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Assessing long-term effects of CAP investment support on indicators of farm performance

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Abstract

In this study of Swedish farms from 2007 to 2016, we estimate the effects of investment support from the Common Agricultural Policy on indicators of farm performance, focusing on long-term effects. To isolate the impact and alleviate problems of selection bias, we employ a counterfactual empirical design using Coarsened Exact Matching and dynamic panel fixed-effects estimations. The average treatment effect on the treated estimates show a positive and significant long-term improvement of farm performance with regard to productivity and turnover. However, the results indicate significant time lags between investments and accumulated observable effects, as we find most short-term effects of the subsidy to be insignificant.

Keywords: CAP investment support, farm performance, long-term effects, Sweden

JEL classification: Q12, Q18, D24

1. Introduction

Investment supports to farms are part of the European Common Agricultural Policy (CAP) as key measures to stimulate farm modernisation and productivity (European Commission, 2010). These subsidies are implemented through each member state's consecutive rural development programmes (RDPs), with the overall aim to stimulate technical progress and labour productivity in agriculture.[1] The impact of CAP subsidies on agricultural production, farm income and productivity has received a great deal of attention in the literature, but the

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1 Implemented as Measure 121 (farm modernisation) in the RDP of 2007–2013 and Measure 4.1/2a (investments in farms) in the subsequent RDP of 2014–2020.

rate of the observed effects often varies and is sensitive to the way subsidies are modelled (Michalek, Ciaian and Kancs D', 2014; Minviel and Latruffe, 2017). Most studies also tend to consider only the total amount of subsidies, making it difficult to disentangle the impact of specific CAP payments. Despite the large number of empirical findings on economic outcomes linked to CAP payments, few studies have investigated any temporal impacts from the perspective of linking farm modernisation support to long-term effects on farm productivity. This study aims to fill in this gap in the literature by applying a dynamic fixed-effects panel model to study the long-term effects of modernisation support on farm performance using a sample of Swedish farms observed over a 10-year period (2007–2016).

In assessing the temporal aspects linked to CAP payments, the literature has been primarily focused on the change of policy regime to decoupled subsidies (Sckokai and Moro, 2009; Rizov, Pokrivcak and Ciaian, 2013; Martinez Cillero, Thorne and Wallace *et al.*, 2018), capitalisation of area payments into land values (Michalek, Ciaian and Kancs D', 2014; Ciaian, Kancs D' and Espinosa, 2018) and redistributive effects (Ciliberti and Frascarelli, 2018; Piet and Desjeux, 2021). Studies have shown that a higher degree of coupling in farm support negatively affects farm productivity, indicating the presence of a productivity effect linked to eligibility conditions, farm factor and production decisions. Studies have also linked a negative productivity effect to the increase in the share of total subsidies relative to total farm income over time (Bergström, 2000; Zhu, Demeter and Oude Lansink, 2012).

The approach of this study is different from that of previous studies in that we follow a sample of Swedish farms over two consecutive RDP periods[2] and assess the direct impact of farm modernisation support on farm productivity and other relevant farm performance indicators. In doing so, we offer a new perspective by investigating the presence of time lags between investments and accumulated observable effects on farm performance (Greenwood, Hercowitz and Krusell, 1997). Hence, the contribution of this paper is strictly empirical, providing novel results that consider a wider coverage of farm economic indicators and a longer panel than has been used before.

Our empirical approach is to first estimate the impact of the investment support (Measure 121) in the first RDP (with supports granted 2007–2013) using dynamic panel fixed-effects models, following Garrone, Emmers and Lee *et al*. (2019). We estimate the impact during the period 2007–2013, which are the years when the programme was implemented, as well as the impact over the longer period 2007–2016, where 2016 is the last year of available microdata. In the second stage, we use the estimated coefficients to forecast the expected effects of investment support (4.1/2a) in the most recent RDP period (with supports granted 2014–2016).

The empirical approach of this study has some aspects in common with Ratinger, Medonos and Hruška (2013), Mary (2013) and Nilsson (2017),

2 RDP 2007–2013 and RDP 2014–2020. The microdata include information on farms receiving support 2007–2016. The latter RDP period (2014–2020) is thus not fully covered.

which are, to the best of our knowledge, the only other studies assessing economic effects of CAP investment support on indicators of farm performance. We apply the Coarsened Exact Matching (CEM) method developed by Iacus, King and Porro (2011, 2012) to estimate the mean difference (the average treatment effect on the treated, ATT) between farm performance indicators for investment support recipients and the control group. This method has some advantages compared to other similar matching techniques in the context of policy evaluation (Bertoni *et al.*, 2020).[3]

Using this approach, we are able to shed new light on the effects on farm performance from the investment support provided in the RDP of 2007–2013 and the expected impact of investment support in the RDP of 2014–2020. The average treatment effect on the treated (ATT) estimates show that, overall, the effects of CAP investment support are largely consistent with policy expectations, leading to a significant long-term improvement of farm productivity. The results indicate a positive and significant influence of investment support on farm labour productivity, total factor productivity (TFP) and turnover (revenue). The estimated effects do not seem to dissipate over time, indicating the presence of long-term effects. Our results also provide support for the presence of significant time lags between investments and accumulated observable effects as we find the short-run effects to be insignificant.

2. Investment support and farm performance: an overview of the literature

Farm investment support is considered a key instrument in European agricultural policy and is granted to a significant number of farms across Europe each year. The aim is to stimulate farm technological progress and labour productivity and to help farms adapt to changing market conditions. This policy is aligned with the idea that productivity growth, to a large extent, is determined by firms' investment activity (Baumol, 1990) and that sustained growth depends on the choice and adaptation of enhanced technologies that are profitable for individual firms to operate (Hansen and Prescott, 2002).

There are theoretical arguments supporting both a positive influence and a negative influence of investment subsidies on indicators of farm productivity. Such capital subsidies can be used to expand and modernise production equipment, which can result in improved farm production capacity and productivity (Harris and Trainor, 2005; Serra, Zilberman and Gil, 2008). The resulting effects can be observed by changes in farm TFP, reflecting a rise in farm productivity due to improvements in the combination of inputs used in production (Sauer and Latacz-Lohmann, 2015). The impacts of CAP subsidies have also been studied using partial productivity indicators, such as labour productivity, which indicates whether labour can be used more efficiently in the agricultural production process (Ratinger, Medonos and Hruška, 2013). However,

3 CEM reduces imbalance in the covariates between the treated and the control groups ex-ante instead of ex-post (Iacus *et al.*, 2012); see Section 4.1 for a detailed discussion.

growth in labour productivity may lead to a redundancy of farm labour, resulting in a negative effect on farm employment (McCloud and Kumbhakar, 2008). Impacts on farm labour will thus be largely dependent on the effects on labour productivity. Previous studies have also assessed influences of CAP payments on indicators of farm business expansion, proxied by gross value added (GVA) or farm turnover, thereby investigating the role of the subsidy in strengthening the ability of farms to meet changes in market conditions indicated by the amount received in sales of production for a stated period. Ratinger, Medonos and Hruška (2013), among others, find significant benefits of CAP investment support on farm GVA and labour productivity in the Czech Republic.

In contrast, arguments validating a negative impact of investment support on farm productivity are often based on the possibility that the presence of a subsidy may lead farmers to make non-optimal investments and/or resource allocation decisions, for example, by favouring investments eligible for CAP subsidies over potentially more productivity-enhancing investments (Baumol, 1990; Bergström, 2000; Tullock, 1980; Schmitz, Moss and Schmitz *et al.*, 2010). Some previous studies tend to find that CAP subsidies impact negatively on farm efficiency and productivity (e.g. Zhu and Oude Lansink, 2010; Latruffe, 2010). However, most studies consider only the total amount of subsidies, which makes it difficult to disentangle the impact of specific CAP payments. The study by Mary (2013) on French crop farms is an exception, examining the impact of different types of Pillar 1 and Pillar 2 subsidies on farm TFP. Adding to previous findings, Mary (2013) shows that selective (targeted) subsidies such as investment and environmental measures have no significant impact on TFP, while farm subsidies that are effectively automatic have negative impacts on TFP. This suggests that not all CAP payments have negative impacts on productivity.

Ratinger, Medonos and Hruška (2013) focus specifically on CAP investment support to farms and find the support to positively influence farm size and labour productivity. By splitting the sample with regard to natural conditions and by size, they show the estimated effects to be higher on medium-size farms and farms in less favoured areas. Comparable results are found in Nilsson (2017) who studied a sample of 4,601 Swedish farms that were granted investment support (Measure 121) over the years 2007–2013. The study finds positive and significant treatment effects on farm TFP but only among small farms.

Like most previous studies on CAP subsidies, we focus our assessment primarily on productivity effects, but we also consider the influence on farm labour and turnover to get a wider perspective. Subsidies represent a large contribution to farm profit and turnover and may work to provide opportunities for farms to invest in the modernisation of capital assets, which in turn can drive productivity and production capacity of the firm (Harris and Trainor, 2005; Serra, Zilberman and Gil, 2008; Kumbhakar and Lien, 2010). Developments in agricultural labour, and more generally job creation in rural areas, stand out as one of the main areas of focus in the CAP (European Commission, 2010). Impact on farm labour is important as it may indicate the role of the subsidy in stimulating increased or maintained employment opportunities in agriculture (Breustedt and Glauben, 2007). Garrone, Emmers and Lee *et al*. (2019) study the relation between CAP subsidies and the outflow of labour from agriculture in 210 European Union regions over the period 2004–2014. They show that subsidies reduce the outflow of labour from agriculture, but the effect is almost entirely attributed to decoupled Pillar 1 payments. They find coupled Pillar 1 payments to have no impact on preserving jobs in agriculture and the impact of Pillar 2 subsidies to be ambivalent. These results call for further investigation as they indicate heterogeneity in the effects on farm labour across different CAP payments.

