Agricultural Patents as Strategy for Climate Adaptation: A European Analysis of Farmer's Efficiency

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Abstract

This paper analyses the effect of innovation encouraged by climate change challenges on European farmers' technical efficiency. Using stochastic frontier approach, we estimate the impact of agricultural patent on farmers' technical efficiency by taking into accounts both unobservable heterogeneity and heteroscedasticity in the inefficiency term. Our findings suggest that European farmers remain quite far from the maximum frontier and irrespective of the country in which they reside; farmers who innovate are more efficient than those who do not. Thus, inefficiency of agricultural agents in the European context leaves space for policies that incentivize firms to adopt climate change adaptation strategies through technological innovation.

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1. Introduction

In 2013, the European Commission has launched the "EU strategy on adaptation to climate change" for promoting the adoption of comprehensive adaptation strategies by EU Members, for supporting better informed decision-making processes by reducing knowledge gaps about adaptation and finally for fostering adaptation in vulnerable key sectors such as agriculture (European Commission, 2013). Even though the EU Adaptation Strategy does not set binding targets or requirements as mitigation policy, it provides recommendations and guidance to aid Member States to develop their own adaptation initiatives, in accordance with the subsidiarity principle, within the 2014-2020 Common Agricultural Policy (CAP).

It has become evident that even if earth's climate has always undergone periodic changes, these recent climate changes (CC) have significantly increased both frequency and severity of certain extreme and climate-related events, such as higher patterns variability of rainfall and temperature. Europe, as many other macro areas, 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). Specifically, CC have led to relevant effects on European agricultural sector in recent years (IPCC, 2012 and 2014; Ciscar et al., 2014; EEA, 2013b and 2017). While climate related impacts on agriculture have largely been negative, positive impacts are limited to temperature increases in northern latitudes (Kovats et al., 2014).

Europe recorded a warming of about 1°C during the last century, faster than the global average. Many Southern European countries suffered for an increase of temperature especially in the summer months with the consequence of economic losses as well as reductions in crop productivity. Meanwhile, in the Northern countries a lengthening of the growing season due to milder weather conditions has improved agricultural production by increasing cultivable varieties (EEA, 2013a, 2013b and 2014). According to medium-term scenarios, many European areas will cope with an increase of warming at the surface and a more frequent extreme of weather conditions, and thus farmers will be affected in terms of their efficiency and productivity. Certainly, smaller farms will be the most vulnerable to CC. They often have fewer resources, face restrictions to innovation technology and show less ability to financial resilience (Campbell and Thornton, 2014). Since these meteo-climatic changes and weather extreme events are projected to continue, adaptation policies are crucial to face CC

impacts. This, in fact, represents a challenge that European agriculture has to tackle in the immediate future.

In a socio-economic sustainable development perspective, the growing issue regards mainly the ability of farmers and institutions to adapt and adequately deal with threats and opportunities that an altered climate may bring. As highlighted by 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 issue, but it has been fundamental for agricultural growth and development for over time (Crosson, 1983). However, it is worth to note that innovation in agriculture has some specific characteristics i.e. the atomistic nature of agricultural production, the demand for reduction to pests and diseases, and the nature of site specificity due to the biological nature of agricultural production (Pardley et al., 2010).

To make Europe more climate-resilient, on the one hand the CAP policy should support climate adaptation by influencing how individual farmers choose to manage their land, crops and livestock and how they use inputs, including energy, fertilizers, water. On the other hand, the adaptation strategy should improve knowledge and the understanding of climate impacts to enable better adaptation responses through boosting innovation in several sectors and in particular in the agricultural one. Introducing new technologies and developing patents represent a concrete action to be supported by improving international cooperation, technology transfer and research (Carlarne, 2010). The EU strategy on adaptation to CC aims precisely to help Member States to adapt to current and future impacts, enhancing national adaptation strategies, increasing and improving sharing of knowledge and mainstreaming adaptation in different policy areas, including agriculture, food and nutrition security, and environmental protection.

