Sustainability Environmental Economics and Dynamics Studies

Working Paper Series

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12/2020

SEEDS Working Paper 12/2020
July 2020
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Keywords: Water scarcity, Innovation, Micro irrigation, Sustainable agriculture, Italian farms

Abstract

This paper aims to analyse how the farmer's choice on adopting innovative and sustainable irrigation systems such as water conservation and saving technologies (WCSTs), induced also by the climatic variability, would shape the economic resilience of the Italian agricultural farms by improving land productivity. A proper water management would increase efficiency in the agricultural activities by improving the use of water endowments and rising agricultural economic performances to address a sustainable development. We used an endogenous switching regression model considering two sources of endogeneity: the selection indicator and a continuous endogenous explanatory variable. By applying the control function method, a correlated random effects probit model for the selection equation and a correlated random effects model for the outcome equation are estimated in a panel data context based on a detailed micro-level dataset of all the Italian farms. Our results confirm that adopting WCSTs increases land productivity of adopters significantly.

1. Introduction

In this last century, the rate of water use has increased all over the world even doubling population growth (UN, 2015). To assure global food security, water scarcity issue will represent the main constraint that each country will face in the next future (Alexandratos and Bruinsma, 2012). Hence, water shortage will become the main socio-environmental challenge even because the increasing variability of climatic conditions, as well as desertification and urbanization processes are intensifying the pressure on water resources, exacerbating the water use and allocation (De Angelis et al., 2017; Mekonnen and Hoekstra, 2016).

Agriculture is responsible for almost 70% of global freshwater withdrawals even though the majority of water is used for crop intensive irrigation implying that most of the water is got lost through evaporation, percolation and runoff (MEA, 2005). Since the ’70s of the last century, the climate change (CC) and its extrermizations have contributed to intensifying the water demand for irrigation in agriculture (Rosenzweig and Tubiello, 1997) putting additional pressures on water resources.

Water shortage and agricultural water use represents one of the most important issues affecting agricultural activities of EU countries in terms of the level of agricultural production and the capability of assuring a good level of food security. This is particularly true for the Mediterranean regions and more specifically for Italy (Goubanova and Li, 2007; IPCC, 2013; Rodríguez Díaz et al., 2007), where during winter significant reductions of rainfalls have been recorded and will continue up to more than 40% in the next future (Ciscar et al., 2014).

The Italian regions, that experienced warmer and drier weather conditions with an increase of extreme events, have suffered for water scarcity during these last decades. They, however, will remain at risk for future water crisis mainly due to the changing climate (Brunetti et al., 2004; Senatore et al., 2011; Toreti et al., 2009). Moreover, differences in water endowments among the Italian regions have been increased and will continue to increase, making the agricultural production more dependence from water irrigation, especially in the water scarce regions (Auci and Vignani, 2020; Tubiello et al., 2000). Normally, small farms are particularly affected by CC events as they present a less capacity for adaptation to climatic extreme conditions (EEA, 2015). Therefore, the Italian agricultural sector, which is mainly based on small farms with low land extensions, family run farms and managed by highly specialized farmers, is at risk to the adverse CC scenarios (Eurostat, 2016). Moreover, heterogeneity among the Italian regions in terms of both geographical characteristics and anthropic factors (such as soil conditions, sensitivity to droughts, intensity of land use and altitude) may further influence water use in the agricultural sector in the next future resulting in increasing production risks due to the effects of higher level of climatic variability (such as reduced yields, higher costs, fragility against pathogens, soil depletion etc..) (Bozzola and Swanson, 2014; Mysiak et al., 2013; Salvati and Carlucci, 2010).

By considering different scenarios, the CC effects on agricultural production are not easily foreseeable in Italy. However, with high probability the impact will be negative on Italian agricultural production, measured both in absolute values and variability of yields (Bocchiola et al., 2013; Bozzola et al., 2018; Toreti et al., 2009; Tubiello et al., 2000; Van Passel et al., 2017). Even though, in the short term, negative effects of droughts and CC could be possibly balanced by raises of agricultural commodity prices due to general scarcities (Musolino et al., 2017, 2018). In the long term, the negative effects may have unpredictable impacts on the entire agricultural productive system, as well as the agri-food chain, exacerbated by severe negative scenarios in terms of less food security, more unemployment, less protection of the environment and worse conditions of public health.

Following an economic sustainability path for the European agricultural system implies mainly the ability of farmers in adapting their irrigation systems in terms of increasing their resilience to weather fluctuations. Innovations and the use of water conservation saving technologies (WCSTs) may reduce the impacts of agricultural activities on water resources and may have important effects on the improvement of agricultural productivity (Expósito and Berbel, 2019). The WCST use may indeed reduce over-irrigation of plants and optimize crop production in those areas where water is scarce and dry seasons accompanied by drought periods are prolonged and severe.

How an agricultural system may react to the different negative CC scenarios may depend mainly on what management practices a farmer will follow for adapting to the extremization of the weather (Tubiello et al., 2000). Therefore, understanding of which are the driving forces for adapting to the climatic changes will be crucial and the analysis of the overall effect induced by CC either at the economic or at the environmental level may be important to design suited policies which may positively influence the behaviour of farmers toward less conservative, or more innovative, practices (Bozzola and Swanson, 2014).

