Productivity effects of CAP investment support: Evidence from Sweden using matched panel data

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Abstract

This paper studies the effects of investment support from the common agricultural policy on labour and total factor productivity of agricultural firms in Sweden. Detailed firm-level data on 34 300 firms are used to estimate a matched panel model that relates firm productivity to a series of factors reflecting internal and external characteristics. The recently developed Coarsened Exact Matching method is used to estimate matched control groups and handle selection bias. Findings show a positive and significant treatment effect of investment support on firm productivity, but only for small firms. The analysis also reveals that an increase in the size of the support in relation to firm income has a negative and significant impact on productivity for all firms. Differentiating between various types of investment supports indicates heterogeneous treatment effects. The policy instrument can improve its efficiency if targeted to small firms and investments that have a link to public good provision.

Keywords: Cap; Investment support; Productivity; CEM

1. Introduction

The Common Agricultural Policy (CAP) outlines the framework for agricultural policies implemented across European Union member states. A specific type of policy instrument included in the Swedish Rural Development Programme (RDP), as well as in other member states, is the investment subsidy. This is included in the first thematic axis of the second pillar and is targeted to agricultural firms that realize investments in primary production. The objective is to modernize agricultural holdings, improve the competitiveness of the agricultural sector, and accelerate the pace of adjustment to new market conditions and changes in demand to promote rural development. A substantial share of the Swedish RDP budget for 2007–2013 was allocated to such subsidies, about SEK 2.7 billion to 7 400 firms. The large amount of funding to agricultural firms naturally gives rise to several questions concerning the effects, particularly on the overall goal, which is to improve the competitiveness of the beneficiaries.

The purpose of this paper is to address the effects of investment support dispersed during the RDP period 2007–2013 on firm labour and total factor productivity, which are common indicators of competitiveness in the literature (Latruffe, 2010; Rizov et al., 2013). Policy-oriented questions addressed in this study concern whether there is heterogeneity in the outcome with respect to firm characteristics and the type of investment granted by the support.

The role played by various types of CAP subsidies has received a great deal of attention in the literature, with mixed results (Kumbhakar and Bokusheva, 2009; Sckokai and Moro, 2009; Weber and Key, 2012; Viaggi et al., 2013; Mary, 2013). Studies that use firm-level data and consider CAP subsidies have found that these impacts both negatively and positively on productivity (McCloud and Kumbhakar, 2008, Zhu et al., 2012; Rizov et al., 2013). Considering the strong focus on the transition from coupled to decoupled subsidies, less focus has been devoted to the productivity effects of investment support of the second pillar. Mary (2013) found that investment subsidies had no significant effect on the productivity of French crop farms, while Ratinger et al. (2013) found a positive effect on labour productivity for medium-sized farms in the Czech Republic. Hence, despite the vast number of studies on different CAP subsidies, it is still difficult to draw major conclusions. As discussed in Michalek et al. (2014), a possible explanation is differences in methodological approaches, particularly the methods used to handle selection bias. Like Mary (2013) and Rizov et al. (2013), many studies treat the assignment of support as random. Most types of capital subsidies included in the CAP are not assigned randomly since they have eligibility conditions and selection criteria that can only be met by certain types of firms. In Sweden, firms granted investment support during the RDP period 2007–2013 are shown to be more productive and capital-intensive, implying that an econometric approach that accounts for selection bias is necessary to avoid biased estimates (Rosenbaum and Rubin, 1983). Firms can also receive different levels of subsidies depending on the nature of the investment project and the characteristics and choice of the firm, which may affect the outcome. This reasoning is in line with Michalek et al. (2014), showing that there is strong heterogeneity in the treatment outcome with respect to different levels of capital subsidies.

This study contributes to the literature on the productivity effects of CAP subsidies and builds on prior research. In contrast to prior studies that tend to treat the assignment of support as random, this study applies the recently developed Coarsened Exact Matching method, derived from the exact matching theory, to model selection bias and to estimate the causal effect (Blackwell et al., 2009; Iacus et al., 2009, 2011). Moreover, while prior studies tend to rely on geographically delimited subsamples or subsets of the agricultural sector using data from the European Farm Accounting Data Network (FADN), this study uses detailed firm-level employer–employee-linked data that comprise all active agricultural firms in Sweden for the period 2007–2012.[1] Having access to detailed micro data enables the study to address intra-industry heterogeneity and examine whether differences on the level of subsidization, firm characteristics, and investment type affect the outcome. A fixed-effects panel model with matched control groups is used to relate firm productivity to factors that reflect internal and external characteristics, which

[1] The FADN data comprise around 10 per cent of agricultural firms in Sweden and have missing values for several key variables.

are hypothesized to improve the possibilities for firms to absorb internal and external knowledge. Despite the increased focus on access to external knowledge as a key determinant of firm productivity and sustained economic activities in rural areas (Gruber and Soci, 2010; Artz et al., 2016), this perspective has been mostly left out in prior studies with this focus.

2. Background and theoretical framework

The question whether subsidies to the agricultural sector give rise to improved productivity and the underlying arguments in support of such policy have received growing attention in the literature (McCloud and Kumbhakar, 2008; Sckokai and Moro, 2009; Kline and Moretti, 2014). Arguments in support of such policy often emphasize that the agricultural sector gives rise to positive externalities through its multifunctionality and that there are market failures that validate government interventions to firms in lagging regions (European Commission, 2010). The issue of food security is also highlighted as countries that cannot domestically produce enough to meet the demand might be vulnerable to trade pressure (Candel et al., 2014). These types of arguments form the basis of the CAP, but different support payments also have their specific targets and objectives.

Support to investment and modernization of agricultural holdings is a capital subsidy that aims to encourage agricultural firms to undertake more gross investment in plant, machinery, and new production equipment on the assumption that this results in increased productivity and output. This can be realized in the form of net investment, which can bring additional productive capacity to the firm, and in the form of replacement investment, which can modernize the firm's stock of production equipment (Harris and Trainor, 2005). Hence, the subsidy can give rise to investment-induced productivity gains because of improved access to capital and possibilities to adopt new production equipment (Serra et al., 2008). The investment subsidy may thus stimulate technological development and market adjustment as it can lower the investment cost and assist firms to better use economies of scale (Blancard et al., 2006). The effect on labour is ambiguous as subsidies can be used to increase the labour stock but may also result in lower labour demand if the subsidy increases labour productivity (McCloud and Kumbhakar, 2008).

