Innovation and Weather Change Adaptation: A Panel Endogenous Switching Regression Analysis

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Abstract.

Technological advancement is among the most frequently advocated strategy for adapting agriculture to possible future changes in climate. However, the actual process of innovation in the context of adaptation to climate change in the agriculture sector has received little explicit consideration. A panel endogenous switching regression modelis applied to estimate the relation between climate change and innovation and the temporal and geographical variability of related revenues in European countries, using disaggregated results at firm level. Our findings confirm that innovation enhances firms' performance and we find that the greatest effect appears to be generated when innovating firms belong to the Northern European countries and when firms issue patents in the agricultural classification of European Patent Office.

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1. Introduction

Over the coming decades several countries and regions around the world will confront both opportunities and challenges deriving from the transition towards low-emission, sustainable societies. Policy makers and scholars concur that this transformation revolves greatly around whether environmentally sound technologies are developed and adopted in production and distribution systems, undermined by climate change effects (Jaffe et al., 2005; Popp et al., 2010; Ahman et al., 2018).

Recent evidence suggests that the increasing variability of meteo-climatic parameters and frequency of extreme weather events will likely raise the incidence of environmental disasters (IPCC 2014), lead to depletion of agricultural resources, and endanger global food supply (Stevanovic et al., 2016; EEA, 2019).

The global phenomenon of climate change (CC) shows marked local consequences that manifest themselves in heterogeneous ways across regions and sectors (IPCC 2014). The economic and social systems will be affected differently by climate change, and also, they will adapt differently as a result of their heterogeneity (Zilberman et al., 2018). The agriculture sector is expected to suffer the most from the negative effects of CC: projected impacts represent a serious threat to crop production and to the sustainability of the agricultural system (IPCC, 2014; EEA, 2019). In2018, European agriculture experienced a temperature that was amongst the three warmest years on record. The length of growing season, flowering, and harvest are already largely affected by CC and the number of warm days[1] have doubled between 1960 and 2018 (EEA, 2019). The effects on European production by 2050 are to be characterized by important regional differences (ECONADPT, 2016).Production and productivity in Northern Europe might increase due to a lengthening of the growing season and to an extension of the frost-free period. Conversely, southern European countries will likely observe a productivity reduction (EEA, 2019), induced by extreme temperature and by lower precipitation and water availability, which will intensify problems of droughts, especially in the Mediterranean region (Goubanova and Li, 2006; Rodriguez Diaz et al., 2007; IPCC 2014).Space-varying climate effects will translate into different climate response as a function of dissimilar adaptive capacity (Vanschoenwinkelaet al., 2016).

Facing CC threatsimpliesacknowledging the pivotal role that environmental technological innovation may play, that is, enabling sufficient adaptation to alleviate most of the negative consequences of CC, or prevent them altogether. Nevertheless, the deployment of technologies and the extent to which they

[1]Warm days are those exceeding the 90th percentile threshold of a baseline period.

affect economic performances is highly idiosyncratic.Developing and adopting climate-related or climate-induced innovation is not merely a matter of facing the weather and climate threats; it may bring about economic opportunities as well (EEA, 2019).

Focusing on the European agricultural sector during 2007-2015, the aim of the present study is to explore the relation between weather variability and firms' economic performance thought the development of innovative capabilities. The latter are captured using data on agricultural patents and biotech innovations, which are claimed to play an importantrole in climate change adaptation, other than mitigation (James 2013). We work with NUT2 level data to account for differences across Europein terms of climate change effects (Iglesias et al., 2009) and adoption of adaptation strategies (Niles et al., 2015) – as innovative capability – under different climate change conditions.

Our paper draws from two literature streams. First, we rely on those studies that investigate whether and to what extent environmental/climatic conditions affect innovation. Therein, the so-called *induced innovation* hypothesis has been explored extensively from different perspectives (for an overview of these studies see Popp et al., 2010). It posits that innovation is affected by the change in the relative price of production factors: i.e. it is introduced to reduce the usage of those factors that become more expensive (Hicks, 1932). This hypothesis provided a solid background for several studies that, for example, explore the impact of energy prices and environmental regulation on the development of green technologies (see e.g. Newell et al., 1999; Popp, 2002; Barbieri, 2015).As CC manifests itself, whether and to what extent climate contingences affect innovation is paramount to understanding the effectiveness of climate adaptation strategies, especially in the agriculture sector (Rodima-Taylor et al., 2012). However, while the research community has devoted some efforts to analyze how innovation contributes to alleviating climate-change impacts, less obvious remains the debate on how climate-induced innovations have responded to climate and weather variability (Su and Moaniba, 2017) as a means of adaptation strategy. A reason explaining this gap may found on the inherent difficulty in testing the role of climate as a stimulant for technological innovation (Abler, et al., 2000). However, some insights suggest that technological innovation strongly responds to climate change (Su and Moaniba, 2017) and that the changing climate induces adaptive capacity, which involves the development and diffusion of innovation both in developed (Smithers and Blay-Palmer, 2001) as well as developing countries (Chhetri and Easterling, 2010). Indeed, innovation allows dealing with the heterogeneous and uncertain impacts of climate and weather change and can complement different forms of adaptation (Zilberman et al., 2018).