While there is a growing consensus on the impact of climate change on agriculture and adaptation strategies (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 farmers' adaptive capacity (Huq et al., 2004; Seo, 2011) and farmers' adaptation strategies in supporting farm productivity are still needed (Di Falco and Veronesi, 2013 and Khanal et al., 2018). We actually contribute to the existing literature on climate change adaptation in agriculture in three ways. First, instead of analyzing the environmental issue as related to economic growth and productivity at country level as in Grossman and Krueger (1995) and Jaffe and Palmer (2003), we consider the environmental issue at the micro level focusing on European farmers' technical efficiency, within a Ricardian framework (Mendelsohn et al., 1994). Second, because adaptation is a

complex phenomenon, which is based on different strategies for supporting farmers' welfare, we focus on patents strategy to address climate change. This was attainable mainly because the analysis was carried on developed countries. Third, we apply the stochastic frontier approach (SFA) as modified by Greene (2005a and 2005b) in which the unobservable heterogeneity and the heteroscedasticity in the inefficiency term are taken into account.

As measures of innovative activity such as patents have become more readily available, empirical analyses have begun to estimate the effects that environmentally-friendly innovations have on productivity and efficiency (Crepon et al. 1998 and Lööf et al., 2017). To the best of our knowledge this is the first attempt to examine the relation between farm climate-related innovation measured by patents and technical efficiency.

Using SFA we compute farmers' 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 heteroscedasticity by specifying explanatory variables in the inefficiency variance function (Hadri et al., 2003). Matching data from the ORBIS (Bureau Van Dijk) database at farm level for Portugal, Spain, Finland, Italy, Sweden, France, Belgium and Germany with the Worldwide Patent Statistical Database (PATSTAT) by the European Patent Office, the effects of innovation in agricultural activity is captured. We used patents as a convenient indicator of innovatio allowing us to illustrate the evolution of inventive capabilities in adaptation-related agriculture and food technology over time.

Patents have the advantage of providing information on countries where innovation takes place and where patent applications are submitted (Agrawala et al., 2012) as well as offering a clear comparison means among countries and sectors (Su and Moaniba, 2017). However, considering patents as a proxy for innovation output should be misleading. As Griliches and Pakes (1980) underline, patents are proxies for knowledge for their closely relation to knowledge generating processes such as R&D. Janger et al. (2017) and Dechezlepretre et al. (2018) stress some drawbacks in using patent as innovation indicator. They argue that some innovations are patented only for impeding competitors' innovations, not all patents are brought into use, and finally not all innovations outputs are patented because some firms prefer the business secret (Popp, 2005). For all these reasons, patent indicator used in this analysis is not representative of innovation outputs but of farm knowledge in line with the knowledge-based view (Nelson, 1991).

Within the environmental innovation literature[1], the use of patents as a proxy of innovation output is relatively common (among others Pavitt, 1985; Acs and Audretsch, 1989; Griliches, 1990; Jaffe and Palmer (1997); Crépon et al., 1998; Acs et al., 2002; Bottazzi and Peri (2003); Popp, 2005; Bronzini and Piselli, 2016; Su and Moaniba 2017).

Additionally, even if not all successful research and innovative efforts are protected through patents, Arundel and Kabla (1998) found that patent propensity rates among European firms increase with firm size. Groombridge (1992) found 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.

Finally, results obtained by our analysis confirm that innovative firms can strengthen their resilience to CC. Increasing agricultural patents, which includes biotechnology patents reduce the farmers' technical inefficiency and thus increase efficiency. Adaptation through patent strategy can improve the quality of life for farmers, farmworkers, consumers, and society as a whole, as well as marginalized groups.

The paper is organized as follows. In the next Section the methodological framework is illustrated, while datasets used in the estimations and the model specification are described in Section 3 and 4, respectively. Section 5 is dedicated to the empirical results and the robustness check analysis. Main conclusions are reported in Section 6.