One perspective that has received little attention in the literature on CAP payments is the potential presence of time lags between investments and accumulated observable effects. Temporal factors can be expected to play a key role as a result of adjustment costs linked to the learning and implementation of a given investment (Gould, 1968). This goes back to Lucas (1967) showing that the cost of adjustment is a function of investment that is internal to the firm, regardless of whether the investment is acquired for expansion or replacement. Indeed, investment support may be used by farms to cover an important part of costs that are necessary for the realisation of investments with various durations. We handle this empirically by following the approach in Garrone, Emmers and Lee *et al*. (2019) and by considering lags of the investment subsidy and other covariates to reflect that farmers need time to learn and adjust to a new situation. We also estimate models with time-interaction effects to get an indication of how long it takes before an impact is observed and how persistent the impact is.

3. Data, variables and summary statistics

The empirical analysis is conducted at the farm level. We link data on investment supports granted by the Swedish Board of Agriculture to farm-level microdata from Statistics Sweden (SCB). The data on investment supports are available from 2007 to 2019 (May), while farm-level microdata are available for 2006–2016. When we refer to farms throughout this paper, our focus is firms that have agriculture as their main economic activity, that is, more than 50 per cent of their turnover is derived from industry activities defined as agriculture.[4] The farms in our sample have been anonymised; the microdata include information about the size, location, industry orientation and financial status of the farms. Through SCB, we also obtain information on the education and age of farm employees by linking farms to individuals. These individual data are extracted from the LISA database, which comprises the whole Swedish workforce (from the age of 16 years). We also utilise data from the Integrated Administration and Control System (IACS) to identify the size of farms in terms of their landholdings in total hectares and hectares entitled for

4 Defined using Standard Industrial Classification Codes.

Table 1. Number of farms that have received investment support (2007–2016) linked to SCB firm data

Year	Support	No. of recipients	No. of matches with SCB microdata
2007	121	1,357	920
2008	121	1,009	706
2009	121	998	712
2010	121	1,307	927
2011	121	1,392	980
2012	121	725	528
2013	121	393	269
2014	4.1/2a	264	183
2015	4.1/2a	597	387
2016	4.1/2a	783	568

area payments (i.e. Single Farm Payments). This study thereby represents one of the first attempts to link IACS data to farm financial account data.

Table 1 shows that interlinking these register data involves some annual dropout of farms, in total 21.9 per cent, mainly because the SCB data only include farms with at least one employee. A discontinuance analysis is presented in Appendix A.

3.1. Outcome variables

There are several outcome variables that can be used to study the impacts of CAP investment support and that can contribute to a wider assessment and understanding of the effects. Following the discussion in Section 2, the empirical analyses include four variables reflecting farm growth in terms of productivity, turnover and labour (Zhu and Oude Lansink, 2010; Latruffe, 2010). Farm productivity is measured in terms of both labour productivity and TFP. Labour productivity is defined as value added per employee (Coad, 2009), and we consider farm TFP to obtain a composite productivity measure to capture the long-term technological change or adaptation (Coelli *et al.*, 2005). In estimating TFP, we follow the two-step approach in Levinsohn and Petrin (2003) to obtain a measure of TFP that is robust to serially correlated unobserved shocks to production.[5] This implies that we use a measure of intermediate inputs in the estimation of TFP to account for potential correlation between input levels and the unobserved firm-specific productivity process. Following this approach, we estimate TFP from the following equations (Petrin, Poi and Levinsohn, 2004):

5 A detailed description of the estimation procedure can be found in Levinsohn and Petrin (2003) and Petrin *et al.* (2004), where the latter also provides guidance for the specific estimation in Stata. The rationale is to account for the possibility of a correlation between unobserved productivity shocks and levels of input used by a firm.

$$y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \omega_t + \eta_t = \beta_l l_t + \phi_t(k_t, m_t) + \eta_t \quad (1)$$

where
$\phi_t(k_t, m_t) = \beta_0 + \beta_k k_t + \omega_t(k_t, m_t)$ and $\omega_t = E[\omega_t|\omega_{t-1}] + \xi_t$

$$TFP_t = \widehat{\eta_t + \xi_t} = y_t - \hat{\beta}_l l_t - \beta_k^* k_t - E\left[\widehat{\omega_t|\omega_{t-1}}\right] \quad (2)$$

where y_t is the output of the firms at time t; l_t and k_t stand for labour (number of employees) and capital (tangible and intangible assets), respectively; and m_t corresponds to cost of material.[6] The error term has two components, ω_t and η_t; the first represents the productivity that can be linked to external shocks and the second is assumed to be independent of farms' input decisions. ω_t is assumed to follow a first-order Markov process (Levinsohn and Petrin, 2003). TFP is then estimated using Equation 2. The rationale for using a control function estimator is to account for unobserved shocks to productivity by observing changes in firm input use, following the argument that intermediate inputs respond more smoothly to productivity shocks than firm investments, as suggested in Olley and Pakes (1996). Another advantage in using this approach is that intermediate inputs will generally respond to the entire productivity term, while investment may respond only to changes in the unobserved term. Moreover, using investments as a proxy is only going to be valid for firms reporting non-zero investments, with the risk that a bias is introduced in excluding zero investment firms.[7]

We also investigate the effect of investment support on farm labour (number of employees) and farm turnover to obtain a wider assessment regarding impacts on market adjustment and employment opportunities in agriculture (Robinson, 1999; Thornhill, 2006; Breustedt and Glauben, 2007; Garrone, Emmers and Lee *et al.*, 2019). Table 2 summarises the outcome variables, which are all measured at the farm level.

3.2. Explanatory variables

The variable of interest indicates whether the farm has received investment support during the programme period 2007–2013. The impact of the support is measured using a variable that takes the value 1 from the year the farm received support or 0 otherwise. To capture both the potential direct effects and the more long-term effects, the impact of investment support is analysed as an average over the periods 2007–2013 (the actual programme period) as well as 2007–2016 (the full period covered by the data). We also estimate annual effects to get an indication of how long it takes before the support has an impact and how persistent the impact is. In addition, we test how the size of the support influences farm performance.

6 Included to control for the productivity effects that are external to the firm but may potentially affect the decisions of the firm regarding input goods. Cost of material here corresponds to turnover less value added.

7 About 60 per cent of the firms in our sample report non-zero investments. See Levinsohn and Petrin (2003: 4) for a discussion about the invertibility condition linked to this argument.

Table 2. Definition of outcome variables

Target variables[a]	Definition
Labour productivity	Value added in Swedish Kronor (SEK) divided by the number of employees
TFP	Estimated as the residual of the production function (labour, capital and cost of materials following the approach in Levinsohn and Petrin, 2003). See Equations 1 and 2
Employment	Number of employees
Turnover	Revenue in SEK

[a]In the empirical part of the article, we consider as dependent variables the annual growth rate of the outcome variables (see Section 4.2 and 5).

Apart from the potential importance of investment support, there are several additional factors expected to explain differences in performance across farms. We include a set of farm- and location-specific factors including farms' access to capital (tangible and intangible assets), labour, land (total acreage and acreage entitled to area payments[8]) and indicators of farm human capital (average age and education of employees[9]). The choice of variables (land, labour, physical capital and human capital) included in the estimated production function is broadly in line with production theory (Romer, 2006), accounting for factors that are central in explaining firm production. We also account for factors that are specific to agricultural production, including farms' organic production, export activity, whether the farm has received additional CAP support payments from the Swedish RDP and natural conditions for agriculture. We also consider the importance of the economic geography of the farm by controlling for the size of the municipality in terms of population per square kilometre, thus controlling for the advantages that can be associated with urban regions, so-called agglomeration economies (Duranton and Puga, 2004). The explanatory variables are defined in Table 3.

3.3. Descriptive statistics

Figure 1 illustrates how the number of investment supports granted to the farms and the total amount of subsidies (in million SEK) have evolved since 2007. The figure displays that both the total number of subsidies and the total amount (sum) of investment subsidies are smaller in the most recent RDP (2014–2020) than in the previous RDP (2007–2013). Since the number of subsidies has

8 Although these measures of landholdings are correlated (0.6), they add important perspectives linked to farm size and entitlement to area payments and are therefore included together in the estimated models. The results are robust to the inclusion/exclusion of one of the land variables in the estimations.

9 Share of employees with at least 3 years of university studies and share of employees with an agricultural-related education (such as studies at an agricultural college or equivalent on a higher level).