In analyzing whether innovation affects firms' performance, the second stream of work on which the present paper relies relates to studies that investigate the economic effects of environmental innovation (see e.g. Barbieri et al., 2016 for a review). The variability of findings retrieved in this literature suggests that the assessment of economic benefits arising from the development and adoption of green innovation is a difficult task. The absence of clear-cut evidence is mainly due to the sector involved, how innovation is measured (e.g. patents, innovation surveys, R&D expenditures), the performance measure (e.g. financial data, employment) or the empirical approaches employed. Overall, we can observe that the creation and diffusion of technical knowledge seems to give rise to win-win situations (Porter and Van der Linde, 1995). That is, environmental innovation favours the reduction of environmentally harmful behaviours and, at the same time, improves trade performance through new markets creation (Duchin et al., 1995), leads to a positive net employment effects (Horbach, 2010; Horbach and Rennings, 2013) and enhances firms' profitability (Rexhäuser and Rammer, 2014; Gagliardi et al., 2016; Leonciniet al., 2018).

As far as agricultural innovation is concerned, the majority of the studies focuses on the effects of agricultural research and development expenditure on productivity at the macro level (Alston et al., 2009; Alston, 2010; Alston et al., 2010; Pardeyet al. 2010;Fuglie, 2012). While some studies focus primarily on innovation within the agri-food sector (Materia et al. 2017; Ghazalian, and Fakih, 2017, Harvey et al., 2017), merely few studies indeed analyze the direct effect of innovation on profit or economic sustainability at the farm level (Karafillis and Papanagiotou, 2011 and Läpple and Thorne, 2019).

Our paper contributes to the present literature by merging these two streams to shed light on the role of technological innovation in the handling of climatic and weather risks and the interaction between the effects of climate and weather variability and innovation capabilities, as firms' adaptation strategy. It contributes to the current debate on innovation in agriculture by offering both an investigation at micro level (firms), as well as by providing regional results to capture differences across the EU geographical extension.

To emphasize the role of agricultural innovation as a firm's adaptation strategy and its impact on firms' outcome, as in Murtazashvili and Wooldridge(2016) we apply a panel endogenous switching regression model with two sources of endogeneity. Since firms who choose to innovate might be different from those who choose not to innovate, the presence of firm unobserved heterogeneity that influences innovation decision represents the main estimation issue. Thus, this unobserved heterogeneity creates selection bias as some firms are more likely to innovate than the other firms. Moreover, as in our analysis some explanatory variables such as inputs of firms' production function might be endogenous. To address self-selection issue and endogenous regressors we applied a control function approach which consists of two stages. In the first stage, a pooled probit is estimated and in the second stage a 2SLS model is implemented adding generalized residuals to account for the endogeneity of the selection variable. In both stages, Mundlak devices (1978) are introduced to combine fixed-effects with random effects estimation approaches.

Our findings confirm that innovation enhances firms' performance and we find that the greatest effect appears to be generated when innovating firms belong to the Northern European countries and when firms issue patents in the agricultural classification of European Patent Office.

The following sections of the article are organized as follows. Section 2 illustrates both the data used (2.1) and the conceptual framework (2.2). Section 3 presents the results while section 4 concludes.

2. Data and methods

2.1 Data

The analysis is based on three main sources of data. The ORBIS database, issued by Bureau van Dijk, provides financial, ownership and legal form information on firms around the world for all the sectors of activities. The Worldwide Patent Statistical Database (PATSTAT), collected by the European Patent Office (EPO), supplies information on all the patents filed across European countries. Finally, the MARS Crop Yield Forecasting System (MCYFS) database by the Joint Research Centre of the European Commission, offered climate-related data. Details on the variables use and elaborations required to reach the objective of this research are provided below for each data source.

Patents and accounting data

The ORBIS dataset provides financial and accountancy data on firms placed in Belgium, Denmark, Finland, Spain, Italy, Greece, France, Germany, UK, Ireland, Portugal, Sweden and the Netherlands. Data are collected yearly 2007-2017and includes 143 firms within the "Agriculture, forestry and fishing" sector (Section A - NACE Rev. 2), i.e., the industry which we focus on. From the PATSTAT dataset, the number of total and agricultural patents are selected.We use patents as a convenient indicator of innovation for presenting the evolution of inventive capabilities in adaptation-related agriculture and food technology over time. Patent counts are indicative of the level of innovative activity itself and not only a measure of innovative output (Popp, 2005).

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

For the scope of our study, from the PATSTAT and the ORBIS databases we analyzed descriptive statistics of major economic financial and accountancy data avoiding the inclusion of variables showing important missing information. Operating revenue, material and employment costs, total assets and shareholders' funds are balance sheets items used for both non-innovative and innovative firms. Table 1 shows that innovative firms present higher operating revenues and a larger size measured by total assets. Potentially these firms seem more incline to hire high-skilled workers and toinvestin the firm itself (higher employment and material costs). Therefore, this evidence does not clearly signal a potential relation between climate-related innovation (adaptation) and firm's performance, but requires additional investigation and the application of methods able to account for endogeneity and selection problems to the aim of disentangling the effect of innovation on performance.