2. Methodological framework

To estimate the impact of climate-related innovations in agriculture on farms' 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 land markets hypothesis, assumes that present land value reflects the present discounted value of land rents into the infinite future. As a consequence this approach implicitly incorporates farmers' adaptive behaviour. However, adaptation is an endogenous process whose factors should be observable and unobservable (Di Falco et al. 2011). In our analysis, we thus introduce as observable adaptation strategy the ability of European farmers of

[1] For a comprehensive survey on environmental innovation see Barbieri et al. (2016).

patenting their own innovations. In this way, we are able to capture the farms' R&D activities or more general the knowledge and the skills within European farms.

Following Deschênes and Greenstone (2007), we modify the Ricardian approach in two ways. First, we control for all unobserved time invariant factors, including farmers' fixed effects under the additive separability assumption. Second, we do not consider land values as independent variable because of the presence of fixed effects and the no time variation in such variable. Land value reflects long-run average values of CC and includes potential adaptation measures without analysing the endogenous adaptation decisions.

By examining the impact of innovation in agricultural revenues, we focus on the relationship between patents and farmers' efficiency accounting for unobservable heterogeneity and heteroscedasticity in the inefficiency term as well as in the idiosyncratic error term by clustering simultaneously for country and year or by applying the White-Huber standard errors procedure. We, hence, apply the stochastic production frontier technique originally developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977)[2] and subsequently modified 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 take into account the random shocks which are beyond producers' control but which may affect the production output.

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

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

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

[2] 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.

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, farm-specific term or the fixed effects, which capture the unobserved heterogeneity among European farmers. As regards the composite error term (ε_{it}), it is subdivided 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 $\varepsilon_{it} = v_{it} - u_{it}$ can be considered as a unique random term which follows an asymmetric mixed distribution and the model is estimated applying maximum simulated likelihood estimation method (MSLE).

This approach allows distinguishing 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 farmers on the inefficient component can be explained. These inefficiency determinants do not represent inputs; however affect the farm's production structure.

The stochastic frontier model as specified in eq. (1) should be enlarged to consider the inefficiency error component as a function of efficiency determinants (z_{it}), as in Hadri *et al.* (2003) but differently from them the inefficiency factors are included in the variance of the inefficiency component to control for heteroscedasticity and to avoid endogeneity issues. Moreover, the variation of $\sigma_{u_{it}}$ over individuals and/or time captures not only the heteroscedasticity but also affects the mean of u_{it} (see Zieba, 2011). To introduce heteroscedasticity, the inefficiency function can be parameterized as:

$$\sigma_{u_{it}} = exp(z'_{it}\gamma) \tag{2}$$

where z_{it} is a vector of variables that may have an indirect effect on farms' performance such 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 two-stage procedure. Second, it permits to control for omitted variable biases due to unobserved heterogeneity of farms and to avoid heterogeneity biases

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, as we expect that territorial characteristics do not affect farms in the same manner and with the same degree, the broad territorial heterogeneity among European countries is taken into account by clustering our estimation by countries. Moreover, since even time should influence differently farmers' performance, we cluster our sample both for country and year.

3. Data description

The proposed empirical analysis represents the first attempt to estimate farm adaptation to CC in Europe combining the ORBIS database provided by Bureau van Dijk with the Worldwide Patent Statistical Database (PATSTAT) collected by the European Patent Office (EPO). The first dataset provides financial, ownership and legal form information on firms around the world for all the sectors of activities whereas the second database supplies 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. 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 farms located in Portugal, Spain, Finland, Italy, Sweden, France, Belgium, and Germany.

In Table 1, the descriptive statistics are reported. 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 by their own and applied to the patent office. This allows measuring the inventiveness of farmers as well as their increasing knowledge.

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)	8034.664	0	4793200	1016
	K	Total asset from balance sheet (in constant 2010 euros)	12670.320	0	5945800	1016
	M	Material cost from income statement (in constant 2010 euros)	3471.705	0	2126600	1016
	H	Employment cost from income statement (in constant 2010 euros)	1115.020	0	626300	1016
Inefficiency model (z_{it})	pat_agri_lag2	2 year lags of n. of patent in CPC A01 "Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing"	0.580	0	23	1016
	pat_agri_share_lag2	Share of 2 year lags of agricultural patents on total patents	0.174	0	1	1016
	pat_agri_lag4	4 year lags of n. of patent in CPC A01 "Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing"	0.484	0	23	1016
	pat_agri_share_lag4	Share of 4 year lags of agricultural patents on total patents	0.161	0	1	1016

