Innovation and Climate Change Adaptation: An Analysis of the Agricultural Firms' Efficiency

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Abstract. Recent evidence suggests an increase in the variability of meteo-climatic parameters and in the frequency of extreme weather events, which will likely raise the incidence of environmental disasters (IPCC 2014). Agriculture is one of the most vulnerable economic sectors to the impacts of climate change (CC). In such a context, there is no doubt that technology will play an important role in enhancing the European capacity of adapting to CC. This paper analyses the effect of innovation driven by climate change challenges on European agricultural firms' technical efficiency. To capture the effects of innovation in agricultural activity, patents are considered a useful indicator as they illustrate the evolution of inventive capabilities in adaptation-related agriculture and food technology over time. Using ORBIS database merged with the Worldwide Patent Statistical Database collected by the European Patent Office, we investigate the determinants of agricultural patents and biotech innovations and their impacts on agricultural firm's efficiency during the period 2007-2015. Following the Wooldridge (2002) approach, we estimate pooled Stochastic Frontier model and pooled selection model using the Mundlak (1978) device. Two main conclusions result from the findings. Firstly, our results empirically prove that innovative firms may strengthen their resilience to CC. Secondly, since European agricultural firms remain quite far from the efficient frontier, this study provides supportive evidence for policy makers to enhance agricultural firms' existing knowledge and skills in adapting to climate change.

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1. Introduction

Over the next decades European regions are expected to confront significant uncertainty due to the opportunities and the challenges emerging in the transition towards environmentally sustainable societies. Even if such a process is touted to bring about benefits in the long-run, policy makers and scholars strive to anticipate the disruptions that are likely to emerge in the near future. In the present paper we acknowledge that a significant part of this transition will take place in the agricultural sector. European agriculture will undergo a transformation by endogenous factors such as environmental-friendly technologies to use in a more efficient way natural resources as well as by exogenous factors as, among others, climate change (CC) (EU SCAR, 2012). Climate change shows a bidirectional relationship with agriculture. CC affects agriculture and in turn agriculture contributes to the change of the global climate (EEA, 2015). Agriculture in food provision activity releases greenhouse gases but CC, although a global issue, has markedly local impacts due to the uneven exposure and sensitivity across climate zones in Europe. It is reasonable to expect that the background economic and social systems will be affected differently by climate change but, also, that they will adapt differently as a result of heterogeneity. There is no doubt that at the heart of this transition stands technological change, which enables to adapt, and in particular, mitigate the disruptions brought about by the changing environment. In this framework, innovation in agricultural sector can be seen as a strategy of adaptation to climate challenges. Climate policy will have potentially significant impacts on agriculture in particular on agricultural innovation. Removing distortions and impediments would foster farm-level innovation. Facilitating investments through the protection of property rights would also be beneficial (OECD, 2013). Thus, it is important to consider the role that technological change may play in solving long-term environmental problems as CC (Popp, 2005)

In the economics of innovation literature, we have identified two main bunches of studies that investigate the role of environmental-related technological change (Barbieri *et al.*, 2016) mainly in the manufacturing sector. First, there are those studies that focus on the drivers and determinants of environmental technologies (see e.g., Cainelli *et al.*, 2012; Cainelli and Mazzanti, 2013; Barbieri, 2015). Therein, environmental policy plays a pivotal role at triggering environmental technological advances, activities, or practices. In addition, given the market failures that pervade such technologies, policy intervention is crucial to set proper incentives for their development and adoption (Jaffe *et al.*, 2005). Second, there are studies that focus on the effects of environmental technologies on firms' performance (Gagliardi *et al.*, 2016; Leoncini *et al.*, 2018) and environmental performance (Mazzanti and Montini, 2010; Costantini *et al.*, 2013).

As far as agricultural innovation is concerned, the majority of the studies focuses on the effects of agricultural research and development (R&D) expenditure on productivity at the macro level (Alston *et al.*, 2009; Alston, 2010; Alston *et al.*, 2010; Pardey *et al.* 2010; Fuglie, 2012). While some

studies focus primarilyon innovation within the agri-food sector (Materia *et al.* 2017; Ghazalian, and Fakih, 2017, Harvey *et al.*, 2017), merely few studies indeed analyse the direct effect of innovation on profit or economic sustainability at the farm level (Karafillis and Papanagiotou, 2011 and Läpple and Thorne, 2019).

The lack of good data on innovation is an impediment to carry out impact analyses for evidence-based policies (Van Galen and Poppe, 2013). However, fostering innovation through more public and private investments in agricultural R&D and agricultural patents may increase long-term agricultural productivity growth in high-income countries (Heiseyand Fuglie, 2018).

The present paper contributes to describe and estimate the potential role of innovative agricultural practices and technologies incorporated in Intellectual Property Right protections, since they can enhance the resilience to climate change. While there is a growing consensus on the impact of climate change on agriculture (Mendelsohn *et al.*, 1994; Schlenker *et al.* 2005; Deschênes and Greenstone 2007; Mendelsohn and Dinar 2009; Deressa and Hassan, 2009; Burke and Emerick, 2016; Van Passel*et al.*, 2017), a better understanding of firms' adaptive capacity (Huq *et al.*, 2004; Seo, 2011) and adaptation strategies in supporting agricultural firms productivity are still needed (Di Falco and Veronesi, 2013 and Khanal *et al.*, 2018). The great attention by governments and by the international community to foster innovation, through a wide range of policies on the creation and diffusion of sustainable technology, in the agriculture and agri-food sector has determined the reform of the Agricultural Innovation System.

