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Climate variability, innovation and firm performance: evidence from the European agricultural sector

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Abstract

It is generally accepted that adaptation to climate variability requires a technological advancement strategy. However, the innovation process has received little explicit consideration in this framework. We employ a panel endogenous switching regression model to explore whether and to what extent climate variability affects firm performance through the ability to induce the development of adaptation innovations in key resource-based sectors in Europe during the period 2007–2017. Our findings confirm that the knowledge generation process at the heart of climate change adaptation technologies enhances firm performance, especially for firms in the aquaculture and fishing sub-sectors in northern European countries.

Keywords: climate variability, adaptation, innovation, patent, panel endogenous switching regression model

JEL classification: Q1, Q16, Q54, C33

1. Introduction

Recent scientific evidence highlights that the increasing variability in meteo-climatic parameters and the increased frequency of extreme weather events are resulting in more frequent environmental disasters (IPCC, 2014). In addition, they are also contributing to the depletion of natural resources, which is threatening their supply (IPCC, 2014; Hernández-Delgado, 2015; Stevanovic

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et al., 2016; European Environmental Agency, 2019). Several resource-based sectors in Europe (i.e. agroforestry, water, animal breeding, fishing and aquaculture) are key for the provision of food but are extremely vulnerable to climatic conditions (IPCC, 2014; Zilberman *et al.*, 2018; European Environmental Agency, 2019). It has also been shown that the extent to which climate change affects the socio-economic systems is contingent on local economic activities (ECONADPT, 2016) and the heterogeneity in adaptive and innovative capacities (Vanschoenwinkela, Mendelsohn and Van Passel, 2017). That is, the ability of modern economies to cope with hazardous climatic conditions depends heavily on the development and adoption of environmentally sound technologies (Jaffe, Newell and Stavins, 2005; Popp, Newell and Jaffe, 2010; Åhman, Skjærseth and Eikeland, 2018; Zilberman *et al.*, 2018; Dechezlepretre *et al.*, 2020). Miao and Popp's (2014) theoretical framework assesses the extent to which innovation is responding to the occurrence of natural disasters. They highlight that 'as climate change unfolds, there has been an increased recognition that climatic conditions may serve as a stimulus for technological innovation, particularly in the agricultural sector' (Miao and Popp, 2014: 282).

The present article explores the role played by the development of innovative capabilities in the context of climatic variability and their effects on the economic performance of European firms in key resource-based sectors (agroforestry, livestock and fishing) during the period 2007–2017. This study contributes to the literature by focusing on the knowledge generation process at the heart of technological change and by exploring the economic impact of a particular instance of innovation related to climate change adaptation strategies.

Although the role of innovation in climate mitigation technologies has been previously investigated (Miao and Popp, 2014; see Barbieri *et al.* (2016) and Popp (2019) for a review), the development and effect of new technical knowledge as an adaptation strategy have received much less attention (Dechezlepretre *et al.*, 2020; Auci *et al.*, 2021). While mitigation technologies are aimed at tackling climate change by reducing the sources of greenhouse gas emissions, adaptation to climate change involves proactive or reactive bottom-up efforts. The development of mitigation technologies is generally triggered by environmental regulation and responds to a demand–pull effect (Popp, 2002), whereas the development of adaptation technologies is triggered mainly by local contingencies such as, for example, climate variability and natural disasters (Miao and Popp, 2014). The type of innovation considered in the present study (i.e. adaptation to climate change) tends to be driven by the need to adapt to the changing environmental conditions. If the increasing costs of climate change are related to policy compliance behaviour or firms' adaptation strategies, the difference between these two could be relevant. Assuming that policymakers can react optimally (Requate, 2005), the direction of technological change in mitigation technologies induced by policy implementation will be towards those technological domains that are already experiencing a growth of innovative activities (Rodrik, 2014). On the other hand, the knowledge creation process involved in climate change adaptation technologies is linked to overcoming the results of and reducing the uncertainty and discontinuities brought by climate change. This type of innovation has been underexplored in the extant literature; however, it is crucial to investigate and understand the causes and the effects of knowledge creation in this domain. Moreover, the effects of innovation on firm performance may not differ depending on whether innovation is the cause or the consequence of climate change in terms of the sign, i.e. both may have a positive impact on productivity; however, the effects can vary in terms of magnitude since the underlined drivers are different.

In developed countries such as Europe, climate adaptation tends to be proactive and to focus on enhancing learning or research activities (Berrang-Ford, Frd and Paterson, 2011). These adaptation measures can be seen as a continuous process responding to external forces and requiring the commitment of private agents to anticipate climate-related damage. Innovation allows the heterogeneous and uncertain impacts of climate and weather variability to be handled (Zilberman *et al.*, 2018). This can result in adaptation actions complementing or coinciding with technological innovations (Smit and Skinner, 2002; Ayers and Huq, 2009; Patt *et al.*, 2010; Berrang-Ford, Frd and Paterson, 2011).

Climate change adaptation strategies include innovation generation that involves highly technical measures (European Environmental Agency, 2019) that often require significant investment in research and development (R&D) (Alene, 2010). The present paper focuses on the knowledge generation process that represents the 'upstream' phase of innovation activities (Tidd, Bessant and Pavitt, 1997), a phase frequently overlooked, especially in the literature on climate adaptation innovations in the agricultural sector.

Our paper draws on two literature streams. First, it relies on those studies that investigate the drivers of innovation. Therein, the so-called induced innovation theory (Hicks, 1932) has been explored extensively from different perspectives (for an overview of these studies see Popp, Newell and Jaffe, 2010) and has earned wide consensus in agricultural economics (Hayami and Ruttan, 1971). It posits that innovation is affected by changes in the relative prices of production factors, i.e. innovations are introduced to reduce the use of those factors that have become more expensive (Hicks, 1932). This work has promoted numerous empirical studies exploring the impact of energy prices and environmental regulation on the development of green technologies (see e.g. Newell, Jaffe and Stavins, 1999; Popp, 2002; Barbieri, 2015). In the context of climate change mitigation studies, it has been suggested that climate-related innovations measured by the numbers of patents respond strongly to natural disasters and changes in climatic conditions (Miao and Popp, 2014; Su and Moaniba, 2017; Miao, 2020). The theory of induced innovation emphasizes that as climate change becomes more prominent, the extent to which climate contingencies affect innovation is the key to understanding the effectiveness of climate adaptation strategies, especially in the agricultural sector (Rodima-Taylor, Olwig and Chhetri, 2012). While much of the literature on environmental innovation focuses on analysing how innovation contributes to mitigating climate-related impacts by reducing their causes, much less attention has been devoted to examining innovations as a strategic response to climate change and weather variability. This oversight is perhaps due to the difficulty inherent in testing the role of climate in triggering technological innovation (Abler *et al.*, 2000).

The second stream of literature we rely on includes investigations of the economic effects of innovation (see e.g. Barbieri *et al.* (2016) for a review). The mixed findings from these studies suggest that assessment of the economic benefits arising from the development of green innovation is difficult. The absence of clear-cut evidence is due mainly to the sector scrutinized, how innovation is measured (e.g. patents, innovation surveys and R&D expenditure), performance indicators (e.g. financial data and employment data) or the empirical approach employed.[1] However, overall, we observe that the creation and diffusion of technical knowledge seem to give rise to win-win situations (Porter and Van der Linde, 1995). That is, environmental innovation reduces environmentally harmful behaviour and, at the same time, improves trade performance by creating new markets (Duchin, Lange and Kell, 1995), leads to a positive net effect on employment (Horbach, 2010; Horbach and Rennings, 2013) and enhances firm profitability (Rexhäuser and Rammer, 2014; Gagliardi, Marin and Miriello, 2016; Leoncini *et al.*, 2019). Bloom and Van Reenen (2002) provide evidence that patenting has a positive impact on firm productivity via two main mechanisms based on embodied and disembodied knowledge. The former, i.e. embodied patents, refers to the knowledge content that firms embody in product and process innovation and that produces a continuous flow of profits. Disembodied patents concern technical knowledge that the firm owns the intellectual property rights to but are still in the development phase. Since a patent provides the firm with exclusive rights to the new technology, it can afford to wait to introduce innovations embodying this knowledge until it becomes profitable to do so. This is a valuable real option. In this context, climate variability increases the uncertainty related to the firm's environment and might affect its innovating behaviour as an adaptation strategy to cope with this uncertainty that in turn might affect the firm's performance.

The contributions of the paper are manifold. First, it contributes to the two streams of literature described above by shedding light on the role of climate adaptation technical knowledge and the interaction between innovation capabilities and firm performance in the agricultural sector.

