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Impacts of the government-supported investments on the economic farm performance in Austria

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Abstract: Farm investments in the European Union are supported by the governmental programmes. The evaluation of this programme is challenged through the voluntary participation and heterogeneous observation units. Therefore, we combine the Matching Method with the Difference-in-Difference estimation in order to overcome these problems and to estimate the impact of supported farm-investment activities on the economic performance of the Austrian farm holdings. In particular, we detect an increase in production, land renting and capital borrowing. Furthermore, a shift from the non-farm to farm activities, but with no statistically significant impact on the total income is shown.

Key words: farm-investment support programme, selection bias, matching, conditional Difference-in-Difference estimation

European agriculture is highly mechanized and its development is clearly determined by the technical progress (Blanford 2006). In order to remain competitive, agricultural holdings have to implement this technical progress. Consequently, the European agriculture is to a large extent shaped by the constant need for investment activities. Also relevant, from the societal perspective, are the investments of agricultural holdings. The society is interested in the competitiveness of agricultural holdings since this is of consequence for the local employment and regional competitiveness (EC 2010; Margarian 2012). Furthermore, agriculture and its investment decisions are important for a multitude of societal reasons, such as the appearance of the cultural landscape, the quality of biotic and abiotic resources and for the animal welfare (MacDonald et al. 2000; Heißenhuber et al. 2001, 2004).

Due to the societal importance of agricultural investment activities, and in line with other economic sectors, the governmental programmes which support the farm investment are well established in the European Union. Farm-investment support is, namely the measure of the ‘Modernisation of agricultural holdings’ with 11.5% of the total funding, the second-most important Rural Development (RD) programme in the period 2007–2014 (EC 2011). While the farm-investment support is the second biggest programme within the RD programme and is applied in all EU member states, it is of special importance in Austria. Here, one of its major goals is to improve the economic performance of farm holdings through a better use of production factors (EC 2005).

In order to evaluate this goal, quantitative approaches have to deal with a fundamental evaluation problem, as agricultural units show a high heterogeneity and the programme participation is voluntary. What needs to be taken into account is that the participants in policy measures tend to select those measures which are the most favourable to them or, alternatively, they make adjustments before the participation. In the case of the farm-investment support, what results is that the investing farms and, therefore, the participants in farm-investment support show a systematic difference when compared to the non-participating farms. In order to analyse the causal effects of such intervention, a counterfactual situation is required to overcome this evaluation problem. Econometric methods can be used to create the counterfactual situation and therefore to reduce the selection bias (Imbens and Wooldridge 2009).

A review of the relevant literature shows that such methodologies are well applied in the impact analyses regarding the non-agricultural investment support throughout Europe. Consequently, the multiple-regression discontinuity design (Cerqua and Pellegrini 2014), the Matching Estimators (Atzeni and Carboni 2008; Duch et al. 2009), the Difference-in-Difference

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estimator (Bronzini and de Blasio 2006) or a combination of both the Matching and Difference-in-Difference estimator, the so-called conditional Difference-in-Difference estimator (Bernini and Pellegrini 2011, Harris and Trainor 2005) are used to analyse the impact of the regional investment-support on the total-factor productivity as well as on employment and steady growth.

This broad application of econometric approaches in the non-agricultural investment-support evaluation is in contrast to the farm-investment support where, to our knowledge, hardly any scientific paper applying such methodologies has been published. The existing evaluation reports of this programme are mostly rather descriptive and based on "naïve" evaluation techniques (Bergschmidt et al. 2006; Bergschmidt 2009; Forstner et al. 2009; Michalek 2012). These approaches do not account for the required counterfactual situation and therefore the result might include a selection bias. Rare exceptions are the application of the conditional difference-in-difference estimators in the working papers for Austria (Kirchweger and Kantelhardt 2012, 2014), Germany (Michalek 2012) and the Czech Republic (Medonos et al. 2012). Another peculiarity with regard to a quantitative analysis of the farm-investment support is that, in general, all investing farms claim the government support. Consequently, it is not possible to find adequate control farms which made investments but did not receive financial support (Forstner et al. 2009). This impedes an exclusive assessment of governmental support but necessitates a combined assessment of investments and the investment support.

Our main objective in this paper is to estimate the impacts of the supported farm-investment activities, on the economic performance of Austrian farm holdings. We solely focus on these farm-investments which are supported by the measure 'Modernisation of agricultural holdings'. Therefore, we apply a Matching procedure in combination with a Difference-in-Difference estimation (conditional Difference-in-Difference estimator). This approach allows us to tackle the selection bias by checking for the observable variables as well as for the non-observable, time-invariant variables.

METHODOLOGICAL APPROACH

A consistent quantitative evaluation of the investment support programmes requires the assessment of the causal treatment effect. Therefore, the Neyman-Rubin-Holland model has been developed (Brady 2008). In this model, the causal effect (Δ_A) for one individual (A) is computed by comparing the outcome in the state of participation (Y_A^1) and the outcome in the state without participation (Y_A^0). This can be formulated as

$$\Delta_A = Y_A^1 - Y_A^0 \tag{1}$$

A problem arises, however, as one of these outcomes is counterfactual because one unit can either be a participant or a non-participant. When the counterfactual situation is created through the use of the observable, the non-participants treatment must be independent of the potential outcome and the participant and non-participant must be homogenous, only differing by the analysed variable. If these are not fulfilled, the results are biased and/or have high variability (Rosenbaum 2005). This occurs in observational studies, where the researcher cannot control the assignment of treatment to the individuals (Rosenbaum 2010). Therefore, participants might select or adjust themselves voluntarily for a certain treatment, which leads to the fundamental problem, the so-called selection bias in the results.