Table 3. Explanatory variables and definitions

Explanatory variables	Level	Definition and unit of measurement[a]
Investment support	Farm	A binary variable taking the value 1 if the farm received investment support (121) during 2007–2013
Total investment support	Farm	Total actual amounts of investment support in SEK
Additional RDP supports	Farm	The amount of other support payments received from the RDP in SEK
Capital	Farm	Total tangible and intangible assets in SEK[b]
Number of employees	Farm	Number of employees
Highly educated	Farm	Share of employees with 3 or more years of higher education
Agricultural-related education	Farm	Share of employees with an agricultural-related education (in agronomy or agricultural college, etc.)
Average age	Farm	Average age of employees
Export	Farm	A binary variable taking the value 1 if the farm exports
Organic production	Farm	A binary variable taking the value 1 if the farm is committed to organic production (includes certified organic producers and farms in transition that are eligible for RDP organic support payments)
Land entitled to area support	Farm	Total number of hectares entitled to area support payments. Does not overlap with support payments defined above. Source: IACS
Land	Farm	Total number of hectares of land. Source: IACS
Population density	Municipality	Number of inhabitants per square kilometre
Natural conditions for agriculture	Production area	Categorical variable including eight production areas indicating natural conditions for agriculture (including structure of soils, bedrock, topography and climate)[c]
Year effects	Year	Categorical variable with 2007 as the base year

(continued)

Table 3. (Continued)

Explanatory variables	Level	Definition and unit of measurement[a]
Industry effects	Industry	Categorical industry variables indicating type of production: - Dairy farms (including the raising of dairy cattle) - Animal production (including egg production) - Growing of crops and plant propagation - Mixed farming - Forestry - Other, e.g. fishing and support activities (base)

[a]All continuous variables are log-transformed.

[b]Capital is measured as a stock variable.

[c]The geographic division into the eight production areas can be found on page number 292 in the following document (the Swedish Board of Agriculture) (south-west Sweden, Gss, is used as the base category): https://djur.jordbruksverket.se/download/18.7502f61001ea08a0c7fff104309/1370043710619/Bil2.pdf.

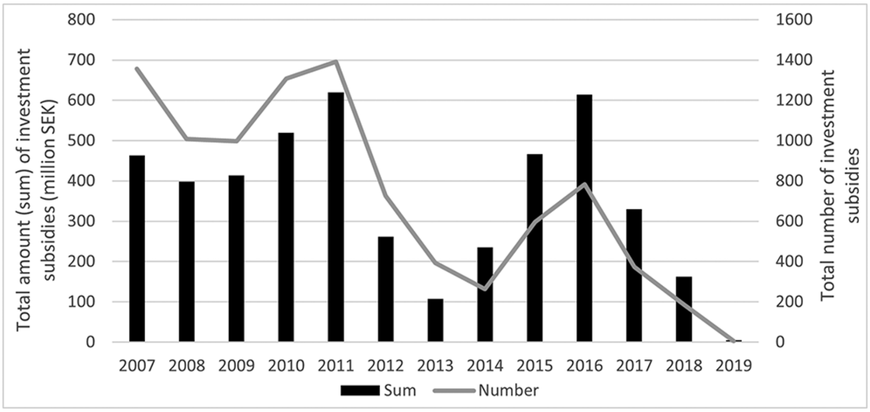

Fig. 1. Actual support amount (2007–2013), amount granted (2014–2019) and number of supports (121 and 4.1/2a) in programme periods 2007–2013 and 2014–2020, respectively (up to and including May 2019). Sums in SEK million.

decreased relatively more than the total amount, it means investment supports are on average larger in the most recent programme period.

Average values for matched farms in the two programme periods are given in Table 4, together with corresponding values for the farms that have not been granted investment support (Measure 121 in RDP 2007–2013 and Measure 4.1/2a in RDP 2014–2020).

Table 4. Average values (means) among farms with and without investment support, programme periods 2007–2013 and 2014–2020[a]

	(1) Farms with support	(2) Farms with support	(3) Farms without support	(4) Farms without support	*p*-Value for t-test of difference in means			
Programme period	2007–2013	2014–2020	2007–2013	2014–2020	(1)–(2)	(3)–(4)	(1)–(3)	(2)–(4)
Target variables								
Labour productivity (SEK thousand)	776	922	318	279	.000	.000	.000	.000
TFP (SEK thousand)	125	135	71.3	71.7	.008	.314	.000	.000
Number of employees	2.74	2.12	1.44	1.36	.001	.000	.000	.000
Turnover (SEK thousand)	5,299	4,765	2,312	1,721	.158	.003	.005	.137
Explanatory variables								
Additional RDP supports (SEK thousand)	12.4	17.5	1.86	0.62	.423	.000	.000	.000
Capital (SEK thousand)	7,482	8,643	2,318	2,298	.014	.920	.000	.015

(continued)

Table 4. (Continued)

	(1) Farms with support	(2) Farms with support	(3) Farms without support	(4) Farms without support	*p*-Value for t-test of difference in means			
Highly educated (%)	2.97	4.39	6.10	8.30	.021	.000	.000	.000
Agricultural-related education (%)	47.3	47.7	23.9	20.6	.818	.000	.000	.000
Average age	42.4	42.5	55.5	59.5	.899	.000	.000	.000
Export	0.021	0.006	0.008	0.005	.008	.000	.000	.824
Organic production	0.196	0.216	0.046	0.031	.217	.000	.000	.000
Land entitled to area support	148	210	31	39	.000	.000	.000	.000
Land	232	202	54	33	.013	.000	.000	.000
Population density	50.4	49.8	98.2	114	.923	.000	.000	.002

[a] For programme period 2014–2020, only farms receiving support 2014–2016 are included in Table 4 as the microdata do not cover the latter years of the programme (2017-2020).

Although the amount of subsidies is on average larger in the later programme period, farms that received investment support seem to be on average smaller in terms of employment than in the former programme period. The average value of turnover is also smaller in the later programme period, but the difference in means is not statistically significant. Both labour productivity and TFP are, however, statistically higher among farms with support in the later years. On the other hand, labour productivity among the farms without support is smaller in the second programme period. Worth noting is the large difference in average age between farms with and without support, which may indicate that agricultural investments go together with generational shifts in farms. There are also relatively large and significant differences regarding education, where farms that received support have, on average, a smaller share of highly educated employees but a larger share with agricultural-related education. Additionally, farms that have not received support seem to decrease in average size in terms of both employment and turnover between the programme periods.

4. Models and estimation methodology

4.1. Coarsened Exact Matching

We apply the CEM method developed by Iacus, King and Porro (2011, 2012) to estimate the impact of investment support on farm performance indicators. This matching method allows us to estimate the ATT and account for selection effects (Michalek, Ciaian and Kancs D', 2014; Bertoni *et al.*, 2020). Selection bias may be present if the observed probability of participation in a particular policy measure is not random. In line with Nilsson (2017), we find some evidence of selection bias in the data showing that farms receiving investment support are significantly larger and more productive and profitable than farms not getting any support.[10]

The rationale for using the CEM rather than other related methods is that it reduces any imbalance in the covariates between the treated and the control groups ex-ante instead of ex-post (Iacus, King and Porro, 2012); the method is also computationally straightforward in dealing with large data sets (Nilsson, 2017; Bertoni *et al.*, 2020). Bertoni *et al.* (2020) apply the CEM to study the effect of agri-environmental measures in improving greener farming practices in the Lombardy region. They find the variability of the results obtained with the CEM to be significantly lower than those obtained using a propensity score matching method.

In applying the method, we initially and temporarily coarsen the data, perform an exact match on the coarsened data and use the un-coarsened data in the final estimation of the model. The matching is done with regard to a set of relevant farm- and localisation-specific variables and results in weights included in the final estimations (Blackwell *et al.*, 2009). The control group is defined

10 We have ensured that these selection effects are statistically significant; the results can be obtained on request.

as farms that have not received investment support in the period 2007–2016. To ensure that farms that have received support are not matched against themselves, we create a reduced data panel used only for the matching and include the support-receiving farms the year before they were granted support and all farms that have not received support during the entire period. The overall idea is that if one can account for the selection that underlies the likelihood of being granted support, the remaining estimated differences in the outcome provide an unbiased estimate of the impact of the support (Rubin, 1974). To establish the reliability of the matching, we consider the multivariate distance specified as:[11]

$$\mathcal{L}_1(f,g) = \frac{1}{2}\sum_{\ell_1\ldots\ell_k} |f_{\ell_1\ldots\ell_k} - g_{\ell_1\ldots\ell_k}| \tag{3}$$

where a value of 0 ($\mathcal{L}_1 = 0$) indicates perfect balance between the treated and the control groups and a value of 1 (the maximum $\mathcal{L}_1 = 1$) indicates total imbalance. We estimate different matching algorithms and employ sensitivity analysis to assess the performance of the matching procedure. Results of the imbalance tests and other CEM outcomes are presented in Appendix B. The fifth matching algorithm produces the smallest multivariate distance (Table B6a—Weight 5) and results in 71 matched strata.

To further validate the matching, we estimate the difference in growth rate means between treated farms and the control groups in the pre-treatment period (that is, 2006–2007).[12] The difference in means is insignificant throughout the strata, with few exceptions. Regarding growth in labour productivity, the difference in means is significant in four strata (one at 1 per cent level, one at 5 per cent level and two at 10 per cent level). The difference in means of growth in TFP is significant in two strata (one at 5 per cent level and one at 10 per cent level). Regarding the growth in employment, the difference in means between the treated farms and the control group is significant at the 5 per cent level in four strata. However, since there is no difference in means in the vast majority of strata, we conclude that the matched treated and non-treated farms seem to follow similar pre-treatment growth patterns. The equal trends assumption is also tested by running placebo tests, that is, estimations using fake treatment groups (Gertler, Martinez and Premand *et al.*, 2016). The results are reported in Section 5.4.

11 In Equation 3, $f_{\ell_1\ldots\ell_k}$ denotes the relative frequencies for the farms with support and $g_{\ell_1\ldots\ell_k}$ denotes the corresponding frequencies for the farms in the control group. A perfect global balance between the groups is indicated by $\mathcal{L}_1 = 0$, and higher values of the indicator signify an increased imbalance with regard to the coarsened explanation variables.

12 Even though some farms are treated already in 2007, the growth between 2006 and 2007 can be considered as the pre-treatment period as the effects of investment support are not immediate; see Section 5.2.