Climate policy will have potentially significant impacts on agriculture in particular on the innovation within the agricultural sector. Removing distortions and impediments would foster farm-level innovation. Facilitating investments in new technologies would also be beneficial (OECD, 2013). Thus, it is worth to consider the role that technological change may play in solving long term environmental problems as CC (Popp, 2005). As far as agricultural innovation is concerned, the majority of literature focuses on the effects of agricultural research and development (R&D) expenditure on productivity at the macro level (Alston, 2010a, 2010b; Alston et al., 2009; Fuglie, 2012; Pardey et al., 2010). While only some studies focus primarily on innovation within the agri-food sector (Ghazalian and Fakih, 2017; Harvey et al., 2017; Materia et al., 2017), very few studies indeed analyse the direct effect of innovation on profit or economic sustainability at the farm level (Karafillis and Papanagiotou, 2011; Läpple and Thorne, 2019). However, the attention by international and national institutions to foster innovation, supporting the starting and the diffusion phase of sustainable technology in the agri-food sector, has determined the reform of the National Agricultural Innovation System (AIS) as underlined by Jaffe and Palmer (1997); OECD (2013) and Läpple and Thorne (2019).

By understanding the relationship between innovation in the irrigation system and agricultural yields is an important issue to analyse the sustainability of the agricultural sector. In fact, innovation within the agricultural sector can be considered as a strategy for the adaptation to climate challenges and water scarcity issues. Thus, this paper wants to contribute to the current debate on how innovation in the irrigation system used in agriculture may have an impact on farm productivity (Läpple and Thorne, 2019; Le Gal et al., 2011; Mofakkarul Islam et al., 2013; OECD, 2013). More specifically, focusing on the Italian farm system, we consider how farmers' choices on the probability of adopting WCSTs may improve land productivity.

In this present paper, our contribution consists in estimating the potential role of choosing WCSTs for irrigation to increase the productivity of yields and thus the resilience of the agricultural sector to climate variability at the farm level in Italy. While there is a growing consensus on the impact of climate variability on agriculture (Burke and Emerick, 2016; Deressa and Hassan, 2009; Deschênes and Greenstone, 2007; Mendelsohn et al., 1994; Mendelsohn and Dinar, 2009; Schlenker et al., 2005; Van Passel et al., 2017), a better understanding of firms' adaptive capacity (Huq et al., 2004; Seo, 2011) and adaptation strategies in supporting agricultural firms productivity are still needed (Di Falco and Veronesi, 2013; Khanal et al., 2018).

To fill this gap, we investigate how farm-level irrigation adaptation strategy to climate variability may have had an impact on land productivity within the Italian agricultural sector. Our main research question may be synthesised as follows: could the choice of adopting WCSTs as a strategy to cope with climate variability have a different effect on land productivity of adopters compared to non-adopters? An endogenous switching regression model with a continuous endogenous explanatory variable may represent a useful methodology to investigate this issue. By applying the control function approach as developed by Murtazashvili and Wooldridge (2016), we may consider two different sources of endogeneity: the selection indicator and an endogenous explanatory variable. Based on a panel dataset, the FADN, representative of the Italian farms, allows us to capture the effect of climate variability on agricultural productivity after having controlled for farmers' WCST choice and unobservable determinants of land value.

The paper is structured as follows: in section 2, a brief literature review on the empirical application of endogenous switching regression models within the agricultural innovation is introduced. In section 3 the methodology applied is described in more details, while the counterfactual analysis and the treatment effects are described in section 4. Section 5 present the dataset and section 6 discusses the main results. Finally, some conclusions are drawn in section 7.

2. Adoption in WCSTs and Endogenous Switching Models for agricultural innovation

Innovation in agriculture has always represented an economic evolution since the first appearance of agricultural communities in the Neolithic era. Economic evolution has always been based on how productive factors and agricultural processes have been recombined in order to obtain efficiency, improvement in food production and food security by reducing risks due to unexpected variability (Perret and Stevens, 2006).

The introduction of an innovation can improve past technologies or technique in terms of resources used in the production process and thus can increase yields. A relevant branch of innovation literature in economics and sociology has focused on the analysis of the factors which may influence the adoption of new technologies in agriculture (Feder, 1982; Feder and Umali, 1993; Rogers, 1971; Shrestha and Gopalakrishnan, 1993). Following these studies, the process of innovation adoption is dynamic

(Rennings, 2000; Stavins et al., 2002) and strongly relies on adopter expectations over the results obtained after the decision to adopt. This process is well-described in the neoclassical economic theory where the final decision is based on the comparison of several alternatives with different levels of expected utility depending on intrinsic and extrinsic characteristics (Baidu-Forson, 1999; Somda et al., 2002). The primary motivation is related to the choice of increasing marginal benefit within a profit maximization procedure or more generally, to the improvement of economic conditions. But there are other elements that might also be considered in the innovation decision process which are not straight observable such as social networks, cultural factors, shared ideas, implementation costs or the ease of adoption (see (Pronti et al., 2020).