In order to assess the effects of innovation activities on farms' performance, once obtained from the ORBIS dataset the publication number of each patent for all the sampled farms, we are able to gather patent data from the PATSTAT database. Within this dataset, raw patent data are supplied for all the published European patent applications and a wide wealth of information on, for example, the name of the applicant/inventor, his/her geographical location, citations to prior patents, and claims, is furnished. On the basis of a structured taxonomy, we are able to retrieve data on those inventions related to the agricultural sector for each farm and in each year of the sample. In fact, the technological content of patents is categorized within a patent classification code, which distinguishes inventions on their technicalities and specifications.

Following the International Patent Classification (IPC) system only the agricultural patents are 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 distinguish the

patents applied in the agricultural sector and held by each farm, we search for the IPC A01 code entitled as "Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing" and its sub-codes within all the patents in the European farmers' portfolio. In this way, we are able to count not only the total number of patents held by farmers but also the number of patents related to the agricultural sector for each farm and in each year of our sample. The variables considered in the empirical analysis, thus, are the amount of agricultural patents as well as the share of agricultural patents with respect to the total patents held in the farmers' portfolio.

The IPC A01 code includes several sub-codes interesting for analyzing innovative adaptation strategies in the agricultural sector. Focusing on innovation for adaptation, agricultural crop biotechnology patents are the most important issue. 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), which are included in the code considered. Moreover, within the innovative adaptation strategies, other typologies of patents are 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 repellant, pest attractant or plant growth regulatory activity of chemical compounds, etc..

As regards the sampled farms, Table 2 shows the amount of farmers and the maximum value of agricultural and total patents in the span of time analyzed classified for the sub-sectors of activities of section A of NACE Rev. 2. It is worth to note that the majority of the sampled farms belongs to the "Support activities for crop production", "Plant propagation" and "Growing of other non-perennial crops" sub-section. These three sub-sectors include respectively the agricultural activities on a fee or contract basis; those activities dedicated to the direct plant propagation based on all vegetative planting materials; and the growing of other non-perennial crops such as the growing of flowers.

Among these sub-sectors, the "Growing of other non-perennial crops" activity is the most innovative one, because it presents the highest maximum value for agricultural patents. "Plant propagation" sub-section, together with "Logging" and "Raising of other animals" sub-sectors, presents a dynamic innovation process in terms of agricultural patents. However, the "Growing of spices, aromatic, drug and pharmaceutical crops" sub-sector presents a very relevant innovation process due to the high value of total patent held by European farmers. In our sample, farmers that hold in their portfolio at least one patent represent around half of the sample (57%) as described in Table 3.

Table 2: Number of farms by NACE code (4 digit), and the maximum value of agricultural and total patents within the period analyzed

NACE code (4 digit)		N. of farms	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 Farmers 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

4. 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 for European farms, output and inputs expressed in natural log values can be written as:

$$\text{(3)} \qquad \ln(Y)_{it} = \alpha_i + \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln M_{it} + \beta_3 \ln \mathrm{H}_{it} + \sum_{j=1}^{10} \beta_j \mathrm{Dyear}_j + (v_{it} - u_{it})$$

where the dependent variable is the logarithm of the operating revenues of the *i-th* farm at time *t* ($i=1,...,N;\ t=1,...,T$) and the independent variables are the logarithm of physical capital proxies such as total assets (K_{it}) and material costs (M_{it}) of the *i-th* farm at time *t* and human capital proxies such as employment costs (H_{it}) of the *i-th* firm at time *t* and α_i are the farmers' specific fixed effects. Year dummies are introduced in the production function to control for possible year-specific fluctuations of the frontier.