4.2. Dynamic panel fixed-effects model

After the matching, we estimate the ATT using the following dynamic panel fixed-effects (FE) model (Garrone, Emmers and Lee *et al.*, 2019):

$$\Delta y_{it} = \alpha + \zeta T_{i-1} + \beta_0 y_{t-1} + \beta_1^{\prime} \boldsymbol{I}_{it-1} + \beta_2^{\prime} \boldsymbol{E}_{it-1} + \tau_t + \nu_i + \varepsilon_{it} \tag{4}$$

where the dependent variable, Δy_{it}, is the annual growth in the target variable for farm i from time $t-1$ to time t, defined as $\ln y_t - \ln y_{t-1}$. The average annual effect of the support is measured by ζ, and T_{i-1} is a categorical variable taking the value 1 if the farm has received support and 0 if not. y_{t-1} is the 1-year lag of the outcome variable, where β_0 is expected to be negative due to convergence. Farm-specific control variables are indicated by $I_{it\,-\,1}$ (including categorical variables of sub-industries, as well as production areas indicating the natural conditions for agriculture where the farm is located) and municipality-specific variables (population density) by E_{it-1}.[13] As indicated in the model, all explanatory variables are lagged 1 year.

The specification on growth in TFP excludes employment and capital, as these variables are already captured in the estimation of TFP. The specification of labour productivity excludes employment and replaces capital with capital intensity (capital per employee) and land-by-land intensity (land per employee), which follows the theoretical production function weighted by labour. τ_t represents time-fixed effects and ν_i farm-fixed effects, where the latter controls for unobserved time-invariant farm heterogeneity. ε_{it} represents the error term, and α is the constant. Given that the estimated CEM weights are included, the model corresponds to a difference-in-difference (Blackwell *et al.*, 2009).

In the model described above, ζ shows the average effect of investment support on the outcome variables for the investment support-receiving farms, irrespective of the size of the support. To test whether the amount matters, we follow Zhu, Demeter and Oude Lansink (2012) and include the size effect by specifying it as support amount divided by farm turnover. Measuring relative rather than absolute support amounts reduces issues of multicollinearity. Additionally, we test whether farms that receive repeated investment support perform differently from those that receive support only once.

5. Estimation results

As a first step, we estimate the impact of investment support in the earlier programme period (2007–2013) and estimate the annual effects to assess the development and persistence of the effects over time. As a second step, we use the estimated model for the earlier programme period to predict the expected effects of investment support on farm performance in the most recent programme period (2014–2020). Due to limitations in microdata availability, we include farms that have received support up to and including 2016.

13 see Table 3 for a full description of control variables.

5.1. Estimated impacts of investment support in RDP 2007–2013

Table 5 shows the estimated coefficients for the dynamic model (Equation 4) with growth in labour productivity (i) and TFP (ii) as outcome variables. In specification (a), the outcome during the actual programme period 2007–2013 is estimated, while specification (b) uses the whole now available period running up to and including 2016. Farms that have received support 4.1/2a in the later RDP (2014–2020) are excluded to not overestimate the effect of investment support 121. Corresponding results for growth in employment and turnover are presented in Table 6.

The results show a positive and statistically significant average annual effect of investment support on growth in labour productivity, TFP and turnover. Regarding employment growth, the effect is only weakly statistically significant for the shorter period. Furthermore, for productivity growth, the effect seems to become stronger in the longer period. This observed difference in coefficient size across the two periods (2007–2013 (a) and 2007–2016 (b)) is not statistically significant for growth in labour productivity. However, for TFP growth, the effect of investment support is significantly larger (at the 10 per cent level) when following the farms up until 2016, as compared to the shorter period.[14] In general, the results indicate that the investments facilitated by the support did contribute to improved performance in the support-receiving farms. This is in line with the results on Swedish agricultural firms by McCloud and Kumbhakar (2008), Zhu and Oude Lansink (2010) and Nilsson (2017).

Regarding productivity, specifications (1b) and (2b) show that investment support has an annual effect of approximately 14 per cent on growth in both labour productivity and TFP when the outcome of the farm is followed until 2016. When it comes to employment growth, the effect is either insignificant or rather small, which supports the results by Rizov, Davidova and Bailey (2018). Our estimates indicate that support-receiving farms increase their number of employees by about 1.5 per cent. As the average number of employees is relatively small to begin with (see Table 4), this means that even farms that receive support continue to be small in terms of employment. Regarding turnover, the average annual effect of investment support is approximately 8–9 per cent, looking at both periods.

The results for the control variables are overall in line with expectations showing that farms with more capital (intensity) have a higher growth rate in terms of both employment and turnover as well as labour productivity. Also, larger landholdings (in total or entitled to area support), organic production and agricultural education are all significantly and positively related to several indicators of farm performance. The influence of the share of employees with a generally higher education is, however, ambiguous, positive for productivity growth but significant only for labour productivity in the longer

14 The Z-score for labour productivity growth is 1.18, which corresponds to a p-value of 0.238. The Z-score for TFP growth is 1.71, which corresponds to a p-value of 0.087. The Z-score is calculated as $\left(\hat{\beta}_b - \hat{\beta}_a\right) / \sqrt{\left(e_b^2 + e_a^2\right)}$, where $\hat{\beta}$ represents the estimated coefficients and e the estimated standard errors.

Table 5. Estimated effects of investment support (121) on farm productivity growth

	(1a) FE-CEM 2007–2013	(1b) FE-CEM 2007–2016	(2a) FE-CEM 2007–2013	(2b) FE-CEM 2007–2016
	Δ *Labour productivity*	Δ *Labour productivity*	Δ *TFP*	Δ *TFP*
Investment support ($t-1$)	0.121***	0.143***	0.103***	0.135***
	(0.0158)	(0.0139)	(0.0139)	(0.0125)
Labour productivity ($t-1$)	−1.076***	−0.950***		
	(0.0066)	(0.0055)		
TFP ($t-1$)			−1.074***	−0.956***
			(0.0068)	(0.0055)
Capital intensity ($t-1$)	0.0401***	0.0439***		
	(0.0033)	(0.0031)		
Land entitled to area support ($t-1$)[a]	0.0804***	0.0040	0.0736***	−0.0001
	(0.0114)	(0.0067)	(0.0114)	(0.0064)
Land ($t-1$)[a]	0.0185**	0.0399***	0.0172**	0.0378***
	(0.0082)	(0.0061)	(0.0078)	(0.0060)
Highly educated ($t-1$)	0.0786	0.115**	0.0496	0.0736
	(0.0695)	(0.0562)	(0.0642)	(0.0544)
Agricultural-related education ($t-1$)	−0.0232	−0.0111	−0.0034	−0.0068
	(0.0262)	(0.0205)	(0.0226)	(0.0182)
Average age ($t-1$)	−0.108***	−0.136***	−0.107***	−0.163***
	(0.0313)	(0.0254)	(0.0263)	(0.0223)
Export ($t-1$)	0.0221	−0.0256	−0.0001	−0.0482*
	(0.0334)	(0.0284)	(0.0307)	(0.0275)
Additional RDP supports ($t-1$)	−0.0031*	−0.0038**	−0.0032*	−0.0041***
	(0.0018)	(0.0015)	(0.0017)	(0.0014)
Organic production ($t-1$)	0.0489***	0.0726***	0.0455***	0.0735***
	(0.0135)	(0.0125)	(0.0127)	(0.0117)
Population density ($t-1$)	0.0276	0.0301	0.0408	0.0379
	(0.0253)	(0.0222)	(0.0249)	(0.0236)
Constant	5.879***	5.325***	4.444***	4.329***
	(0.197)	(0.174)	(0.179)	(0.169)
Industry FE ($t-1$)	Yes	Yes	Yes	Yes
Production area FE ($t-1$)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	180,697	281,499	169,492	261,331
Within R^2	0.522	0.460	0.531	0.469
F-value	1,106***	1,106***	1,099***	1,145***

***, ** and * indicate statistical significance at the levels of 1, 5, and 10 per cent, respectively. Robust standard errors in parentheses.
[a]In specifications 1a–b, both land variables are weighted by labour.