The main argument is that an investment subsidy can form an incentive for firms to invest while the support is in effect. The q-theory of capital investment provides a framework for modelling the investment behaviour of firms and can be used to investigate this argument. This framework assumes that there are capital installation costs associated with investment in capital goods that are strictly convex, e.g., costs related to installation and reorganization in addition to the direct cost of buying the capital goods.[2] For simplicity's sake, the subsidy can be assumed temporary and take the form of a direct rebate to the firm of fraction θ of the price of capital and apply to the price but not to the adjustment costs. In the presence of a subsidy of this form and under the assumption that the purchase price of capital is fixed at 1, the firm invests as long as the value of the capital plus the subsidy exceeds the capital costs. This condition can be written as:[3]

$$q(t) + \theta(t) = 1 + C(I(t)) \tag{1}$$

where $\theta(t)$ denotes the subsidy at time *t*, $q(t)$ denotes the value to the firm of an additional unit of capital at time *t*, e.g., the market value of a unit of capital (Tobin's q (Tobin, 1969), and $C(I(t))$ shows the cost of firms' investment I at time *t*. The theory predicts that a capital subsidy will cause an increase in investment when it is in place, but when it expires, investment will return to the old equilibrium steady state. It also predicts that a temporary investment subsidy will cause a larger effect on investment, compared with a permanent, as firms adjust their intertemporal investment plans to take advantage of the subsidy (Abel, 1983). Sckokai and Moro (2009) address firms' investment behaviour in the context of the CAP and show that among the effects of CAP payments on farmers' decisions, the impact on farm investment is the most relevant.

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[2] Firms face costs of adjusting their capital stocks and the adjustment costs, $C(\dot{\kappa})$, satisfy $C(0) = 0$, $C'(0) = 0$, and $C''(\cdot) > 0$.

[3] Equation 1 shows the first-order condition for current investment obtained from the maximization of the current-value Hamiltonian (Romer, 2006, p. 413).

Given that firms adjust their investment behaviour in the presence of a subsidy, a policy-oriented question that arises is whether the subsidy leads to improvements in productivity. Specifically, following the view that it is the “residual” (total factor productivity, TFP) that drives long-run growth (Solow, 1956), a relevant approach is to examine if investment subsidies affect this measure of firm productivity (Easterly and Levine, 2001). Increases in TFP reflect a rise in productivity that is not attributable to any of the production inputs of labour and capital but to improvements in the combination of inputs used in production, e.g., to technological development or improvement (Romer, 1990). Therefore, an investment-induced subsidy should result in a positive effect on firm TFP, given that the investment spurs technological development. Sauer and Latacz-Lohmann (2015) investigate the link between subsidy-induced investments and TFP using panel data of German dairy farms (1996 to 2010). They find that investments in new technology increase TFP of dairy production by shifting out the production frontier.

The literature on the productivity effects of subsidies highlight that capital subsidies may also lead to a negative effect on productivity because of allocative inefficiencies. Baumol (1996) addresses this and argues that a negative productivity effect may result if subsidies make firms adjust their behaviour and realize investments that grant subsidies in favour of more productive investments. This follows the view of Tullock (1980), emphasizing that rent-seeking behaviour may induce firms to re-allocate productive resources to the process of seeking support, which may result in a negative effect on productivity. Similar arguments are put forward by Bergström (2000), in that subsidies may result in a lack or slack of effort to seek cost-improving methods, which may negatively affect firm productivity. The rationale is that the motivation to work efficiently and increase productivity falls as the firm increases its dependence on subsidies as a source of income.

Zhu et al. (2012) focus on dairy farms in Germany, the Netherlands, and Sweden and find a significant negative marginal effect of the share of total subsidies in total farm income. They find that an increase of one percentage point in the share of total subsidies in total farm income leads to a 0.89 decrease in technical efficiency among

Swedish dairy farms. The studies by Brummer and Loy (2000) on dairy farmers in northern Germany and Zhu et al. (2010) on German, Dutch, and Swedish crop farms lend support to a negative or insignificant impact of subsidies on technical efficiency and/or productivity. However, most of the studies have focused on subsidies that are part of the first pillar, particularly the effects of the transition from coupled production subsidies to decoupled payments (Sckokai and Moro, 2009; Rizov et al., 2013). Moreover, as noted in Mary (2013), studies also tend to consider the total amount of subsidies received by firms, with the limitation that they are unable to disentangle the effects of specific policy instruments. As mentioned, the specific targets and objectives vary across different types of CAP support payments, which makes them difficult to evaluate in aggregate.

Another policy-oriented question that arises with instruments that aim at modernization and increasing the competitiveness of agricultural firms that has received little attention is whether the impacts are similar across different types of investments. Investment support can be granted to physical assets (e.g., production equipment such as tractors, milk robots, barns, cowsheds), and to investments that aim to stimulate the production of renewable energy (e.g., biogas, renewable and low-energy equipment). This study contributes to the literature by addressing the question whether these different investments have the same impact on productivity, or whether there are heterogeneous treatment effects within the measure. The authors are unaware of any prior attempt to disentangle whether the effects differ depending on the type of investment granted by the support. Although there are several studies showing a positive relationship between firm performance and involvement in environmental activities (Porter and van der Linde,1995; Reinhardt, 1999), these results do not indicate the direction of causality. Masini and Manichetti (2012) argue that there is a need to explore this association, as there is a wide acceptance of the positive correlation between environmental and firm performance but little evidence concerning the strength or direction of the relationship.

3. Model and methods

To assess the productivity effects of investment support, this study uses TFP and labour productivity as the dependent variables.[4] TFP is estimated using the Levinsohn and Petrin (2003) two-stage approach with intermediate inputs and the following Cobb-Douglas-type production function:

$$y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \beta_m m_t + \omega_t + \eta_t \tag{2}$$

where y_t denotes value added as a proxy for the firm's output at time t, l_t denotes labour input, m_t denotes the intermediate input (materials), and k_t denotes the state variable capital. The error term consists of two components, the productivity transmitted from external shocks assumed to influence firms' input choices ω_t, and η_t, which is assumed uncorrelated with firms' input choices. The main advantage of using this approach is that it accounts for the simultaneity bias that may arise if production inputs are not chosen independently by the firm, e.g., if there are correlations between the level of inputs and unobserved productivity shocks (Marschak and Andrews, 1944). Further, using intermediated inputs to control for external productivity shocks, compared with investments as in Olley and Pakes (1996) and Mary (2013), is motivated by the argument that these should be more responsive to external shocks (Levinsohn and Petrin, 2003). Hence, TFP is estimated in the following:

$$TFP_t = \widehat{\eta_t + \varepsilon_t} = y_t - \hat{\beta}_l l_t - \hat{\beta}_k k_t - E\left[\widehat{\omega_t | \omega_{t-1}}\right] \tag{3}$$

where the estimated $\hat{\beta}_l$, $\hat{\beta}_k$, and $E\left[\widehat{\omega_t | \omega_{t-1}}\right]$ are obtained from a two-stage estimation procedure. Demand for intermediate input m_t is assumed dependent on the firm's state variables $m_t = (k_t, \omega_t)$. Making assumptions about the firm's production technology, Levinsohn and Petrin (2003), show that the demand function is increasing in ω_t so it can be written as: $\omega_t = \omega_t(k_t, m_t)$.

[4] See Latruffe (2010) for a detailed discussion on different indicators of competitiveness in connection with the CAP and its overall objectives.

Having defined the outcome variables, the measure of interest in this study is the counterfactual mean difference in the outcome variables (the average treatment effect on treated (ATT)), which can be defined in the following:

$$ATT = E(Y_1 - Y_0|X, T = 1) = E(Y_1|X, C = 1) - E(Y_0|X, C = 1) \qquad (4)$$

where $E(\cdot)$ denotes the expectation operator, X is a vector of relevant control variables, and $T = 1$ indicates that a firm received treatment. Further, Y_1 denotes the outcome for a firm in case it did receive treatment, and Y_0 denotes the outcome for the same firm in case it did not receive treatment. The problems using observational non-randomized data is that the counterfactual outcome $E(Y_{1i} - Y_{0i})$ cannot be directly observed and that simple mean value comparisons between the treated and untreated firms could result in biased estimates (Rosenbaum and Rubin, 1983).