The so far mainly used "naïve" evaluation techniques in farm-investment evaluation do not consider this fundamental evaluation problem. In order to do so, econometric methods can be used to reduce both the bias and variability. One approach is the Matching procedure, where, based on the Conditional Independence Assumption (CIA), the treated and untreated are paired on similar observable covariates (Rubin 1977). Matching controls for the selection bias by balancing the determinants Z of the treatment T (Morgan and Winship 2010). Furthermore, the combination of the Matching with the Difference-in-Difference estimator allows to integrate a before-after-analysis into the model and to monitor therefore for unobservable, linear and time-invariant effects such as price fluctuations. The combination of both methods is preferable over the cross-sectional Matching (Smith and Todd 2005).

Our Matching model is based on the nearest neighbour approach: for each investing and therefore supported unit (participant), we determine the non-investing (control) unit with the smallest distance to the treated unit with regard to the selected covariates. In order to test the robustness of our results, we apply two models to identify the nearest neighbours: the first model is to match directly the covariates

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Z, the so-called Direct Covariate Matching (DCM). This model represents a very straightforward, non-parametric and exact Matching procedure (Ho et al. 2007; Sekhon 2009). However, it can only be applied with a small number of matching variables and the availability of many control units. To understand whether the increase of the number of variables leads to different results, we implement as our second model the Propensity Score Matching (PSM) approach which is introduced by (Rosenbaum and Rubin 1985) and commonly applied in agricultural studies i.e. (Michalek 2012; Pufahl and Weiss 2009). In this second model, the nearest neighbours are matched to the estimated propensity score p(Z) as an aggregate measurement. We estimate p(Z) on the fitted values with a parametric logit model, using the observed treatment assignment (yes/no) as the explained and Z as the explanatory variable.

In both Matching models, we apply a Greedy Pair Matching algorithm without replacement. This means that each non-participant can serve only once as a control. With regard to the maximum selection boundaries, we apply the exact cut-off values for dummy and the multinomial covariates in the case of the DCM model. In the case of the PSM model and of the continuous covariates (applied in the DCM model), we use callipers. These callipers define the maximum allowed divergence between the treated unit and the respective control unit. If there is no control unit within the boundary defined by the calliper, the treated unit will be dropped from the sample.

Basically, narrow callipers entail a high similarity of the treated unit and the control unit. Consequently, narrow callipers raise the quality of the Matching (Caliendo and Kopeinig 2008) and safeguard the compliance of the common support condition. However, overly narrow callipers lead to a loss of treated units. In this context, Augurzky and Kluve (2007) argue that it is better to choose a calliper width which is not too narrow when the heterogeneous effects of treatment are expected, even when this might reduce the effect of the bias reduction. It becomes clear that there is no general optimal calliper size. The optimal size depends on the data set and the respective indicators are necessary to judge the chosen calliper size. In our case, we use the number of excluded units and the quality of Matching as indicators. The matching quality can be considered successful when the mean of the covariates between treated and the control group is balanced. In order to judge the balance, the ordinary independence tests can be used. The quantity of balance is measured by the Percentage Bias Reduction (PBR) mentioned in (Rosenbaum and Rubin 1985).

Based on the matched datasets, we calculate the average treatment effect on the treated (ATT) by using a DiD-estimator. It is computed as the difference of the progress of the participant and the non-participant from one point before (t') to one point after (t) the time of treatment (t_T) (Heckman et al. 1998). The implementation of such an estimator allows us to integrate a before-after-analysis into our model and to monitor therefore for the unobservable, linear and time-invariant effects such as price fluctuations. So a positive (or negative) ATT indicates a better (or worse) development of the outcome variables for participating farms in comparison to similar non-participating farms[1].

Finally, we note that we execute our analysis with the help of the R-CRAN package "Matching", developed by (Sekhon 2011).

EMPIRICAL DESCRIPTION AND DATA BASIS

The measure 'Modernisation of agricultural holdings' is a part of the second pillar of the Common Agriculture Policy (CAP). The programme supports the farmers' investments by covering a certain percentage of their costs. Alongside the goal of increasing the economic performance of farms holdings, the programme aims to enhance new technologies and innovations, organic production and on/off-farm diversification as well as to improve the environmental and occupational safety, hygiene and animal-welfare status of the farm (EC 2005). Therefore, the European Union allocates 11 billion or 11.5 % of its total RD budget to the farm-investment programme. In Austria, however, next to the agri-environmental and the less favoured area scheme, €311 million were spent in the period 2000–2006 and a further €467 million have been spent in the current period (2007–2013) up to 2011. The means have been granted to more than 40 000 farms, which have mainly invested in stables and other housings.

Our analysis is based on the data of 1636 voluntary bookkeeping farms in Austria for the period 2003 to 2010. Participants and non-participants are matched

[1]An operational definition of terms of the applied procedures is given in the Appendix.

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Table 1. Sample selection criteria and programme participation

	Nr. of farms
Voluntary bookkeeping farms from 2003 to 2010	1 636
Of this number:	
Dropped investing farms because investment was in 2003 to 2004 and 2010, or farm-investment support payment was less than €5,000	587
Investing farms used in the assessment investment only from 2005 to 2009)	239
Non-investing (potential controls) farms used in the assessment (no investment from 2000 to 2010)	810

Source: Own calculations

on the basis of data from 2003. Data from the farms which attended the farm-investment programmes in 2003 and 2004 as well as 2010 are excluded from the analysis in order to avoid any influence of the farm-investment (programme) on matching variables and the after-treatment-situation. So our analysis explicitly focuses on farms participating in the measure 'Modernisation of agricultural holding' in the European Operational Programme (2005–2006) as well as in the European Rural Development Programme (2007–2009). Furthermore, we do not consider farms receiving less than €5000 in the investment subsidy. By applying these restrictions, we identify 239 investing farms (participants) and 810 non-investing (potential control) farms (Table 1). The effect on the economic performance of investing farms is then measured as the development from the 2003 to 2010 of the following variables. On the one hand, we use the utilized agricultural area (UAA), the total livestock units (LU) and farm output indicating farm growth. On the other hand, we look at the farm/non-farm income as well as the share of the net worth in total assets, in order to analyse the economic stability of farms.