Table 6. Estimated effect of investment support (121) on growth in farm employment and turnover

	(3a) FE-CEM 2007–2013	(3b) FE-CEM 2007–2016	(4a) FE-CEM 2007–2013	(4b) FE-CEM 2007–2016
	Δ *Employment*	Δ *Employment*	Δ *Turnover*	Δ *Turnover*
Investment support ($t-1$)	0.0160*	0.0110	0.0856***	0.0780***
	(0.0089)	(0.0077)	(0.0087)	(0.0084)
Employment ($t-1$)	−0.814***	−0.692***	0.133***	0.158***
	(0.0096)	(0.0079)	(0.0088)	(0.0080)
Turnover ($t-1$)			−0.852***	−0.707***
			(0.0088)	(0.0070)
Capital ($t-1$)	0.0165***	0.0190***	0.113***	0.140***
	(0.0025)	(0.0018)	(0.0072)	(0.0057)
Land entitled to area support) ($t-1$)	0.0153***	0.0059***	0.129***	0.0310***
	(0.0041)	(0.0022)	(0.0083)	(0.0044)
Land ($t-1$)	−0.0026	−0.0006	0.0132***	0.0321***
	(0.0032)	(0.0021)	(0.0046)	(0.0038)
Highly educated ($t-1$)	−0.0534	−0.0840**	−0.0958*	−0.0225
	(0.0426)	(0.0327)	(0.0520)	(0.0417)
Agricultural-related education ($t-1$)	0.0295*	0.0250**	0.0385**	0.0352***
	(0.0159)	(0.0127)	(0.0162)	(0.0131)
Average age ($t-1$)	−0.0788***	−0.0624***	−0.0786***	−0.0989***
	(0.0203)	(0.0158)	(0.0180)	(0.0163)
Export ($t-1$)	−0.0194	−0.0214*	0.0013	−0.0173
	(0.0171)	(0.0129)	(0.0168)	(0.0137)
Additional RDP supports ($t-1$)	0.0019**	0.0012*	0.0014*	0.0012
	(0.0008)	(0.0007)	(0.0008)	(0.0008)
Organic production ($t-1$)	−0.0129*	−0.0058	0.0125	0.0547***
	(0.0069)	(0.0056)	(0.0078)	(0.0083)
Population density ($t-1$)	−0.0006	−0.0100	0.0227	0.0338
	(0.0086)	(0.0084)	(0.0224)	(0.0206)
Constant	0.258**	0.158**	3.880***	2.802***
	(0.105)	(0.0796)	(0.201)	(0.171)
Industry effects ($t-1$)	Yes	Yes	Yes	Yes
Production area FE ($t-1$)	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	238,579	392,030	203,926	328,530
Within R^2	0.400	0.344	0.398	0.325
F-value	306.0***	300.4***	548.9.9***	557.6***

***, ** and * indicate statistical significance at the levels of 1, 5, and 10 per cent, respectively. Robust standard errors in parentheses.

period, and even significantly negative when it comes to employment and turnover. Furthermore, having older employees decreases farm performance, as the estimates for average age are negatively significant throughout. The effect of being an exporting farm is mainly insignificant, while farms that receive other RDP support show a lower productivity growth but generally higher turnover and employment growth. The type of region where the farm is located, in terms of population density, seems to play an insignificant role for the outcome variables and, consequently, the performance of the support-receiving farms. Finally, the lagged target variables are negatively significant in all specifications, showing the expected β-convergence.

As mentioned in Section 4.2, we have run additional estimations investigating the influence of receiving a larger amount of support, as well as repeated supports. The results of these estimations are insignificant throughout; hence, we find no growth effects (neither positive nor negative) of receiving a higher amount of support (relative to the farms' turnover)[15] or of receiving investment support more than once in the programme period. The non-positive results point in the same direction as those of Zhu, Demeter and Oude Lansink (2012) as well as Skevas, Emvalomatis and Brümmer (2017), who even show that an increasing amount of subsidies leads to lower technical efficiency. There are also theoretical arguments that explain non-positive productivity effects of farm support as a result of a tailored investment behaviour and a reduced motivation to search for cost-saving methods (Baumol, 1990). It may be, for example, that investments that can be granted support are prioritised over other more productive investments. It may also be a result of the so-called *rent-seeking behaviour*, where farms reallocate productive resources to the support-application process itself (Bergström, 2000; Schmitz, Moss and Schmitz *et al.*, 2010). Based on our results, we can only conclude that farms do not seem to experience any additional growth effect from receiving a larger amount of, or repeated, investment support. However, the disentanglement of the mechanisms behind this result requires a different methodological approach and is beyond the scope of this study.

5.2. Change in the effect of investment support over time

The somewhat weaker effect of the support in the period 2007–2013 compared with 2007–2016, although statistically significant only for TFP growth, indicates that the full effect of the support is not immediate but grows stronger over time. To test how the effect of the support changes over time, specifications 1–4(b) are estimated with interaction terms between annual effects and the binary variable stating whether the farm has received support in the year $t - 1$ or earlier. The point estimates in Figures 2–5 refer to the coefficient for the interaction. The two brighter curves indicate the lower limit and the upper limit for a 95 per cent confidence interval around the point estimate. If *both* bright

15 In a previous version of this paper, when explaining the levels of the target variables rather than the annual growth, the size of the support was significantly negatively related to all target variables.

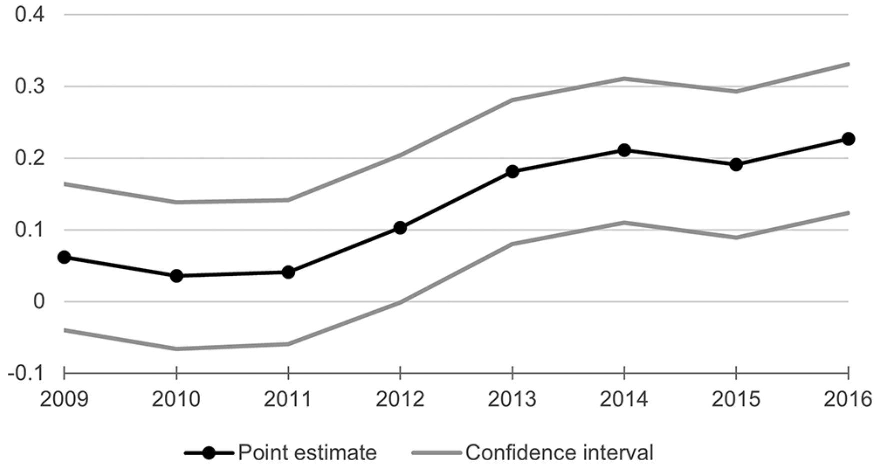

Fig. 2. Annual change in the effect of investment support on growth in farms' labour productivity.

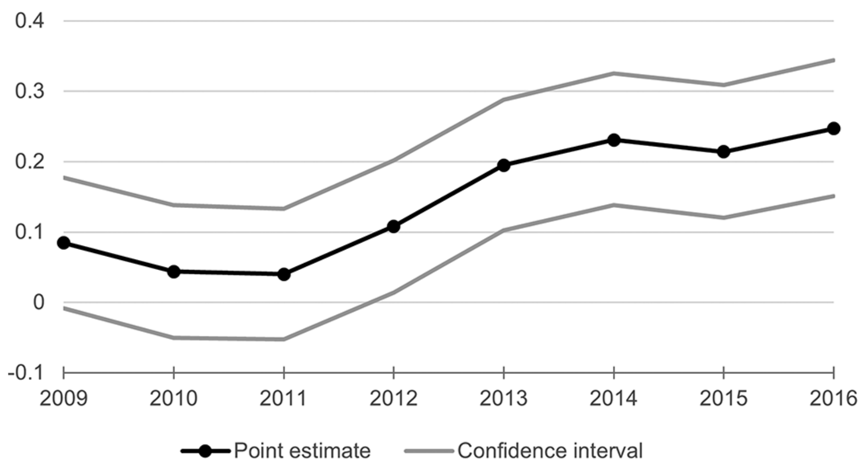

Fig. 3. Annual change in the effect of investment support on growth in farms' TFP.

curves are above 0, or below 0, the point estimation is significant, which means that the coefficient is statistically different from 0.

Figures 2, 3 and 5 show that the effects of the support on growth in productivity and turnover are insignificant during the first years. This can likely be explained by the fact that the farms go through an adaptation period during the implementation phase, and it therefore takes some time before the investment results in increased productivity and turnover. However, the trends for the effect on growth in productivity and turnover seem to be positive throughout, which indicates an increasingly stronger (positive) effect of the support

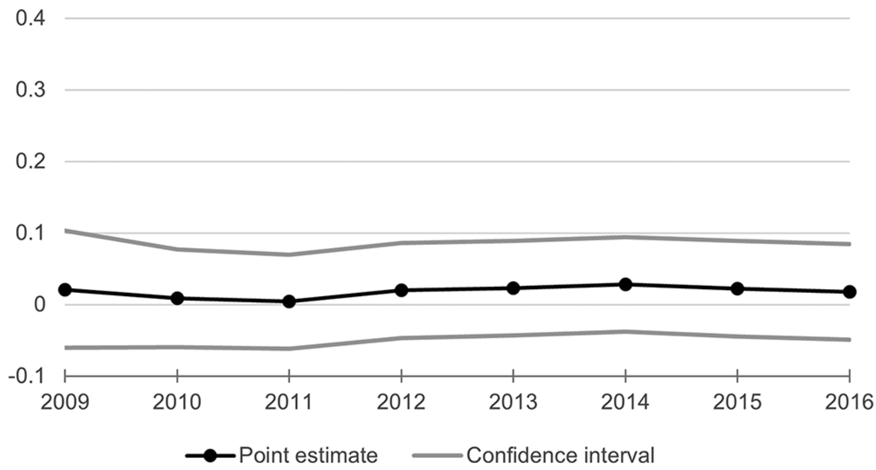

Fig. 4. Annual change in the effect of investment support on farms' employment growth.

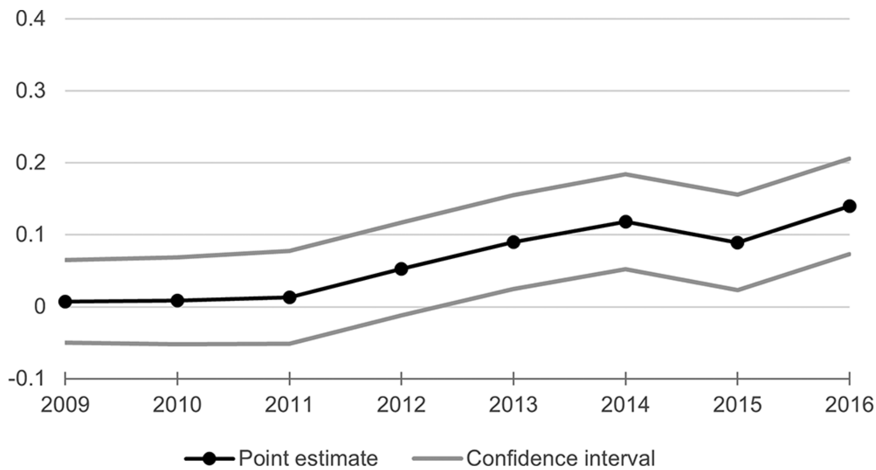

Fig. 5. Annual change in the effect of investment support on farms' growth in turnover.

over time. At the same time, the largest increase in growth rates comes in the middle of the period, and then the effects seem to stabilise in the later years.