Table 1. Summary statistics. Innovative and non-innovative firms

	Mean	p50	sd	min	max	N
Non-innovative firms (0 patents declared)						
Operating revenue	11.515	11.409	0.376	11.376	15.943	655
Materialcosts	10.618	10.494	0.396	10.395	15.307	655

Employmentcosts	9.497	9.390	0.355	9.343	13.996	655
Total assets	11.220	11.043	0.573	10.983	15.920	655
Shareholder' funds	10.433	10.241	0.607	9.719	14.819	655
Innovative firms (patents declared>= 1)						
Operating revenue	11.861	11.440	0.962	11.377	15.744	178
Materialcosts	10.947	10.516	1.000	10.469	15.099	178
Employmentcosts	9.867	9.429	0.968	9.343	13.738	178
Total assets	11.634	11.078	1.185	10.983	15.777	178
Shareholder' funds	10.827	10.282	1.159	10.188	14.661	178
Total						
Operating revenue	11.589	11.413	0.573	11.376	15.943	833
Materialcosts	10.689	10.497	0.595	10.395	15.307	833
Employmentcosts	9.576	9.392	0.567	9.343	13.996	833
Total assets	11.308	11.046	0.765	10.983	15.920	833
Shareholder' funds	10.517	10.246	0.776	9.719	14.819	833

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

Climate data

Observed monthly precipitation cumulates as well as monthly averages of minimum, maximum and mean daily air temperatures were obtained from the MARS Crop Yield Forecasting System (MCYFS) database, established and maintained by the Joint Research Centre of the European Commission for the purpose of crop growth monitoring and forecasting (Biavetti et al. 2014). In short, daily meteorological data are obtained from around 4200 weather stations, quality controlled, gap-filled and interpolated into a regular 25x25 km grid over Europe and neighboring countries. Daily interpolated meteorological data is available since 1975 up to near-real time. For the purpose of this study, the daily gridded climatic data between 2000 and 2017 have been first used to calculated gridded monthly averages (in case of temperature) and cumulates (in case of precipitation), which were then spatially aggregated over arable land for each NUTS2 administrative level. Resulting variables were used at seasonal resolution, where season is defined by the climatological classification, e.g. winter is December, January and February. In particular, following the literature on seasonality (Mendelsohn et al. 1994; Van Passelet al., 2017) we use backward-looking rolling means of differences in minimum and maximum temperatures and precipitations (Henderson et al. 2017;Woodill and Roberts, 2018), which are assumed to affect firms' probability to innovate.Table 2 presents main climate-related statistics where the rolling mean window is calculated over a period of 5 years.

Table 2. Summary statistics
Climatic variables expressed in mm (precipitation) and °C (temperature)

Variable	Mean	p50	sd	min	max	N
Precipitation during spring season (rolling mean window over 5 years)	18.972	13.832	13.212	3.517	57.749	833
Maximum temperature during summer season (rolling mean window over 5 years)	25.989	27.202	4.101	18.015	32.276	833
Minimum temperature during spring season (rolling mean window over 5 years)	9.701	10.321	2.886	3.459	14.346	833

2.2 Conceptual and Empirical framework

Theoretical Model

Since innovation may be considered as an improvement over past technologies and techniques used in terms of efficiency (resources used over results obtained) and effectiveness (objective over results), the choice of innovating depends mainly on firms' ability and motivation and on the higher values of firms' outcome after technology innovation (Läpple and Thorne, 2019). As a consequence, firms who choose to innovate may be different from those who choose not to innovate. Comparing the outcomes of these two different kinds of firms, whether or not exposed to the treatment, represents the main object of the program evaluation literature (see for a comprehensive literature review Imbens and Wooldridge, 2009).

Firms' ability and motivation as well as technology innovation impacts should be evaluated controlling for potential selection bias and unobserved heterogeneity. Since these firms' characteristics are not fully (if at all) observable, they may cause endogeneity issues (Lapple and Thorne, 2019). When the unobserved heterogeneity linked to the selection process is time-invariant, a panel estimator without using instrumental variables can be applied; while whenever time-varying unobserved heterogeneity is present in the selection process, self-selection or endogeneity models are needed. The presence of time-varying unobserved heterogeneity in the innovation choice of an agricultural firm implies that standard regression techniques are biased, and an endogenous switching regression model should be estimated (Wooldridge, 2010; Kassie, et al. 2018).

In the endogenous switching regression model, the innovation decision is modeled on the basis of firm-level characteristics and climatic indicators and subsequently the relationship between the variable of interest (i.e. operating revenue) and a set of explanatory variables may vary across the two discrete regimes (i.e., innovators and non-innovators firms). More specifically, in the first stage, a self-selection equation is estimated applying a binary variable estimator and in the second stage, the outcome equation conditional on the treatment (i.e. innovation decision) is modeled using a standard estimator (see among others Fuglie and Bosch, 1995; Alene and Manyong, 2007; Di Falco et al., 2011; Teklewold et al., (2013); Läpple et al., 2013; Abdulai and Huffman, 2014; Kassie et al., 2016). In the context of a firm's production function, the switching regression model allows the interaction between inputs and technology (i.e. the innovation) meaning that the effect of an innovative choice should be evident not only through the intercept of the outcome equation but also across the slope (Murtazashvili and Wooldridge, 2016; Kassie et al., 2018).

The two-stage switching regression model hence has the advantage of estimating separate regression equations for innovators and non-innovators as well as determining the counterfactual based on returns to characteristics of adopters and non-adopters. This means that even if the average values of these characteristics may be the same, they may have different impacts on outcome and innovation choice in terms of coefficient estimates (Wooldridge, 2010). Another advantage of the switching regression model over, for example, the propensity score matching model consists in overcoming the unconfoundedness assumption, which assumes that after controlling for observable characteristics, the selection variable i.e. innovation decision may be random and uncorrelated with the outcome variable. Actually, differences between innovators and non-innovators are systematic since selection is based on unobservable characteristics (Smith and Todd, 2005; Abdulai and Huffman, 2014).

