts the application of econometric estimations (Piattoni & Polverari, 2016).

4. For the background information on the RDP support, see Appendix A in the supplemental data online.

5. For more information about the food processing sector in Poland, see Appendix B in the supplemental data online.

6. For a more detailed explanation about the challenges when identifying the RDP effects, see Appendix C in the supplemental data online.

7. The regional approach estimates the average RDP effect of the impacts occurring at the firm-level across regions. In contrast, one can estimate the region-specific direct effects of the RDP support (Effect I) using firm-level data if a sufficient number of firm-level observations are available for each region. However, as argued above, such estimations might be biased due to the presence of the general equilibrium effects.

8. Based on gross domestic product (GDP) data from the Eurostat and RDP budget from ENRD (2015b), the share of the T-RDP (FP-RDP) support for the period 2007–13 is 4.4 (0.24%) of GDP in 2013 and 0.69% (0.04) of the sum of GDP over the whole support period 2007–13.

9. All variables were checked for consistency and outliers. Correlation and covariance analysis was carried out in order to sort out variables which were almost perfectly correlated to each other.

10. For a more detailed explanation about the selection of covariates, see Appendix D in the supplemental data online.

11. The number of exiting food processing firms was measured as the number of food processing firms crossed off from the firm registry (inter alia, due to bankruptcy).

12. As in Blackwell, Iacus, King, and Porro (2010).

13. The list of selected covariates includes: total population, natural population growth, three environmental pollution variables (i.e., emissions of dust/smog, emission of gas and percentage of sewage cleaned), employment per 1000 population, unemployment rate, number of dwellings per population, investment in enterprises, gross salary, value of fixed assets, urban population (per cent of the total), rural unemployment and other public funds. These covariates were selected because they are important determinates in the allocation of the RDP funds between regions.

14. For a description of the GPS approach, see Appendix F in the supplemental data online (see also Hirano & Imbens, 2004; Michalek et al., 2014).

ORCID

Pavel Ciaian http://orcid.org/0000-0003-2405-5850

REFERENCES

Abebaw, D., & Haile, M. G. (2013). The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia. *Food Policy*, *38*, 82–91. doi:10.1016/j.foodpol.2012.10.003

Arata, L., & Sckokai, P. (2016). The impact of agri-environmental schemes on farm performance in five E.U. member states: A DID-matching approach. *Land Economics*, *92*(1), 167–186. doi:10.3368/le.92.1.167

Bakucs, Z., Ferto, I., & Benedek, Z. (2019). Success or waste of taxpayer money? Impact assessment of rural development programs in Hungary. *Sustainability*, *11*(4), 1–23.

Bartova, L. and Hurnakova, J. (2016). Estimation of farm investment support effects: A counterfactual approach. In Proceedings of the International Scientific Conference Quantitative Methods in Economics: Multiple Criteria Decision Making XVIII, pp. 19–24.

Basile, R., Castellani, D., & Zanfei, A. (2008). Location choices of multinational firms in Europe: The role of EU Cohesion Policy. *Journal of International Economics*, *74*(2), 328–340. doi:10.1016/j.jinteco.2007.08.006

Becker, S., Egger, P. H., & von Ehrlich, M. (2010). Going NUTS: The effect of EU Structural Funds on regional performance. *Journal of Public Economics*, *94*(9–10), 578–590. doi:10.1016/j.jpubeco.2010.06.006

Bia, M., & Mattei, A. (2008). A Stata package for the estimation of the dose–response function through adjustment for the generalized propensity score. *Stata Journal: Promoting Communications on Statistics and Stata*, *8*(3), 354–373. doi:10.1177/1536867X0800800303

Blackwell, M., Iacus, S., King, G., & Porro, G. (2010, February 22). *cem: Coarsened exact matching in Stata*. Retrieved from http://gking.harvard.edu/files/gking/files/cem-stata.pdf