As shown in Figure 4, the effect of investment support on growth in employment is insignificant throughout the whole period, which is in line with the results presented in Table 6. With the exception of employment growth, Figures 2–5 show the importance of following the farms during a longer period to be able to evaluate the effects of farm support, such as investment support. Using a short period of time carries the risk of underestimating the effects or may even result in false conclusions, for example, that the effects of the support on farm performance are insignificant.

Table 7. Estimated effects of support (121) on farm performance (growth) per sub-industry

	(1b$^{\text{i-vi}}$) FE-CEM 2007–2016	(2b$^{\text{i-vi}}$) FE-CEM 2007–2016	(3b$^{\text{i-vi}}$) FE-CEM 2007–2016	(4b$^{\text{i-vi}}$) FE-CEM 2007–2016
	Δ Labour productivity	*Δ TFP*	*Δ Employment*	*Δ Turnover*
(i) Dairy	0.171***	0.166***	0.0134	0.0617***
	(0.0221)	(0.0188)	(0.0127)	(0.0123)
(ii) Animals	0.215***	0.206***	0.0024	0.118***
	(0.0294)	(0.0253)	(0.0170)	(0.0164)
(iii) Crops	0.152***	0.138***	−0.0042	0.0323
	(0.0297)	(0.0280)	(0.0163)	(0.0204)
(iv) Mixed	0.120***	0.107***	0.0036	0.0566***
	(0.0285)	(0.0265)	(0.0152)	(0.0174)
(v) Forestry	0.0582	0.0689	0.0380	0.0964**
	(0.0687)	(0.0652)	(0.0359)	(0.0410)
(vi) Other	0.116	0.117	0.0422	0.0718
	(0.105)	(0.117)	(0.0575)	(0.0596)

*** and ** indicate statistical significance at the levels of 5 and 10 per cent, respectively. Robust standard errors in parentheses.

5.3. Differences in the effect of investment support across industries

The estimation results presented in Tables 5–6 include controls for industry types, distinguishing between (i) dairy farms, including raising of dairy cattle (*Dairy*); (ii) animal production, including egg production (*Animals*); (iii) growing of crops and plant propagation (*Crops*); (iv) mixed farming (*Mixed*); (v) forestry (*Forestry*) and (vi) other, for example, fishing and support activities (*Other*). To test whether the effect of the support differs across these agricultural sub-industries, as well as whether the overall effect is driven by farms operating in any particular industry or industries, we run separate regressions at the industry level. The results are presented in Table 7. The specifications of the models, and thus the included variables, underlying the results in Table 7 correspond to specifications 1b and 2b in Table 5 and specifications 3b and 4b in Table 6.[16]

Table 7 shows that the effect does differ across industries, with significant productivity effects for *Dairy, Animals, Crops* and *Mixed* farming. Farms in livestock raising and egg production gain the most from investment support, with a 20 per cent increase in productivity growth. This effect is significantly larger than the effect on mixed farms. The *Animals* industry also experiences the greatest effect on growth in turnover, where the coefficient is significantly larger than for *Dairy, Crops* and *Mixed* farming. Additionally, investment support has a relatively strong and significant positive effect on turnover growth in the *Forestry* industry. Regarding *Forestry* and *Other* industries, the coefficients

16 Full regression results can be obtained from the corresponding author.

in Table 7 are largely insignificant. This can at least partly be explained by the fact that few farms in these industries receive investment support. Less than 1 per cent of the forestry and other farms were supported in the programme period 2007–2013, while almost 19 per cent of the farms operating in the dairy sector obtained financial support for their investments via the RDP. In the remaining industries, between 4 and 8 per cent of the farms were supported during 2007–2013.

5.4. Further robustness and placebo tests

To test the equal trends assumption and the validity of the difference-in-difference estimates for investment support reported above, we run placebo tests for specifications 1–4b, that is, the estimations covering the whole period 2007–2016. We conduct the placebo tests by running additional difference-in-difference estimations using fake treatment groups (Gertler, Martinez and Premand *et al.*, 2016). No impact of the fake treatment supports the assumption of equal trends. We find the fake treatment groups by randomly treating non-treated farms (by the same number as the actually treated farms), that is, farms that have not received investment support in programme period 2007–2013 nor in programme period 2014–2020. Repeated estimations on the full specifications 1–4b, using 10 different fake treatment groups and excluding the actually treated farms, show mainly insignificant results for the fake investment support coefficient. Just 3 out of totally 40 estimates (10 for each dependent variable) are statistically significant, although only at the 10 per cent level. Additionally, the magnitude of these significant estimates is small, 0.0325 and 0.0362 for growth in labour productivity, and 0.0339 for growth in TFP. The coefficients of all other variables are robust across all placebo estimations and correspond to the estimates in Table 5 (specifications 1b and 2b) and Table 6 (specifications 3b and 4b).[17]

The coefficients reported in Tables 5 and 6 are estimated based on the matched control groups identified by CEM, using the weights that minimise the imbalance between the treated farms and the control groups (as described in Section 4.1). Since the CEM matching accounts for the selection that underlies the likelihood of being granted support (Rubin, 1974), we expect that the better the matching, the more correct is the estimated impact of investment support on farm growth. To test the robustness of the results, we run additional estimations using the weights obtained from different matching strategies (as reported in Appendix B), as well as regular fixed effects estimations without matching. We expect the coefficients under matching to be smaller than if no weights are used. The results on the impact of investment support are presented in Table 8.

Indeed, Table 8 shows that the used matching strategy (xii Weight 5) produces smaller estimates for investment support than if no matching was employed (vii No weights). This points to an upward bias in regular fixed

17 The full regression results on the placebo tests and the further robustness tests can be obtained from the corresponding author.

Table 8. Estimated effects on farm performance (growth) using different control groups (weights)

	(1b$^{vii\text{-}xii}$) FE-CEM 2007–2016	(2b$^{vii\text{-}xii}$) FE-CEM 2007–2016	(3b$^{vii\text{-}xii}$) FE-CEM 2007–2016	(4b$^{vii\text{-}xii}$) FE-CEM 2007–2016
	Δ *Labour productivity*	Δ *TFP*	Δ *Employment*	Δ *Turnover*
(vii) No weights	0.166***	0.153***	0.0139***	0.134***
	(0.0104)	(0.00939)	(0.00521)	(0.00773)
(viii) Weight 1	0.170***	0.155***	0.0146**	0.139***
	(0.0118)	(0.0108)	(0.00620)	(0.00846)
(ix) Weight 2	0.143***	0.117***	−0.00520	0.0993***
	(0.0120)	(0.0106)	(0.00827)	(0.00801)
(x) Weight 3	0.170***	0.155***	0.0134**	0.139***
	(0.0119)	(0.0109)	(0.00573)	(0.00854)
(xi) Weight 4	0.146***	0.136***	0.00983	0.0782***
	(0.0142)	(0.0128)	(0.00784)	(0.00855)
(xii) Weight 5	0.143***	0.135***	0.0110	0.0780***
	(0.0139)	(0.0125)	(0.00765)	(0.00837)

*** and ** indicate statistical significance at the levels of 5 and 10 per cent, respectively. Robust standard errors in parentheses.

effects estimates, especially for growth in turnover. Using Weight 2 produces rather similar impacts as Weight 5, with even smaller estimates for growth in TFP and employment. Except for Weight 1 and Weight 3, the results are relatively robust and statistically similar across the matching strategies.

5.5. Expected effects of investment support in RDP 2014–2020

The model estimated in Section 5.1 is applied here to estimate the expected effects of investment support (4.1/2a) granted in the RDP of 2014–2020. To find the expected average effect of the support, a counterfactual method is used, where the support-receiving farms are compared exclusively with themselves. This means that values (growth rates) of the dependent variables are predicted for farms on the condition that they are (i) granted support and (ii) not granted support. Table 9 shows the expected effects for farms that were granted support between 2014 and 2016[18] according to the new programme period.

The table also shows expected values for farms that have not been granted support, neither in the first nor in the second programme period, which indicates relatively large differences compared to farms with support. Table 9 shows that farms without support exhibit a positive predicted growth in all target variables, while the predicted average growth rates of supported farms are negative. Hence, even though supported farms are on average larger and more productive than farms that do not receive support (Table 4), their

18 2016 is the latest year with available microdata on the firm level. Supplementary estimates with comparable results have been made, where firms receiving support between 2017 and 2019 have been matched to their firm data for 2016.

Table 9. Predicted growth rates for farms in programme period 2014–2020

Average annual growth	Farms with support 2014–2016 (1) Support	(2) No support	Difference	Farms without support
Labour productivity	−0.3875	−0.4450	0.0575[a]	0.4224
TFP	−0.3741	−0.4284	0.0542[a]	0.3786
Employment	−0.0994	−0.1039	0.0045[a]	0.0251
Turnover	−0.4211	−0.4528	0.0317[a]	0.4874

[a]Indicates statistical significance at the 1 per cent level.

average growth rates are expected to be lower and even negative. This may indicate that the investment support may be viewed as an opportunity to boost productivity growth and/or farm growth in general, for farms that face challenges with their growth rates. At the same time, it may indicate a convergence in productivity across farms, where smaller farms tend to exhibit higher growth rates than larger farms.