Starting from the endogenous switching regression approach, first developed by Lee (1982), where selectivity is considered as an omitted variable problem (Heckman, 1979), we follow Murtazashvili and Wooldridge (2016)' model to allow for two sources of endogeneity: the selection variable and an endogenous explanatory variable. Following this extension, a two-stage switching regression model with endogenous switching and endogenous explanatory variables with constant coefficients for panel data is implemented. This methodology combines the Mundlak–Chamberlain approach to heterogeneity with control function methods for continuous and discrete endogenous variables.

More specifically, as in Murtazashvili and Wooldridge (2016), the procedure for estimating a control function model consists of two stages. In the first step, to take into account of the selection indicator a probit correlated random effects model is run. This aims to estimate the relationship between innovation choice and firm accounting items as well as environmental variables. In the second step, the selection bias is addressed by adding generalized residuals. When a continuous endogenous

explanatory variable is included in the outcome equation a two-stage least squares (2SLS) model is estimated. Otherwise when all the variables are exogenous an OLS estimation is applied.
Given that the innovation decision allows observing two different outcomes with different coefficients across the different regimes:

$$y_{it1}^{(0)} = x_{it1}\beta_0 + c_{i10} + u_{it10}$$
$$y_{it1}^{(1)} = x_{it1}\beta_1 + c_{i11} + u_{it11} \qquad \forall\ i = 1, \dots, N \text{ and } t = 1, \dots, T \qquad (1)$$

where $y_{it1}^{(0)}$ and $y_{it1}^{(1)}$ represent the outcomes in the two regimes for the *i-th* firm in year *t*, the vector of explanatory variables x_{it1} includes an intercept, a set of time dummies or a time trend, some continuous endogenous explanatory variables (EEVs) defined y_{it2}, as well as some exogenous explanatory variables defined z_{it1}. The time-constant individual-specific unobserved effects in both regimes are c_{i10} and c_{i11}. Finally, u_{it10} and u_{it11} are the idiosyncratic errors in both regimes which are strictly independent of the exogenous explanatory variables z_{it1}.
A panel data version of a switching regression model with constant coefficients which linearly combines the two regimes (0 and 1), as developed by Murtazashvili and Wooldridge (2016), can be written as:

$$y_{it1} = x_{it1}\beta_0 + y_{it3}x_{it1}\gamma_1 + c_{i10} + y_{it3}(c_{i11} - c_{i10}) + u_{it10} + y_{it3}(u_{it11} - u_{it10})$$
$$\forall\ i = 1, \dots, N \text{ and } t = 1, \dots, T \qquad (2)$$

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 of the coefficients of x_{it1} in the two regimes which means $(\beta_1 - \beta_0)$.
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 applying the Mundlak (1978) device. Including the Mundlak assumption of unobserved heterogeneity linearly related to the mean in time of the exogenous variables, the switching regression model with constant coefficients can be re-written as follows:

$$y_{it1} = x_{it1}\beta_0 + y_{it3}x_{it1}\gamma_1 + \bar{z}_i\rho_0 + y_{it3}\bar{z}_i\rho_1 + r_{it0} + y_{it3}r_{it1} \forall\ i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (3)$$

where the Mundlak devices$\bar{z}_i$ are the mean of the exogenous variables $\bar{z}_i = T^{-1}\sum_{t=1}^{T} z_{it}$, r_{it0} and r_{it1} are the idiosyncratic errors of the Mundlak relationship assumed to be independent of the exogenous variables and ρ_0 andρ_1 represent the parameters to be estimated.

Using the Mundlak (1978) version of Chamberlain's binary response correlated random effects model, we get the following selection equation:

$$y_{it3} = 1[k_{t3} + z_{it}\pi_3 + \bar{z}_i\delta_3 + v_{it} > 0],\ v_{it} \sim N[0,1] \forall\ i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (4)$$

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 may affect the endogenous input y_{it2} and the selection variable y_{it3}. k_{t3} represents the time-specific intercepts usually common in panel data applications. Finally, v_{it} is the usual error term normally distributed with zero mean and variance equals to one.

Under these assumptions, the conditional expectation of the Mundlak-Chamberlain correlated random effects model can be written as a generalized residual function $\left(h(.)\right)$ (Vella, 1998):

$$E(v_{it}|y_{it3}, z_i) = h(y_{it3}, k_{t3} + z_{it}\pi_3 + \bar{z}_i\delta_3) = y_3\lambda(k_{t3} + z_{it}\pi_3 + \bar{z}_i\delta_3) - (1 - y_3)\lambda(-k_{t3} - z_{it}\pi_3 - \bar{z}_i\delta_3) \forall\ i = 1, \dots, N \text{and } t = 1, \dots, T \quad (5)$$

where $\lambda(.)$ is the inverse Mills ratio function. 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 unobservables error term of equation (3) as a linear function and combining the estimated generalized residual function (5) with the outcome equation (3), we may obtain the final and complete outcome equation:

$$y_{it} = x_{it1}\beta_0 + y_{it3}x_{it1}\gamma_1 + \bar{z}_i\rho_0 + y_{it3}\bar{z}_i\rho_1 + \xi_0\hat{h}_{it3} + \xi_1 y_{it3}\hat{h}_{it3} + a_{it}$$

with $E(a_{it}|y_{it3}, z_{it}) = 0 \forall\ i = 1, \dots, N$ and $t = 1, \dots, T$ (6)

where $\hat{h}_{it3}$ is the generalized residuals which account for the endogeneity of the selection variable; and x_{it1} incorporates the continuous endogenous explanatory variable. Equation (6) is then estimated applying an instrumental variables method for panel data. In this stage, since the estimated generalized residuals are included, the standard error should be adjusted through the bootstrapping procedure. The only exception to this method arises when the switching model is exogenous. For this reason, the joint significance of the parameters $\xi_0$and ξ_1 should be tested by applying the Wald test.