As mentioned in Belotti et al. (2013), neglecting heteroscedasticity in u_{it} leads to biased inefficiency estimates. Thus, inefficiency determinants of European farms are introduced as shown in the following equation:

$$(4) \quad \sigma^2_{u_{it}} = \beta_0 + \beta_1 pat\_agri_{it} + \beta_2 pat\_agri\_share_{it} + \eta_{it}$$

Eq. (4) specifies that the technical inefficiency component is heteroscedastic, with the variance expressed as a function of the patents' number in CPC A01 "Agriculture; Forestry; Animal Husbandry; Hunting; Trapping; Fishing" including biotechnology and patents' number in all sections (PATSTAT dataset). To examine the lagged effect of patent applications on operated revenue lagged values of patents variables are included in Eq. (4). Based on findings from the empirical literature, a plausible time period for lagged effect can be assumed up to 4-year lag (Ernst, 2001; Griliches, 1990; Griliches, Hall, & Pakes, 1991). Agricultural patents with 2-year lag are introduced and then for sensitivity analysis the 4-year lag patent variables are replaced.

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 $E\{exp(-u_{it}|\eta_{it})\}$ proposed by Battese and Coelli (1988) and is given by:

$$(5) \quad TE_{it} = e^{(-u_{it})} = e^{(-z'_{it}\gamma - \eta_{it})}$$

The technical inefficiency values will oscillate between 0 and 1, being the latter the most favourable case. Technical efficiency refers to the ability to obtain maximum output from a given input vector. If $TE_{it} < 1$ then the observable output is less than the maximum feasible output, meaning that the statistical unit is not efficient. After computing technical inefficiency, we are able to rank farmers from the least to the most efficient and to find which countries are on average the most efficient. Moreover, we compare farmers applying for patents from those who do not innovate.

5. Empirical results

In this section, main empirical results are presented and discussed as well as a robustness check analysis.

5.1 Main results

Table 4 presents our first set of results of the TFE model. We distinguish between the two-year lag and the four-year lag model. Since innovations are not the direct consequence of patent, a lag of time span for the implementation is needed, as underlined by Janger et al. (2017) and Griliches, Hall, & Pakes (1991). Additionally, for each lag-model the relationship between climate-related innovations in agriculture and farmers' technical efficiency is estimated in two different ways depending on the patent index considered. 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. Each index is used in turn as a robustness check.

While the first section of Table 4 exhibits the estimated coefficients of the production frontier, the second section shows the coefficients that explain the inefficiency. The estimation of the production function is stable across models and the coefficients are significant and with the expected positive signs (Battese and Coelli, 1995). Total assets, material costs as capital inputs and employment costs as labour input are all productive inputs for operating revenues of European farmers. 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 should be subjected to shifts for all the years considered.

As regards the inefficiency model, the negative expected signs of parameters imply their inverse effect on technical inefficiency or, in a different way, positive effects on technical efficiency. As in Jaffe and Palmer (1997), Griliches, et al. (1991) and Ernst (2017), who highlight that patents have a positive effect on manufactory firms' productivity, we find a negative and significant relationship between agricultural patent variables and inefficiency. Patents thus increase farmers' technical efficiency. Accordingly, enhancing the number of patents in agricultural sector can increase farmers' efficiency. This finding is also confirmed by introducing the share of agricultural patents on total patents in the inefficiency model. This ratio positively affects European farmers' 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 lag model as well as in the four-year lag model.

Table 4: TFE estimations for a two-lag and four-lag model with heteroscedasticity among groups

Dep. Var.	TFE – two-year lag Model		TFE – four-year lag 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. of farmers	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*

In Table 5 and 6, technical efficiency scores of Model 2 for the two-year lag and four-year lag estimations are shown. The choice of focusing on Model 2 depends on the fact that patent variables have a greater influence on technical efficiency rather than Model 1. Table 5 summarizes technical efficiency mean values of European farmers grouped by countries. They vary in a range that goes from 0.66 to 0.86, meaning that in average, European farmers remain distant from the maximum frontier where the technical efficiency value is equal to one. Focusing on the two-year lag model, farmers residing in Germany and Belgium are the most efficient with respect to farmers 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 even though it is situated in the Northern part

of Europe. Substantially, same results are obtained by using the four-year lag model, confirming Mediterranean countries at the bottom of the rank of farmers' efficiency. It is worth to note that there is a switch in the upper positions of the ranking. Belgium, ranked at the second place, is replaced by Sweden in the four-year lag model.