Still, looking at the difference in growth rates for supported farms only (fourth column in Table 9), the expected effect of investment support is significantly positive. The predicted growth rates of the supported farms are higher when they get support than when they do not get support. The greatest effect can be expected on productivity, where the support results in an annual average increase in growth of 5–6 percentage points. As expected, based on the previous results, the effect seems to be lowest for employment, where the support is expected to increase employment growth by only 0.5 percentage points.

Since the base model in the previous section builds on a period of 10 years (2007–2016), the expected average effects in Table 9 can be assumed to be materialised for farms during the 10 years after they have been granted support. Section 5.2 shows, however, that the effects on target variables are statistically

Table 10. Differences in predicted growth rates between farms with support in programme period 2007–2013 and farms with support in programme period 2014–2020

Average annual growth	Farms with support 2014–2016[b]	Farms with support 2007–2013	Difference
Δ Labour productivity	−0.4531	−0.2946	−0.1584[a]
Δ TFP	−0.4878	−0.3429	−0.1449[a]
Δ Employment	−0.2241	−0.2089	−0.0152
Δ Turnover	−0.5256	−0.4222	−0.1038[a]

[a]Indicates statistical significance at the 1 per cent level.

[b]The predicted growth rates for supported firms in programme period 2014–2020 differ from Table 9 since Table 9 excludes firms that received support in the programme period 2007–2013.

insignificant during the beginning of the period, which means that the effects cannot be expected to kick in until towards 2020.

Table 10 shows how the expected average values of the outcome variables differ between farms that have received support in the earlier (support 121) and the most recent (support 4.1/2a) programme periods. Even though supported farms are on average more productive during the later period (Table 4), the predicted growth in TFP and average labour productivity is significantly higher (less negative) for farms that were granted support in the earlier period. A similar pattern is found for growth in turnover, while the growth rates are not significantly different across programme periods for employment growth.

The general negative sign found on the expected average annual growth rates of supported farms indicates that it is not the fastest-growing farms that seek and are granted support in the Swedish RDP. This adds to the debate on whether investment support is merely artificial respiration, and whether this can be expected to contribute to long-term rural development, thus fulfilling the goals of the programme.

6. Conclusions

In this paper, we estimate the effects of investment support in the earlier RDP (Measure 121 in programme period 2007–2013) on farm performance, measured as annual growth in labour productivity, TFP, employment and turnover (outcome variables). A second aim of the paper is to estimate the expected effects on the performance of investment support granted in the most recent RDP (support 4.1/2a in the programme period 2014–2020). This is achieved by using the estimated model of the effects of the support in the earlier programme period to forecast the effects of support in the present programme period. Information about support received by farms is matched to farm-level data from SCB. This type of microdata is available up to and including 2016, which means that farms that have received support in the earlier programme period are followed over (a maximum of) 10 years.

The results show positive estimated growth effects of investment support on all target variables except employment, meaning that farms receiving support in the earlier RDP achieve increased performance in terms of both productivity and turnover. Even if the annual average effect of the support is positive over the whole 10-year period, the effect on growth rates is non-significant during the first years. This may indicate that farms go through a period of adjustment when they are granted support before they see an increase in performance. Furthermore, as no weakening of the growth effect is seen towards the end of the 10-year period, we can conclude that the effects of investment support are long term. We can also conclude that to evaluate the effects of investment support, such as in the RDP, a long-enough period must be available. Otherwise, there is a risk that the effects will be underestimated, leading to misleading conclusions and policy recommendations.

The expected effects of investment support in the most recent programme period are in line with the estimated effects of support in the earlier programme period. The expected effects are based on the assumption that estimated relationships and external conditions are consistent across the two programme periods. The greatest effects can be expected on productivity growth, while the effect seems weakest on employment, indicating that supported farms tend to continue to be small (on average) in terms of employees. Considering that an increased productivity growth may reduce the farms' requirements for labour input, these results can be expected. Even though the expected effects on growth in turnover and productivity are positive, supported farms show lower (even negative) growth rates than non-supported farms. This may question the resulting impact on rural development, as investment support may be merely artificial respiration for declining farms.

Since the forecast model builds on a 10-year period (2007–2016), the expected effects of the support can be assumed to be materialised for the farms during the 10 years after the programme was introduced. However, as the estimated effects on the target variables are non-significant during the first half of the period, the effects can be expected to kick in only towards 2020. This can be considered a relatively long delay. A recommendation for future RDPs would thus be to reconsider, for example, through case studies, how the period of adjustment could be shortened for the farms; this could involve efforts towards advisory service or faster processes for payments of support. Worth noting is that the effect of the support does not seem to diminish in the latest years of the forecast model, which again indicates that the effects are long term. However, this means that we cannot draw any conclusions about how long the effect lasts, nor on when the support has reached its full effect.

We provide additional estimations, showing that it is primarily farms in the dairy and animal sectors that experience positive effects on performance. Additionally, the effects of investment support can differ based on other farm characteristics as well as between farms that receive different types of support. These issues are, however, beyond the scope of this study but could preferably be elucidated in deeper studies of investment support in the RDPs.

Finally, the fact that there are systematic differences between farms that do and do not receive investment support makes it challenging to interpret our results. The matching of farms that have received support against a control group of farms that have not received support is a widely accepted evaluation method and is also the method recommended in the guidelines formulated for the final evaluation of the RDP (see European Communities, 2014). However, the method is not free from objections, and the fact that some farms seek and are granted support may have a number of different explanations that are not taken into account in the present analysis. Esposti and Sotte (2013) provide an overview of possible methodological considerations for further studies on policy evaluation.

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Appendix A: Discontinuance analysis

The discontinuance analysis can only be made with regard to the variables available in the support data of the Board of Agriculture. Total dropout is 21.9 per cent, which means that just above every fifth farm that received support during the programme period 2007–2013 cannot be matched to the firm data of SCB. The dropout differs somewhat between the counties, from 16.5 per cent in the counties of Kalmar and Södermanland to 27.3 per cent in Kronoberg and Västerbotten. However, Figure A1 shows that the geographic distribution of matched farms with support relatively well agrees with the total distribution.

Figure A2 shows that the distribution of matched farms over the years follows the total annual distribution of farms with support. According to Figure A3, limited companies comprise a somewhat larger part of matched firms than of all farms with support, while sole proprietorships are a smaller part. The dropout is thus larger among sole proprietorships, 24.9 per cent against 10.1 per cent among limited companies. The dropout is also larger among beef producers, 33.2 per cent, than dairy farms, 12.7 per cent.

Figures A3 and A4 indicate certain differences between matched and non-matched farms. Table A1 also shows that there are statistical differences between the two groups of farms, which indicates that matched farms do not completely represent all farms with support. Matched farms seem on average to apply for support for somewhat larger investments; the mean age of the applicants is also somewhat higher.

Appendix B: Matching of control group, outcome and comparative statistics

Table A1. T-test for differences in average means between matched and non-matched farms

	Mean			
	All	Non-matched	Matched	Difference
Cost entitled to support	1,962,096	1,678,697	2,041,741	363,044[a]
Actual amount support	383,714	339,085	396,256	57,172[a]
Age of the applicant	52.22	51.38	52.51	1.13[a]

[a]Indicates statistical significance on a 1 per cent level.

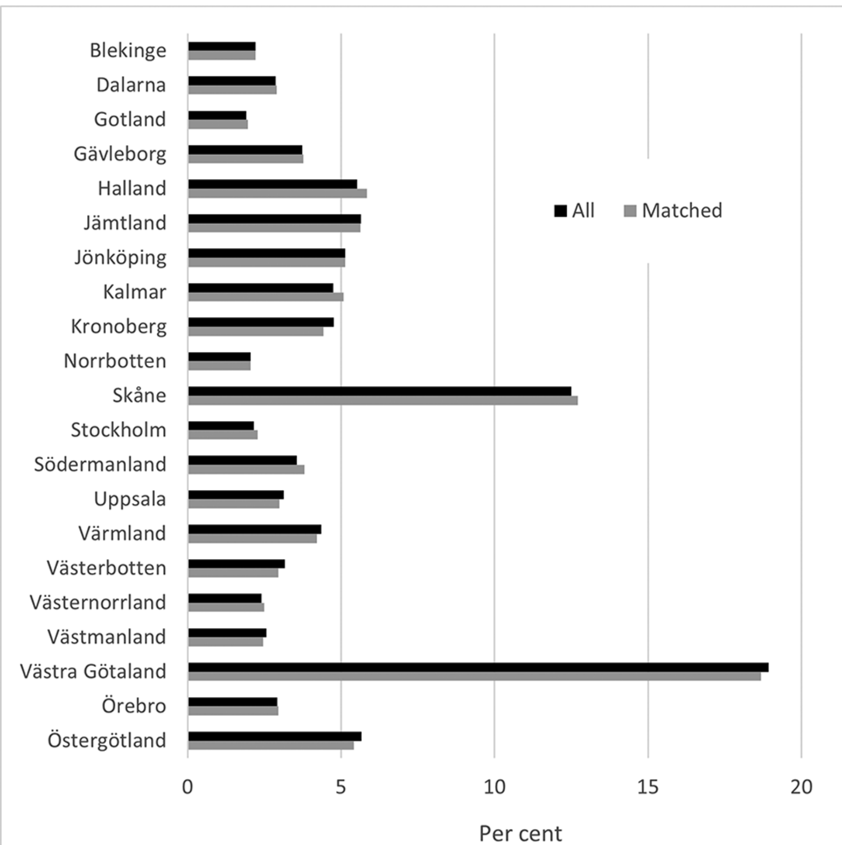

Fig. A1. Distribution across counties of all farms with support and matched farms with support.