Second, we complement the extant literature in which most of the studies focus on the adoption of already available technologies/practices to cope with climate change (see among others, Di Falco, Veronesi and Yesuf, 2011; Läpple, Hennessy and Newman, 2013; Abdulai and Huffman, 2014; Di Falco and Veronesi, 2013; Teklewold *et al.*, 2013; Kassie *et al.*, 2015, 2018; Asfaw,

1 In terms of empirical approaches, one of the most commonly used are integrated assessment models which analyse the benefits of adaptive actions including innovation but do not capture the regional drivers of those benefits or information on their geographic distribution which are needed to inform policy (Patt *et al.*, 2010).

Pallante and Palma, 2018; Teklewold, Mekonnen and Kohlin, 2019; Bozzola and Smale, 2020) by investigating on a less explored framework that concerns the development of climate-related technical innovation and therefore the creation of new technical knowledge. Although several studies explore the innovation adoption stage, they overlook the upstream phase in which original technical knowledge is created and how this affects firm performance. To capture the upstream knowledge generation phase, we focus on patents that allow us to measure the original and novel contribution in terms of technical progress.

Third, the paper focuses on climate adaptation innovations. The use of patents related to adaptations to climate change highlights one of the novelties of our study compared to most of the empirical work on the role of mitigation technologies or practices. Examining the development of innovations related to adaptation to climate change avoids problems of reverse causality between climate variability and innovation. We exclude patents related to mitigation technologies aimed at tackling climate change.

Fourth, this paper contributes to the current debate on innovation in climate-sensitive sectors by providing a micro-level (firm level) investigation and regional results to capture previously mentioned differences across European Union (EU) countries. Our firm-level data are supported by regional information that allows us to capture differences in the effects of climate variability across European regions (Iglesias *et al.*, 2009; IPCC, 2014). In the case of agricultural innovations, most works focus on the effects of agricultural R&D expenditure on productivity at the macro-level (Alston *et al.*, 2009, 2010; Alston, 2010; Pardey, Alston and Ruttan, 2010; Fuglie, 2012). While some studies focus primarily on innovation in the agri-food sector (Materia, Pascucci and Dries, 2017; Ghazalian and Fakih, 2017; Harvey *et al.*, 2017), few analyse the direct effect of innovation on profit or economic sustainability at the firm/farm level (Karafillis and Papanagiotou, 2011; Läpple and Thorne, 2019).

Finally, we provide a rigorous empirical analysis of firms' innovation behaviour based on panel data. Previous empirical studies using a range of regression models (e.g. endogenous switching regression and generalized propensity score matching) focus mainly on analysing technology adoption and its impacts on farm outcomes based on cross-section data (Di Falco, Veronesi and Yesuf, 2011; Läpple, Hennessy and Newman, 2013; Abdulai and Huffman, 2014; Di Falco and Veronesi, 2013; Teklewold *et al.*, 2013; Kassie *et al.*, 2015, among others). Analysis of the role of innovation as a firm adaptation strategy can involve unobserved firm heterogeneity that may influence the innovation decision and raise concerns over selection bias (i.e. that some firms are more likely to innovate than others). This endogeneity of the selection indicator is addressed by using a panel endogenous switching regression model that accounts for systematic differences in operating revenues between innovators and non-innovators. Meteorological parameters, considered as exogenous and random in economic applications, are used as selection instruments (Angrist and Krueger, 2001). Their validity is confirmed by performing a falsification test (Di Falco, Veronesi and Yesuf, 2011; Di Falco and

Veronesi, 2013). The explanatory variables (e.g. firm inputs in the production function) can also be a source of endogeneity (Lien, Kumbhakar and Alem, 2018). In our empirical strategy, total assets that are used to proxy for the firm size (Gugler and Weigand, 2003; Coles, Lemmon and Meschke, 2012) are determined endogenously and shareholder funds are used as the instrument. In a principal–agent context, shareholders' and managers' interests are conflicting (Jensen and Meckling, 1976) that ensures a weak relationship between shareholder funds and operating revenues and a strong correlation between shareholder funds and total assets. This latter relationship is a measure of financial leverage (Wagner *et al.*, 2002; Hart and Ahuja, 1996) and means that the variable *shareholders' funds* is a good instrument. Following Murtazashvili and Wooldridge (2016), we apply an endogenous panel switching regression model with two sources of endogeneity. As a robustness check and for completeness, we estimate and compare different panel models depending on the endogeneity/exogeneity of regressors and switching indicator assumptions. Finally, we implement a counterfactual analysis that provides insights into the potential operating revenue levels if the innovative firm had not innovated.

The paper is organized as follows. Section 2 describes the data and the empirical strategy. Section 3 presents and discusses the results, and Section 4 concludes the paper.

2. Data and empirical strategy

2.1. Data description

The analysis uses three main sources of data. The ORBIS database published by Bureau van Dijk provides financial, ownership, and legal information on firms around the world for all market sectors.[2] The Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO) supplies information on all patents filed worldwide. The Monitoring Agricultural Resources Crop Yield Forecasting System (MCYFS) database provided by the Joint Research Centre of the European Commission includes climate-related data. Details related to the variables used are provided below for each data source.

2.1.1. Accounting and patent data

The ORBIS dataset provides financial and accountancy unbalanced panel data on firms in Belgium, Denmark, Finland, Spain, Italy, Greece, France, Germany, the UK, Ireland, Portugal, Sweden and the Netherlands. We obtained annual data for 2007–2017 on 448 firms in the 'agriculture, forestry and fishing' sector (Section A—NACE Rev. 2), our sector of interest that we term 'agriculture' in what follows. Since the objective is to explore the impact of knowledge generated by climate adaptation-related innovation on firm productivity, we focus on European firms that use patenting as a means

2 The Bureau van Dijk ORBIS database provides comparable financial information on companies and financial and ownership indicators for each firm.

of protecting their intellectual property. This excludes smallholder farmers that rely on rainfed land and enables us to focus on medium-large European firms (limited liability companies and corporations) operating in the agricultural, forestry and fishing sector and involved in crop biotechnological activities.

Our empirical analysis exploits the wealth of information provided by patents. The use of patent data allows us to focus on the upstream phase of the innovation process and observe the effects of inventive activities on firm performance. Patents are the only measure available that allows identification of climate change adaptation technologies via technology classification codes (e.g. CPC—Cooperative Patent Classification and IPC—International Patent Classification codes).[3]

Climate-related patents are drawn from the PATSTAT dataset. We use the CPC to identify patents on technologies related to adaptation to climate change that are selected for the analysis. Specifically, we collect patents assigned to CPC code Y02A 'Technologies for adaptation to climate change'. We also include patents related to the technological classifications provided by Agrawala *et al.* (2012). Based on IPC codes, the authors identify the A01H code related to the required new plants and processes; the C12N 15/82 code related to mutation or genetic engineering for plant cells; the C12N 15/29 code related to genes encoding plant proteins; and the C12N 15/05 code related to preparation of hybrid cells by fusing two or more plant cells.

Table 1 shows that the agriculture sub-sector contributes 96.7 per cent to the total number of climate-related patents, and each firm holds between 0.05 and 0.87 patents. We use patents to measure innovation in the form of evolution of inventive capabilities in climate-adaptive fishing, agroforestry and food technology over time. In addition to being a measure of innovative output, patents are also indicative of the degree of innovation (Popp, 2005).

R&D spending and patent counts are used widely to measure innovative activity. However, they have some limitations. R&D expenditure as an innovation input does not provide any information on innovation success and, therefore, is a poor indicator of innovation when it does not involve R&D activities. Patent counts are a good proxy for invention success although their economic value is highly heterogeneous (Hall, 2011). However, patent data focus on the outputs of the inventive process, provide relevant information on the nature of the invention and the patent applicant, are readily accessible via databases, are discrete, are not subject to problems of vague definition and allow comparability among firms (Ernst, 2001; Popp, 2005; Haščič *et al.*, 2012). The disadvantages related to using patent data are that not all inventions developed by firms are either patented or are technically patentable

3 The CPC and IPC codes provide technology classification codes that are assigned to each patent and describe the technical content of the invention in a structured way. These classification systems are characterized by a hierarchical structure in which a higher (lower) number of digits corresponds to more (less) narrow technological fields. The CPC is maintained by the EPO and the US Patent and Trademark Office and complements the IPC by adding classification codes related to technologies for mitigation or adaptation to climate change (https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/classification/cpc.html).

Table 1. Distribution of climate-related patents by sub-sector

NACE codes	Agricultural sub-sector	Patent counts over 10 years	Average number of patents per firm and per year	Per cent contribution over the total amount of patents (%)
110–130; 160; 161; 163;164	Agriculture	2,976	0.87	96.7
210; 220; 230; 240	Forestry	28	0.10	0.9
141–150; 162; 170	Animals breeding and hunting	50	0.06	1.6
311; 312; 320; 321; 322	Aquaculture and fishing	22	0.05	0.7
	Total	3,076		

Source: Elaboration from ORBIS/PATSTAT. Griliches, 1990.