Brandsma, A., Kancs, D., & Ciaian, P. (2013). The role of additionality in the EU Cohesion Policies: An example of firm-level investment support. *European Planning Studies*, *21*, 838–853. doi:10.1080/09654313.2012.722928

Bronzini, R., & De Blasio, G. (2006). Evaluating the impact of investment incentives: The case of Italy's Law 488/1992. *Journal of Urban Economics*, *60*, 327–349. doi:10.1016/j.jue.2006.03.005

Castaño, J., Blanco, M., & Martinez, P. (2019). Reviewing counterfactual analyses to assess impacts of EU rural development programmes: What lessons can be learned from the 2007–2013 ex-post evaluations? *Sustainability*, *11*(4), 1–22. doi:10.3390/su11041105

Coppola, G., & Destefanis, S. (2015). Structural Funds and regional convergence: Some sectoral estimates for Italy. In Mussida, C., & Pastore, F. (Eds.), *Geographical labor market imbalances* (pp. 307–333). Berlin: Springer.

Crescenzi, R., & Giua, M. (2018). *One or many Cohesion Policies of the European Union? On the diverging impacts of Cohesion Policy across member states* (SERC Discussion Paper No. 230). Spatial Economics Research Centre.

Daly, D., Gorman, I., Lenjosek, G., MacNevin, A., & Phiriyapreunt, W. (1993). The impact of regional investment incentives on employment and productivity. *Regional Science and Urban Economics*, *23*(4), 559–575. doi:10.1016/0166-0462(93)90047-I

De Castris, M., & Pellegrini, G. (2016). *Neighbourhood effects and propensity score matching* (Working Papers No. 0515). Rome: CREI Università degli Studi Roma Tre.

De Dominicis, L. (2014). Inequality and growth in European regions: Towards a place-based approach. *Spatial Economic Analysis*, *9*(2), 120–141. doi:10.1080/17421772.2014.891157

Démurger, S., & Wan, H. (2012). Payments for ecological restoration and internal migration in China: The sloping land conversion program in Ningxia. *IZA Journal of Migration*, *1*(10), 1–22.

Desjeux, Y., Dupraz, P., Latruffe, L., Maigne, E., & Cahuzac, E. (2014). Evaluating the impact of rural development measures on farm labour use: A spatial approach. Paper presented at the EAAE 2014 Congress Agri-Food and Rural Innovations for Healthier Societies, Ljubljana, Slovenia, August 26–29, 2014.

Dwyer, J. (2013). Transformation for sustainable agriculture: What role for the second Pillar of CAP? *Bio-based and Applied Economics*, *2*(1), 29–47.

European Commission. (2006). *Rural development 2007–2013: Handbook on common monitoring and evaluation framework* (Guidance Document). Brussels: Directorate General for Agriculture and Rural Development.

European Commission. (2013). *Overview of CAP reform 2014–2020* (Agricultural Policy Perspectives Brief No. 5*). Brussels: European Commission. Retrieved from https://ec.europa.eu/agriculture/sites/agriculture/files/policy-perspectives/policy-briefs/05_en.pdf

European Commission. (2017). *CAP implementation: Flexibility given to member states: State of play and perspectives*. Luxembourg: Publications Office of the European Union.

European Commission. (2019). Rural development 2014–2020. Agriculture and rural development, European Commission. Retrieved from https://ec.europa.eu/agriculture/rural-development-2014-2020_en

European Court of Auditors (ECA). (2016). *Is the Commission's system for performance measurement in relation to farmers' incomes well designed and based on sound data?* (Special Report No. 01). Luxembourg: European Court of Auditors.