To fill the gap in the literature, we investigate how firm-levelinnovation strategies interact and impact agricultural firms' efficiency within the European agricultural sector using the Stochastic Frontier Approach (SFA). In this setting, we compute agricultural firms' technical efficiency by estimating simultaneously a production function and a technical inefficiency equation. Following Greene (2005a and 2005b), a True Fixed Effect (TFE) model is applied to disentangle time-invariant heterogeneity from time-varying inefficiency and to control for double heteroscedasticity in the idiosyncratic error term as well as in the inefficiency variance function by specifying suitable explanatory variables (Hadri *et al.*, 2003). Matching data from the ORBIS (Bureau Van Dijk) database at the agricultural firm level for Portugal, Spain, Finland, Italy, Sweden, France, Belgium and Germany with the Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO), the effects of innovation in agricultural activities is captured. We use patents as a convenient indicator of innovation for presenting the evolution of inventive capabilities in adaptation-related agriculture and food technology over time. Patent counts are indicative of the level of innovative activity itself and not only a measure of innovative output (Popp, 2005).

As measures of innovative activity, R&D spending and patent counts have been widely used. However, some drawbacks of these two measures can be underlined. R&D expenditure as an input

of innovation does not provide any information about the success of the innovation and therefore it fails as indicator when innovation takes place without any R&D expenditures. On the other hand, patent counts can be considered a good proxy of invention success even if most of them are associated with inventions of little value (Hall, 2011). Although patent numbers as a measure of innovative activity have been criticized (Griliches, 1990), it is the most commonly used indicator when studying technological change and its effect on the environment (Popp, 2005). The use of patents entails particular advantages because patent data are easily accessible via databases, are not subject to the problems of vague definition and allow comparability between firms (Ernst, 2001, Popp, 2005).

Focusing directly on the relationship between innovation and agricultural firm's efficiency, we analyse technical efficiency (TE), as a component of the total factor productivity jointly with technical change and economies of scale. TE is defined according to Farrell (1957) and measured following the analysis of Kumbhakar and Wang (2005), Kumar and Russell (2002), Kumbhakar and Lovell (2000). Measuring efficiency of innovation activities from the technical efficiency perspective is not new but the empirical evidence is rather limited (Cruz-Cázares *et al.* 2013). Moreover, to date, the evidence of a direct effect of innovation on TE at the firm level and more generally on sustainable economies, is quite scarce.

The present paper contributes to the existing literature on efficiency, innovation and CC effects in agriculture in four ways. First, since adaptation is a complex phenomenon we focus on private business innovation output i.e. how patenting activities may influence agricultural firms' efficiency. We explicitly introduce technological change since a time trend may not be considered as a substitute (Popp, 2005). Second, we use a unique dataset which collects firm patents within the agricultural sector. Therefore, we analyse agricultural innovation capturing adaptation strategy at the micro-level rather than at the macro-level (Alston, 2010; Alston *et al.*, 2010) and further we show the non-linearity of innovation on firms' profitability (Läpple and Thorne, 2019). Third, within a Ricardian framework (Mendelsohn *et al.*, 1994), European agricultural firms' technical efficiency is estimated without disregarding the other two components of total factor productivity, technological change and scale economies. Fourth, we apply a stochastic frontier approach in which the unobservable heterogeneity and the heteroscedasticity in the inefficiency term are considered (Greene 2005a; 2005b).

The paper is organized as follows. In the next Section the theoretical and policy background is illustrated, while methodological framework, datasets used in the estimations and the model specification are described in Section 3. Section 4 is dedicated to the empirical results and the robustness check analysis. Main conclusions are reported in Section 5.

2. Theoretical and policy background

Europe has been influenced by changes in meteorological phenomena seasonality and by the occurrence of extreme events with various degrees of intensity and duration such as very heavy precipitation, floods and droughts, heat waves, cyclones, out of season frost days. During the last century, Europe recorded a warming of about 1°C, higher than the global average and smaller farms are the most vulnerable. They often have fewer resources, face restrictions to innovation technology and show less ability to financial resilience (Campbell and Thornton, 2014).

In a sustainable development perspective, the growing issue regards mainly the ability of agricultural firms and institutions to adapt and deal with threats and opportunities that an altered climate may bring. As highlighted in the related literature (Rosenberg, 1992; Smithers and Blay-Palmer, 2001; Chhetri *et al.*, 2012), strategies for climate adaptation are mainly related to technology research and development in agriculture. Technology innovation is not only crucial to climate adaptation (EU, 2015), but it has proved to be fundamental to agricultural growth and development over time (Crosson, 1983).

To make Europe more climate-resilient, the Common Agricultural Policy supports climate adaptation strategy by influencing how individual agricultural firms choose to manage their land, crops and livestock and how they use inputs, including energy, fertilizers, and water. The adaptation strategy in fact improves the knowledge and the understanding of climate impacts promoting better adaptation responses through innovation in several sectors as well as in the agriculture. Upholding the diffusion of new technologies and the development of patents represents a tangible action which implies international cooperation, technology transfer, and research (Carlarne, 2010; OECD, 2013). The EU strategy on CC adaptation aims to support Member States in adapting to current and future impacts andin enhancing national adaptation strategies in different policy areas, including agriculture, food and nutrition security, and environmental protection (EEA, 2015).

As patent data have become more readily available, empirical analyses have begun to estimate the effects that innovations have on productivity especially in the manufacturing sector (see among othersGriffith *et al.*, 2006; Boldrin and Levine, 2013; Chang *et al.*, 2018). In the agricultural sector, Groombridge (1992) finds that patents are widely used to secure companies' investments in agricultural biotechnology and Agrawala *et al.* (2012) argue that OECD member countries dominate innovation in adaptation-related biotechnology patents. In the review of patenting activity, Kim *et al.* (2018) underline that there are very few studies on agricultural innovation and even less on food safety patent activity.