(Popp, 2005), also patents differ based on the commercial value of the invention and show heterogeneity across sectors and countries (Griliches, 1990; Archibugi and Pianta, 1996). Nevertheless, patents are widely employed in studies on technological change and its effect on the environment (Popp, 2005; Barbieri, Marzucchi and Rizzo, 2020).

The distribution of patents highlights that most firms own one or two patents (see Figure 1); the mass of the frequency is located around these two values. We divided the sample into two subsamples based on innovation activity, no innovation activity regardless of the number of patents. In our context, the choice of a binary model seems appropriate.

Using data from the PATSTAT and ORBIS databases, we obtained descriptive statistics of the major economic-financial and accountancy data, excluding variables with missing information. Operating revenue, material and employment costs, total assets and shareholder funds are balance sheet items included by both non-innovative and innovative firms. Table 2 shows that innovative firms show higher operating revenues and are larger in size measured by total assets. It is possible that these firms will be more likely to hire high-skilled workers and invest in the firm (higher employment and material costs). Therefore, this is not evidence of a potential relation between climate-related innovation (adaptation) and firm performance but requires additional investigation and application of methods able to account for endogeneity and selection problems to disentangle the effects of innovation on performance.

2.1.2. Climate data

Observed monthly precipitation and monthly average minimum, maximum and mean daily air temperatures were obtained from the MCYFS database

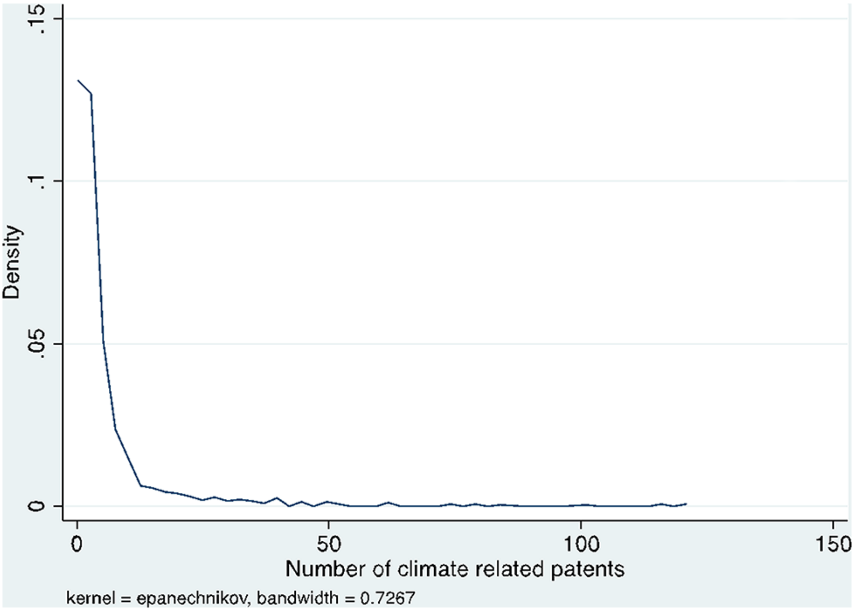

Fig. 1. Kernel density of the climate-related patent number.

that is used to monitor crop growth and enable forecasting (Biavetti *et al.*, 2014). We obtained daily meteorological data from around 4,200 weather stations, quality controlled, gap-filled and interpolated on a regular 25×25 km grid covering Europe and neighbouring countries. Daily interpolated meteorological data are available from 1975 up to near real-time. We use daily grid climatic data for 2007–2017 to calculate monthly grid averages (in the case of temperature) and cumulates (in the case of precipitation). The resulting parameters were spatially aggregated over arable land for each NUTS2 administrative level.[4] The resulting variables are at seasonal resolution where the season sequence is represented by the climatological classification. In particular, in line with the literature on seasonality (Mendelsohn, Nordhaus and Shaw, 1994; Van Passel, Massetti and Mendelsohn, 2017) we measure climate variability as the 2-year lagged standard deviation of precipitation in summer, and minimum and maximum temperatures in spring, minimum temperature in winter and maximum temperature in summer that are assumed to affect firms' probability to innovate. Table 3 presents the climatological statistics.

4 The NUTS (Nomenclature of territorial units for statistics) classification is a hierarchical system that identifies economic territory at different levels. The NUTS2 level employed in our analysis corresponds to the regional level.

Table 2. Summary statistics: innovative, non-innovative and all firms

	Mean	p50	sd	min	max	*N*
Non-innovative firms						
Operating revenue	11.523	11.404	0.421	11.376	15.943	917
Material costs	10.621	10.494	0.435	10.395	15.307	917
Employment costs	9.513	9.390	0.410	9.343	13.996	917
Total assets	11.226	11.034	0.610	10.982	15.920	917
Shareholders' funds	10.438	10.240	0.636	9.719	14.819	917
Innovative firms						
Operating revenue	11.909	11.457	0.976	11.376	15.506	108
Material costs	11.003	10.542	1.034	10.471	14.880	108
Employment costs	9.935	9.462	0.991	9.343	13.656	108
Total assets	11.675	11.135	1.152	10.983	15.575	108
Shareholders' funds	10.871	10.285	1.122	10.189	14.595	108
Total						
Operating revenue	11.564	11.409	0.521	11.376	15.943	1,025
Material costs	10.661	10.495	0.543	10.395	15.307	1,025
Employment costs	9.557	9.391	0.520	9.343	13.996	1,025
Total assets	11.273	11.038	0.700	10.982	15.920	1,025
Shareholders' funds	10.484	10.244	0.715	9.719	14.819	1,025

Note: All values are expressed in constant 2010 Euros and are at the logarithm level.
Source: Elaboration from ORBIS/PATSTAT.

2.2. Empirical strategy

2.2.1. Theoretical model

Since innovation can be considered as an improvement allowing greater efficiency (resources used over results obtained) and effectiveness (objective over results) compared to earlier technologies, the choice to innovate depends mainly on the firm's ability and motivation and expected firm outcomes as a result of the innovation (Läpple and Thorne, 2019; Auci *et al.*, 2021). Therefore, innovating firms may be systematically different from those that do not innovate. Comparing the outcomes of the two groups of firms, whether or not exposed to the treatment (innovation decision), is the main objective in the program evaluation literature (for a comprehensive review see Imbens and Wooldridge, 2009).

Table 3. Summary statistics of climatic variables

	Mean	p50	sd	min	max
Two-year lagged SD of winter minimum temperature	4.576	4.390	0.906	3.098	6.166
Two-year lagged SD of spring maximum temperature	3.786	3.718	0.427	3.088	4.529
Two-year lagged SD of spring minimum temperature	2.868	2.887	0.172	2.436	3.165
Two-year lagged SD of summer precipitation	10.332	10.157	2.584	7.727	16.057
Two-year lagged SD of summer maximum temperature	4.217	4.253	0.318	3.550	4.726

Note: The spring season includes the March-April-May months; the summer season includes the June-July-August months; while the winter season includes the December–January–February months. Precipitations are expressed in mm and temperature in $^{\circ}$C. The sample size is 1,028 observations.

In the innovation adoption literature, most empirical studies analyse the determinants of technology adoption as a strategy for adaptation to climate variability and its impact on farm outcomes in a cross-section context. These studies use different models such as endogenous switching regression (Fuglie and Bosch, 1995; Alene and Manyong, 2007; Di Falco, Veronesi and Yesuf, 2011; Läpple, Hennessy and Newman, 2013; Abdulai and Huffman, 2014; Kassie *et al.*, 2018), multinomial endogenous switching regression (Di Falco and Veronesi, 2013; Teklewold *et al.*, 2013; Kassie *et al.*, 2015) and propensity score models (Kassie, Shiferaw and Muricho, 2011; Läpple and Thorne, 2019). More recently, panel data analyses have been developed (Kassie *et al.*, 2018; Asfaw, Pallante and Palma, 2018; Bozzola and Smale, 2020). In line with this literature stream, we use a panel endogenous switching regression model but focus not on adoption of inventions or practices but on the firm's innovation behaviour as a climate change adaptation strategy.

Firms' ability and motivation and the effects of their technology innovations need to be evaluated controlling for potential selection bias and unobserved heterogeneity (Läpple and Thorne, 2019). Since these firms' characteristics are not fully (if at all) observable, they may cause endogeneity issues (Wooldridge, 2010). If the unobserved heterogeneity linked to the selection process is time invariant, the fixed-effect (FE) panel estimator produces unbiased estimates without the need for an instrumental variable (IV). However, if the selection process is based on time-varying unobserved heterogeneity, a FE model does not solve the problem and an alternative analytical strategy is required (Dustmann and Rochina-Barrachina, 2007; Semykina and Wooldridge, 2010).