Of significant interest is also the analysis of the impacts of innovation decision on operating revenues for the European agricultural firms. A counterfactual analysis should be carried on by first specifying the expected values of the outcomes in the two regimes. The endogenous switching regression model can be a useful methodology to compare the expected values of operating revenues of agricultural firms which innovate with respect to agricultural firms that do not innovate. Moreover, it allows investigating the counterfactual outcomes when the innovating agricultural firms do not innovate, and the non-innovating agricultural firms do innovate. Splitting equation (6) into the two regimes, we may generate the conditional actual and counterfactual expectation of operating revenues for the agricultural firms. The expected actual operating revenues of innovating firms and non-innovating firms observed in the sample may be computed respectively as:

$$E\left(y_{it1}^{(1)}|y_{it3}=1\right)=x_{it1}\beta_{11}+\bar{z}_i\rho_{11}+\xi_{11}\hat{h}_{it3} \tag{7}$$

$$E\left(y_{it1}^{(0)}|y_{it3}=0\right)=x_{it1}\beta_{00}+\bar{z}_i\rho_{00}+\xi_{00}\hat{h}_{it3} \tag{8}$$

The expected values of the counterfactual operating revenues of innovating firms had they chosen not to innovate (Eq. 11) and non-innovating firms had they chosen to innovate (Eq.12) are given as follows:

$$E\left(y_{it1}^{(1)}|y_{it3}=0\right)=x_{it1}\beta_{10}+\bar{z}_i\rho_{10}+\xi_{10}\hat{h}_{it3} \tag{9}$$

$$E\left(y_{it1}^{(0)}|y_{it3}=1\right)=x_{it1}\beta_{01}+\bar{z}_i\rho_{01}+\xi_{01}\hat{h}_{it3} \tag{10}$$

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

Following Heckman *et al*. (2001) and Imbens and Wooldridge (2009), we may calculate the average treatment effect on treated firms (ATET). In other words, we may assess the impact on the operating revenues of innovation choice on those firms that receive the treatment as the difference between the expected outcomes in both regimes for the treated agricultural firms. Combining equations (9) and (12), we obtain:

$$ATE = E\left(y_{it1}^{(1)} | y_{it3} = 1\right) - E\left(y_{it1}^{(0)} | y_{it3} = 1\right) = x_{it1}(\beta_1 - \beta_0) + \bar{z}_i(\rho_1 - \rho_0) + \hat{h}_{it3}(\xi_1 - \xi_0)$$

which represents the effect of an innovating behaviour induced by climate change on agricultural firms' operating revenues that actually choose to innovate. It is worth to note that if comparative advantage is at the basis of selection, then the choice of innovating would imply higher operating revenues (Abdulai and Huffman, 2014).

Empirical Specification

Previous empirical studies have analyzed the issue of technology adoption and its impacts on farms' outcomes as a strategy for adaptation to climate change (CC) in a cross-section context using an endogenous switching regression (Fuglie and Bosch, 1995; Alene and Manyong, 2007; Di Falco et al., 2011; Läpple et al., 2013; Abdulai and Huffman 2014; Kassie et al., 2018), a multinomial endogenous switching regression model (Di Falco and Veronesi 2013; Teklewold et al. 2013; Kassie et al., 2015) or a propensity score methodology (Kassie, et al. 2011; Läpple and Thorne 2019). However, none of these studies has considered the innovation behavior of an agricultural firm in a panel structure as a strategy for CC adaptation. Focusing on the capability of firms of issuing at least one patent, our analysis models innovation decision as a selection process, where the expected benefits drive agricultural firms' choices.

Whenever an agricultural firm has to decide whether or not to innovate, potential outcomes such as operating revenues are normally taken into consideration. Under the risk-neutral assumption, firms may choose to follow an innovative behavior if they may gain maximum operating revenues. In doing so, the output equation of the European agricultural firms should be represented as follows:

$$Operating\ revenues_{it} = \beta_0 + \beta_1 Material\ costs_{it} + \beta_2 Employment\ costs_{it} + \beta_3 Total\ assets_{it} + \gamma_1 Innovation_{it} + \gamma_2 Material\ costs_{it} * Innovation_{it} + \gamma_2 Employment\ costs_{it} * Innovation_{it} + \gamma_2 Total\ assets_{it} * Innovation_{it} + \bar{z}_i \rho_0 + Innovation_{it} \bar{z}_i \rho_1 + \xi_0 \hat{h}_{it} + \xi_1 Innovation_{it} \hat{h}_{it} + \delta_1 trend + \delta_2 D\_region + a_{it} \quad \text{with } E(a_{it} | Innovation_{it}, z_{it}) = 0 \forall\ i = 1, \dots, N \quad \text{and} \quad t = 1, \dots, T \tag{11}$$

where the main inputs of a 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* at agricultural firm level *i*. Since *Total assets* variable is a proxy of firm size, it might be endogenously determined (Gugler and Weigand, 2003; Coles *et al*., 2012). As a consequence, in our analysis *Total assets* variable is assumed first as an exogenous regressor and then the endogeneity issue is addressed. While in the former model, exogenous *Total assets* variable involves a pooled OLS estimation, in the latter, tangible and intangible assets as inputs of a firm's production function are instrumented by *Shareholders' funds* variable in the pooled instrumental variable (IV) estimation[2].