As far as the methodology used to investigate firms' performance, productivity and efficiency is concerned, Lampe and Hilgers (2015) in their survey concentrate on two approaches widely applied: The Data Envelopment Analysis (DEA) based on the linear programming non-parametric

technique and the SFA approach based on the parametric technique. The majority of the studies has applied the DEA input or output-oriented methodology to measure production efficiency (Guan *et al.*, 2006; Revilla *et al.*, 2003; Díaz-Blateiro *et al.*, 2006; Wang and Huang, 2007; Guan and Chen, 2010). The use of non-parametric methods for productivity and efficiency analysis using deterministic indicators and the linear programming technique does not consider any kind of random noise or stochastic component. As regards SFA, the approach preferred in the agricultural field (Lampe and Hilgers, 2015), several studies analyse the technical efficiency scores in dairy farms as in Hadley, (2006) and Barnes, (2008), and the effects of direct payments on technical efficiency as in Martinez Cillero *et al.* (2018) or the risk attitude and technical efficiency as in Mishra*et al.* (2018).

Among the few studies which apply the SFA for investigating the relationship between technical efficiency, innovation or indirectly technical progress, and performance, Wang (2007) estimates the technical efficiency scores at the aggregate level for 30 countries, of which 23 OECD members and 7 non-OECD economies chosen among those that engage in R&D intensively. He finds that any country that manages its R&D resources efficiently could benefit in terms of achieving better economic performance. However, he uses Battese and Coelli (1992)'s model, which does not allow to control for heteroscedasticity. At regional level, chosen a parametric approach, Sotnikov (1998)evaluates the effects of price and trade liberalisation on technical efficiency for Russian regions' agricultural productions and dwells on the no-homogeneous effect of technological progress in reducing technical inefficiency across the Russian regions. Using a parametric two-step approach, and considering for input factors endogeneity, Bokusheva *et al.* (2012) analyse the development of productivity, technical efficiency, and technical progress in Russian agriculture over the period 1991 - 2008.The impact of technical progress was negative in the early years of the transition but became positive after the Russian financialcrisis in 1998 which represents a turning point for the Russian agriculture.Based on a directional distance frontier approach and on the Luenberger index, Sauer and Latacz-Lohmann (2014) empirically estimate the impact of innovations on efficiency and productivity with respect to dairy farms in Germany over the period 1996–2010. They point out that investments in innovative technology increase the productivity of dairy production by shifting out the production frontier. While Sauer and Latacz-Lohmann (2014) analyse investment in innovation, Karafillis and Papanagiotou (2011) assess the impact of innovation measured by the adoption of ten technologies on total factor productivity for Greek organic olive farmers. By implementing the single-stage parametric estimation procedure, introduced by Battese and Coelli (1995), they use the index of innovation as a proxy for technical change over time and as an efficiency-increasing factor in the inefficiency model. Applying the stochastic frontier profit function in a cross-section dataset, they find that more innovative farmers perform better than less innovative ones.

We depart from the previous studies in two ways. First, we analyze the impact of innovation, measured in terms of patent counts as suggested by Popp (2005), on European firms' efficiency in

the agricultural sector. To this end, PATSTAT data is merged with the farm level ORBIS dataset. Second, we apply the TRE model developed by Greene (2005a, 2005b), which can be used to exploit the assumption of time-varying technical efficiency and dynamic phenomenon. The model treats all time-invariant effects as unobserved heterogeneity. In line with Karafillis and Papanagiotou (2011), we include innovation in the variance of the inefficiency error to take into account for heteroscedasticity (Hadri*et al.* 2013) and non-linearity (Läpple and Thorne, 2019). The production function and the inefficiency equation are simultaneously estimated, providing a synthetic measure of productivity and discriminating between production inputs and technical efficiency factors.

3. Methodological framework

To estimate the impact of climate-related innovations on agricultural firms' technical efficiency, our empirical analysis is performed within a Ricardian setting. As underlined by Deschênes and Greenstone (2007), the hedonic approach, based on the perfect markets' hypothesis, assumes that land present values or revenues reflect the present discounted value of rents into the infinite future. As a consequence, this approach implicitly incorporates firms' adaptive behaviour. However, adaptation is an endogenous process whose factors are observable and unobservable (Di Falco *et al*. 2012). We introduce as observable adaptation strategy the ability of European agricultural firms of patenting their own innovations. In this way, we are able to capture the firms' R&D activities or more generally the knowledge and the skills of European firms within the agricultural sector.

Following Deschênes and Greenstone (2007) and Di Falco *et al*. (2012), we modify the Ricardian approach in three ways. First, we control for unobserved time invariant factors such as firms' fixed effects. Second, as dependent variable agricultural revenues instead of land present values are introduced as proxy for the full range of potential and unobservable adaptive responses of European agricultural firms. Third, we introduce patent variables in the inefficiency model to assess the impact of observable adaptation decisions of European agricultural firms.

By examining the impact of innovation on agricultural revenues, we focus on the relationship between patents and agricultural firms' efficiency. In doing so, unobservable heterogeneity and heteroscedasticity is taken into account in the inefficiency term. Moreover, the heteroscedasticity of the idiosyncratic error term is also considered by clustering for country and year following the White-Huber standard errors procedure. To verify our research hypothesis, we employ the stochastic

production frontier technique originally developed by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977)[1]and subsequently extended by Greene (2005a and 2005b).

This methodology is based on parametric SFA models which estimate both frontier and inefficiency parameters simultaneously by using likelihood-based techniques. In contrast to non-parametric methods, such as data envelopment analysis, SFA models consider the random shocks which are beyond producers' control, but which may affect the production output.