An IVs methodology is not appropriate since the endogenous selection indicator is defined as a binary variable. This method would require a two-step procedure where the first step is a linear model. Including an IVs methodology in a nonlinear model (as in the case of a binary variable) could lead to the forbidden regression problem (Angrist and Pischke, 2008). To handle endogeneity in nonlinear models, an endogenous switching regression model based on the control function (CF) approach should be employed (Wooldridge, 2010; Kassie *et al.*, 2018).

In an endogenous switching regression model, the innovation decision is modelled based on firm-level characteristics and climate indicators, and the relationship with the variable of interest (i.e. operating revenue) and a set of explanatory variables can vary across discrete regimes (i.e. innovating and non-innovating firms). More specifically, in the first stage, we estimate a self-selection equation applying a binary variable estimator. In the second stage, the outcome equation conditional on the treatment (i.e. innovation decision) is modelled using a standard estimator (see among others Fuglie and Bosch, 1995; Alene and Manyong, 2007; Di Falco, Veronesi and Yesuf, 2011; Teklewold *et al.*, 2013; Läpple, Hennessy and Newman, 2013; Abdulai and Huffman, 2014; Kassie *et al.*, 2015). In the context of the firm's production function, a switching regression model allows interaction between inputs and technology (i.e. the innovation) meaning that the effect of the choice to innovate should be revealed by the intercept of the outcome equation and by the slope (Murtazashvili and Wooldridge, 2016; Kassie *et al.*, 2018).

Hence, the two-stage switching regression model allows the estimation of separate regression equations for innovators and non-innovators and determines the counterfactual based on the returns to the characteristics of innovating and non-innovating firms. This means that although the average values of these characteristics may be identical, they may have different impacts on outcome and innovation choice in terms of the coefficient estimates (Wooldridge, 2010). Another advantage of the switching regression model over propensity score matching, for example, is that it overcomes the unconfoundedness assumption that after controlling for observable characteristics, the selection variable (i.e. the innovation decision) may be random and uncorrelated with the outcome variable. The differences between innovators and non-innovators are systematic since selection is based on unobservable characteristics (Smith and Todd, 2005; Abdulai and Huffman, 2014).

We follow the empirical strategy developed by Murtazashvili and Wooldridge (2016), which allows for two sources of endogeneity: the selection variable and an endogenous explanatory variable. Following this, we run a two-stage switching regression panel data model with endogenous switching and endogenous explanatory variables and constant coefficients. This methodology combines the Mundlak–Chamberlain approach[5] to heterogeneity with the CF method for continuous and discrete endogenous variables.

5 This approach follows Mundlak (1978) and Chamberlain (1982, 1984), and it is known as the CREs probit model.

Specifically, the procedure for estimating a CF model consists of two stages. In the first stage, a correlated random effect (CRE) probit model is employed to take account of the selection indicator:

$$y_{it3} = 1\left[k_{t3} + z_{it}\pi_3 + \underline{z}_i\delta_3 + v_{it} > 0\right], v_{it} \sim N[0,1]\,\forall\, i = 1,\ldots,N \text{ and } t = 1,\ldots,T \tag{1}$$

where $\mathbf{1}[\cdot]\in\{0,\ 1\}$is the indicator function that is equal to 1 if the statement in brackets is true and is zero otherwise. The arguments of $\mathbf{1}[\cdot]$ are the regressors z_{it} that contain all the exogenous variables. This implies that z_{it} includes the exogenous variables of the outcome equation, any IVs that may affect the endogenous input and the selection variable y_{it3}. $\underline{z}_i$ are the Mundlak devices, i.e. the mean of the exogenous variables. The time-specific intercepts are represented by k_{t3}, which is common in panel data applications. Finally, v_{it} is the error term that is normally distributed with zero mean and variance equal to 1. This estimates the relationship between innovation choice and firm accounting items and the climate variables.

In the second stage, selection bias is addressed by adding the generalized residuals estimated in the first stage. The outcome equation is given by

$$y_{it1} = x_{it}\beta_0 + y_{it3}x_{it}\gamma_1 + \underline{z}_i\rho_0 + y_{it3}\underline{z}_i\rho_1 + \xi_0\hat{h}_{it3} + \xi_1 y_{it3}\hat{h}_{it3} + a_{it}$$
$$\text{with}\, E(a_{it}|y_{it3}, z_{it}) = 0\ \forall\, i = 1,\ldots,N \text{ and } t = 1,\ldots,T \tag{2}$$

where y_{it1} represents the outcome of interest as a linear combination of the two regimes. The endogenous switching variable y_{it3} at the basis of the sample selection interacts with both time-constant and time-varying unobservables. γ_1 is the difference between the coefficients of x_{it} in the two regimes, i.e. $(\beta_1 - \beta_0)$. $\hat{h}_{it3}$ are the generalized residuals that account for the endogeneity of the selection variable, and x_{it} incorporates the continuous endogenous explanatory variable (see Appendix A for a detailed description of the model).

When a continuous endogenous explanatory variable is included in the outcome equation, a two-stage least squares model is estimated. If all the variables are exogenous, then an ordinary least squares estimation is appropriate. This methodology leads to the estimation of the impact of innovation activity on European agricultural firms' performance in a counterfactual framework.

The analysis first specifies the expected values of the outcomes for the two regimes. The endogenous switching regression model is a useful methodology to compare the expected values of the operating revenues of innovative agricultural firms with respect to non-innovators. It also allows us to investigate the counterfactual outcomes if the innovating agricultural firms do not innovate and the non-innovating agricultural firms do innovate. Splitting the outcome equation into the two regimes, we can generate the conditional actual and counterfactual expectations of operating revenues for the agricultural firms.

The expected actual operating revenues of both innovators and non-innovators observed in the sample are computed respectively as follows:

$$E\left(y_{it1}^{(1)}|y_{it3}=1\right)=x_{it}\beta_1+\underline{z}_i\rho_1+\xi_1\hat{h}_{it3} \tag{3}$$

$$E\left(y_{it1}^{(0)}|y_{it3}=0\right)=x_{it}\beta_0+\underline{z}_i\rho_0+\xi_0\hat{h}_{it3} \tag{4}$$

The expected values of the counterfactual operating revenues of innovating firms had they chosen not to innovate (Eq. 5) and non-innovating firms had they chosen to innovate (Eq. 6) are given as follows:

$$E\left(y_{it1}^{(0)}|y_{it3}=1\right)=x_{it}\beta_0+\underline{z}_i\rho_0+\xi_0\hat{h}_{it3} \tag{5}$$

$$E\left(y_{it1}^{(1)}|y_{it3}=0\right)=x_{it}\beta_1+\underline{z}_i\rho_1+\xi_1\hat{h}_{it3} \tag{6}$$

where the parameters β_1, ρ_1 and ξ_1 are the estimated coefficients and the variables are as defined above.

Following Heckman, Tobias and Vytlacil (2001) and Imbens and Wooldridge (2009), we can calculate the average treatment effect on the treated (ATET) firms. In other words, we can assess the impact of innovation on the operating revenues for those firms that received the treatment as the difference between the expected outcomes in both regimes for the treated agricultural firms. Combining Equations (3) and (5), we obtain:

$$\begin{aligned} ATET=E\left(y_{it1}^{(1)}|y_{it3}=1\right)-E\left(y_{it1}^{(0)}|y_{it3}=1\right)&=x_{it}\left(\beta_1-\beta_0\right)\\ +\underline{z}_i\left(\rho_1-\rho_0\right)+\hat{h}_{it3}\left(\xi_1-\xi_0\right)& \end{aligned} \tag{7}$$

which represents the effect of an innovating behaviour induced by climate variability on an agricultural firm's operating revenues if it chooses to innovate. Note that if comparative advantage is at the basis of the selection, then the choice to innovate will imply higher operating revenues (Abdulai and Huffman, 2014).