The empirical approach to estimate the ATT is to use fixed-effects panel estimations on the outcome variables. One advantage of the fixed-effects panel model is that it can account for time-invariant heterogeneity, e.g., that better skilled farmers are more likely to seek the possibility to take advantage of investment opportunities. Hence, should there be any selection bias resulting from time-invariant individual factors, a fixed-effects panel model should address this (Mundlak, 1978). However, there are additional confounding factors that make evaluation difficult. One issue concerns the assignment of agricultural programmes, which may not be random but directed at larger and more profitable firms. As discussed in the introduction, there are reasons to be concerned about such effects in the evaluation of Pillar 2 investment support since these are coupled with selection criteria and eligibility conditions that can only be met by certain types of firms. Table B1 in Appendix B displays summary statistics for the support- and non-support-receiving firms indicating that support-receiving firms are larger and more capital-intensive. Should these programme placement effects not be accounted for, estimates will be biased (Robins et al., 2000).

The empirical approach to handle the non-random assignment of support is to estimate a control group that has distributional characteristics as similar as possible to the treatment group. This approach follows Pufahl and Weiss (2009) and Michalek et al. (2014), with the difference that this study uses the CEM method rather than propensity score matching (PSM). The main justification for CEM is that it allows the balance between the treatment and the control group to be chosen ex-ante rather than being revealed through an iterative process of ex-post balance checking (Iacus et al., 2009, 2011).[5] The CEM guarantees that adjusting the imbalance on one variable has no effect on the balance of other covariates, and since the matching is done before the regression analysis, it reduces the degree of model dependence (Ho et al., 2007). Hence, the treated firms are matched using CEM and variables that reflect heterogeneity in terms of size and performance, e.g., number of employees, capital stock, location, and industry belonging (three-digit SIC codes). The matching procedure generates weights that are used in the subsequent weighted fixed-effects panel regressions.[6] Since there will naturally remain an imbalance even after the matching, as it is impossible to obtain an exact match on all covariates, including the covariates in the subsequent regression analysis can reduce the remaining heterogeneity between the groups (Iacus et al., 2011). The estimated fixed-effects panel models can be written as

$$y_{it} = \beta_0 + \beta_1' I_{it} + \beta_2' E_{it} + \zeta T_i + \tau_t + \upsilon_i + \varepsilon_{it} \quad (5)$$

$$y_{it} = \beta_0 + \beta_1' I_{it} + \beta_2' E_{it} + \zeta T_i + \rho \Gamma_i + \tau_t + \upsilon_i + \varepsilon_{it} \quad (6)$$

where y_{it} denotes the dependent variable (labour or total factor productivity) of firm *i* at time *t*, internal firm-specific covariates are included in the vector I_{it}, and E_{it} is a vector of relevant external controls. T_i is a dichotomous variable indicating whether the firm has received investment support and ζ is the coefficient that indicates the effect of the investment support on productivity. Further, τ_t and υ_i are time-specific and firm-specific fixed effects and ε_{it} is an idiosyncratic error term. To assess whether the size of the support influences the outcome, this study follows

[5] See Iacus et al. (2009, 2011) for a formal description and details on its implementation in Stata.
[6] Iacus et al. (2011) show that using the pre-estimated weights in a subsequent weighted regression model is equivalent to a difference-in-difference and yields an unbiassed estimate of the ATT.

the approach in Zhu et al. (2012) and uses the share rather than the actual level of subsidies in the estimated model (Equation 6). The reason behind this is that the size of the investment project increases with the size of the firm, which gives rise to multicollinearity. Following their approach, the share of subsidies in total income is included in Γ_i and ρ is the estimated coefficient. As noted in Zhu et al. (2012), using the share of subsidies in total income implies that it is the share of subsidy in total income that provides the incentive for firms to become productive. To test whether the results hold across investment types, the binary treatment variable is also re-specified into T_{i1}, indicating support to physical assets, and T_{i2}, indicating support to renewable energy, where Γ_{i1} and Γ_{i2} denote the size of the supports, respectively.[7]

4. Data and variables

Firm-level data are obtained from Statistics Sweden and contain detailed information about the characteristics of firms and their employees in Sweden. These data are matched with data from the Swedish Board of Agriculture that contain information about firms that have received subsidies from the Swedish RDP 2007–2012, type of support, and the amount of funding received. A total of 6 667 firms were granted investment support during the program period, of which it is possible to link 4 601 to firm-level data by identity numbers. Of the total number of granted firms linked to firm-level data, 1 103 firms were granted support for realizing investment in renewable energy, and 3 248 and 250 firms were granted support for investments in physical assets and improved animal welfare and working conditions, respectively. Since 2012 is the latest year for which firm-level data are available from Statistics Sweden, it is not possible to include the firms that were granted support during the last year of the programme. However, most of the supports were distributed before 2012 and the sample includes almost 70 per cent of the total number of support-receiving firms. Data allow for identification of industry belonging at the five-digit level using Standard Industrial Classification

[7] The third category (support to animal welfare and improved working conditions) is omitted as there are too few supports granted to obtain reliable estimates.

codes (SIC), and only firms in the agricultural, forestry, and food sectors are included in the panel. This results in an unbalanced panel with 224 100 observations for the period 2007–2012. Table 1 shows a breakdown of treated firms matched to firm-level data by SIC.

Table 1. Breakdown of granted firms 2007–2012 by SIC

Breakdown by 2-digit SIC	Number of granted firms
Agriculture (11–17)	4 377
Forestry (21–24)	196
Food (10)	28
Total number of treated firms	4 601
Breakdown of agricultural firms (11–17) by 5-digit SIC	
Dairy (1 410)	1 635
Crop (1 110–1 302)	632
Miscellaneous (1 491–1 700)	2 110

4.1 Firm-specific variables

To control for the potential productivity gains linked to firm-specific characteristics, seven variables are included. Firm size is measured using the number of employees and capital is measured using the book value of material assets. Two dummy variables are included to control for export firms and for size effects (multiple establishments). Firms that export are predicted to have a higher productivity because of knowledge flows from international buyers and competitors (Bernard and Jensen, 2004), while the influence of firm size on productivity is ambiguous. A negative association may reflect that small firms have better managerial efficiency, generally exhibit a higher profit rate, and are more motivated to undertake actions that make them more productive compared with large firms (Acs and Audretsch, 1990). Large firms, on the other hand, face less uncertainty and are less capital-constrained, which may imply a positive association between firm size and productivity (Williamson, 1967).

Knowledge characteristics of the employees play an important role in determining a firm's productivity as they indicate managerial and innovative capacity. The average age and educational attainment of employees are therefore included. Education is measured as the share of employees at each firm with three or more years of university education and is hypothesized to be positively associated with productivity, as better educated employees can be expected to have more skills to run their firm efficiently (Furtan and Sauer, 2008). The association between age and productivity is ambiguous in that a positive association may indicate that older farmers are more experienced and can use inputs more efficiently, whereas a negative association may reflect that older farmers are more reluctant to adopt new technology (Brummer and Loy, 2000).