There are several reasons why SFA can be considered as the best methodology to estimate firms' productivity. First, technical efficiency computed by using stochastic frontier approach allows to include several input dimensions in evaluating productivity. Output is compared to all inputs as labour, physical and human capital, providing a synthetic measure of productivity. Second, this methodology provides a relative productivity measure and therefore each firm can be compared to the best practice firm. This means to assess the distance of each firm's actual frontier to its optimal production given the same bundle of inputs. Finally, SFA allows disentangling the distance from the production frontier into an inefficiency term and a random error.

Following Greene (2005a and 2005b) who proposes the TFE model as an extension of the parametric stochastic frontier approach for panel data, we are also able to disentangle time-varying inefficiency from firm-specific time-invariant unobserved heterogeneity. The production function within the TFE model can be parameterized as:

$$(1) \qquad y_{it} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \qquad i=1,\dots, N; \quad t=1,\dots, T$$

$$\varepsilon_{it} = v_{it} - u_{it}$$

where y_{it} and x_{it} represent respectively the observed output and inputs of firm i in period t and α_i is the time invariant, firm-specific term or the fixed effects, which captures the unobserved heterogeneity among European agricultural firms. As regards the composite error term (ε_{it}), it is split into two components. The first component, v_{it}, represents the idiosyncratic error which follows the usual assumption of normally distributed error term (*i.i.d.*, N(0, $\sigma_{v_{it}}$)). The second independent component, defined as u_{it}, denotes the degree of inefficiency. It is distributed as a non-negative normal random variable ($N^+(0, \sigma_{u_{it}})$) and captures the transient effect of inefficiency. As argued by Greene (2005a, 2005b), in this model the two components of ε_{it} can be considered as a unique random term

[1] A firm could be considered technically efficient when it reaches the maximum level of output using the best combination of inputs within the existing technology. The estimated production frontier coincides with the optimal output level and represents the benchmark in respect to which the firm-level efficiency is measured. SF approach allows including in the model exogenous variables that are supposed to affect technical inefficiency.

which follows an asymmetric mixed distribution and the model is estimated applying maximum simulated likelihood estimation method.

This approach allows to distinguish between production inputs and inefficiency factors, which directly affect the time-varying inefficiency. By including a set of exogenous variables in the inefficiency model, the influence of observed heterogeneity of agricultural firms on the inefficient component can be explained. These inefficiency determinants, although they are not inputs, affect the agricultural firm's production structure.

The stochastic frontier model as specified in eq. (1) should be extended to correct for heteroscedasticity in both error terms. As in Hadri *et al.* (2003), the double heteroscedasticity means to correct both in the one-sided (u_{it}), and in the two-sided error term (v_{it},). The first correction, as suggested by Caudill et al. (1995), implies that the variance of the inefficiency error component is considered as a function of efficiency determinants (z_{it}). Ignoring the heteroscedasticity in the two-sided error term may also lead to inconsistent maximum likelihood (ML) estimators, thus an assumption on the structure of the heteroskedasticity is imposed. We suppose that the variance is homoscedastic within a group but not across groups.

As far as the inefficiency factors are concerned, they are included in the variance of the inefficiency component to control for heteroscedasticity as well as to avoid endogeneity issues. This specification also permits considering the non-monotonic effects on efficiency (Wang, 2002) and, specifically, the non-linearity of innovation (Läpple and Thorne, 2019). The variation of $\sigma_{u_{it}}$ over individuals and/or timenot only captures the heteroscedasticity but also affects the mean of u_{it} (see Kumbhakar *et al.*, 2018). The inefficiency function can be parameterized as:

$$(2) \qquad \sigma_{u_{it}} = exp(z_{it}^{'}\gamma)$$

where z_{it} is a vector of variables that may have an indirect effect on agricultural firms' performance as their ability to innovate incorporated into patents; and γ is a $1\times p$ vector of unknown parameters to be estimated. The advantage of this approach is twofold. First, it allows estimating simultaneously the parameters of equation (1) and (2) by performing a single-stage procedure. Second, it permits controlling for omitted variable bias due to unobserved heterogeneity of agricultural firms and to avoid heterogeneity bias in the estimated values of technical inefficiency. To capture the effect of the "environment" in which a firm produces its output (Kumbhakar and Lovell, 2000), agricultural and total patent variables, as innovation indicator, are introduced in the inefficiency model. These exogenous variables are supposed to affect the distribution of inefficiency.

Finally, since territorial characteristics are not likely to affect agricultural firms in the same manner and with the same degree, the broad territorial heterogeneity among European countries is

taken into consideration by clustering our estimation. Besides, given that time should influence differently agricultural firms' performance, we cluster our sample both for country and year.

3.1 Data

The proposed empirical analysis which represents an attempt to estimate the impact of innovation through patents on agricultural firms' technical efficiency and performance combines the ORBIS database with the PATSTAT. The first dataset provides financial, ownership, legal form and patent code information about firms cross the world for all the sectors of activities whereas the second database supplies detailed information on all the patents filed across European countries.

The ORBIS dataset is employed to identify those firms within the "Agriculture, forestry and fishing" sector (Section A - NACE Rev. 2) that are located in the EU countries. For each of them, we obtain information on operating revenues, total assets, material cost and employment cost over the period 2007-2017. The final unbalanced dataset comprises 143 agricultural firms located in Portugal, Spain, Finland, Italy, Sweden, France, Belgium, and Germany.

Table 1 shows the descriptive statistics of data used in the analysis. It is worth to note that even if the ORBIS dataset has the disadvantage of presenting several missing values, it has the unique and special advantage of associating firms with patents developed on their own and taken out from the patent office. This allows measuring the inventiveness of agricultural firms as well as their increasing knowledge.