The prior-treatment data show that, statistically, farms with the supported investments differ significantly in a lot of variables from the non-investing farms (see Table 2, Columns 1 and 2). Statistically, the group of investing farms shows a significant higher percentage of dairy and granivore farms but a lower percentage of cash-crop farms. This result is not unexpected, as the farm-investment support is mainly used for buildings and mechanization on animal husbandry farms. Consequently, those farms show higher values in the total labour input (1.82 and 1.49 working units respectively), in total livestock units (31.34 and 18.74 livestock units respectively), livestock density (1.12 and 0.85 livestock units per ha of the utilized agricultural area respectively) and depreciation (about €16 000 and €12 000 respectively).

Furthermore, the farmers with supported investments are also about two years younger and have a higher share of rented land (+5%). Their total output and farm income are respectively about €30 000 and about €7000 higher in comparison to non-participating farms.

Table 2. Mean values of variables for participants and controls before matching, after the Direct Covariate Matching (DCM) and after the Propensity Score Matching (PSM)

	Before matching		After DCM		After PSM	
	investing farms	potential controls	investing farms	selected controls	investing farms	selected controls
Number of farms	239	810	147	147	217	217
Dairy farms (%)	45 (50)	31*** (46)	50 (50)	50 (50)	46 (50)	46 (50)
Forage farms (%)	03 (17)	03 (18)	01 (08)	01 (08)	03 (18)	03 (16)
Cash-crop farms (%)	13 (34)	28*** (45)	14 (35)	14 (35)	14 (35)	13 (34)
Granivore farms (%)	16 (37)	10** (29)	12 (32)	12 (32)	13 (34)	15 (35)

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	Before matching		After DCM		After PSM	
	investing farms	potential controls	investing farms	selected controls	investing farms	selected controls
Permanent crop farms (%)	05 (22)	06 (24)	05 (23)	05 (23)	05 (21)	04 (20)
Other farm types (%)	18 (38)	23 (42)	18 (38)	18 (38)	19 (39)	19 (40)
Region South (%)	25 (43)	25 (43)	20 (40)	20 (40)	24 (42)	25 (43)
Region west (%)	10 (30)	09 (28)	10 (29)	10 (29)	11 (31)	09 (28)
Region North (%)	65 (48)	67 (47)	70 (46)	70 (46)	65 (48)	66 (47)
Organic farming (%)	18 (39)	18 (39)	20 (40)	23 (42)	19 (40)	21 (41)
Farmer's age (year)	52.28 (9.05)	54.21** (9.12)	52.59 (8.56)	52.66 (8.18)	52.70 (8.98)	52.92 (8.66)
Total labour input (WU)	1.82 (0.71)	1.49*** (0.70)	1.68 (0.54)	1.66 (0.56)	1.74 (0.59)	1.74 (0.61)
UAA (ha)	37.79 (25.14)	34.51 (28.33)	36.56 (25.69)	36.82 (28.28)	36.26 (24.09)	39.37 (32.98)
Share of rented land in UAA (%)	29 (22)	24** (24)	25 (21)	24 (24)	27 (22)	27 (24)
Livestock units (LU)	31.34 (24.48)	18.74*** (17.39)	26.08 (18.43)	24.75 (16.86)	28.22 (19.31)	28.05 (19.48)
Stocking density (LU/ha)	1.12 (0.69)	0.85*** (0.69)	1.04 (0.66)	1.00 (0.59)	1.09 (0.64)	1.10 (0.69)
Depreciation (€)	16 283 (7 811)	12 433*** (7 314)	14 376 (6 475)	14 338 (6 504)	15 161 (6 709)	15 879 (7 917)
Share of net worth in total assets (%)	91 (16)	90 (18)	93 (11)	92 (14)	91 (16)	92 (13)
Total output (€)	111 742 (78 273)	79 682*** (54 620)	85 702 (41 125)	85 165 (41 990)	100 804 (66 768)	100 639 (60 216)
Non-farm income (€)	7 596 (10 276)	8 881 (12 227)	6 687 (9 327)	5 997 (9 538)	7 512 (10 072)	7 289 (10 652)
Farm income (€)	31 259 (24 536)	24 462*** (22 192)	26 368 (19 861)	27 272 (17 003)	29 720 (24 504)	30 957 (24 210)
Propensity Score	0.33 (0.16)	0.20 (0.14)	– –	– –	0.30 (0.14)	0.30 (0.13)

Numbers in parentheses show standard deviation; WU = working unit; UAA = utilized agricultural area; LU = Livestock unit; *t*-test, Chi square test and McNemar test are used for equally of means: Signif. codes: ***0.001. **0.01, *0.05

Source: Own calculations

RESULTS

In our DCM model, we consider three types of the prior-treatment variables as matching variables: the farm type and region as multinomial variables, the part-time farming as a binary dummy variable, and age, depreciation and the total output as continuous variables. The visual comparison of the histograms for the continuous variables indicates a significant overlap between the treated and control group for all variables (Figure A-1). As a result of the Matching procedure, 92 participants are dropped from the sample, so that the resulting DCM sample consists of 147 pairs. This leads to a good balance between

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Table 3. The Percentage Bias Reduction (PBR) of Direct Covariates Matching and Propensity Score Matching

	Before matching	After DCM		After PSM	
	SD	SD	PBR	SD	PBR
Dummy dairy farms	30.1	0.0	–	0.9	97
Dummy cash-crop farms	37.7	0.0	–	1.3	96
Dummy granivore farms	20.4	0.0	–	4.0	81
Farmer`s age	21.2	0.9	96	2.6	88
Total labour input	47.8	3.8	92	0.9	98
Share of rented land on UAA	18.9	2.8	85	1.5	92
Livestock units	59.3	7.6	87	0.8	99
Stocking density	39.8	6.0	85	1.6	96
Depreciation	50.9	0.6	99	9.8	81
Total output	47.5	1.3	97	0.3	99
Farm income	29.1	4.9	83	5.1	83
Mean	36.6	2.6	91	2.6	92

SD = standard difference (for definition see the appendix); PBR = percentage bias reduction (for definition see the appendix); Mean does not include standardized bias and PBRs for the farm type variables, which are used as exact matching variables in the DCM model and therefore reduce the bias to zero.