4.2 External controls

Besides firm-specific factors, there are several external characteristics that influence the productivity of agricultural firms, including their access to external knowledge. Knowledge spillovers can be industry-specific and provide similar firms that are geographically clustered the opportunity to share common resources and exploit external advantages related to more knowledge in similar production activities (Marshall, 1920). Firms may also benefit from co-locating with firms from a diverse set of industries as it provides them access to a broader knowledge base, which allows them to combine knowledge from different activities and come up with more radical innovations (Jacobs, 1969). Agricultural firms located in areas with a more diversified industrial structure may also have a greater potential to develop economies of scope in production, which makes them more flexible to adapt to changing market conditions (Hansson et al., 2013; Barnes et al., 2015).

To control for the potential productivity gains linked to external economies of scale, three variables are included. The first is a location quotient used to measure industrial specialization (Feldman and Audretsch, 1999). The measure is calculated to reflect regional (municipal) specialization relative to the nation and is calculated with respect to the number of workers in the agricultural sector in the following:

$$LQ_{a,r} = \frac{e_{a,r}/e_r}{e_a/e} \quad (7)$$

where e_a denotes the number of employees in the agricultural sector a in municipality r, e_r denotes the total number of employees in the municipality (regardless of industry), and e_a is the share of agricultural employees out of the total number of employees in the nation. If the quotient is larger than one, the municipality has a larger share of agricultural employees relative to the national average, indicating agricultural specialization. The second is a measure of industrial diversity, calculated using the entropy approach (Jacquemin and Berry, 1979) and with respect to the number of employees in different SIC categories in the following:

$$D_r = -\sum_{I=1}^{S} \left(\frac{e_{I,r}}{e_r}\right) ln \left(\frac{e_{I,r}}{e_r}\right) \quad (8)$$

where D_r denotes industrial diversity in municipality *r*, and $e_{I,r}$ denotes number of employees in two-digit industry *I* and municipality *r*, and e_r is the total number of employees in the agricultural sector in the municipality. The diversity measure ranges from zero diversity to maximum diversity (*ln*(*n*)), where *n* is the total number of two-digit industries in the agricultural sector in the municipality. The third measure is population density (population per square kilometre) to control for pure size effects, e.g., the density of economic activity irrespective of its industry composition (Ciccone, 2000). Lastly, the share of total land in the municipality that consists of agricultural land is included to control for natural prerequisites. Table 2 presents definitions of all variables included in the estimations; Table A1 in Appendix A provides summary statistics for the whole sample and Table B1 in Appendix B presents summary statistics for the support-receiving and the non-support-receiving firms. To account for selection bias in the fact that the treated and the non-treated firms are not identical before treatment, the CEM method is used to estimate a control group using a set of pre-treatment covariates. Results of the matching are presented in Table C1 in Appendix C showing the univariate imbalance between the two groups after matching, which is set to satisfy Equation 6. Three different matching algorithms are used to assess robustness.

Table 2. Variable definitions

Variable	Definition
TFP	Dependent variable, estimated according to Equation 3.
Labour productivity	Dependent variable, defined as value added per employee.
Internal characteristics	
Capital	Value of material assets.
Labour	Number of full-time-equivalent employees.
Age	Average age of the employees.
Education	Share of employees with three or more years of university education.
Female	Percentage of female employees.
Exports	Dummy=1 if the firm is exporting.
Multi-firm	Dummy=1 if the firm has more than one establishment.
Investment support T_i	Dummy=1 if the firm has received investment support.
Investment support Γ_i	Amount of investment support divided by firm turnover.
Investment support T_{i1}	Dummy=1 if the firm has received support for investment in physical assets.
Investment support Γ_{i1}	Amount of investment support to physical assets divided by firm turnover.
Investment support T_{i2}	Dummy=1 if the firm has received support for investment in renewable energy.
Investment support Γ_{i2}	Amount of investment support to renewable energy divided by firm turnover.
External characteristics	
Population density	Population per square kilometre in municipality.
Industrial diversity	Distribution of employees across industries defined in Equation 8.
Specialization	Municipal share of employees in agriculture relative to the national share defined in Equation 7.
Land	Share of agricultural land (meadows and pasture) of total land area in municipality.

Data sources: Statistics Sweden and the Swedish Board of Agriculture

5. Estimation results

Results are presented in Tables 3–5 and all estimations have either TFP or labour productivity as the dependent variable. Before turning to the interpretation of the results, there are some issues that complicate the evaluation of most types of subsidies. There is a possibility that firms have received multiple support from different sources, which may affect the outcome. Some agricultural firms that received investment support during the RDP period 2007–2013 have also received other types of funding in the framework of the RDP. Disentangling the effect of one support becomes difficult because of the spillover effects that may occur. Summary statistics show that two per cent of the firms granted investment support were also granted support from other RDP subsidies (e.g., for vocational training and information actions or for adding value to agricultural products, measures 111 and 124). Only one per cent of the firms were granted additional support from Axis 3 (e.g., for undertaking agricultural diversification, measures 311–313). To exclude unwanted spillover effects, the firms that were granted multiple support (n=138) were excluded from the analysis.

Results using TFP and value added per employee as dependent variables are reported in Table 3 in four model specifications. The first specification is included mainly for comparison and reports the results from estimating a naive fixed effects model that excludes the pre-estimated CEM weights and only considers the binary treatment effect as indicated by T_i. These results are followed by three estimations using the DiD model in Equations 8 and 9. Results from estimations based on simple mean value comparison show a significant and positive correlation between firm TFP and investment subsidies. Results are robust using labour productivity as the dependent. Results from estimating Equation 8, using the binary treatment effect and including the CEM weights on TFP show comparable results, though the coefficient is indicated to be biased upwards when the matching weights are excluded. Although the results do not differ markedly with regard to the sign, the coefficient reported in the first column can only be a correlation, whereas the coefficient in column two reflects a causal effect, which is more reliable for policy impact analysis. So far, results indicate a positive mean difference (ATT) between the treated and untreated firms, e.g., that granted firms have a higher level of total factor and labour productivity compared with the untreated. This may be reflective of investment-induced productivity effects because of improved access to credit as argued in Blancard et al. (2006) and Serra et al. (2008), meaning that the support has enabled firms to modernize their holdings and realize investments in new production techniques, which in turn has improved their productivity.

Estimating the model with the variable that indicates the size of the support in relation to firm income (Equation 6) gives a different image of the productivity effects associated with investment support. Results are reported in specifications 3 and 4 in Table 3. The coefficient reflecting the binary treatment effect is significant and positive in both estimations, while the coefficient reflecting the size of the support in relation to firm income is significant and negative. These results are interesting as they indicate that firms in the treatment group have a higher level of productivity compared with the control group, however, as they increase their dependence on investment support as a source of income, the effect on productivity is negative.