In order to assess the effects of innovation activities on firms' performance, we extracted the publication number of each patent for all the sampled firms from the ORBIS dataset and merged them with patent data from the PATSTAT database. In this dataset, raw patent data are supplied for all the published European patent attainments and a wide wealth of information on the name of the applicant/inventor, his/her geographical location, citations to prior patents and claims, is provided. On the basis of a structured taxonomy, for each firm of the sample and for each year of the period considered, we were able to retrieve data on the inventions related to the agricultural sector.

Following the International Patent Classification (IPC) system only the agricultural patents were collected from the PATSTAT dataset. The IPC is characterized by a hierarchical structure that provides classification codes related to different level of technological specificity. In order to select agricultural firms' patents applied in the agricultural sector, we counted the IPC A01 code entitled as "Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing" and its sub-codes within all the patents in the European agricultural firms' portfolio. Thus, the variables used in the empirical analysis are the number of agricultural patents as well as the share of agricultural patents with respect to the total patents held in the agricultural firms' portfolio.

The IPC A01 code includes several sub-codes useful for analysing innovative adaptation strategies in the agricultural sector. Focusing on innovation for adaptation, agricultural crop biotechnology patents are the most important sub-code. Agricultural sector should innovate in plant breeding to develop new crop varieties that are more resilient to climate change impacts and this is captured with the IPC A01H and sub-codes (Agrawala *et al.*, 2012). Moreover, by the innovative adaptation strategies point of view, other typologies of patents can be involved. They may refer to a wide variety of technologies developed to alleviate the abiotic stress associated with CC, such as water system of irrigation, devices or methods for influencing weather conditions, biocide, pest repellent, pest attractant or plant growth regulatory activity of chemical compounds, etc.

As regards the agricultural firms sampled, Table 2 reports the total number of agricultural firms as well as the maximum number of agricultural and total patents within each sub-sector of activities of section A of NACE Rev. 2. It is worth to note that the majority of the sampled firms belongs to the sub-section "Support activities for crop production", "Plant propagation" and "Growing of other non-perennial crops". These three sub-sectors include the agricultural activities on a fee or contract basis, the activities dedicated to the direct plant propagation based on all the vegetative planting materials, and the growing of other non-perennial crops such as the growing of flowers, respectively.

Among these sub-sectors, the "Growing of other non-perennial crops" activity is the most innovative one, since it presents the highest maximum value for agricultural patents. "Plant propagation", "Logging" and "Raising of other animals" sub-sections present a dynamic innovation process in terms of agricultural patents. As described in Table 3, agricultural firms that hold in their portfolio at least one patent represent more than half of the sample (65 per cent).

3.2 Model specification

By implementing the empirical analysis in a Ricardian setting, the specification of a mathematical form of the production function is required. The Cobb-Douglas (C-D) and translog functions are commonly used in the stochastic frontier literature as underlined by Greene (2008). On the one hand, the translog functional form is the most flexible because it allows the output elasticities and returns to scale to vary with the inputs levels and it also places no restrictions on substitution elasticities. However, it requires the estimation of a large number of parameters, which provides the potential risk of multicollinearity. On the other hand, the C-D production function, which has universally smooth and convex isoquants, requires a limited number of variables. This has a practical advantage in statistical estimations over more complicated models like the one we estimated.

Following the standard C-D production function, our stochastic frontier production model for European firms in agricultural sector can be specified as follows:

(3) $$ln(Y)_{it} = \alpha_i + \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln M_{it} + \beta_3 \ln H_{it} + \sum_{j=1}^{10} \beta_j \, Dyear_j + (v_{it} - u_{it})$$

where the dependent variable is the logarithm of the operating revenues of the *i-th* firm at time *t* (*i=1,...,N; t=1,...,T*) and the independent variables are the logarithm of total assets as proxy for physical capital (K_{it}) and material costs (M_{it}) of the *i-th* firm at time *t* and employment costs as proxy for human capital (H_{it}) of the *i-th* firm at time *t* and α_i are the firms' specific fixed effects. Year dummies are introduced in the production function to control for possible year-specific fluctuations of the frontier. All the variables are deflated by the national GDP deflators provided by EUROSTAT.

To consider the non-linearity of innovation (Läpple and Thorne, 2019) the second component of the error term is defined as a function of several non-stochastic observable explanatory variables. As mentioned in Hadri *et al.* (2013), neglecting heteroscedasticity in u_{it} leads to biased inefficiency estimates. Thus, inefficiency determinants of European agricultural firms are introduced as shown in the following variance equation:

(4a) $$\sigma^2_{u_{it}} = \beta_0 + \beta_1 pat\_agri_{it}$$

(4b) $$\sigma^2_{u_{it}} = \beta_0 + \beta_1 pat\_agri\_share_{it}$$

Eq. (4a) and Eq. (4b) specify that the technical inefficiency component is heteroscedastic. In Eq. (4a) the variance is expressed as a function of the numbers of agricultural patents included in theIPC A01 "Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing" code which includes biotechnology patents. In Eq. (4b) the share of agricultural patents with respect to the total patents belonging to all the sections of the IPC system (PATSTAT dataset) is introduced.

Moreover, the lagged effects of the patent variables on the performance variables are captured. To consider a hysteric period for the influence of patents within a firm process or product, lagged values of patent variables are included in Eq. (4a) and Eq. (4b). Findings drawn from the literature suggest that a plausible period of time for lagged effect can be assumed to vary from twoup to four-year lags (Grilicheset *al.*, 1991; Ernst, 2001; Yin *et al.*, 2015; and Huang *et al.*, 2016). Two-year lagged agricultural patent variables are introduced and then for sensitivity analysis the four-year lagged patent variables are tested.