As described above, the Mundlak devices $(\bar{z}_i)$ and the generalized residuals $\left(\hat{h}_{it}\right)$ of the probit correlated random effect model and their interactions with the *Innovation* variable are also included. The presence of a time trend (k_{t3}) and the regional dummies is often comprised in panel data estimations.

Assuming that innovation decision may be represented as a dichotomous choice which is observable, agricultural firms choose to adopt an innovation behavior only if the difference between operating revenues of innovating and not innovating is positive. As a consequence, the panel probit model for innovation behavior should be written as:

$$Pr(Innovation_{it} = 1 | z_{it}) = \alpha_0 + \alpha_1 Material\ costs_{it} + \alpha_2 Employment\ costs_{it} + \alpha_3 Total\ assets_{it} + \alpha_4 Rain\_spring_{it} + \alpha_5 Max\_temp\_summer_{it} + \alpha_6 Min\_temp\_spring_{it} + \bar{z}_i \rho_0 + k_{t3} + \delta_2 D\_region + v_{it} \forall\ i = 1, \dots, N \text{ and } t = 1, \dots, T \tag{12}$$

where (z_{it}) are the exogenous explanatory variables coming from the outcome equation such as *Material costs*, *Employment costs*, and *Total assets* and the exclusion restrictions of the selection

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[2] As underlined by Murtazashvili and Wooldridge (2016), accounting for time-invariant unobservables makes plausible to hypotheses that *Shareholders' funds* may satisfy the strict exogeneity requirement and may be considered as a valid instrument for *Total assets*.

equation such as the climatic variables. These variables are measured by the rolling mean window over the 5 years in precipitation during spring season (*Rain_spring*), the rolling mean window over the 5 years in maximum temperature during summer season (*Max_temp_summer*), and finally, the rolling mean window over 5 years in minimum temperature during spring season (*Min_temp_spring*). It is worth to note that when *Total assets* variable is assumed endogenous, it is replaced by its instrument (*Shareholders' funds*) in equation (8). As usual, a time trend (k_{t3}), regional dummies and Mundlak devices are introduced.

To study the effect of innovation decision on agricultural firms' operating revenues, we compare several panel data methods to the control function technique. Specifically, we estimate the panel data using the fixed-effects (FE) estimator when *Total assets* is considered as exogenous and the instrumental variable fixed effects (IV-FE) estimator if *Total assets* is endogenously determined.

3. Results and Discussion

The estimates of the determinants of innovation and the impact of innovation on operating revenues are estimated in a selection and an output equation jointly. In fact, the firms that innovate typically present a different level of operating revenues with respect to those firms that do not innovate. An endogenous switching regression model is advocated as better way of modeling the joint determination of firm's innovation and operating revenue. The endogeneity of switching from innovating to non-innovating comes from the fact that the decision to innovate and the level of operating revenues are not independent.

Moreover, as highlighted in Section 2.2, one of the main determinants of the operating revenues, the total asset, might be affected by potential endogeneity. W with χ^2 (1)=3.364 and p-value= 0.066. Since there are two endogenous components in our estimated model, at least two instrumental variables are needed. First, as exclusion restrictions we exclude from the outcome equations climatic variables in order to exploit them as instrument for the decision to innovate. We basically argue that climatic variables have no direct effects on firms' operating revenues once we control for the firm's innovation decision. Second, shareholder funds are used as an instrument for total asset variable in the outcome equation. Since time-invariant unobservable heterogeneity is taken into account, it is assumed that shareholder funds variable satisfies the strict exogeneity requirement and can be considered as a valid instrument for total asset.

Table 3 and 4 show results of the first and second stage coefficient estimates that are used to estimate the operating revenue equation. More specifically, Table 3 reports the estimation coefficients of the first stage. Column (1) reports the first stage results of the FE-IVREG where total asset is an endogenous regressor and the decision of innovating is an exogenous explanatory variable (see column (2) of Table 4 for the second stage). Columns (2) and (3) show the estimation coefficients of the first step (pooled) probit for the choice of innovating that is then used in the second step of the CF approach where the total asset is exogenous and endogenous, respectively. Regression (1), (2) and (3) in Table 3 include regional and trend variables. In addition, regression (2) and (3) include time averages of the corresponding set of explanatory variables (Mundlak devices) except for time-invariant variables such as regional and trend variables, as they are perfectly collinear with their time averages.

Results in the first regression of Table 3 suggest that shareholder funds are statistically significant at the 1% level where it is used as instrument. As shown, the included exogenous variables are all positive and significant with the exception of the interaction terms of material and employment costs. It is worth to note that, as expected, innovation has a positive and significant effect on firms' operating revenue.

As results in columns (2) and (3) show, climatic variables are statistically significant in both regressions. Additionally, an increase in the rolling mean of precipitation during spring season reduces the probability of innovating. In this case the positive effect of rainfall decreases the need of pushing innovation both for farmers and for firms in agricultural sector. On the other hand, with the increase of the maximum temperature average during the summer season the firms are more likely to innovate, as reaction to the adverse climatic conditions. Moreover, the negative and significant relationship between the minimum temperature during spring season and the innovation effort can be explained by the fact that a more moderate weather during the growing season might have a positive effect on the yield and consequently on the entire agricultural sector.