These results are consistent with theory (Bergström, 2000) and the findings in Zhu et al. (2012), in that increased dependence on subsidies may lower the motivation and give rise to a lack of effort, which results in a negative effect on firm productivity. These results may also be reflective of rent-seeking behaviour in that firms may choose to re-allocate productive resources to the process of seeking subsidies as argued in Holmström (1999). An alternative approach to capture level effects of investment subsidies would be to estimate the binary treatment effect as in Equation 8 and compare the outcome between small, medium, and large firms as in Ratinger et al. (2013). Considering that almost 80 per cent of agricultural firms in Sweden have fewer than five employees, it is impossible to find enough matched control firms for medium-sized or large firms, implying that such an approach may give rise to biased estimates.

Table 3. The effects of investment support on firm productivity

	1. FE (TFP)	2. FE-CEM (TFP)	3. FE-CEM (TFP)	4. FE-CEM (VA/empl.)
Variable	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)
Labour (ln)	-	-	-	-0.653*** (0.010)
Capital (ln)	-	-	-	0.232*** (0.036)
Age (ln)	0.078*** (0.028)	-0.013 (0.036)	-0.017 (0.037)	-0.018 (0.034)
Education	0.091*** (0.025)	0.092*** (0.026)	0.168*** (0.026)	0.041*** (0.010)
Female	-0.116*** (0.021)	-0.104*** (0.021)	-0.104*** (0.021)	-0.059*** (0.010)
Exports	0.044** (0.019)	0.047** (0.021)	0.047** (0.021)	0.031*** (0.010)
Multi-firm	-0.542*** (0.008)	-0.531*** (0.008)	-0.532*** (0.008)	-
Investment support T_i	0.136*** (0.012)	0.108*** (0.016)	0.121*** (0.016)	0.116*** (0.040)
Investment support Γ_i	-	-	-0.379*** (0.054)	-0.309*** (0.041)
Population density (ln)	0.004 (0.014)	-0.002 (0.014)	-0.002 (0.014)	-0.001 (0.016)
Industrial diversity (ln)	0.181*** (0.067)	0.253*** (0.066)	0.252*** (0.066)	0.284*** (0.054)
Specialization (ln)	-0.045 (0.026)	-0.013 (0.027)	-0.015 (0.027)	-0.016 (0.024)
Land (ln)	0.019 (0.106)	0.073 (0.101)	0.073 (0.102)	0.062 (0.110)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R square between	0.170	0.255	0.322	0.301
Matching algorithm[a]	-	1	2	1
Observations	223 962	208 596	208 595	222 044

***, ** indicate significance at the one and five per cent levels, respectively. The estimated models are weighted fixed-effects models with weights (defined in Equation 7) constant within the panel. The Hausman test statistic is not significant at the five per cent level when the models are estimated as weighted fixed-effects models using the pre-estimated CEM weights. Table C in Appendix C display the details for the CEM match

5.1 Heterogeneous treatment effects

To further disentangle the productivity effects of investment support, the sample is split with respect to firm size and type of agricultural firm (by SIC). These results are displayed in Table 4 in four model specifications including small firms (1 employee), larger firms (more than 1 employee), dairy firms (SIC 1410) and crop firms (SIC 1110–1302). Results show that there is intra-industry heterogeneity regarding several variables. Starting with the investment subsidy, which is the focus of the present study, results show a consistent and positive binary treatment effect for all subcategories except for the subsample that contains larger firms. These results are interesting as they indicate that the significant and positive average treatment effect on treated firms holds only for the smallest agricultural firms, i.e., larger support-receiving firms are not more productive than their non-support-receiving counterparts because of the subsidy. However, the coefficient reflecting the increase in support in relation to firm income is still negative and significant across the estimations. These estimates are in line with the results in Ratinger et al. (2013), showing that Pillar 2 investment subsidies had a positive and significant effect on firm productivity only for the small and medium-sized firms.

These results can also be related to the estimates in Zhu et al. (2012), who found a significant negative marginal effect of the share of total subsidies in total farm income for Swedish dairy firms. Specifically, they found that an increase of one percentage point in the share of total subsidies in total farm income led to a 0.89 decrease in technical efficiency. However, given that they assume random assignment of support and do not control for external scale economies, their estimates may be biased. A concern is that eligibility conditions vary across Sweden, such that agricultural firms located in the northern parts are eligible up to 50 per cent of the total investment, whereas firms in other areas may only apply for support up to 30 per cent. To test whether this affects the results, the models are estimated including locational controls (LFA dummy); the results are the same.

Table 4. The effects of investment support on TFP (FE-CEM)

	5. 1 employee	6. > 1 employee	7. Dairy firms	8. Crop firms
Variable	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)
Age (ln)	-0.129** (0.058)	-0.014 (0.037)	0.086** (0.040)	0.013 (0.102)
Education	0.048 (0.053)	0.156*** (0.031)	0.044 (0.068)	0.073 (0.050)
Female	-0.007 (0.048)	-0.251*** (0.023)	-0.174*** (0.042)	-0.092 (0.046)
Exports	-0.072** (0.031)	0.013 (0.021)	0.016 (0.067)	0.062 (0.041)
Multi-firm	-	-	-0.590*** (0.017)	0.585*** (0.018)
Investment support T_i	0.136*** (0.026)	0.017 (0.017)	0.157** (0.025)	0.106** (0.040)
Investment support Γ_i	-0.354*** (0.069)	-0.347*** (0.082)	-0.273*** (0.204)	-0.430** (0.200)
Population density (ln)	-0.010 (0.018)	-0.033 (0.024)	0.065 (0.049)	-0.053 (0.040)
Industrial diversity (ln)	0.283*** (0.083)	0.139 (0.093)	-0.032 (0.225)	0.220 (0.040)
Specialization (ln)	-0.013 (0.033)	0.034** (0.019)	0.054 (0.077)	-0.047 (0.056)
Land (ln)	0.067 (0.127)	0.080 (0.159)	-0.776** (0.369)	0.381 (0.214)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Matching algorithm[a]	1	1	1	1
R square between	0.205	0.200	0.236	0.200
Observations	164096	46 536	25 000	54 509

***, ** indicate significance at the one and five per cent levels, respectively. All model specifications were estimated using value added per employee as the dependent variable and results are comparable. The estimated models are weighted fixed-effects models with weights (defined in Equation 7) constant within the panel. The Hausman test statistic is not significant at the five per cent level when the model is estimated as a weighted fixed-effects model using the pre-estimated CEM weights.

To test whether the results hold across investment types, the binary treatment variable is re-specified into T_{i1}, indicating support to physical assets, and T_{i2}, indicating support to renewable energy, where Γ_{i1} and Γ_{i2} denote the size of the supports, respectively. Results are displayed in Table 5 and show that both investment types give rise to a significant and positive mean difference (ATT). However, the coefficient reflecting the size of the support is not significant when the binary treatment effect is reflective of renewable energy investments. These results are interesting as they indicate heterogeneity, not only regarding the size of the support and the firm, but also regarding investment type. It seems that the negative effect of increased support in relation to income only applies to investment in physical assets and not to investments in renewable energy. Turning to the control variables, most of the internal and external characteristics have their anticipated signs when estimating average effects. The coefficients labour and multi-firm, as indicators of firm size, are both significant and negative reflecting that smaller firms are more productive, which may be due to better managerial and organizational efficiency (Acs and Audretsch, 1990). The coefficient reflecting capital is significant and positive, indicating that improved access to material assets has a positive effect on productivity. Exports and education both give rise to improved productivity, which may reflect the positive role played by learning-by-exporting (Bernard and Jensen, 2004) and imply that better educated employees can run their firm more efficiently (Furtan and Sauer, 2008).