The technical efficiency of the *i-th* firm in the *t-th* time period is estimated by using the conditional mean of the inefficiency term $E\{exp(-u_{it}|\varepsilon_{it})\}$ proposed by Battese and Coelli (1988) and is given by:

(5) $$TE_{it} = e^{(-u_{it})}$$

The technical inefficiency values oscillate between 0 and 1. If TE_{it}=1 the country is on the frontier, i.e. the actual value of country production is equal to the maximum value of production. When TE_{it}<1 then the observable output is less than the maximum feasible output, meaning that the country is not efficient. After computing technical inefficiency, we are able to rank agricultural firms from the least to the most efficient and to find which countries are on average the most efficient.

4. Empirical results

In this section, main empirical results are presented and discussed. Finally, robustness check analysis is reported.

4.1 Main results

Table 4 presents the first set of results obtained by applying the TFE model. We distinguish between the two-year and the four-year lagged model. Since innovations are not the direct consequence of patent, a lag of time span for the implementation is needed (Janger*et al.*, 2017 and Grilicheset *al.*,1991). As a consequence, results for the two-year and the four-year lagged model are reported.

Additionally, within each lag-model the relationship between climate-related innovations and agricultural firms' technical efficiency is estimated according to two different innovation variables adopted. In Model 1 the number of agricultural patent variable is included in the inefficiency equation whereas the share of agricultural on total patent is considered in Model 2. As a robustness check, each variable is added one-by-one.

In the first section of Table 4 the estimated coefficients of the production frontier are reported, while in the second section the inefficiency coefficients are shown. As regards the estimations of the production function, they are stable across models with significant and positive sign of coefficients as expected (Battese and Coelli, 1995). Since total assets and material costs are introduced as capital inputs and employment costs as labour input, the estimations show that all inputs are productive for the European agricultural firms. This means that operating revenues may increase by enhancing the use of capital as well as labour inputs. Year-dummies exhibit significant coefficients, indicating that the frontier is subjected to shifts for all the years considered.

As far as the inefficiency model is concerned, a negative sign of parameters implies an inverse effect on technical inefficiency or, in other words, a positive effect on technical efficiency. Similarly, as in Jaffe and Palmer (1997), Griliches *et al.* (1991) and Ernst (2001), who highlight that patents have a positive effect on manufacturing firms' productivity, and in Karafillis and Papanagiotou

(2011) where innovation has a negative and direct effect on technical inefficiency, we find a negative and significant relationship between agricultural patent variables and technical inefficiency variance. Patents thus increase agricultural firms' technical efficiency. Accordingly, enhancing the number of patents in agricultural sector can increase agricultural firms' efficiency and in turn operating revenues. As in Läpple and Thorne (2019), innovation encourages economic sustainability but not in a linear way. This finding is also confirmed when the share of agricultural patents on total patents is introduced. This ratio positively affects European agricultural firms' technical efficiency, confirming the fact that agricultural patents which also include bio-technology patents play a crucial role in coping with climate change effects. These results are verified in the two-year lagged model as well as in the four-year lagged model.

Table 5 reports summary statistics of technical efficiency scores of Model 2 for the two-year and four-year lagged estimations. The mean technical efficiency is very similar within the two models; its estimated value being0.76 implies that the average agricultural firm is quite far from the efficient frontier and could increase revenues by 24% by optimising technical efficiency. However, about half of the agricultural firms of the sample are in the last quantile.

In Table 6and 7, technical efficiency mean values are shown by country and by holding at least one patent or none. Table 6summarizes technical efficiency mean values of European agricultural firms for all the European countries of the sample. For both lagged models, European agricultural firms exhibit a wide range of inefficiency ranging from 0.66 to 0.86. This means that on average European agricultural firms are quite distant from the maximum optimal frontier where the technical efficiency assumes unitary value.

Focusing on the two-year lagged model, agricultural firms residing in Germany and Belgium are the most efficient with respect to agricultural firms situated in the South of Europe as Portugal and Spain. Finland represents an exception because it presents technical efficiency mean values similar to the southern European countries. Similarly, the four-year lagged model results confirm that Mediterranean countries are at the top of the inefficiency ranking. It is worth to note that the more efficient agricultural firms belong to Germany and Sweden. Belgium, ranked at the second place in the two-year lagged model, is replaced by Sweden in the four-year lagged one.

Additionally, a test on the statistical significance of the difference among countries' mean values is reported. Thus, the rejection of the null hypothesis confirms that European countries' technical efficiency mean values are statistically different.

The most striking result, which is central in our analysis, is reported in Table 7. Classifying agricultural firms in two groups, we note that those who possess at least one patent in their portfolio are more efficient than agricultural firms that do not innovate. This is particularly true for technical efficiency estimated by using the four-year lagged model. The technical efficiency mean values are statistically different for the two groups as confirmed by the Anova test. Thus, more innovative

agricultural firms are closer to the optimal frontier than less innovative ones, in line with Läpple and Thorne (2019) for the Irish dairy firms and Karafillis and Papanagiotou (2011) for the Greek organic olive farmers. However, European agricultural firms remain quite far from the maximum frontier. There might be room to improve. Thus, inefficiency of European agricultural firms leaves space for governments to design economic sustainable policies, to incentivize firms and foster technological innovation in adapting agriculture to present and future changes in climate (Smithers and Blay-Palmer, 2001 and OECD, 2013).