European Network for Rural Development (ENRD). (2015a). *State of play of total public and EAFRD expenditure per measure in EU-27*. Retrieved from https://enrd.ec.europa.eu/sites/enrd/files/mi_financial_fiche_2015_eu27_0.pdf

European Network for Rural Development (ENRD). (2015b). *State of play of total public and EAFRD expenditure per measure in Poland*. Retrieved from https://enrd.ec.europa.eu/sites/enrd/files/mi_financial_fiche_2015_pl_0.pdf

European Network for Rural Development (ENRD). (2019). *Priority & focus area Summaries*. Retrieved from https://enrd.ec.europa.eu/policy-in-action/rural-development-policy-figures/priority-focus-area-summaries_en

Fratesi, U., & Perucca, G. (2014). Territorial capital and the effectiveness of cohesion policies: An assessment for CEE regions. *Investigaciones Regionales*, *29*, 165–191.

Fucilli, V. (2009). Mid-term evaluation of rural development plans in Italy: Comparing models. *New Medit*, *8*(4), 13–21.

Garrone, M. (2019). Jobs and agricultural policy: Impact of the Common Agricultural Policy on EU agricultural employment. In *Essays on EU agriculture, food and the Common Agricultural Policy*. PhD dissertation, KU Leuven.

Hagen, T., & Mohl, P. (2009). *Econometric evaluation of EU Cohesion Policy: A survey* (Discussion Paper No. 09-052). Mannheim: ZEW.

Heckman, J. (1997). Instrumental variables: A study of implicit behavioral assumptions used in making program evaluations. *Journal of Human Resources*, *32*(3), 441–462. doi:10.2307/146178

Heckman, J., & Robb, R. (1985). Alternative methods for evaluating the impact of interventions. In Heckman, J., & Singer, B. (Eds.), *Longitudinal analysis of labor market data* (pp. 156–246). Cambridge: Cambridge University Press.

Hirano, K., & Imbens, G. W. (2004). The propensity score with continuous treatments. In Gelman, A., & Meng, X.-L. (Eds.), *Applied Bayesian modeling and causal inference from incomplete-data perspectives* (pp. 73–84). Chichester: Wiley InterScience.

Iacus, S. M., King, G., & Porro, G. (2009). Cem: Software for coarsened exact matching. *Journal of Statistical Software*, *30*(9), 1–27. doi:10.18637/jss.v030.i09

Kancs, D., & Siliverstovs, B. (2016). R&D and non-linear productivity growth. *Research Policy*, *45*(3), 634–646. doi:10.1016/j.respol.2015.12.001

Kirchweger, S., & Kantelhardt, J. (2015). The dynamic effects of government-supported farm-investment activities on structural change in Austrian agriculture. *Land Use Policy*, *48*, 73–93. doi:10.1016/j.landusepol.2015.05.005

Kirchweger, S., Kantelhardt, J., & Leisch, F. (2015). Impacts of the government-supported investments on the economic farm performance in Austria. *Agricultural Economics – Czech*, *8*, 343–355.

Kuhfuss, L., & Subervie, J. (2018). Do European agri-environment measures help reduce herbicide use? Evidence from viticulture in France. *Ecological Economics*, *149*, 202–211. doi:10.1016/j.ecolecon.2018.03.015

Louhichi, K., Espinosa, M., Ciaian, P., Perni, A., Vosough Ahmadi, B., Colen, L., & Gomez y Paloma, S. (2018). *The EU-wide individual farm model for Common Agricultural Policy analysis* (IFM-CAP v.1: Economic Impacts of CAP Greening. EUR 28829 EN). Luxembourg: European Commission, Joint Research Centre, Publications Office of the European Union.

Mack, G., Fîntîneru, G., & Kohler, A. (2018). Do rural development measures improve vitality of rural areas in Romania? *AgroLife Scientific Journal*, *7*(2), 82–98.

Maynou, L., Saez, M., Kyriacou, A., & Bacaria, J. (2014). The impact of Structural and Cohesion Funds on Eurozone convergence, 1990–2010. *Regional Studies*, *50*(7), 1127–1139. doi:10.1080/00343404.2014.965137

Medonos, T., Ratinger, T., Hruška, M., & Špička, 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), 35–48.