Estimating the model across firm sizes and agricultural sub-sectors shows significant intra-industry heterogeneity in most of the internal and external controls (Table 4). An interesting finding is the role played by external factors. The coefficient of industrial diversity is significantly positive and large for small firms, whereas the coefficient of industrial specialization is significant and positive only for larger firms. These results may reflect that small agricultural firms benefit from geographic proximity to a diverse set of non-agricultural activities as it provides them access to non-agricultural markets and a greater potential to develop economies of scope in agricultural production. This seems plausible as smaller firms can be assumed more vulnerable to changing market conditions but may also be anticipated to have a higher motivation to undertake actions that make them more productive compared with large firms (Acs and Audretsch, 1990). Such actions may include diversification into non-agricultural markets to spread or avoid risk (Hansson et al., 2013; Barnes et al., 2015). Larger firms, on the other hand, tend to run more specialized agricultural units and it seems plausible that they benefit from co-locating with similar firms as it provides them the opportunity to exploit knowledge spillovers in similar production activities.

Table 5. Results; heterogeneous treatment effects (FE-CEM)

	9. TFP	10. TFP	11. VA/empl.
Variable	Coef. (Std. Err.)	Coef. (Std. Err.)	Coef. (Std. Err.)
Labour (ln)	-	-	-0.577*** (0.015)
Capital (ln)	-	-	0.178*** (0.003)
Age (ln)	-0.063 (0.035)	-0.064 (0.036)	-0.093** (0.035)
Education	0.092*** (0.026)	0.097*** (0.026)	0.059** (0.026)
Female	-0.103** (0.021)	-0.101*** (0.022)	-0.034 (0.022)
Exports	0.048** (0.021)	0.048** (0.021)	0.047** (0.021)
Multi-firm	0.531*** (0.008)	-0.532*** (0.007)	-0.065*** (0.014)
Investment support T_{i1} (physical assets)	0.130*** (0.026)	-	-
Investment support Γ_{i1} (physical assets)	-0.156*** (0.049)	-	-
Investment support T_{i2} (renewable energy)	-	0.132*** (0.032)	0.150*** (0.032)
Investment support Γ_{i2} (renewable energy)	-	-0.326 (0.296)	-0.345 (0.293)
Population density (ln)	0.002 (0.015)	-0.001 (0.015)	-0.002 (0.015)
Industrial diversity (ln)	0.255*** (0.066)	0.256*** (0.066)	0.267*** (0.066)
Specialization (ln)	-0.015 (0.027)	-0.012 (0.027)	-0.012 (0.027)
Land (ln)	0.072 (0.100)	0.067 (0.103)	0.070 (0.104)
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes
Matching algorithm[a]	1	1	1
R square between	0.209	0.206	0.198
Observations	210 601	210 651	210 643

***, ** indicate significance at the one and five per cent levels, respectively. The estimated models are weighted fixed-effects models with weights (defined in Equation 7) constant within the panel. The Hausman test statistic is not significant at the five per cent level when the model is estimated as a weighted fixed-effects model using the pre-estimated CEM weights.

5.2 Robustness tests

Several robustness tests are performed to validate the results. One issue concerning the negative effect on productivity is that there are time lags in the effects, e.g., that firms may be unproductive at the time when they are granted support and subsequently increase their productivity because of the subsidy. To test this, the weighted fixed-effects models are estimated using lagged variables as in Gustafsson et al. (2016). If the size of the subsidy induces firms to become more productive in the subsequent period and if there are time lags, the coefficients of the lagged variables should be positive. Results show no evidence of this. Furthermore, due to data limitations, this study can only address other supports dispersed through Pillar 2 influence the results. To test if the presence of other supports influences the results, the models were also estimated including the share of other Pillar 2 payments in total income dispersed to each firm (as in Michalek et al., 2014); the coefficient is insignificant and the results are robust.

6. Conclusions

The purpose of this paper is to assess the effects of CAP Pillar 2 support on the total factor productivity and labour productivity of Swedish agricultural firms. The focus is on investment subsidies, dispersed during the RDP period 2007–2013, a specific type of support that has received limited attention in the literature (Ratinger et al., 2013; Mary, 2013). The overall goal is to clarify whether the effects differ across agricultural subsectors, firm sizes, and investment types. To reach this goal, detailed firm-level employer–employee-matched data that comprise all active agricultural firms in Sweden for the period 2007–2012 are used to estimate a matched panel model. A concern is the lack of random assignment in that investment support is targeted to more capital-intensive and more productive firms. To account for the selection bias attached to the assignment of support, the recently developed Coarsened Exact Matching (CEM) method is used to estimate control groups that have as similar as possible distributional characteristics of pre-treatment covariates as the granted firms (Iacus et al., 2011).

Findings indicate that investment support has two effects. The first is the mean difference in productivity, i.e., the average treatment effect on treated, which is positive and significant, but only for small firms. This indicates that small agricultural firms that are granted support have a higher level of total factor and labour productivity than the control group. The second effect is tied to the increase in payments in relation to firm income, which is found to be negative and significant for all firms. These results are consistent with theory and previous findings emphasizing that the productivity effects of capital subsidies may vary from a positive to a negative effect and decrease as the size of the support in relation to firm income increases (Bergström, 2000; Blancard et al., 2006). These results are robust across agricultural subsectors. Assessing heterogeneous treatment effects shows several novel findings. Differentiating between support to physical assets and support to renewable energy shows that while both supports give rise to a significant and positive mean difference effect in productivity, the relative size of the support is only negative and significant for investments in physical assets. These results indicate that there are significant inefficiencies attached to higher levels of investment in physical assets. Since there is only a weak link to externalities and public goods provision for these investments, this policy instrument may lack any clear market failure rationale if granted to large firms and to investments in physical assets. Hence, the instrument can improve its efficiency if targeted to small firms that have the potential to become productive but lack sufficient credit to realize investments. Results also add a behavioural dimension in that renewable energy technologies are sometimes perceived as unproven technologies with greater technological uncertainty; firms may thus be more reluctant to make such investments in the absence of support (Masini and Menichetti, 2012).

The approach of this paper is useful from both a methodological and a policy viewpoint because it applies a new matching technique that improves the balance between treated and untreated firms (Iacus et al., 2011) and because it provides new evidence on the heterogeneous productivity effects associated with investment support directed to agricultural firms. A better understanding of the impacts could help in refining current agricultural policy instruments for improving the efficiency of the current Swedish RDP. Moreover, by extending the empirical analysis to include a broad set of internal and external factors and firms across different sub-sectors, this study will contribute to extending the validity of previous findings to a more general context. Given that one of the main results of the paper is that the marginal effect of the investment subsidy is negative, further analyses of the size of the support appears to be a fruitful way forward using continuous treatment analysis.