4.2. Robustness checks

As shown in the previous Sections, we checked the robustness of our results in three ways. First, we ran each estimation replacing one variable at a time in the inefficiency model, i.e. the number of agricultural patent and the ratio of agricultural on total patent, to test the steadiness of our results to patent indicator. Second, to verify the robustness of our estimations to the time span in implementing innovations, we estimate eq. (4) by introducing the lagged patent variables using two-year and four-year lags, respectively. Third, in this Section, we run each model by modifying the assumption of heteroscedasticity of the idiosyncratic error term. In Table 4, we hypothesize that the variance of the idiosyncratic error term, v_{it}, was homoscedastic within a country-year group but not between groups. Thus, the variance of operating revenue of agricultural firms who belong to the same country and at the same year does not vary. In this way, we imposed an *a priori* assumption on the structure of the heteroscedasticity. To verify whether this assumption is overly restrictive, we relax the hypothesis on the structure of heteroscedasticity as in Table 8, which reports the coefficients of the same models using robust standard errors or White-Huber standard errors.

This robustness analysis reinforces the previous results for all the models estimated. The production function inputs are confirmed to be productive since they increase operating revenues of European agricultural firms. The two-year lagged model confirms negative and significant coefficients for agricultural patents and its share. As for the four-year lagged model, even though the coefficients are not statistically relevant, the signs are as expected.

Therefore, our findings have survived robustness checks, showing innovation coefficients consistent with the hypothesis that agricultural patents are relevant for enhancing European agricultural firms' efficiency. An increase in the number of agricultural patents, held by agricultural firms in their portfolio, reduces technical inefficiency.

5. Conclusions

In recent years, the effects of climate change have upheld the transition of the European agricultural sector towards a more sustainable one. While there is a wide consensus on the negative impact of climate change on agriculture and on the strategies to be adopted, a better understanding of agricultural firms' adaptive capacity is still needed. Technology innovation represents a crucial strategy for climate adaptation and a fundamental impulse for agricultural transformation. Agricultural sector may benefit from innovation. Thus, climate policy has the main role of removing distortions and impediments to foster farm-level innovation and to solve long-term environmental problems as CC.

Within a Ricardian framework, we have investigated the impact of firm-levelinnovation strategies on agricultural firms' efficiency using the Stochastic Frontier Approach (SFA). Within the agricultural sector,wehave estimated the effect of innovation measured by the number of patents on the agricultural firms' technical efficiency. We have applied a TFE model by Greene (2005a and 2005b) to estimate simultaneously a production function and a technical inefficiency equation. The analysis has been based on the stochastic frontier theory in order to verify gains or losses in efficiencies over time, expressed by the estimated parameters of variables that explain technical inefficiency. This technique has been extended to control for double heteroscedasticity in both error terms (Hadri*et al.*, 2003). By specifying, for the one-sided error component, explanatory variables such as agricultural innovation we control for the increase dispersion of technical efficiency. This has meant including innovation within the inefficiency variance function. The two-sided error term is also corrected for heteroscedasticity by assuming homoscedasticity within a country-year group but not between groups or by not imposing any assumptions on the structure of the heteroscedasticity. To this end, we matched data on agricultural firms' balance sheets from the ORBIS dataset for the production function with data collected by EPO for the inefficiency model. Innovation in agricultural activity is captured by the number of agricultural patents developed by European agricultural firms. Since we are aware of the fact that using patents as innovation indicator may have some drawbacks, we have followed the well-established literature in considering patents as an index for knowledge as well as for knowledge generating processes instead of a simple innovation output variable.

From our analysis emerges that inputs such as capital and labour are productive inputs, enhancing operating revenues of European agricultural firms. As regards the inefficiency model, the negative expected signs of coefficients imply their inverse effect on technical inefficiency or, in other words, a positive effect on technical efficiency. The number of patents in agricultural sector as well asthe share of agricultural patents on total patents increase agricultural firms' technical efficiency. Finally, this study uncovers that agricultural firms residing in Germany and Belgium are the most efficient with respect to agricultural firms situated in the South of Europe as Portugal and Spain.

Moreover, it reveals that agricultural firms who possess at least one patent in their portfolio are more efficient with respect to agricultural firms who do not innovate. In line with Läpple and Thorne (2019) for the Irish dairy firms and Karafillis and Papanagiotou (2011) for the Greek organic olive farmers we have found that innovative agricultural firms perform better than the non-innovative firms and may gain by further innovation.

Two main conclusions can be drawn from our empirical findings. Firstly, our results prove that innovative firms may strengthen their resilience to CC. Increasing agricultural patents which includes biotechnology patents reduce the agricultural firms' technical inefficiency. The impact is higher when patents in agricultural sector, as a share of the total patents, are considered. Secondly, since European agricultural firms are quite far from the maximum frontier, this study provides supportive evidence for policy makers to enhance agricultural firms' efficiency.

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Tables and Figures

Table 1. Descriptive statistics

Variable		Description	mean	min	max	N
Production function model (X_{it})	Y	Operating revenues from income statement (in constant 2010 euros)	8034.66	0	4793200	1016
	K	Total asset from balance sheet (in constant 2010 euros)	12670.32	0	5945800	1016
	M	Material cost from income statement (in constant 2010 euros)	3471.71	0	2126600	1016
	H	Employment cost from income statement (in constant 2010 euros)	1115.02	0	626300	1016
Inefficiency model (z_{it})	pat_agri_lag2	Two-year lags of n. of patent in IPC A01 "Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing"	0.580	0	23	1016
	pat_agri_share_lag2	Share of two-year lags of agricultural patents on total patents	0.174	0	1	1016
	pat_agri_lag4	Four-year lags of n. of patent in IPC A01 "Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing"	0.484	0	23	1016
	pat_agri_share_lag4	Share of four-year lags of agricultural patents on total patents	0.161	0	1	1016

Table 2. Number of agricultural firms by NACE code (4 digit), and the maximum value of agricultural and total patents within the period analysed