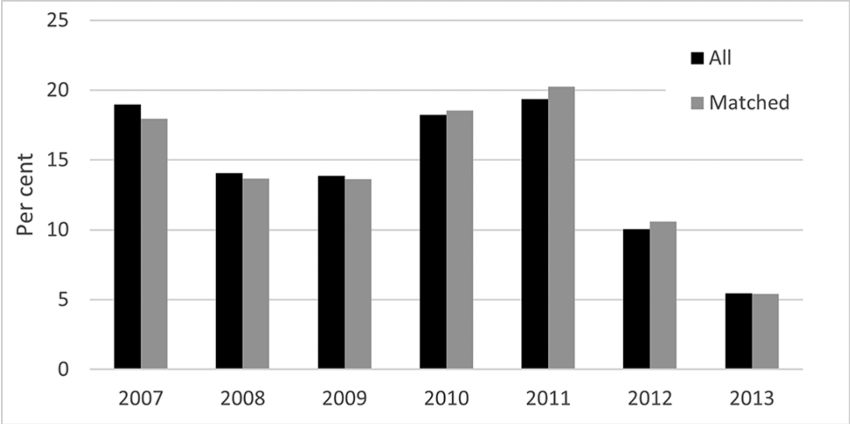

Fig. A2. Distribution across years of all firms with support and matched firms with support.

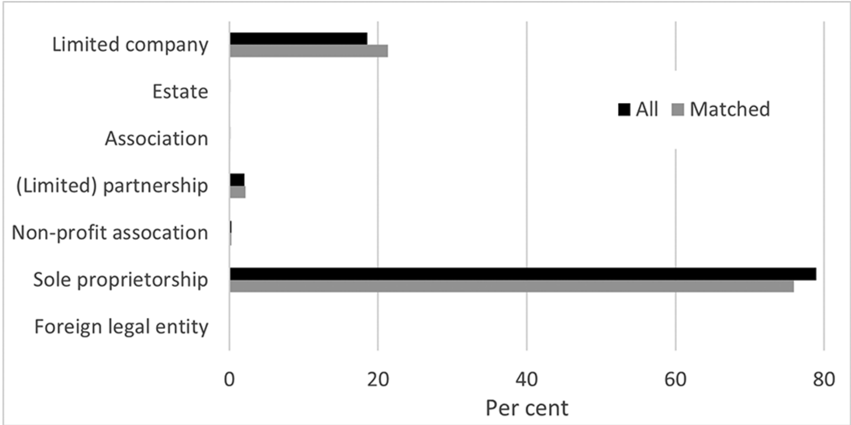

Fig. A3. Distribution across types of farms of all farms with support and matched farms with support.

Table B1a. Differences in means of key variables between farms with and without support

Variables	2007–2013 Diff. (*p*)	2014–2016 Diff. (*p*)
Labour productivity	−486.13 (0.000)	−663.00 (0.000)
TFP	−57.23 (0.000)	−77.27 (0.000)
Employment	−1.24 (0.000)	−1.40 (0.000)
Capital	−5514.89 (0.000)	−7167. 89 (0.000)

Values indicate results of t-test significant at 95 per cent level. *p*-Values in parentheses.

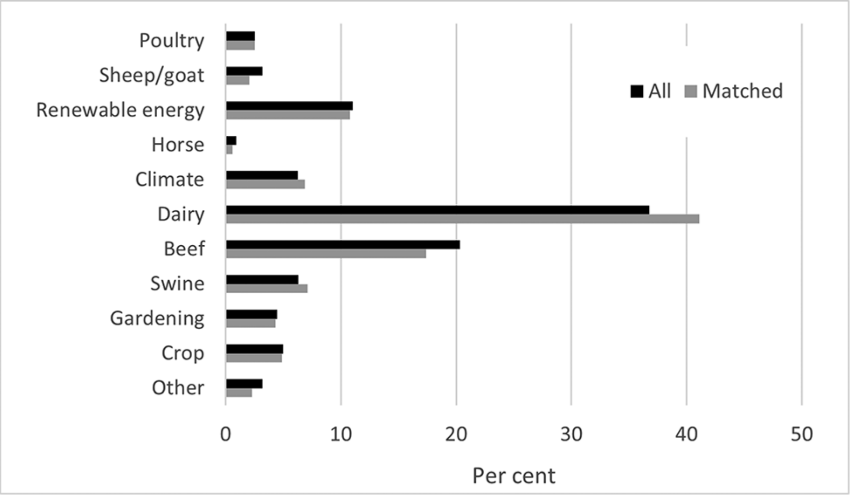

Fig. A4. Distribution across categories of all farms with support and matched farms with support.

Table B1b. Differences in means of key variables between farms with support in the two programme periods

Variabler	Diff. (p)
Labour productivity	137.028 (0.000)
TFP	20.391 (0.000)
Employment	0.073 (0.212)
Capital	1,632.447 (0.000)
Turnover	776.501 (0.008)

Values indicate results of t-test significant at 95 per cent level. p-Values in parentheses.

Table B2a. Weight 1. CEM matching of control group (target variables; labour productivity, TFP)

	$\mathcal{L}_1$	Mean	Min	25%	50%	75%	Max
Employees	0.330	0.988	0	0	0	2	−23
Capital	0.551	7.1e+06	8.8e+06	2.3e+06	5.1e+06	9.8e+06	.
Industry[a]	0.248	0.248	0	0	1	0	0
Population density	0.137	3.003	0	2.7	4.5	8.1	0
Multivariate distance: 0.76, no of strata: 138, no. of matched strata: 24							

[a]Industries are classified as (standard industrial classifications, SNI, in parenthesis). *Cultivation* (1110–1302), *Dairy* (1410), *Breeding* (1420–1472) and Other agriculture.

Table B2b. Weight 1. No. of farms in control group (0) and support group (1)

	0	1
All	608,670	4,532
Matched	599,989	4,530
Non-matched	8,681	2

Table B3a. Weight 2. CEM matching of control group (target variables; labour productivity, TFP)

	$\mathcal{L}_1$	Mean	Min	25%	50%	75%	Max
Employees	0.123	0.206	0	0	0	1	−18
Capital	0.429	5.8e+06	8.8e+06	2.2e+06	4.6e+06	8.2e+06	.
Industry[a]	0.213	0.213	0	0	1	0	0
Population density	0.119	1.755	0	1.6	3.35	3.5	0
Agriculture-related education	0.01	−7.7e−06	0	0	0	0	0
Multivariate distance: 0.82, no. of strata: 154, no. of matched strata: 27							

[a]Industries are classified as (SNI in parenthesis) Cultivation (1110–1302), Dairy (1410), Breeding (1420–1472) and Other agriculture.

Table B3b. Weight 2. No. of farms in control group (0) and support group (1)

	0	1
All	608,670	4,532
Matched	599,989	4,524
Non-matched	11,903	8

Table B4a. Weight 3. CEM matching of control group (target variables; employment, turnover)

	$\mathcal{L}_1$	Mean	Min	25%	50%	75%	Max
Capital	0.552	7.2e+06	8.8e+06	2.4e+06	5.1e+06	9.8e+06	.
Industry[a]	0.248	0.248	0	0	1	0	0
Population density	0.137	3.017	0	2.7	4.66	8.3	0
Multivariate distance: 0.68, no of strata: 138, no of matched strata: 24							

[a]Industries are classified as (SNI in parentheses) Cultivation (1110–1302), Dairy (1410), Breeding (1420–1472) and Other agriculture.

Table B4b. Weight 3. No. of farms in control group (0) and support group (1)

	0	1
All	608,670	4,532
Matched	600,521	4,532
Non-matched	0	0

Table B5a. Weight 4. CEM matching of control group (all target variables)

	$\mathcal{L}_1$	Mean	Min	25%	50%	75%	Max
Area (block)	1.4e−06	1.4e−06	1	0	0	0	0
Capital	0.371	5.7e+06	8.8e+06	1.8e+06	4.1e+06	7.8e+06	.
Industry[a]	0.064	0.064	0	0	0	0	0
Geography (NUTS2)	0.007	0.007	0	0	0	0	0
Multivariate distance: 0.536, no of strata: 150, no of matched strata: 93							

[a]Industries are classified as (SNI in parentheses) Cultivation (1110–1302), Dairy (1410), Breeding (1420–1472) and Other agriculture.

Table B5b. Weight 4. No. of farms in control group (0) and support group (1)

	0	1
All	608,670	4,532
Matched	601,464	4,532
Non-matched	7,206	0

Table B6a. Weight 5. CEM matching of control group (all target variables)

	$\mathcal{L}_1$	Mean	Min	25%	50%	75%	Max
Area (block)	1.5e−06	1.5e−06	1	0	0	0	0
Industry[a]	0.073	0.073	0	0	0	0	0
Geography (NUTS2)	0.007	0.007	0	0	0	0	0
Multivariate distance: 0.08, no of strata: 72, no of matched strata: 71							

[a]Industries are classified as (SNI in parentheses) Cultivation (1110–1302), Dairy (1410), Breeding (1420–1472) and Other agriculture.

Table B6b. Weight 5. No. of farms in control group (0) and support group (1)

	0	1
All	608,670	4,532
Matched	608,512	4,532
Non-matched	158	0