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 among them.

Table 5: Technical efficiency scores by country based on Model 2

TFE– two-year lag model		**TFE– four-year lag 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 6: Technical efficiency scores by holding at least one patent or none based on Model 2

TFE– two-year lag model		**TFE - four-year lag 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

The most striking result, which is central in our analysis, is reported in Table 6. Classifying farmers in two groups, we note that those who possess at least one patent in their portfolio are more efficient than farmers that do not innovate. This is particularly true for technical efficiency estimated by using the four-year lag model. The technical efficiency mean values are statistically different for the two groups as confirmed by the Anova test.

Results confirm that European farmers remain quite far from the maximum frontier. Thus, inefficiency of agricultural agents in the European context leaves space for policies that incentivize firms to adopt climate change adaptation strategies through technological innovation (Smithers and Blay-Palmer, 2001).

5.2. Robustness checks

As shown in the previous Sections, we checked the robustness of our results in threefold. 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 estimated 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. In Table 4, we hypothesized 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 farmers who belong to the same country and at the same year is not varying. In this way, we imposed an *a priori* assumption on the structure of the heteroskedasticity. To verify if this assumption is overly restrictive, we relax the hypothesis on the structure of heteroscedasticity as in Table 7, 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 farmers. The two-year lag model confirms negative and significant coefficients for

agricultural patents and its share. As for the four-year lag model, even though the coefficients are not statistically relevant, the signs are as expected.

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

Table 7: TFE estimations for a two-year lag and four-year lag model with robust standard errors.

Dep. Var.	TFE - two-year lag Model		TFE – four-year lag 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)
Observations	1,004	1,004	1,004	1,004
Number of farmers	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*

6. Conclusions

Climate change has caused negative effects on European agricultural sector in these recent years. While there is a wide consensus on the impact of climate change on agriculture and on the strategies to

be adopted, a better understanding of farmers' adaptive capacity in supporting farm productivity is still needed. Technology innovation is a crucial strategy for climate adaptation and a fundamental impulse for agricultural growth.

Within a Ricardian framework, we estimated the impact of innovation in agricultural sector on farmers' technical efficiency by using a TFE model. The analysis in fact is 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 allows us to control for heteroscedasticity by specifying explanatory variables in the inefficiency variance function such as agricultural innovation. To this end, we matched data on farmers' balance sheets from the ORBIS dataset for the production function with data collected by European Patent Office for the inefficiency model. Innovation in agricultural activity, then, is captured by the number of agricultural patents developed by farmers. Since we are aware of the fact that using patents as innovation indicator may have some drawbacks, we have followed the established literature in considering patents as an index for knowledge as well as for knowledge generating processes instead of as an innovation output.

From our analysis emerges that inputs such as capital and labour are productive inputs, enhancing operating revenues of European farmers. As regards the inefficiency model, the negative expected signs of parameters imply their inverse effect on technical inefficiency or, in other words, positive effects on technical efficiency. Both the number of patents in agricultural sector and the share of agricultural patents on total patents increase farmers' technical efficiency. Finally, this study uncovers that farmers residing in Germany and Belgium are the most efficient with respect to farmers situated in the South of Europe as Portugal and Spain. Moreover, it reveals as a striking result that farmers who possess at least one patent in their portfolio are more efficient with respect to farmers who do not innovate.

Two main conclusions can be drawn from these empirical findings. Firstly, our results empirically prove that innovative firms may strengthen their resilience to CC. Increasing agricultural patents which includes biotechnology patents reduce the farmers' technical inefficiency. The impact is higher when agriculture-related patents, as a share of the whole patents, are included. Secondly, since European farmers remain quite far from the maximum frontier, this study provides supportive evidence for policy makers to enhance farmers' existing knowledge and skills in adapting to climate change. From a policy perspective, to incentivize farms in being innovative through the development of one or more agricultural patents – specifically biotech patents – may strengthen their capacity to adapt to climate change.

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