Table 3. First stage coefficient estimation

	(1) First stage FE-IVREG	(2) Pooled Probit	(3) Pooled Probit with total asset endogenous
Dependent variable	Total asset	Innovation	Innovation
Material costs	0.235***	-0.164	-0.091
	(0.062)	(0.891)	(0.852)
Employment costs	0.263***	-3.240**	-3.147**
	(0.080)	(1.309)	(1.292)

Total assets		-0.013	
		(0.940)	
Innovation (yes=1)	0.253**		
	(0.119)		
Material costs * Innovation	-0.082**		
	(0.038)		
Employment costs* Innovation	-0.006		
	(0.043)		
Total assets *Innovation	0.060**		
	(0.027)		
Shareholder funds	0.384***		-0.267
	(0.051)		(0.621)
Rolling mean window over 5 years in precipitation during spring season		-0.007*	-0.007*
		(0.004)	(0.004)
Rolling mean window over 5 years in maximum temperature during summer season		0.066**	0.068**
		(0.027)	(0.027)
Rolling mean window over 5 years in minimum temperature during spring season		-0.073*	-0.076**
		(0.039)	(0.039)
Constant		-11.715***	-11.918***
		(1.590)	(1.711)
N	1014	833	833
Log-likelihood	1860.109	-443.613	-443.916

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

Table 4 provides the coefficient estimates of the operating revenues equation using four different estimation methods under different assumptions. First, in columns (1) and (2) we report the FE and FE-IV coefficient estimates of the operating revenues, respectively, where all the outcome equation determinants are treated as exogenous and when total asset is considered as an endogenous regressor. Then, we move to more plausible operating revenue equations. Particularly, in columns (3) and (4) of Table 4 we allow for endogeneity of the innovation by using a CF approach and total asset is considered as an exogenous and endogenous regressor, respectively. Note that regressions (3) and (4) of Table 4 are the second step estimations of regressions (2) and (3) of Table 3. All regressions reported in Table 4 include full sets of regional and trend variables as well as interactions with the dummy for whether the firm produced patents or not. Moreover, regressions (3) and (4) contain specific additional regressors such as generalized residuals, time averaging covariates and their interactions with innovation dummy[3] .

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 used in columns (1) and (2), interaction terms change their signs, even if they are mostly no significant. In line with the accounting literature, we find that material and employment costs and total assets positively affect the operating revenues. Firms that hire more employees or increase their wages and companies which increase their investments are predicted to reach a better performance. This effect is statistically significant at 1% level in all the regressions considered but one, the parameter of total assets in regression (3).

Furthermore, estimation results suggest that the decision of innovating does not affect positively the operating revenues, regardless of the estimation method used. However, the coefficients are in all the cases not significant, but in one case (regression 3). Apparently, this finding seems to contradict the standard wisdom in the field of innovation. This contradiction is actually not that puzzling; it might be related to the fact that the lagged effects of the patent variable on the performance was not directly considered in the analysis. Producing patents at time t might have a positive effect in $t + n$. Findings drawn from the literature suggest that a plausible period of time for lagged effect can be assumed to vary from 2 up to 4-year lag (Griliches et al., 1991; Ernst, 2001; and Huang et al., 2016). Although this lagged effect is not directly addressed in our model, introducing generalized residuals in the outcome equation allow us to capture the lagged effect of innovation related to weather variability. In fact, generalized residuals estimated in the first stage include the influence of backward-looking rolling climatic variables and thus show positive and significant coefficients.

We observe substantial variability in the parameter estimates of the interaction terms across different methods and specifications. When assuming exogeneity of innovating, parameters are statistically significant at least at some conventional level in both regressions (1) and (2). Material costs interact positively with innovation increasing operating revenues, on the other hand, employment costs and total assets interacted with innovation dummy are predicted to result in a decrease in outcome variable.

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3 To save space, we do not report in Table 4 the last two set of variables. Results are available under request.

The generalized residuals from the pooled probit for the indicator of innovation are statistically significant at 5% level. Given this evidence, the endogeneity of the innovation decision in the operating revenue equation is confirmed. The endogeneity of switching from innovating to non-innovating is also tested and verified by the result of the Wald test reported in the last row of Table 4. When assuming endogeneity of the total assets regressor, an under-identification test is provided (in the last panel of Table 4). A rejection of the null hypothesis indicates that the matrix is full column rank, thus the model is identified.

Overall, we can conclude that the CF approach allows us to obtain the most plausible regression results under the assumption of endogeneity in the innovation decision and in the total assets regressor.

Table 4. Second stage coefficient estimation

	(1) FE	(2) FE-IV	(3) CF	(4) CF with total asset endogenous
Material costs	0.499***	0.477***	0.558***	0.537***
	(0.070)	(0.037)	(0.073)	(0.075)
Employment costs	0.338***	0.312***	0.328***	0.312***
	(0.051)	(0.047)	(0.106)	(0.106)
Total assets	0.129***	0.197***	0.115	0.170***
	(0.035)	(0.046)	(0.092)	(0.028)
Innovation (yes=1)	-0.051	-0.067	-0.367*	-0.355
	(0.071)	(0.061)	(0.212)	(0.220)
Material costs*Innovation	0.056***	0.062***	-0.110	-0.091
	(0.021)	(0.021)	(0.143)	(0.146)
Employment costs*Innovation	-0.039**	-0.038*	0.004	0.022
	(0.019)	(0.020)	(0.167)	(0.144)
Total assets*Innovation	-0.015*	-0.020	0.020	-0.032
	(0.009)	(0.014)	(0.129)	(0.038)
Generalized residuals			0.050**	0.046**
			(0.024)	(0.022)
Generalized residuals*Innovation			-0.001	0.001
			(0.012)	(0.012)
Constant	1.565**		1.800***	1.799***
	(0.620)		(0.239)	(0.243)
N	1027	1014	833	833
Log-likelihood	2749.401	2689.698	1578.556	1574.979
Kleibergen-Paaprk LM statistic$\chi^2(1)$		17.142		46.949