References

Abel, A. B. (1983). Optimal investment under uncertainty. Am Econ Rev. *73*(1), 228-233.

Acs, Z.J., Audretsch, D.B. (1990). The determinants of small-firm growth in US manufacturing. Appl. Econ. 22(2), 143-153.

Artz, G.M., Kim, Y., Orazem, P.F. (2016). Does agglomeration matter everywhere? New firm location decisions in rural and urban markets. J. Reg. Sci. 56(1), 72–95.

Barnes, A.P., Hansson, H., Manevska-Tasevska, G., Shrestha, S.S., Thomson, S.G. (2015). The influence of diversification on long-term viability of the agricultural sector. Land Use Policy 49, 404-412.

Baumol, W.J. (1996), Entrepreneurship: Productive, unproductive and destructive. J. Bus. Venturing 11(1), 3-22.

Bergström, F. (2000). Capital subsidies and the performance of firms. Small Bus. Econ. 14(3), 183-193.

Bernard, A.B., Jensen, J.B. (2004). Why some firms export. Rev. Econ. Stat. 86(2), 561-569.

Blackwell, M., Iacus, S., King, G., Porro, G. (2009). cem: Coarsened exact matching in Stata. Stata J. 9(4), 524–546.

Blancard, S., Boussemart, J.-P., Briec, W., Kerstens, K. (2006). Short and long-run credit constraints in French agriculture: A directional distance function framework using expenditure-constrained profit functions. Am. J. Agric. Econ. 88(2), 351-364.

Brummer, B., Loy, J.-P. (2000). The technical efficiency impact of farm credit programmes: A case study of Northern Germany. J. Agric. Econ. 51(3), 405-418.

Candel, J.J.L., Breeman, G.E., Stiller, S.J., Termeer, C.J.A.M. (2014). Disentangling the consensus frame of food security: The case of the EU Common Agricultural Policy reform debate. Food Policy, 44, 47-58.

Ciccone, A. (2000). Agglomeration effects in Europe. Eur. Econ. Rev. 46(2), 213-227.

Easterly, W., and Levine, R. (2001). What have we learned from a decade of empirical research on growth? It's not factor accumulation: Stylized facts and growth models. World Bank Econ. Rev. 15(2), 177-219.

European Commission (2010). Europe 2020: A European strategy for smart, sustainable and inclusive growth. European Commission, Brussels.

Feldman, M.P., Audretsch, D.B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. Eur. Econ. Rev. 43(2), 409-429.

Furtan, W.H., Sauer, J. (2008). Determinants of food industry performance: Survey data and regressions for Denmark. J. Agric. Econ. 59(3), 555-573.

Gruber, S., Soci, A. (2010). Agglomeration, agriculture, and the perspective of the periphery. Spat. Econ. Anal. 5(1), 43-72.

Gustafsson, A., Stephan, A., Hallman, A., Karlsson, N. (2016). The "sugar rush" from innovation subsidies: a robust political economy perspective. Empirica 43(4), 729-756.

Hansson, H., Ferguson, R., Olofsson., C., Rantamäki-Lahtinen, L. (2013). Farmers' motives for diversifying their farm business – The influence of family. J. Rural Stud. 32, 240-250.

Harris, R., Trainor, M. (2005). Capital subsidies and their impact on total factor productivity: Firm-level evidence from Northern Ireland. J. Reg. Sci. 45(1), 49-74.

Ho, D.E., Imai, K., King, G., Stuart, E.A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. Political Anal. 15(3), 199-236.

Holmström, B. (1999). Managerial incentive problems: A dynamic perspective. Rev. Econ. Stud. 66(1), 169-182.

Iacus, S.M., King, G., Porro, G. (2009). cem: Software for coarsened exact matching. J. Stat. Softw. 30(9), 1-27.

Iacus, S.M., King, G., Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. J. Am. Stat. Association, 106(493), 345-361.

Jacobs, J. (1969). The Economy of Cities. Vintage, New York, NY.

Jacquemin, A.P., Berry, C.H. (1979). Entropy measure of diversification and corporate growth. J. Industrial Econ. 27(4), 359-369.

Kline, P., Moretti, E. (2014). Local economic development, agglomeration economies, and the big push: 100 years of evidence from the Tennessee Valley Authority. Q. J. Econ. 129(1), 275-331.

Kumbhakar, S.C., Bokusheva, R. (2009). Modelling farm production decisions under an expenditure constraint. Eur. Rev. Agric. Econ. 36(3), 343-367.

Latruffe, L. (2010), Competitiveness, productivity and efficiency in the agricultural and agri-food sectors. OECD Food, Agriculture and Fisheries Working Papers, No. 30, OECD Publishing, Paris.

Levinsohn, J., Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. Rev. Econ. Stud. 70(2), 317-341.

Marschak, J., Andrews, W.H. (1944). Random simultaneous equations and the theory of production. Econometrica 12(3/4), 143-205.

Marshall, A. (1920). Principles of Economics: An introductory volume. Macmillan, London, UK.

Mary, S. (2013). Assessing the impacts of Pillar 1 and 2 subsidies on TFP in French crop farms. J. Agric. Econ 64(1), 133-144.

Masini, A., Menichetti, E. (2012). The impact of behavioral factors in the renewable energy investment decision making process: Conceptual framework and empirical findings. Energy Policy, 40, 28-38.

Michalek, J., Ciaian, P., Kancs, d'A. (2014). Capitalization of the single payment scheme into land value: Generalized propensity score evidence from the European Union. Land Econ. 90(2), 260-289.

McCloud, N., Kumbhakar, S.C. (2008). Do subsidies drive productivity? A cross-country analysis of Nordic dairy farms. In Chib, S., Griffiths, W., Koop, G., Terrell, D. (Eds.) Bayesian Econometrics (Advances in Econometrics, Volume 23) Emerald Group Publishing, pp. 245-274.

Mundlak, Y. (1978). On the pooling of time series and cross section data. Econometrica 46(1), 69-85.

Olley, G.S., Pakes. A. (1996). The dynamics of productivity in the telecommunications equipment industry. Econometrica 64(6), 1263–1297.

Porter, M. E., & Van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. J Econ Perspect 9(4), 97-118.

Pufahl, A., Weiss, C.R. (2009). Evaluating the effects of farm programmes: results from propensity score matching. Eur. Rev. Agric. Econ. (1), 79-101.

Ratinger, T., Medonos, T., Hruska, M. (2013). An assessment of the differentiated effects of the investment support to agricultural modernisation: the case of the Czech Republic. AGRIS on-line Papers in Economics and Informatics, 5(4), 153-164.

Reinhardt, F. (1999). Market failure and the environmental policies of firms: Economic rationales for “beyond compliance” behavior. J. Ind. Ecol. 3(1), 9-21.

Rizov, M., Pokrivcak, J., Ciaian, P. (2013). CAP subsidies and productivity of the EU farms. J. Agric. Econ. (3), 537-557.

Robins, J.M., Rotnitzky, A., Scharfstein, D.O. (2000). Sensitivity analysis for selection bias and unmeasured confounding in missing data and causal inference models. In Halloran, M.E., Berry, D. (Eds.) Statistical Models in Epidemiology, the Environment, and Clinical Trials. Springer, New York, NY, pp. 19-4.