2.2.2. Empirical specification

Focusing on firm capability to apply for at least one patent, our analysis models the innovation decision as a selection process in which the expected benefits drive the firm's choice. Assuming that the innovation decision can be represented as a dichotomous choice that is observable, agricultural firms choose to adopt an innovation behaviour only if the difference between operating revenues from innovating and not innovating are positive. As a consequence, the

CRE probit model for innovation behaviour can be written as follows:

$$
\begin{aligned}
&Pr(Innovation_{it} = 1|z_{it}) \\
&\quad = \alpha_0 + \alpha_1 Material\ costs_{it} + \alpha_2 Employment\ costs_{it} + \alpha_3 Total\ assets_{it} \\
&\qquad + \alpha_4 SD\ of\ winter\ minimum\ temperature_{it-2} \\
&\qquad + \alpha_5 SD\ of\ spring\ maximum\ temperature_{it-2} \\
&\qquad + \alpha_6 SD\ of\ spring\ minimum\ temperature_{it-2} \\
&\qquad + \alpha_7 SD\ of\ summer\ precipitation_{it-2} \\
&\qquad + \alpha_8 SD\ of\ summer\ maximum\ temperature_{it-2} + \underline{z}_i \rho_0 + \delta_1 Trend \\
&\qquad + \delta_2 Dregion + v_{it}\ \forall\ i = 1, \ldots N \text{ and } t = 1, \ldots, T
\end{aligned} \tag{8}
$$

where (z_{it}) is the matrix of the exogenous explanatory variables from the outcome equation (*material costs*, *employment costs* and *total assets*) and the exclusion restrictions from the selection equation such as past climate variables. These last are measured as 2-year lagged standard deviations of the climate parameters and measure the behaviour of climate variability rather than the isolated effects of extreme events. These include the standard deviations of minimum temperature during the winter season (*SD of winter minimum temperature*), maximum and minimum temperature during the spring season (*SD of spring maximum temperature and SD of spring minimum temperature*) and precipitation and maximum temperature during the summer season (*SD of summer precipitation and SD of summer maximum temperature*). Note also that if *total assets* is assumed to be endogenous, in Equation (8) it is replaced by its instrument (*shareholders' funds*). As usual, trend and regional dummies and Mundlak's devices are introduced.

Whenever an agricultural firm has to decide whether or not to innovate, potential outcomes such as operating revenues need to be considered. Under a risk-neutral assumption, firms may choose to adopt innovative behaviour if they expect to maximize their operating revenues. Therefore, the output equation of the European agricultural firm *i* should be written as follows:

$$
\begin{aligned}
&Operating\ revenues_{it} \\
&\quad = \beta_{00} + \beta_{01} Material\ costs_{it} + \beta_{02} Employment\ costs_{it} + \beta_{03} Total\ assets_{it} \\
&\qquad + \gamma_{10} Innovation_{it} + \gamma_{11} Material\ costs_{it} * Innovation_{it} \\
&\qquad + \gamma_{12} Employment\ costs_{it} * Innovation_{it} + \gamma_{13} Total\ assets_{it} * Innovation_{it} \\
&\qquad + \underline{z}_i \rho_0 + Innovation_{it} \underline{z}_i \rho_1 + \xi_0 \hat{h}_{it} + \xi_1 Innovation_{it} \hat{h}_{it} \\
&\qquad + \delta_1 Trend + \delta_2 Dregion + a_{it} \\
&\text{with } E\left(a_{it}|Innovation_{it}, z_{it}\right) = 0 \qquad \forall\ i = 1, \ldots, N \text{ and } t = 1, \ldots, T
\end{aligned} \tag{9}
$$

where the main inputs of the production function such as *material costs*, *employment costs* and *total assets* and their interactions with the selection variable *innovation* are included for each year *t* and each agricultural firm *i*. Since *total assets* could be a better proxy for firm size than the other inputs, it might be determined endogenously (Gugler and Weigand, 2003; Coles, Lemmon and Meschke, 2012).[6] When *total assets* variable is considered as an endogenous regressor, it is instrumented by *shareholders' funds* in the pooled IV estimation.[7]

As described above, the Mundlak device $\left(\underline{z}_i\right)$ and the generalized residuals $\left(\hat{h}_{it}\right)$ from the CRE probit model and their interaction with the *innovation* variable are also included. The presence of a trend and regional dummies is typical of panel data estimations.

To study the effect of the innovation decision on agricultural firms' operating revenues, we compare several panel data methods to the CF technique. Specifically, we use a FE estimator with *total assets* considered as exogenous and the IV FE estimator if *total assets* variable is determined endogenously.

3. Results and discussion

The determinants of innovation and the impact of innovation on operating revenues are estimated jointly in a selection and output equation. Innovative firms typically present different levels of operating revenues compared to non-innovative firms. The endogeneity of switching from innovating to non-innovating derives from the fact that the decision to innovate and the level of operating revenues are not independent. Also, as highlighted in Section 2.2, *total assets*—one of the main determinants of operating revenue—might be affected by potential endogeneity. We performed a Durbin–Wu–Hausman test that rejected the null hypothesis that the specified endogenous regressor should be treated as exogenous with $\chi^2(1) = 4.623$ and P-val. $= 0.031$. These results suggest that in our data the book assets variable better captures firm size compared to the other two inputs.[8] Since there are two endogenous components, endogenous switching and an endogenous explanatory variable, at least two IVs are needed. First, as an exclusion restriction, we exclude the climate variables from the outcome equations and use them as instruments for the decision to innovate. We argue that after controlling for the firm's innovation decision, variables for past climate have no direct effects on the firm's *operating revenues*. This is confirmed by the falsification test. In the Appendix B, Table B1 shows that 2-year lagged climatic variables are

6 In relation to the exogeneity of *material costs* and *employment costs*, see section 3.

7 According to principal–agent theory *shareholders' funds* may satisfy the strict exogeneity requirement and may be considered a valid instrument for *total assets*. This implies a weak relationship between *shareholders' funds* and firms' operating revenues and a high correlation with total assets.

8 The results of the Durbin–Wu–Hausman test for endogeneity of material costs and employment costs show that we cannot reject the null hypothesis of exogeneity ($\chi^2(1)= 0.006$, P-val.= 0.9394) and ((1)= 1.236, P-val.= 0.2663); thus, in our data, they are not endogenous. For instance, firms in the agricultural sector may be similar in terms of employment costs but their different recruitment of workers with different skills and capacity means that they are likely to have different numbers of employees. Therefore, employment costs cannot be used to proxy for firm size.

valid selection instruments. These instruments together are statistically significant drivers of the decision to innovate but do not affect the operating revenues of non-innovative firms (the results of the Wald test for exogenous and endogenous total assets are respectively F-stat.(5) = 0.60, P-val. = 0.701 and $\chi^2(5) = 2.69$, P-val. = 0.747). These results are as expected since we focus on European medium-large firms involved in both farming and ancillary activities such as development of crop biotechnologies, new irrigation systems and advanced weather forecasting tools. Therefore, climate variability is likely not to have a significant direct effect on firm outcomes.

Second, based on the principal–agent theory, *shareholders' funds* are used as an instrument for *total assets* in the outcome equation. This relationship, as a measure of financial leverage, is used as a control variable to assess the impact on economic performance (Wagner *et al.*, 2002; Hart and Ahuja, 1996).

Tables 4 and 5 present the results of the first and second stage estimated coefficients used to estimate the operating revenue equation. Table 4 reports the coefficients of the first stage. Column (1) shows the first-stage results for FE-IVREG with *total asset* an endogenous regressor and the decision to innovate an exogenous explanatory variable (Table 5 column (2) shows the second stage coefficients). Columns (2) and (3) present the coefficients of the first step of the CF approach, that is the CRE probit model for the choice to innovate when the *total asset* variable is exogenous and endogenous. In Table 4, regressions (1), (2) and (3) include regional dummies and trend variables; regressions (2) and (3) also include time averages of the corresponding set of explanatory variables (Mundlak devices) with the exception of the time-invariant variables such as regional dummies and trend variables that are perfectly collinear with their time averages.

The results of the first regression in Table 4 suggest that *shareholders' funds* variable is statistically significant at the 1 per cent level when used as an instrument. Also, with the exception of the interaction term between material and employment costs, the exogenous variables included are all positive and significant. Note that as expected, by increasing the intangible component, innovation has a positive and significant effect on *total assets*.

Columns (2) and (3) show that with the exception of the 2-year lagged standard deviation of minimum spring temperature the climate variables are statistically significant in both regressions. The two-year lagged standard deviations of minimum winter temperature, maximum spring temperature summer precipitation and maximum summer temperature can be considered valid selection instruments. The Wald tests on exclusion restrictions reported in the last panel in Table 4 confirm that jointly the instruments are statistically significant drivers of the innovation decision. While an upward trend in the standard deviation of the minimum temperature during the winter and precipitation and maximum temperature during the summer season increase the probability of innovating, an upward trend in the variability of the maximum spring temperature reduces innovation activities. The first three outcomes can be explained by the fact that higher variability of these climatic variables means that colder or milder winters, heat waves and droughts during the summer