Source: Own calculations

the participant and control group in all variables and – in comparison to the non-matched sample – to no significant differences (Table 2, Columns 3 and 4). Furthermore, the SD is computed for those variables showing significant differences in the non-matched sample. While mean SD in the non-matched sample accounts for 36.6 (ranging from 18.9 to 59.3), mean SD in the DCM matched sample is reduced to a value of 2.6 (ranging from 0.6 to 7.6)[2]. The outcome of this is a mean PBR of 91%, with the lowest PBR value of 83% for the farm income and the highest of 99% for depreciation (Table 3).

The application of the PSM model allows the use of more prior-treatment covariates in the binomial-logit model (see Table A-1).[3] The results of the multinomial-logit estimation indicate that dairy farms, as well as farms with high values of the UAA, the total labour input, livestock density, the non-farm income and total output, are more likely to invest and receive farm-investment support. In contrast to this, cash-crop farms and farms with older managers are less likely to invest (Table A-1). The binary-logit estimation shows a fit (Pseude-R^2) of about 12% and correctly predicts about 78% of the farms attending the programme. The inclusion of more observable variables such as the number of dairy cows does not contribute to the overall fit of the binary-logit estimation or to the rate of correctly predicted programme participations. A separate visualization of the estimated propensity scores for the treated and non-treated farms shows that for both groups the distributions are quite similar and share therefore a suitable overlap (Figure A-2). In the case of the PSM model, only 22 participants are discarded, which results in a PSM sample of 217 pairs. Through this, the sample increased the balance in all variables so that no significant differences remain (Table 2, Columns 5 and 6). The mean SD is reduced to 2.6 (ranging from 0.3 and 9.8), which is a mean PBR of 92% with the lowest for the dummy variable granivore farms (81%)

[2]This does not include the standardized bias and PBRs for the farm type variables, which are used as the exact matching variables in the DCM model and therefore reduce the bias to zero.

[3]Applying the conditional DiD estimator, it is encouraged to include the prior-treatment outcome variables in the model, as those are highly correlated with the outcome variables but are not influenced by treatment Cook et al. (2008, 2009). Furthermore, because of the inclusion of more variables multicollinearity might occur in the model, but Conniffe et al. (2000) argue that this is not the difficulty as it can be in regression analysis.

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and the highest for the total output (99%, see Table 3). The PBR results in the PSM sample are therefore quite similar to the DCM sample.

In the following section, we present the results from the Difference-in-Difference (DiD) estimator applied on both, the DCM and the PSM sample. Therefore, the development of farms with supported investments (investing farms) and their control farms as well as the average treatment effects on the treated (ATT values) for the selected outcome variables are displayed in Table 4. The resulting ATT values of the both models, DiD-PSM and DiD-DCM, are to a large extent comparable. Consequently, we primarily focus on the following presentation of the results of one model: the DiD-DCM model. The results of the PSM model are presented in the parentheses and highlighted only in case of conspicuous divergences.

We find that the the supported investments cause an increase in farm growth with regard to the total and rented UAA. However, the ATT values are quite moderate and not statistically significant at the 5%-level. This results from the fact that, even though treated farms increase the total UAA by 4.31 (4.85) hectares during the observation period, the control farms also raise their total UAA by 2.46 (2.73) hectares. In both cases, the growth is basically grounded in additional land rents. Thus, the treated farms increase their rented land by 3.53 (3.50) additional hectares and the control farms by 1.97 (1.84) hectares.

Table 4. Development of the treated and control farms as well as the ATT values for certain variables using the Conditional Difference-in-Difference estimation with Direct Covariates Matching and Propensity Score Matching

	Direct covariates matching			Propensity score matching		
	investing farms	selected controls	ATT	investing farms	selected controls	ATT
Number of farms	147	147		217	217	
Total UAA (ha)	4.31 (10.64)	2.46 (8.19)	1.85 (13.81)	4.85 (10.77)	2.73 (11.90)	2.13 (16.30)
Rented UAA (ha)	3.53 (7.27)	1.97 (7.25)	1.56 (10.93)	3.50 (8.11)	1.84 (9.78)	1.66 (12.53)
Total livestock units (LU)	4.62 (11.48)	–0.98 (8.61)	5.60*** (13.40)	6.13 (14.48)	–0.63 (10.35)	6.76*** (17.84)
Stocking density (LU/ha)	0.08 (0.33)	–0.07 (0.30)	0.15*** (0.42)	0.08 (0.36)	–0.07 (0.33)	0.15*** (0.52)
Total output (€)	44 678 (42 486)	19 766 (31 389)	24 911*** (53 471)	47 332 (66 117)	22 042 (33 448)	25 290*** (73 084)
Total labour input (WU)	–0.01 (0.51)	–0.07 (0.46)	0.06 (0.65)	–0.03 (0.49)	–0.10 (0.47)	0.08 (0.72)
Farm income (€)	13 369 (24 145)	7 723 (18 400)	5 646* (29 612)	13 723 (32 057)	8 104 (19 807)	5 619* (39 424)
Non-farm income (€)	601 (8 421)	3 192 (10 256)	–2 591* (12 958)	682 (10 270)	2 443 (9 830)	–1 761 (15 272)
Total income (€)	13 970 (25 096)	10 915 (19 632)	3 055 (30 941)	14 405 (32 291)	10 548 (21 725)	3 857 (40 662)
Share of net worth on total assets (%)	–8 (14)	–1 (12)	–7*** (19)	–6 (6)	0 (13)	–6*** (21)

Numbers in parentheses show standard deviation; ATT = average treatment effect on the treated; WU = working unit; UAA = utilized agricultural area; LU = Livestock unit; *t*-test is used for equally of means: Signif. codes: ***0.001, **0.01, *0.05