Rosenbaum, P.R., Rubin, D.B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika 70(1), 41-55.

Romer, D. (2006). Advanced Macroeconomics. 4th ed. McGraw-Hill, New York, NY.

Romer, P.M. (1990). Endogenous technological change. J. Political Economy, 98(5), Part 2, S71-S102.

Sauer, J., Latacz-Lohmann, U. (2015). Investment, technical change and efficiency: empirical evidence from German dairy production. Eur. Rev. Agric. Econ. 42(1), 151-175.

Sckokai, P., Moro, D. (2009). Modelling the impact of the CAP Single Farm Payment on farm investment and output. Eur. Rev. Agric. Econ. 36(3), 395-423.

Serra, T., Zilberman, D., Gil, J.M. (2008). Differential uncertainties and risk attitudes between conventional and organic producers: the case of Spanish arable crop farmers. Agric. Econ. 39(2), 219-229.

Solow, R. (1956). A contribution to the theory of economic growth. Q. J. Econ. 70(1), 65-94.

Tobin, J. (1969). A general equilibrium approach to monetary theory. J Money Credit Bank. 1(1), 15-29.

Tullock, G. (1980) ‘Efficient Rent Seeking’, in Buchanan, J. M., Tollison, R. D. and Tullock, G. (ed.) Toward a Theory of the Rent-Seeking Society (Texas A&M University Press: College Station, Texas), pp. 269-282.

Viaggi, D., Gomez y Paloma, S., Mishra, A., Raggi, M. (2013). The role of the EU Common Agricultural Policy: Assessing multiple effects in alternative policy scenarios. Land Use Policy 31, 99-101.

Weber, J., Key, N. (2012). How much do decoupled payments affect production? An instrumental variable approach with panel data. Am. J. Agric. Econ. 94(1), 52-66.

Williamson, O.E. (1967). Hierarchical control and optimum firm size. J. Political Economy, 75(2), 123-138.

Zhu, X., Demeter, R.M., Lansink, A.O. (2012). Technical efficiency and productivity differentials of dairy farms in three EU countries: the role of CAP subsidies. Agric. Econ. Rev. 13(1), 66-92.

APPENDIX A

Table A1. Descriptive statistics, total sample

Variable	Minimum	Maximum	Mean	Median	SD
Firm characteristics					
Total factor productivity	0.16	9 560.315	122.85	97.509	131.90
Value added per employee	0.50T	44 992T	351.28T	230T	2.29T
Capital	0.60T	9 810T	4 086.33T	751T	122 759T
Labour	1	4 256	2.329	1	24.84
Age	16	75	52.783	52.891	2.29
Education	0	1	0.128	0	0.32
Female	0	1	0.210	0	0.38
Exports	0	1	0.013	0	0.11
Multi-firm	0	1	0.173	0	0.38
Investment support T_i	0	1	0.04	0.04	0.19
Investment support, amount Γ_i	1500	1.32-+07	428 912.8	270 000	562 641.6
Regional characteristics					
Population density	0.24	4 685.92	116.56	27.81	504.69
Industrial diversity	0.00	0.42	0.21	0.19	0.12
Specialization	0	0.65	0.09	0.10	0.52
Land	0	0.84	0.21	0.14	0.19

Note: T, in thousand SEK.

APPENDIX B

Table B1. Descriptive statistics, treated and control group

	Treated	Control	Treated	Control
Variable	Mean	Mean	SD	SD
Firm characteristics				
Total factor productivity	178.70	119.71	142.94	130.54
Value added per employee	794.25T	331.46T	758.66T	551.38T
Capital	8 639.16T	3 897.04T	14 456.38T	125 445T
Labour	2.82	2.32	5.39	25.33
Age	42.56	52.93	8.07	1.43
Education	0.11	0.12	0.26	0.32
Female	0.11	0.13	0.016	0.014
Exports	0.02	0.01	0.14	0.11
Multi-firm	0.054	0.009	0.024	0.020
Investment support T_i	0.04	-	0.19	-
Investment support, amount Γ_i	0.06	-	0.42	-
Regional characteristics				
Population density	53.35	119.18	177.56	513.62
Industrial diversity	0.82	0.83	0.18	0.21
Specialization	2.78	2.76	0.29	0.29
Land	0.25	0.21	0.25	0.19

Note: T, in thousand SEK.

APPENDIX C

Table C1. Results and diagnostics of the three matching algorithms using Coarsened Exact Matching

	L1	Difference in mean	25 %	50 %	75 %
Algorithm 1[a]					
Labour	0.238	0.487	0	0	0.510
Capital	0.385	3299	1969	3086	5366
Education	0.008	0	0	0	0
Population density	0.035	-2.990	-0.72	-1.90	-1.65
Land	0.103	0	0	0	0
3-digit SIC	0.221	-0.221	1	0	-1
L1 (Pre-match imbalance) test	0.899				
L1 (Post-match imbalance) test	0.604				
Algorithm 2[b]					
Capital	0.384	3236	1696	3085	5364
Education	0.010	0	0	0	0
Population density	0.035	-2.990	-0.722	-1.900	-1.651
L1 (Pre-match imbalance) test	0.901				
L1 (Post-match imbalance) test	0.695				

[a] Number of strata=1466, number of matched strata=241. [b] Number of strata=1406, number of matched strata=201

Table C2. Number of matched and unmatched observations

	0	1
Algorithm 1		
All	219499	4601
Matched	217939	4565
Unmatched	1560	36
Algorithm 2		
All	219499	4601
Matched	218393	5578
Unmatched	1106	23

APPENDIX D

Table D1. Correlation matrix for the log-transformed data

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. Total factor productivity	1														
2. Value added per employee	0.97	1													
3. Capital	0.29	0.50	1												
4. Labour	0.10	0.17	0.29	1											
5. Age	-0.03	-0.05	-0.10	-0.08	1										
6. Education	-0.02	-0.02	0.01	-0.02	-0.01	1									
7. Female	-0.13	-0.14	-0.11	0.14	-0.02	0.14	1								
8. Exports	0.03	0.06	0.11	0.31	-0.01	0.01	0.04	1							
9. Multi-firm	0.14	0.20	0.27	0.81	-0.10	-0.02	0.12	0.15	1						
10. Investment support T_i	0.12	0.16	0.22	0.11	-0.36	-0.00	0.00	0.00	0.17	1					
11. Investment support, amount Γ_i	0.01	0.01	0.02	0.02	-0.08	0.00	0.00	0.00	0.02	0.09	1				
12. Population density	0.07	0.08	0.08	0.12	0.01	0.108	0.06	0.06	0.07	-0.01	0.00	1			
13. Industrial diversity	0.04	0.05	0.03	0.04	0.03	0.04	0.02	0.03	0.03	-0.01	0.00	0.433	1		
14. Specialization	-0.01	-0.01	-0.01	0.04	-0.02	0.03	0.03	0.02	0.01	0.02	0.00	0.229	0.593	1	
15. Land	0.10	0.13	0.16	0.02	-0.01	0.04	-0.03	0.01	0.03	0.03	0.00	0.425	0.224	-0.01	1