Table 4. First-stage coefficient estimation

	(1) First-stage FE-IVREG	(2) CRE probit	(3) CRE probit with total asset endogenous
Dependent variable	Total asset	Innovation	Innovation
Material costs	0.227***	0.305	0.230
	(0.057)	(0.790)	(0.744)
Employment costs	0.276***	−0.463	−0.508
	(0.080)	(1.257)	(1.108)
Total assets		−0.598	
		(1.299)	
Innovation (yes = 1)	0.195**		
	(0.090)		
Material costs * Innovation	−0.062		
	(0.048)		
Employment costs* Innovation	−0.007		
	(0.049)		
Total assets * Innovation	0.048		
	(0.046)		
Shareholder funds	0.386***		−0.648
	(0.052)		(0.925)
Two-year lagged SD of winter minimum temperature		0.221***	0.223***
		(0.078)	(0.078)
Two-year lagged SD of spring maximum temperature		−1.282***	−1.280***
		(0.237)	(0.236)
Two-year lagged SD of spring minimum temperature		0.480	0.481
		(0.733)	(0.734)
Two-year lagged SD of summer precipitation		0.184**	0.184**
		(0.078)	(0.078)
Two-year lagged SD of summer maximum temperature		1.203*	1.199*
		(0.615)	(0.617)
Constant		−12.000	−12.500
		(14.646)	(14.633)
Wald test on exclusion restrictions $\chi^2(5)$		57.84***	57.93***
N	1,014	1,028	1,028
Log-likelihood	1,850.494	−302.139	−302.427

Note: Trend variable and regional effects are included. Columns (2) and (3) include Mundlak's correction. Fully robust standard errors are shown in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

season can occur more frequently. These adverse weather conditions might be translated into poorer vegetation, forest biomes, animals and soil health and could imply lower agriculture and livestock productivity and production. This would increase the motivation to adapt and produce innovation. In other

Table 5. Second stage coefficient estimation

	(1) FE	(2) FE with firm-specific linear trend	(3) FE-IV	(4) CF	(5) CF with total asset endogenous
Material costs	0.514***	0.471***	0.492***	0.513***	0.500***
	(0.068)	(0.077)	(0.036)	(0.068)	(0.070)
Employment costs	0.327***	0.353***	0.300***	0.302***	0.285***
	(0.050)	(0.129)	(0.044)	(0.071)	(0.068)
Total assets	0.116***	0.177*	0.189***	0.116*	0.154***
	(0.037)	(0.092)	(0.044)	(0.059)	(0.015)
Innovation (yes = 1)	0.073	0.037	0.042	−0.106	−0.038
	(0.076)	(0.072)	(0.086)	(0.163)	(0.146)
Material costs*innovation	0.018	0.014	0.011	0.042	0.055
	(0.027)	(0.026)	(0.023)	(0.160)	(0.152)
Employment costs*innovation	−0.005	−0.034	−0.020	0.074	0.196
	(0.027)	(0.028)	(0.039)	(0.181)	(0.150)
Total assets*innovation	−0.019	0.013	0.003	0.106	−0.088***
	(0.024)	(0.030)	(0.030)	(0.144)	(0.031)
Generalized residuals				−0.047***	−0.044***
				(0.017)	(0.017)
Generalized residuals*innovation				0.054**	0.045*
				(0.025)	(0.024)
Constant	1.638**	1.177		1.774***	1.751***
	(0.645)	(1.259)		(0.094)	(0.090)
N	1,025	1,025	1,014	1,025	1,025
Log-likelihood	2,725.901	2,931.688	2,668.931	1,958.284	1,953.753
Kleibergen–Paap LM statistic $\chi^2(1)$			18.132***		42.907***
Wald test on generalized residuals $\chi^2(2)$				8.04**	6.95**

Note. Fully robust standard errors for FE and FE-IV approaches and bootstrapped standard errors for the CF approaches are reported in parentheses. Trend variable is included in columns (1), (3), (4) and (5). Column (2) comprises firm-specific linear trend. Columns (4) and (5) include Mundlak's correction. All estimations comprise regional effects. The entire results for the reported regressions are available upon request.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

words, increasing variability drives the development of genetic material and new crop varieties and livestock breeds resistant to these changes. Development of new technologies to facilitate adaptation to climate changes are valuable and should be promoted (Zilberman *et al.*, 2018). On the other hand, an increase in the standard deviation of the maximum temperature during the spring season does not seem to stimulate innovation due to its lower variability compared to the other two climate variables, as shown in the descriptive statistics. In addition, the variability in maximum temperatures during spring may be less harmful due to use of greenhouses, stables, irrigation systems, resilient crops, etc. To summarize, in line with Su and Moaniba (2017) and

Miao (2020), our empirical results highlight that climate-induced innovation responds to changes in climate variables. Unlike Su and Moaniba (2017) who estimated the cause of climate change by measuring CO_2 emissions at the global scale, we provide a micro-level analysis capturing climate signals based on temperature and precipitation variation. Similarly, to Miao (2020), we find that firms respond to climatic variations by increasing innovation activities.

Table 5 provides the coefficient estimates of the operating revenues equation using three different estimation methods. First, columns (1), (2) and (3) report the FE (with and without firm-specific linear trend[9]) and FE-IV coefficient estimates of the operating revenues with respectively all outcome equation determinants treated as exogenous and *total assets* considered an endogenous regressor. Table 5 columns (4) and (5) allow for the endogeneity of innovation using a CF approach, and *total assets* is used respectively as an exogenous and endogenous regressor. Note that regressions (3), (4) and (5) in Table 5 are second step estimations of regressions (1), (2) and (3) in Table 4. All regressions reported in Table 5 include full sets of regional dummies and trend variables and the interactions with the selection indicator to account for whether the firm patents or not. Regressions (4) and (5) include generalized residuals, time-averaging covariates and their interactions with the innovation dummy.[10]

We observe substantial homogeneity in the parameter estimates across different methods and specifications except for the interaction terms. In the CF approach compared to the estimation methods in columns (1), (2) and (3), the interaction terms change signs although they are mostly not significant. This means that the difference between the coefficients in the two regimes is not statistically significant. Recalling Equation (2), since the outcome equation is a linear combination of the operating revenues of the two regimes the coefficients cannot be interpreted in the same way as in a standard regression. On the one hand, the coefficient vector of the interaction terms $\gamma_1$is equal to $(\beta_1 - \beta_0)$, the difference between the coefficients in the two regimes β_1 that relates to innovating firms. On the other hand, the vector of the coefficients β_0 corresponds to non-innovating firms.

In line with the accounting literature, we find that if firms do not innovate, material and employment costs as well as total assets have a positive and significant effect on operating revenues. The difference between $\beta_1 - \beta_0$ i.e. the coefficient vector of the interaction terms is not statistically significant, which implies that the impact of the accounting explanatory variables on operating revenues is essentially the same for innovative and non-innovative firms. Regardless of whether the firm is innovative, those firms that hire more employees or increase their wage costs and those firms that increase their material costs are predicted to achieve better performance.

The exception is the interaction coefficient of *total assets* in model (5). The negative sign of γ_{13} (-0.088) reduces the magnitude of β_{03} (0.154) to obtain

9 As robustness check, we introduced firm-specific linear trend in the FE model to relax the assumption of a common time trend.

10 For space reasons, the last two sets of variables are not reported in Table 4 but are available on request.

β_{13} (0.066). In other words, the effect of increasing assets (increasing firm size) on operating revenues is lower for innovating compared to non-innovating firms. This result is in line with decreasing marginal productivity theory. Asan innovating firm employs more *assets,* the extra revenue from one extra unit of this input becomes smaller. It is likely that in innovative firms the level of total assets is higher than in non-innovative firms. This is because *total assets* also includes intangible assets (i.e. patents) and generally defines larger firms with a higher capability to innovate.

Interpretation of the results for the dummy variable *innovation* is not straightforward. As stated in Section 2.2, there are two different intercepts in the two regimes (β_{00} and $\beta_{10} = \beta_{00} + \gamma_{00}$). Focusing on model (5), we observe that the innovation dummy coefficient γ_{00} is not statistically significant. This means that the coefficients of the constant term in the two regimes β_{00} (1.751) and β_{10} (1.713) are not statistically different.

In models (4) and (5), the generalized residuals computed after the first-stage estimation are statistically significant at the conventional level of significance. This confirms the endogeneity of the innovation decision in the operating revenue equation. The endogeneity of switching from innovating to non-innovating is tested and verified using a Wald test (last row in Table 5). Under the assumption of endogeneity of the *total assets* regressor, we run a Kleibergen–Paap under-identification test (last panel in Table 5). Rejection of the null hypothesis indicates that the matrix is full column rank and thus the model is identified. Overall, we can conclude that the CF approach provides the most plausible regression results under the assumption of endogeneity in the innovation decision and the *total assets* regressor.

Starting from Table 5 specification (5), we compute the ATET to assess the effect of innovation on firm performance. Table 6 presents the actual (column A) and counterfactual (column B) operating revenues on treated firm (companies that are effective innovators). Column A reports the actual expected outcomes observed in the data for innovating firms, and column B provides the counterfactual expected values i.e. the operating revenues of those firms that innovate if they had decided to not innovate. The results are presented in the three panels. First, the ATET is computed by distinguishing between the northern and the southern parts of Europe. Second, the impact on innovating firm's operating revenues is reported based on the four NACE Rev. 2 sub-sectors in section A. Finally, the last panel presents the overall impact of innovation. Unlike the mean difference in operating revenues between innovating and non-innovating firms presented in Table 2, the ATET estimates allow for systematic difference between the two kinds of firms by accounting for selection bias.