Source: Own calculations

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As mainly livestock-keeping farms participate at the investment-support programme, the significant ATT values with regard to livestock production is to expect. Our results acknowledge this presumption, as the number of livestock units of the treated farms grows by 22% (18%) or 4.62 (6.13) livestock units (LU), whereas the livestock units of the control farms decline in the observation period by 4% (2%) or 0.98 (0. 63) LU. Overall this results in a significant ATT value of 5.60 (6.76) LUs. Since the total UAA is growing more slowly than the total livestock units, we furthermore observe positive ATT values for stocking density of (0.15 LU per hectares in both models) indicating an intensification of the livestock production. The structural growth and intensification of livestock production also causes - with regard to the total output – positive ATT values of about €25 000 (€25 000). Despite the apparent growth and intensification of investing farms, we observe no statistical significant effect on the total labour input. Mean working units per treated farm even decrease slightly. However, since control farms also realize a decrease of working units, a positive, but not statistical significant, ATT value occurs with regard to the total labour input results.

One of the main aims of the farm-investment support programme is to foster the farm income. Our analysis shows that this is actually the case: the participating farms succeed in increasing their farm income by 51% (46%) (which means €13 400 or €13 700 respectively) in the observation period, whereas the control farms only realize an incline of 28% (26%) (€7800 or €8100 respectively). However, our results display that the participating farms specialize in the on-farm activities and reduce their non-farm activities. Consequently, we see negative ATT values with regard to the non-farm income (–€2600 or –€1800). In both models, the negative ATT values are not caused by declining non-farm activities of participating farms but from smaller increases in comparison to non-participating farms. Both developments – the positive effect of farm investments on farm income and the negative effect on the non-farm income – result overall in a small and non-significant positive effect on total income.

With regard to farm stability, our analysis shows that the farms tend to lose stability. The ATT for the share of net worth accounts for minus 7% (6%), since the development of share of net worth for treated farms declines by 8% (6%) and for the control farms solely by 1% (0%). Investment activities frequently require borrowing of capital, which entails the declining share of the net worth in comparison to the non-investing farms.

DISCUSSION AND CONCLUSIONS

The main challenges in achieving a consistent evaluation of the policy interventions in agriculture are the heterogeneity of the participating farms and the resulting problem of self-selection (Pufahl and Weiss 2009). As our study shows, these challenges apply particularly in the case of the (Austrian) farm investment programme, since the participating farms are very heterogeneous and the participation is voluntary. However, the application of adequate econometric methods in combination with a profound understanding of the selection mechanism can help to overcome these problems (Imbens and Wooldridge 2009). In our study, we combine Matching with a DiD-estimation and use this approach to analyse the impacts of farm-investment activities, which are supported by the measure 'Modernisation of agricultural holdings', on the economic performance of farm holdings.

In order to estimate the sensitivity of the results, we do not limit our analysis to only one Matching model, but we apply both a DCM model and a PSM model. These two display specific advantages or disadvantages: while the DCM allows the integration of only a very limited number of covariates (which forces us to neglect valuable information explaining treatment selection), we find that the PSM tends to have higher values for the standard deviation of treatment estimates. This finding goes back to bigger sample sizes in the PSM model, which in the observational studies leads to an increase in heterogeneity (Sekhon 2009). In our case, both models lead to appropriate balanced datasets and the ATT-results which are fairly comparable. Consequently, this supports the quality of our results, since they are achieved with two fairly different models.

The results of the treatment-effect estimation show that farms participating in the Austrian farm-investment programme increase their production significantly more than the non-participating farms. This is indicated by the positive ATT values with regard to the UAA, LU and the total output. Similar results are also found in another study, where the IACS data of Austrian farms and therefore more observation units are used (Kirchweger and Kantelhardt 2014). Furthermore, the studies in the Czech Republic

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(Medonos et al. 2012) and Germany (Michalek 2012) confirm these findings, where the farm growth is measured in the gross value added and milk production, respectively.

Somewhat small and insignificant ATT values with regard to the total income show that investing farms do not (or do so only to a very limited extent) succeed in converting ever-increasing production into a higher income. This is in contrast to the findings of (Michalek 2012), who found a higher increase in profits for German farms. Apart from the insufficient selection of investment activities by the government, there are two further reasons why the investing farmers in our analysis do not succeed in increasing their total income. Firstly, the observation period might be too short to measure the full implementation success of investments.[4] Secondly, the farmers do not exclusively pursue the income augmentation with their investment, but they also try to achieve a variety of non-economic goals such as a reduction in workload, the improvement of the work quality and the adjustment of the daily farm work balanced with the family life (Viaggi et al. 2011). In this context, it can be said that our results indicate that the investing farmers cannot reduce their workload significantly more than their controls. They succeed, however, in increasing the labour productivity, since the increased production goes alongside almost stable workload levels. Such increased the labour productivity is also observed by Michalek (2012), as well as by Medonos et al. (2012).

All in all, the rather small and insignificant impact of investment activities on the total income underlines the importance for the government to select appropriate and efficient investment activities. A further policy concern is that government-supported investment activities reduce the off-farm employment of farmers, which leads to a decrease in the income diversification and the increased land renting and capital-borrowing activities. Consequently, the policymakers have to consider that investment activities tend to make farms more dependent on external stakeholders and to increase their vulnerability to pricing and unpredictable environmental disasters (Escalante and Barry 2003; Theuvsen 2007). However, with regard to the Austrian case, one can say that the share of the rented land (32%) and debt (14%) still remains at a low level, so that in the short term no negative consequences are to be expected for Austrian farmers. One final conclusion of the relevance for policy is that animal husbandry intensifies as the livestock density increases through supported investments. This intensification might lead to a conflict of objectives with the societal interests and the agri-environmental support, which is also a part of the RD programme (EC 2005).