Michalek, J. (2012a). *Counterfactual impact evaluation of EU rural development programmes – Propensity score matching methodology applied to selected EU member states*, Vol. 1: *A micro-level approach*. Luxembourg: Publications Office of the European Union.

Michalek, J. (2012b). *Counterfactual impact evaluation of EU rural development programmes – Propensity score matching methodology applied to selected EU member states*, Vol. 2: *A regional approach*. Luxembourg: Publications Office of the European Union.

Michalek, J., Ciaian, P., & Kancs, D. (2014). Capitalization of the single payment scheme into land value: Generalized propensity score evidence from the European Union. *Land Economics*, *90*(2), 260–289. doi:10.3368/le.90.2.260

Michalek, J., Ciaian, P., & Kancs, D. (2016). Investment crowding out: Firm-level evidence from northern Germany. *Regional Studies*, *50*(9), 1579–1594. doi:10.1080/00343404.2015.1044957

Michalek, J., Ciaian, P., & Pokrivcak, J. (2018). The impact of producer organizations on farm performance: The case study of large

farms from Slovakia. *Food Policy*, *75*, 80–92. doi:10.1016/j.foodpol.2017.12.009
Mitze, T., Paloyo, A., & Alecke, B. (2012). *Quasi-experimental methods in empirical regional science and policy analysis: Is there a scope for application?* (Ruhr Economic Papers No. 367). RWI – Leibniz-Institut für Wirtschaftsforschung, Ruhr-University Bochum, TU Dortmund University, University of Duisburg-Essen.
Nilsson, N. (2017). Productivity effects of CAP investment support: Evidence from Sweden using matched panel data. *Land Use Policy*, *66*, 172–182. doi:10.1016/j.landusepol.2017.04.043
Olper, A., Raimondi, V., Cavicchioli, D., & 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. doi:10.1093/erae/jbu002
Petrick, M., & Zier, P. (2011). Regional employment impacts of Common Agricultural Policy measures in Eastern Germany: A difference-in-differences approach. *Agricultural Economics*, *42*(2), 183–193. doi:10.1111/j.1574-0862.2010.00509.x
Piattoni, S., & Polverari, L. (2016). *Handbook of Cohesion Policy in the EU*. Cheltenham: Edward Elgar.
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. doi:10.1093/erae/jbp001
Rodríguez-Pose, A., & Fratesi, U. (2004). Between development and social policies: The impact of European Structural Funds in Objective 1 regions. *Regional Studies*, *38*, 97–113. doi:10.1080/00343400310001632226
Salvioni, C., & Sciulli, D. (2018). Rural development policy in Italy: The impact of growth-oriented measures on farm outcomes. *Agricultural Economics (Zemědělská Ekonomika)*, *64*(3), 115–130. doi:10.17221/73/2016-AGRICECON
Slavin, R., & Smith, D. (2009). The relationship between sample sizes and effect sizes in systematic reviews in education. *Educational Evaluation and Policy Analysis*, *40*, 215–229.
Smith, J., & Todd, P. (2004). Does matching overcome Lalonde's critique of nonexperimental estimators? *Journal of Econometrics*, *125*(1–2), 305–353. doi:10.1016/j.jeconom.2004.04.011
Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, *25*, 1–21. doi:10.1214/09-STS313
Udagawa, C., Hodge, I., & Reader, M. (2014). Farm level costs of agri-environment measures: The impact of entry level stewardship on cereal farm incomes. *Journal of Agricultural Economics*, *65*, 212–233. doi:10.1111/1477-9552.12043
Wells, A. R., Hamar, B., Bradley, C., Gandy, W. M., Harrison, P. L., Sidney, J. A., … Pope, J. E. (2013). Exploring robust methods for evaluating treatment and comparison groups in chronic care management programs. *Population Health Management*, *16*(1), 35–45. doi:10.1089/pop.2011.0104
Winters, P., & Rubio, S. S. (2010). *Evaluating the impact of regional development programs: Impact-evaluation guidelines* (Technical Notes No. IDB-TN-157). Inter-American Development Bank.