NACE code (4 digit)		N. of agricultural firms	pat_agri	pat_tot
110	Growing of non-perennial crops	4	3	3
111	Growing of cereals (except rice), leguminous crops and oil seeds	6	9	11
113	Growing of vegetables and melons, roots and tubers	7	9	9
119	Growing of other non-perennial crops	11	23	23
120	Growing of perennial crops	2	9	11
121	Growing of grapes	6	2	2
123	Growing of citrus fruits	1	1	3
124	Growing of pome fruits and stone fruits	6	1	1
126	Growing of oleaginous fruits	1	7	7
128	Growing of spices, aromatic, drug and pharmaceutical crops	1	4	42
130	Plant propagation	12	10	10
142	Raising of other cattle and buffaloes	1	2	2
143	Raising of horses and other equines	1	0	0
145	Raising of sheep and goats	1	4	4
146	Raising of swine/pigs	3	3	3
147	Raising of poultry	4	2	2
149	Raising of other animals	6	10	11
150	Mixed farming	7	7	7
161	Support activities for crop production	21	8	9
162	Support activities for animal production	5	0	3
163	Post-harvest crop activities	2	2	3
164	Seed processing for propagation	2	1	1
170	Hunting, trapping and related service activities	1	1	1
210	Silviculture and other forestry activities	4	2	2
220	Logging	6	10	17
230	Gathering of wild growing non-wood products	2	0	1
240	Support services to forestry	6	2	2
311	Marine fishing	3	4	4
321	Marine aquaculture	10	1	3
322	Freshwater aquaculture	1	1	2

Table 3. Number and frequency of agricultural firms holding at least one patent or none

	Count of farms	Frequency of obs.	Percent of frequency
Farms without patents	61	353	34.74
Farms with patents	82	663	65.26
Total	143	1,016	100

Table 4. TFE estimations for a two-year and four-year lagged model with heteroscedasticity among groups

Dep. Var.	**TFE – two-year lagged Model**		**TFE – four-year lagged Model**	
Operating revenue	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Production Function Model				
K	0.294***	0.165**	0.231***	0.304***
	(0.000)	(0.029)	(0.000)	(0.000)
M	0.196***	0.206***	0.204***	0.196***
	(0.000)	(0.000)	(0.000)	(0.000)
H	0.230***	0.213***	0.221***	0.214***
	(0.006)	(0.000)	(0.000)	(0.006)
Dyear	Yes	Yes	Yes	Yes
Inefficiency Model				
pat_agri_lag2	-0.132**			
	(0.033)			
pat_agri_share_lag2		-0.690**		
		(0.033)		
pat_agri_lag4			-0.026	
			(0.341)	
pat_agri_share_lag4				-0.397**
				(0.043)
Constant	-1.187***	-1.097***	-1.201***	-1.232***
	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	1,004	1,004	1,004	1,004
N. ofagricultural firms	131	131	131	131
N. of cluster	85	85	85	85
Chi2	3918000	542177	813229	803064
p-value	0.00	0.00	0.00	0.00

*Note: Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Table 5. Summary statistics of technical efficiency scores

	TFE– two-year lagged model	TFE– four-year lagged model
Efficiency frequency (%)		
0.00-0.19	1.99	1.99
0.20-0.39	4.28	4.28
0.40-0.59	11.75	11.75
0.60-0.79	31.77	31.77
0.80-1.00	50.2	50.2
Mean efficiency level	0.76	0.76
Standard deviation	0.19	0.19
Minimum	0.0011	0.0015
Maximum	0.98	0.99
Number of obs.	1004	1004

Table 6. Technical inefficiency scores by country

TFE– two-year lagged model		TFE– four-year lagged model	
Country	**Mean efficiency**	**Country**	**Mean efficiency**
Portugal	0.66	Portugal	0.65
Spain	0.71	Spain	0.72
Finland	0.74	Finland	0.75
Italy	0.76	Italy	0.77
Sweden	0.80	Belgium	0.81
France	0.80	France	0.81
Belgium	0.80	Sweden	0.83
Germany	0.86	Germany	0.85
ANOVA test			
F	7.84		8.04
Prob> F	0.00		0.00

Table 7. Technical inefficiency scores by holding at least one patent or none

TFE– two-year lagged model		TFE - four-year lagged model	
Dummy patent	**Mean efficiency**	**Dummy patent**	**Mean efficiency**
0	0.71	0	0.70
1	0.76	1	0.77
ANOVA test			
F	2.48		3.63
Prob> F	0.11		0.05

Table 8. TFE estimations for a two-year and four-year lagged model with robust standard errors.

Dep. Var.	**TFE - two-year lagged Model**		**TFE – four-year lagged Model**	
Operating revenue	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Production Function Model				
K	0.309**	0.165	0.371**	0.294
	(0.031)	(0.211)	(0.032)	(0.102)
M	0.201***	0.206***	0.196***	0.200***
	(0.005)	(0.001)	(0.005)	(0.003)
H	0.219*	0.213**	0.222*	0.212*
	(0.093)	(0.024)	(0.069)	(0.084)
Dyear	Yes	Yes	Yes	Yes
Inefficiency Model				
pat_agri_lag2	-0.134***			
	(0.000)			
pat_agri_share_lag2		-0.690**		
		(0.020)		
pat_agri_lag4			-0.034	
			(0.212)	
pat_agri_share_lag4				-0.520
				(0.105)
Constant	-1.199***	-1.097***	-1.279***	-1.190***
	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	1,004	1,004	1,004	1,004
N. of agricultural firms	131	131	131	131
Chi2	6810000	890916	8479	405239
p-value	0.00	0.00	0.00	0.00

*Note: Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1*