An important task for the future research is to broaden the database in order to increase the possibility to model the causal interactions within the area of farm-policy evaluation more accurately. As our analysis shows, this is of particular importance in our research field, since the agricultural-investment decisions are in general dependent on a broad variety of very heterogeneous factors. The principal missing variables are with regard to personal attitudes of the farm manager, including the personal goal of the investment, and the needs and requirements of the farmer's family. All of these factors are at present hardly included in the agricultural databases. Consequently, it is necessary to go beyond the classic statistical sources and to include qualitative aspects in the analysis by conducting a qualitative in-depth research (Viaggi et al. 2011).

However, despite these remaining challenges, our study clearly shows that the conditional DiD-estimation is well suited to the analysis of the investment support programmes, since the pre- and after-treatment data is obtainable and it helps to develop a data basis on which the policy makers can readjust and enhance the agri-political programmes. Due to its simplicity, the Matching analysis allows the opening of an integrative process, where the researchers and policymakers can jointly reflect on causal exposures and develop new ideas for existing data limitations. Therefore, we conclude that the Matching should join other methodologies as a standard approach in evaluating the agricultural policy programmes.

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[4]It should be noted that dairy farms in particular, which are mainly represented in this study, might need more time to tap the full growth potential created by investments (see Kirchweger and Kantelhardt 2012, 2014).

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APPENDIX

A-1 Operational definitions of terms

The computation of the Percentage Bias Reduction:

The PBR is computed for all significant different covariates by dividing the standardized difference (SD) before matching with SD after matching.

$$\mathrm{PBR} = 1 - \frac{\mathrm{SD}_{\mathrm{after}}}{\mathrm{SD}_{\mathrm{before}}} \tag{2}$$

The standardized difference in percentage after matching represents, for a given independent covariate X, the difference in sample means in the participating ($\bar{X}_T$) and non-participating ($\bar{X}_{NT}$) sub-samples as a percentage of the square root of the average sample variances (s_T^2 and s_{NT}^2)(Rosenbaum and Rubin, 1985):

$$\mathrm{SD}_{\mathrm{before}}(X_n) = \left| \frac{(\bar{X}_T - \bar{X}_{NT})}{\left(0.5 \times (s_T^2 + s_{NT}^2)\right)^{\frac{1}{2}}} \times 100 \right| \tag{3}$$

For the computation of $\mathrm{SD}_{\mathrm{after}}(X_n)$, the means in the participating ($\bar{X}_T$) and controls ($\bar{X}_C$) sub-samples are used. The denominator remains the same. (Equation 4)

The mathematical descriptions of our models are the following:

For DCM this can be expressed as Equation 4, where $Y_{A,t}^1$ is the outcome for a treated unit after the treatment and $Y_{A,t}^1$ before the treatment, Z a vector of observable covariates and n_A the number of used participants. The second term expresses the same but for controls. When PSM is applied, the vector Z is substituted by a single variable, the propensity score p(Z) (Equation 6).

Table A-1. Covariates estimates of the logit-model explaining the programme participation

Variable	Estimate
Dummy permanent crop farms	0.362 (0.476)
Dummy dairy farms	0.472* (0.240)
Dummy forage farms (exclusive dairy)	–0.049 (0.491)
Dummy cash-crop farms	–0.939** (0.347)
Dummy granivore farms	0.100 (0.325)
Dummy region South	0.047 (0.213)
Dummy region West	–0.074 (0.299)
Dummy conventional farming	–0.041 (0.217)
Age	–0.020* (0.009)
Total labour input	0.315* (0.138)
Utilized agricultural area (log)	0.260 (0.189)
Share of rented land	0.340 (0.380)
Livestock density	0.276 (0.195)
Share of net worth in total assets	0.819 (0.514)
Non-farm income (log)	0.145*** (0.040)
Depreciation (log)	0.277 (0.235)
Total output (log)	0.699** (0.255)
Intercept	–14.224*** (2.321)

Signif. codes: ***0.001, **0.01, *0.05

Source: Own calculations

$$\mathrm{SD}_{\mathrm{after}}(X_n) = \left| \frac{(\bar{X}_T - \bar{X}_C)}{\left(0.5 \times (s_T^2 + s_{NT}^2)\right)^{\frac{1}{2}}} \times 100 \right| \tag{4}$$

$$\tau \,|\, (T=1) = \sum_{A=1}^{n} (Y_{A,t}^1 - Y_{A,t'}^1) \,|\, Z/n_A - \sum_{B=1}^{n} (Y_{B,t}^0 - Y_{B,t'}^0) \,|\, \mathrm{Z}/n_B \tag{5}$$

$$\tau \,|\, (T=1) = \sum_{A=1}^{n} (Y_{A,t}^1 - Y_{A,t'}^1) \,|\, \mathrm{p(Z)}/n_A - \sum_{B=1}^{n} (Y_{B,t}^0 - Y_{B,t'}^0) \,|\, \mathrm{p(Z)}/n_B \tag{6}$$