The results confirm that there are significant differences in firm operating revenues depending on whether the firm innovates or not (last row in Table 6). The impact is positive in the CF model specification where total assets is endogenous. The operating revenues are on average 8 percentage points higher

Table 6. Impact of innovation on operating revenues (CF model with total asset endogenous)

	Actual outcome (operating revenue if a firm innovates)	Counterfactual outcome (operating revenue if a firm does not innovate)	ATET	*P*-values	Percentage
	A	*B*	*C* = *A*-*B*		
Northern EU countries	1,308,093	1,209,998	98,095	(0.005)	8
Southern EU countries	148,339	139,143	9,196	(0.000)	7
Agriculture	144,579	135,643	8,937	(0.000)	7
Forestry	3,323,020	3,073,858	249,162	(0.004)	8
Animals breeding and hunting	121,733	112,905	8,828	(0.000)	8
Aquaculture and fishing	87,325	78,007	9,318	(0.079)	12
Overall	406,062	377,111	28,952	(0.000)	8

Note: All values are expressed in constant 2010 Euros. The standard errors are corrected using bootstrapping to account for first-stage estimation. *P*-values in parenthesis.

with innovation. Based on studies of the lagged effect of patents (Griliches, Hall and Pakes, 1991; Ernst, 2001; Yin, Zheng and Chen, 2015; Huang, Wu and Tsai, 2016), this percentage is supposed to increase in the subsequent 2–4 years as a consequence of the hysteric period hypothesis. This hypothesis is related to the time lag needed by patents to affect the firm's economic performance.

Our results suggest also that the economic impact of innovation is higher in the northern compared to the southern European countries (8 versus 7 percentage points). Based on this finding, firms in the agricultural sector and located in the South of Europe might experience lower returns to innovation due, for example, to the social and institutional frameworks (Chhetri *et al.*, 2012; Rodima-Taylor, Olwig and Chhetri, 2012; Massard and Autant-Bernard, 2018) amongst other aspects. Thus, they should be better supported to make climate change adaptations through targeted fiscal policies such as tax allowances and incentives for R&D investment and improvements to the local infrastructures. Innovation in the southern and Mediterranean areas should receive special support (Goubanova and Li, 2007; Rodriguez Diaz *et al.*, 2007; IPCC, 2014). This is an important issue since these areas are likely to experience higher average temperature increases during hot seasons that will intensify already existing drought problems with implications for the feed industry and food security of Europe. Finally, comparing the results between the four sub-sectors it emerges that the causal effect of innovation on the aquaculture and fishing sub-sectors is to increase operating revenues by 12 per cent, suggesting a higher performance margin compared to the other sub-sectors in relation to climate-related patents. In the last 40 years, aquaculture has experienced the most rapid growth rates in the world among agricultural production systems (FAO, 2020). In aquaculture, continuous innovation has played a significant role although its ecological and social sustainability have been criticized and pose new challenges for future innovation processes.

3.1. Number of patents

If we examine the innovation regime further, we see that the probability of the firm owning one patent can differ from the probability of owning two or more patents. This is because the firms' experience and the know-how gained from producing one patent may increase innovation capacity and favour production of more patents. We use the number of patents as an ordinal variable and run an ordered probit model. Compared to Poisson regression used in the count models, this has the advantage of relaxing the underlying assumption that all events have the same probability of occurrence (Wollni, Lee and Thies, 2010). We classify patents in six number categories where the sixth category is more than five patents. Tables 7 and 8 report the results of the CRE ordered probit model with total assets, respectively, exogenous and endogenous. As expected, the signs and significance of the coefficients confirm the probit results reported in Table 4. With the exception of the 2-year lagged SD of maximum spring temperature, the weather variables have a positive and significant effect on increasing the number of patents. However, the marginal probabilities vary across the dependent ordinal variable categories, with the highest impact for firms that own one patent. For example, the increase of 1 per cent in the SD of summer precipitation raises the marginal probability of producing one patent by 0.95 per cent. This probability is halved as the number of patents increases (Tables 7 and 8).

4. Concluding remarks

Less stable weather due to climate variability increases the risk of negative effects on the economy and society. This calls for adaptation measures especially in climate-sensitive regions and sectors where productivity is strictly linked to the status of the natural resources such as land, soil and water. While the effect of climate variability on agricultural systems has been explored widely, we have a poor understanding of how climate-induced innovations have evolved in response to climate drivers and the implications for firm performance. This paper contributes by investigating the impact of climate variability on the development of climate change adaptation technical knowledge captured by patents and the impact of these patents on firm productivity. We focus on the interactions between climate variability and innovation capabilities conceived as the firm adaptation strategy. To capture differences across EU regions and trends over time, the analysis uses unbalanced panel at the firm level. To avoid potential selection bias affecting the innovation choice, unobserved heterogeneity affecting firm performance and the endogenous explanatory variable problem, we use a CF approach.

Table 7. Coefficient estimates and marginal effects of the CRE ordered probit model—Total asset as an exogenous variable

		Marginal effects					
	Coefficients	Pr(P =0|Z)	Pr(P =1|Z)	Pr (P =2|Z)	Pr(P =3|Z)	Pr(P =4|Z)	Pr(P =5|Z)
Total assets	−0.732 (1.314)	0.1172	−0.0409	−0.0256	−0.0104	−0.0120	−0.0282
Material costs	0.272 (0.636)	−0.0436	0.0152	0.0095	0.0039	0.0045	0.0105
Employment costs	−0.199 (1.074)	0.0319	−0.0111	−0.0070	−0.0028	−0.0033	−0.0077
Two-year lagged SD of summer precipitation	0.169** (0.071)	−0.0271	0.0095	0.0059	0.0024	0.0028	0.0065
Two-year lagged SD of spring maximum temperature	−1.174*** (0.231)	0.1879	−0.0656	−0.0411	−0.0167	−0.0193	−0.0453
Two-year lagged SD of spring minimum temperature	0.370 (0.692)	−0.0592	0.0207	0.0130	0.0053	0.0061	0.0143
Two-year lagged SD of winter minimum temperature	0.201*** (0.064)	−0.0321	0.0112	0.0070	0.0028	0.0033	0.0077
Two-year lagged SD of summer maximum temperature	1.142** (0.558)	−0.1829	0.0638	0.0400	0.0162	0.0188	0.0441
cut1	9.751 (14.889)						
cut2	10.084 (14.900)						
cut3	10.355 (14.905)						
cut4	10.493 (14.913)						
cut5	10.695 (14.912)						
N	1028						

Note: Robust standard errors in parentheses.
$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 8. Coefficient estimates and marginal effects of the CRE ordered probit model—Total asset as an endogenous variable

		Marginal effects					
	Coefficients	Pr(P = 0|Z)	Pr(P = 1|Z)	Pr(P = 2|Z)	Pr(P = 3|Z)	Pr(P = 4|Z)	Pr(P = 5|Z)
Total assets	0.202 (0.615)	−0.0323	0.0112	0.0071	0.0029	0.0033	0.0078
Material costs	−0.349 (0.917)	0.0559	−0.0194	−0.0122	−0.0050	−0.0058	−0.0135
Employment costs	−0.678 (0.849)	0.1086	−0.0377	−0.0237	−0.0096	−0.0112	−0.0263
Two-year lagged SD of summer precipitation	0.170** (0.071)	−0.0272	0.0095	0.0059	0.0024	0.0028	0.0066
Two-year lagged SD of spring maximum temperature	−1.172*** (0.230)	0.1878	−0.0653	−0.0410	−0.0167	−0.0193	−0.0454
Two-year lagged SD of spring minimum temperature	0.361 (0.693)	−0.0579	0.0201	0.0127	0.0051	0.0060	0.0140
Two-year lagged SD of winter minimum temperature	0.204*** (0.064)	−0.0327	0.0114	0.0071	0.0029	0.0034	0.0079
Two-year lagged SD of summer maximum temperature	1.147** (0.559)	−0.1837	0.0638	0.0401	0.0163	0.0189	0.0444
cut1	10.367 (14.871)						
cut2	10.699 (14.882)						
cut3	10.970 (14.888)						
cut4	11.109 (14.894)						
cut5	11.311 (14.893)						
n	1,028						

Note: Robust standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results of our analysis are summarized as follows. First, the climate variables have a statistically significant impact on the probability that the firm will innovate to avoid the threats brought by climate change. This adds to the empirical evidence on whether and how climate adaptation innovations respond to climate variability. Higher variability in minimum temperatures during the winter season and precipitation and maximum temperatures during the summer season stimulate climate adaptation innovations. Appropriate technologies enable European countries to adapt their agroforestry, aquaculture and breeding systems to the changing climate. However, it also depends on parallel policy and institutional innovations and the transfer and diffusion of innovation across Europe as a function of the differences in climate zones. The European Common Agriculture policy for 2021–2027 has an adaptation strategy as a clear object that should encourage member states to increase their investment in creating and adopting adaptation measures (European Environmental Agency, 2019).