P-value		0.000		0.000
Wald test $\chi^2(2)$			11.84	11.55
P-value			0.003	0.003

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 and regional effects are included. Columns (3) and (4) include Mundlak correction. The entire results for the reported regressions are available upon request.
$^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$

Starting from the specifications (3) and (4), we computed Average Treatment Effects on Treated to assess the effect of innovation on firms' performance. Table 5 presents the actual (column A) and counterfactual (column B) operating revenues on treated (enterprises that are effectively innovators). The column A reports the actual expected outcomes that are observed in the data for those firms that innovate, while column B provides the counterfactual expected value, i.e. the operating revenues of those firms that innovate if they decided to not innovate. Results are split in three panels. First, ATET are computed distinguishing between the northern and the southern part of Europe. Second, the impact on the operating revenues of firms that innovate is reported according to agricultural and no-agricultural patents. Finally, in the last panel the overall impact of innovation is described.

As shown in the last line of Table 5, results confirm that there are significant differences in terms of firms' performance between operating revenues whether a firm innovates or not. The impact is positive in both model specifications. The operating revenues are 18.8 percentage points higher with innovation, though this percentage substantially decreases at 8.6 after controlling for endogeneity of total assets. Our results also suggest that the innovation impact is higher in the Northern European countries compared to the Southern ones (0.26 versus 0.06 percentage points higher when total assets is treated as exogenous and 0.14 versus -0.01 percentage points higher when total assets is considered as endogenous). It is worth to point out that for Southern countries benefits from innovation are statistically and significantly close to zero or even less than zero. Based on this finding, firms in agricultural sector and located in the South of Europe should be supported in following a more innovative behavior through tax allowances and incentives in R&D investments as well as improving local infrastructures. This is mainly true given that increasing in average temperature due to CC will intensify problems of droughts, especially in the Mediterranean region (Goubanova and Li, 2006; Rodriguez Diaz et al., 2007; IPCC 2014).

Finally, comparing the results between the two specifications also emerges that investing in the production of agricultural patents compared to the other typologies slightly increase the firms' performance in agricultural sector.

Table5. Impact of innovation on operating revenues

	OLS - Pooled with total assets exogenous				IVREG - Pooled with total assets endogenous			
	Actual outcome (Operating revenue if firm innovates)	Counterfactual outcome (Operating revenue if firm does not innovate)	ATET	P-values	Actual outcome (Operating revenue if firm innovates)	Counterfactual outcome (Operating revenue if firm does not innovate)	ATET	P-values
	A	*B*	*C=A-B*		*A*	*B*	*C=A-B*	
Northern EU countries	1,035,696	818,915.6	216,780.5	(0.000)***	1,035,416	909,579	125,836.6	(0.001)***
Southern EU countries	124,048.5	117,506.6	6,541.89	(0.000)***	124,043.1	125,110.3	-1,067.17	(0.000)***
Agricultural patents	298,177.8	256,551.5	41,626.26	(0.048)**	299,256.2	279,049.2	20,206.92	(0.079)*
No agricultural patents	193,475.9	169,039.8	24,436.09	(0.037)**	194,267.3	182,979	11,288.33	(0.111)
Overall	306,378	257,788.4	48,589.62	(0.000)***	306,317.6	282,004	24,313.58	(0.001)***

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; $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$

4. Concluding remarks

The increasing frequency of extreme weather events due to CC will likely raise the incidence of environmental disasters and the depletion of agricultural resources with negative consequences on global food supply. As the agriculture sector is expected to suffer the most from the negative effects of CC, we focused on firms operating in this sector and on how they will react to these new climatic challenges. Specifically, we investigate the role of technological innovation in the handling of climate and weather risks and the interaction between the effects of climate and weather variability and innovation capabilities, as firms' adaptation strategy. To capture differences across the EU regions and the trend during the selected period, the analysis is based on an unbalanced panel at the firms' level.

Evaluating the impacts of innovation and its effect on the firms' outcome requires controlling for potential selection bias and unobserved heterogeneity. When the selection process might be generated by time-varying unobserved heterogeneity that affects firms' performance, a panel estimator alone might not be sufficient. To overcome this issue, we apply the control function approach which allows us to address self-selection issue and the endogenous explanatory variable problem.

Controlling for the time-varying selection bias affecting innovation choice our results find that climatic variables have a statistically significant impact on firms' probability of innovating. This enhances the empirical evidence on whether and how climate-induced innovations have responded to weather variability. Taking into consideration the generalized residuals of the probit estimation and the endogeneity issue of one production input as total assets, we may affirm that bigger firms in terms of higher employees' costs or investments are predicted to reach a better performance. The same positive effect is obtained by the generalized residuals which including the influence of backward-looking rolling climatic variables may raise the operating revenues of firms belonging to the agricultural sector.

Finally, the average treatment effect (ATT) results confirm that innovative firms are substantially different from those who do not innovate. More specifically, if a firm chooses of innovating, this has a positive effect on its performance which rises. The greater is this effect the more likely the firm is innovative and resides in the northern European countries. Moreover, whenever a firm issues patents which belong to the agricultural code classification of the European Patent Office, the higher is the benefit that gains in terms of operating revenues.

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