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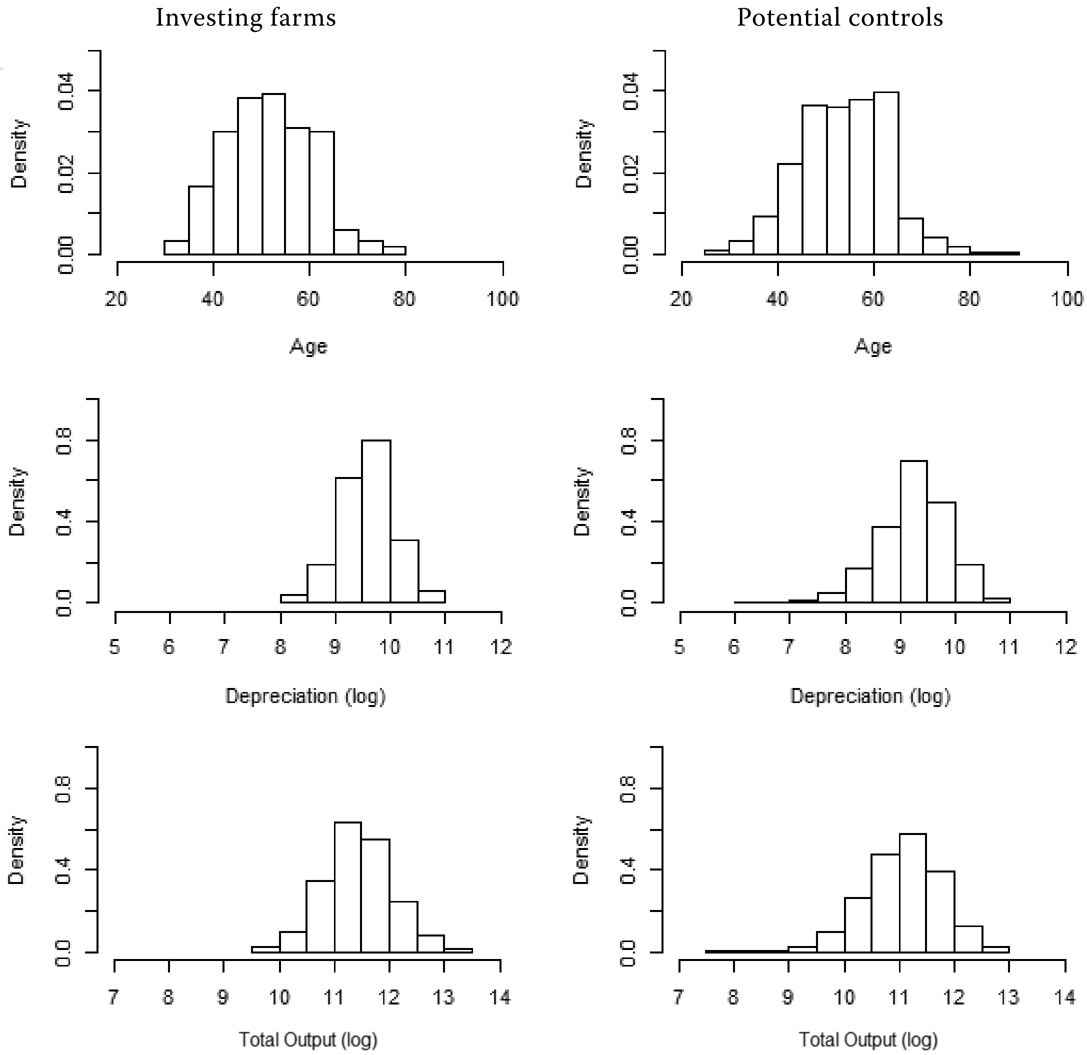

Figure A-1. Distribution of covariate age (first row), depreciation (second row) and total output (third row) for investing farms (left) and potential controls (right) before matching

Source: Own illustration

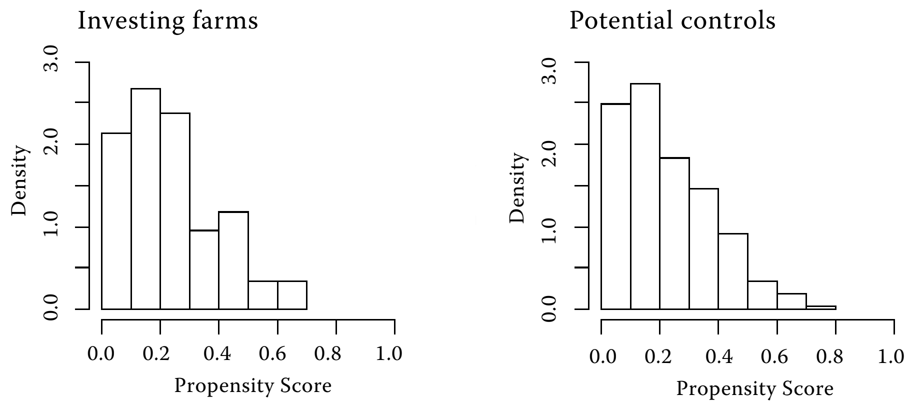

Figure A-2. Distribution of propensity scores for investing farms (left) and potential controls (right) before matching

Source: Own illustration

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REFERENCES

Atzeni G.E., Carboni O.A. (2008): The effects of grant policy on technology investment in Italy. Journal of Policy Modeling, 30: 381–399.

Augurzky B., Kluve J. (2007): Assessing the performance of matching algorithms when selection into treatment is strong. Journal of Applied Econometrics, 22: 533–557.

Bergschmidt A. (2009): Powerless evaluation. EuroChoices, 8: 37–42.

Bergschmidt A., Dirksmeyer W., Efken J., Forstner B., Uetrecht I. (eds) (2006): Proceedings of the European Workshop on the Evaluation of Farm Investment Support, Investment Support for Improvement of Processing and Marketing of Agricultural Products. Arbeitsberichte des Bereichs Agrarökonomie, No. 03/2006; Thünen Instiut, Braunschweig.

Bernini C., Pellegrini G. (2011): How are growth and productivity in private firms affected by public subsidy? Evidence from a regional policy. Regional Science and Urban Economics, 41: 253–265.

Blanford D. (2006): Pressures for adjustment in the agricultural sectors of developed countries. In: Blanford D., Hill B. (eds): Policy Reform and Adjustment in the Agricultural Sectors of Developed Countries. Cromwell Press Ltd., Trowbridge: 43–54.

Brady H.E. (2008): Causation and explanation in social science. In: Box-Steffensmeier J.M., Brady H.E., Collier D. (eds): The Oxford Handbook of Political Methodology. Oxford University Press, Oxford: 217–270.

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.

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

Cerqua A., Pellegrini G. (2014): Do subsidies to private capital boost firms' growth? A multiple regression discontinuity design approach. Journal of Public Economics, 109: 114–126.

Conniffe D., Gash V., O'Connell P.J. (2000): Evaluating state programmes: "Natural experiments" and propensity scores. Economic and Social Review, 31: 283–308.

Cook T.D., Shadish W.R., Wong V.C. (2008): Three conditions under which experiments and observational studies produce comparable causal estimates: New findings from within-study comparisons. Journal of Policy Analysis and Management, 27: 724–750.