Second, including the generalized residuals in the outcome equation and the endogeneity of the explanatory variable, our findings suggest that the impact of the accounting explanatory variables on operating revenues is positive and mostly the same for innovative as well as non-innovative firms.

The exception is *total assets* that proxies for the firm size where the effect of increased assets on operating revenues is lower for innovating compared to non-innovating firms due to the fact that the former are usually larger than the latter firms. Third, the ATET confirms that innovating companies gain from innovation in terms of operating revenue compared to the counterfactual outcome. More specifically, the choice to innovate translates into a positive effect on firm performance. This effect is greater if the firm is located in a northern European country and operates in the aquaculture and fishing sub-sector. Although the overall ATET may seem unremarkable (8 per cent), it should be borne in mind that these results are restricted only to the effect of climate adaptation innovations.

The main implication from our study is that although climate change leads to increased costs for the society, facing this challenge through the development of new technical knowledge leads to improved economic performance. From a societal perspective, investment in knowledge creation to adapt to climate variability can have positive externalities and compensate for the initial cost associated with the consequences of climate change. This aspect should be considered in the aftermath of the economic benefits and costs of such disruption. Further research from different perspectives is required to confirm this finding. A possible extension of the present study would be to quantify the economic benefits of adaptation innovation at the aggregate level and estimate the value of the positive knowledge externalities.

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Appendix A

Following Murtazashvili and Wooldridge (2016), we model the innovation decision by observing two different outcomes with different coefficients across the different regimes, as in the counterfactual framework:

$$
\begin{aligned}
y_{it1} &= (1 - y_{it3})\, y_{it1}^{(0)} + y_{it3} y_{it1}^{(1)} \\
y_{it1}^{(0)} &= x_{it}\beta_0 + c_{i0} + u_{it0} \\
y_{it1}^{(1)} &= x_{it}\beta_1 + c_{i1} + u_{it1} \\
&\forall\, i = 1, \ldots, N \,\text{and}\, t = 1, \ldots, T
\end{aligned} \tag{A1}
$$

where $y_{it1}^{(0)}$ and $y_{it1}^{(1)}$ represent the outcomes in the two regimes for the ith firm in year t, and y_{it3} is the endogenous switching indicator. The vector of the explanatory variables x_{it} includes an intercept, a set of time dummies or a time trend, some continuous endogenous explanatory variables (EEVs) defined y_{it2} and some exogenous explanatory variables defined z_{it1}. The time-constant individual-specific unobserved effects in both regimes are c_{i0} and c_{i1}. Finally, u_{it0} and u_{it1} are the idiosyncratic errors in both regimes that are strictly independent of the exogenous explanatory variables z_{it1}.

A panel switching regression model with constant coefficients linearly combines the two regimes (0 and 1) and can be written as follows:

$$
\begin{aligned}
y_{it1} = {} & x_{it}\beta_0 + y_{it3}x_{it}\gamma_1 + c_{i0} + y_{it3}\left(c_{i1} - c_{i0}\right) + u_{it0} + y_{it3}\left(u_{it1} - u_{it0}\right) \\
& \forall\, i = 1, \ldots, N \text{ and } t = 1, \ldots, T
\end{aligned} \tag{A2}
$$

where y_{it1} represents the outcome of interest as a linear combination of the two regimes. The endogenous switching variable on which sample selection is based interacts with both the time-constant and time-varying unobservables. γ_1 is the difference between the coefficients of x_{it} in the two regimes i.e. $(\beta_1 - \beta_0)$.

Since the parameters of interest are β_0 and γ_1, the correlation between individual-specific unobserved effects and the strictly exogenous variables is allowed by applying the Mundlak (1978) devices. Including Mundlak's assumption of unobserved heterogeneity linearly related to the mean of the exogenous variables over time, the switching regression model with constant coefficients can be re-written as follows:

$$
y_{it1} = x_{it}\beta_0 + y_{it3}x_{it}\gamma_1 + \underline{z}_i\rho_0 + y_{it3}\underline{z}_i\rho_1 + r_{it0} + y_{it3}r_{it1} \forall\, i = 1, \ldots, N \,\text{and}\, t = 1, \ldots, T \tag{A3}
$$

where the Mundlak devices $\underline{z}_i$ are the mean of the exogenous variables $\underline{z}_i = T^{-1}\sum_{t=1}^{T} z_{it}$, r_{it0} and r_{it1} and include the idiosyncratic errors of the Mundlak relationship and the errors of the outcome equation and are assumed to be independent of the exogenous variables. The parameters to be estimated are ρ_0 and ρ_1.

Using Mundlak's (1978) version of Chamberlain's binary response CREs model, we obtain the following selection equation:

$$
y_{it3} = 1\left[k_{t3} + z_{it}\pi_3 + \underline{z}_i\delta_3 + v_{it} > 0\right], v_{it} \sim N[0,1] \forall\, i = 1, \ldots, N \,\text{and}\, t = 1, \ldots, T \tag{A4}
$$

where the vector z_{it} contains all the exogenous variables. This implies that z_{it} includes the exogenous variables of the outcome equation z_{it1}, any instrumental variables that might be affecting the endogenous input y_{it2} and the selection variable y_{it3}. The time-specific intercepts are represented by as is usual in panel data applications. Finally, v_{it} is the usual error term and is normally distributed with zero mean and variance equal to 1.

Under these assumptions, the conditional expectation of the Mundlak–Chamberlain CREs model can be written as a generalized residual function $(h(.))$ (Vella, 1998):

$$E(v_{it}|y_{it3}, z_i) = h\left(y_{it3}, k_{t3} + z_{it}\pi_3 + \underline{z}_i\delta_3\right) = y_{it3}\lambda\left(k_{t3} + z_{it}\pi_3 + \underline{z}_i\delta_3\right) - (1 - y_{it3})\lambda\left(-k_{t3} - z_{it}\pi_3 - \underline{z}_i\delta_3\right) \quad \forall\, i = 1, \ldots, N \text{ and } t = 1, \ldots, T \tag{A5}$$

where $\lambda(.)$ is the inverse Mills ratio. As underlined by Vella (1998), this term has two important characteristics: (i) zero mean and (ii) no correlation with the explanatory variables of the probit model.

Assuming r_{it0} and r_{it1} the unobservable error terms in Equation (3) as a linear function and combining the estimated generalized residual function (5) with the outcome Equation (3), we obtain the final and complete outcome equation:

$$y_{it1} = x_{it}\beta_0 + y_{it3}x_{it}\gamma_1 + \underline{z}_i\rho_0 + y_{it3}\underline{z}_i\rho_1 + \xi_0\hat{h}_{it3} + \xi_1 y_{it3}\hat{h}_{it3} + a_{it}$$
$$\text{with } E(a_{it}|y_{it3}, z_{it}) = 0\ \forall\, i = 1, \ldots, N \text{ and } t = 1, \ldots, T \tag{A6}$$

where $\hat{h}_{it3}$ is the generalized residuals that account for the endogeneity of the selection variable and x_{it} incorporates the continuous EEV. Equation (6) is then estimated by applying an instrumental variables method for panel data. In this stage, since the estimated generalized residuals are included, the standard error must be adjusted using the bootstrap procedure. The exception is if the switching model is exogenous. This means that the joint significance of the parameters ξ_0 and ξ_1 should be tested using a Wald test.

Appendix B

Table B1. Test on the validity of the selection instruments

	Operating revenue by firms that did not innovate—total asset exogenous	Operating revenue by firms that did not innovate—total asset endogenous
Material costs	0.520***	0.505***
	(0.064)	(0.066)
Employment costs	0.291***	0.274***
	(0.068)	(0.064)
Total assets	0.108 *	0.151***
	(0.059)	(0.013)
Two-year lagged SD of summer precipitation	0.000	0.000
	(0.002)	(0.002)
Two-year lagged SD of spring maximum temperature	−0.007	−0.007
	(0.006)	(0.006)
Two-year lagged SD of spring minimum temperature	0.015	0.015
	(0.015)	(0.015)
Two-year lagged SD of winter minimum temperature	−0.002	−0.001
	(0.002)	(0.002)
Two-year lagged SD of summer maximum temperature	−0.005	−0.005
	(0.013)	(0.013)
Constant	1.697***	1.680***
	(0.090)	(0.087)
N	917	917
Log-likelihood	1,749.421	1,746.868
Wald test on instrumental variables (F-statistic(5)/χ^2(5))	0.60	2.69

Note: Robust standard errors in parentheses. Mundlak's correction and dummy years are included.
$^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.