Cook T.D., Steiner P.M., Pohl S. (2009): How bias reduction is affected by covariate choice, unreliability, and mode of data analysis: Results from two types of within-study comparisons. Multivariate Behavioral Research, 44: 828–847.

Duch N., Montolio D., Mediavilla M. (2009): Evaluating the impact of public subsidies on a firm's performance: a two-stage quasi-experimental approach. Investigaciones Regionales, 16: 143–156.

EC (2005): Council Regulation (EC) No 1698/2005 of 20 September 2005 on support for rural development by the European Agricultural Fund for Rural Development (EAFRD). Official Journal of the European Union. Available at http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32005R1698&qid=1398775467048 (accessed March 2014).

EC (2010): The CAP towards 2020: Meeting the food, natural resources and territorial challenges of the future. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions, 672. Available at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2010:0672:FIN:en:PDF (accessed March 2014).

EC (2011): Rural Development in the European Union. Statistical and economic information. (Directorate-General for Agriculture and Rural Development).

Escalante C.L., Barry P.J. (2003): Determinants of the strength of strategic adjustments in farm capital structure. Journal of Agricultural and Applied Economics, 35: 67–78.

Forstner B., Bergschmidt A., Dirksmeyer W., Ebers H., Fitschen-Lischewski A., Margarian A., Heuer J. (2009): Ex-Post-Bewertung des Agrarinvestitionsförderungsprogramms (AFP) für den Förderzeitraum 2000 bis 2006. (Ex-post evaluation of the German farm-investment support programme from 2000–2006.) Länderübergreifender Bericht 98, Thünen Institut, Braunschweig.

Harris R., Trainor M. (2005): Capital subsidies and their impact on total factor productivity: Firm-level evidence from Northern Ireland. Journal of Regional Science, 45: 49–74.

Heckman J., Ichimura H., Smith J., Todd P. (1998): Characterizing selection bias using experimental data. Econometrica, 66: 1017–1098.

Heißenhuber A., Kantelhardt J., Osinski E. (2001): Ökonomische Aspekte einer ressourcen schonenden Landnutzung. (Economic aspects of a resource-saving land use.) In: Beiträge zur Entwicklung ökologisch und ökonomisch nachhaltiger Landnutzungssysteme in Agrarlandschaften. (In: Contributions to the development of ecologically and economically sustainable land-use systems in agricultural landscapes.) Agrarspektrum 31: 20–30.

doi: 10.17221/250/2014-AGRICECON

Heißenhuber A., Kantelhardt J., Schaller J., Magel H. (2004): Visualisierung und Bewertung ausgewählter Landnutzungsentwicklungen. (Visualisation and valuation of selected land use dynamics.) Natur und Landschaft: Zeitschrift für Naturschutz und Landschaftspflege, 79: 159–166.

Ho D.E., Imai K., King G., Stuart E.A. (2007): Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. Political Analysis, 15: 199–236.

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

Kirchweger S., Kantelhardt J. (2012): Improving Farm Competitiveness through Farm-Investment Support: a Propensity Score Matching Approach. In: 131st Seminar European Association of Agricultural Economists, Sept. 18–19, 2012, Prague. Available at http://purl.umn.edu/135791 (accessed March 2014).

Kirchweger S., Kantelhardt J. (2014): Structural Change and Farm Investment Support in Austria. In: 88th Annual Conference of the Agricultural Economics Society, April 9–11, 2014, AgroParisTech, Paris. Available at http://purl.umn.edu/170545 (accessed March 2014).

MacDonald D., Crabtree J.R., Wiesinger G., Dax T., Stamou N., Fleury P., Gutierrez Lazpita J., Gibon A. (2000). Agricultural abandonment in mountain areas of Europe: Environmental consequences and policy response. Journal of Environmental Management, 59: 47–69.

Margarian A. (2012): The relation between agricultural and non-agricultural economic development: Technical report on an empirical analysis of European regions. Thuenen Working Papers. Available at http://purl.umn.edu/126870 (accessed March 2014).

Medonos T., Ratinger T., Hruska M., Spicka J. (2012): The assessment of the effects of investment support measures of the Rural Development Programmes: the case of the Czech Republic. Agris on-line Papers in Economics and Informatics, 4: 35–48.

Michalek J. (2012): Counterfactual impact evaluation of EU rural development programmes – Propensity Score Matching methodology applied to selected EU Member States. Vol. 1: A micro-level approach. Joint Research Centre, Institute for Prospective Technological Studies, European Commission, Luxembourg.

Morgan S.L., Winship C. (2010): Counterfactuals and Causal Inference: Methods and Principles for Social Research. Cambridge University Press, New York.

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.

Rosenbaum, P.R. (2005): Heterogeneity and Causality. The American Statistician, 59: 147–152.

Rosenbaum P.R. (2010): Design of Observational Studies. Springer-Verlag, New York.

Rosenbaum P.R., Rubin D.B. (1985): Constructing a Control group using multivariate matched sampling methods that incorporate the propensity score. The American Statistician, 39: 33–38.

Rubin D.B. (1977): Assignment to treatment group on the basis of a covariate. Journal of Educational Statistics, 2: 1–26.

Sekhon J.S. (2009): Opiates for the matches: matching methods for causal inference. Annual Review of Political Science, 12: 487–508.

Sekhon J.S. (2011): Multivariate and propensity score matching software with automated balance optimization: The matching package for R. Journal of Statistical Software, 42: 1–52.

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

Theuvsen L. (2007): Pachtpreisanpassungsklauseln: Ein Beitrag zum Risikomanagement landwirtschaftlicher Betriebe? (Land-rent adjustment clauses: A contribution to the risk management of agricultural holdings?) German Journal of Agricultural Economics, 56: 337–339.

Viaggi D., Raggi M., Paloma S.G.y. (2011): Understanding the determinants of investment reactions to decoupling of the Common Agricultural Policy. Land Use Policy, 28: 495–505.

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