An effective strategy to obtain sustainable irrigation at the high scale level consists of improving water use on the demand side. Improving the efficiency of irrigation technologies implies a reduction of the volume of water absorbed effectively by the plant with respect to the total amount of water used by a farmer (Berbel et al., 2018). In several situations of water scarcity, increasing the adoption of WCSTs can contribute to reduce the pressure on water resources due to the limited use of inefficient irrigation practices (Expósito and Berbel, 2019). WCSTs such as drip irrigation, low pressure micro-sprinkling and sub-irrigation can optimize the application of water directly to plants root reducing water stress through a high frequency water application which decreases the difference between evapotranspiration and the plant extraction of water (Dasberg and Or, 1999; Pereira et al., 2002; Schuck et al., 2005). In terms of efficiency, the adoption of WCSTs compared to traditional irrigation methods (such as furrow, normal sprinkler and flooding) can satisfy both the water requirements by crops/plants and the reduction of water losses due to over-irrigation (Taylor and Zilberman, 2017; Wheeler et al., 2010). The use of WCSTs can improve water productivity considered as the biomass output per unit of water used which can represent an economic valuation of agricultural water if the price of crop over the amount of water used is considered (Expósito and Berbel, 2019). Moreover, WCSTs can improve fertilizers absorption and reduce soil erosion due to run-off, salinization and crop diseases (Alcon et al., 2019; Skaggs, 2001). However, these benefits depend mainly on the ability and the knowledge of a farmer regarding the application of a new technology (Levidow et al., 2014).

The decision of implementing innovations may depend mainly on farmer' ability and motivations as well as her/his expected benefits, in nature or in economic value, that might be gained after the adoption of new technologies (Kesidou and Demirel, 2012). During the process of adopting innovations which could be beneficial in the environmental terms, other distinctive aspects can arise such as environmental responsibility, coping with natural resource scarcity or reducing risks to exogenous shocks. Therefore, the choice of adoption is influenced by intrinsic characteristics of a farmer as well as the farm structure, such as motivations and ability, adaptability to change or green aptitudes with systematic differences with farmers which do not adopt. For example, high performing farmers could be more willing to adopt innovation than poor performers bringing to selection bias. Because of this systematic unobservable differences using naïve method of analysis which simply compare differences between adopters and non-adopters would give misleading information over the effect of the adoption (Läpple et al., 2013). For accounting the effect of the innovation, properly selection bias should be considered in order to obtain unbiased and consistent estimations.

The endogenous switching regression method (ESRM) was firstly introduced by Lee (1983) as an extension of the Heckman's selection model (Heckman, 1979) for dealing with problems of self-selection. It has been extensively used for innovation adoption studies especially for empirical analysis in the agriculture sector dealing with selection problems. Fuglie and Bosch (1995) have used ESRM for studying the N test adoption on fertilizer efficiency among Nebraska corn growers. Di Falco et al. (2011), Di Falco and Veronesi (2013) and Zeweld et al. (2020) have followed the ESRM approach for testing the effect of climate change adaptation strategy adoption on productivity in Ethiopia. Abdulai and Hoffman (2014) have analysed the effect on productivity and returns of soil and water conservation technique adoption among rice producers in Ghana.

Other empirical works with a ESRM approach have been done for evaluating agricultural development programs in Ethiopia and Tanzania (Asfaw et al., 2012), Nigeria (Donkor et al., 2019), Nepal (Paudel et al., 2019), Timor-Leste (Noltze et al., 2013), China (Gao et al., 2019; Sha et al., 2019) and India (Mishra et al., 2017). All the above mentioned studies used principally regional surveys with small datasets, whereas very few analyses had adopted wider dataset at the farmer level for all the country studied such as Teklewold (2013) for Ethiopia and Coromaldi et al. (2015) for Uganda (Coromaldi et al., 2015; Teklewold et al., 2013). Anyway, all of them relied on cross-sectional data structures.

At the best of our knowledge, no previous studies attempted to apply ESRM for technological innovation in agriculture using panel data. The only analysis that applied a ESRM approach with panel data is the study of Teklewold and Mekonnen (2017) which analysed the elements influencing the choices related to tillage strategies and their effect on farm returns on income using a random effect ordered probit ESRM (Teklewold and Mekonnen, 2017).

Furthermore, the large majority of analyses are focused on developing countries, whereas empirical works on ESRM applied to western countries for technological innovation analysis are limited. Only Läpple et al. (2013) have used the ESRM for testing the effectiveness of an extension program on profits for dairy farmers in Ireland (Läpple et al., 2013). Moreover, in terms of agricultural water management, the only authors analysing specifically this issue with a ESRM were Da Cunha et al. (2014) and Abdulai and Hoffman (2014) (Abdulai and Huffman, 2014; da Cunha et al., 2015).

In this paper, we contribute to the existing literature on agricultural water management and WCST adoption applying one of the last econometric development for the ESRM in panel data framework. Following the extension of Murtazashvili and Wooldridge (2016), 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 a control function method for continuous and discrete endogenous variables and consists of two stages. In the first step, to take into account the selection indicator related to the WCST choice, a probit-correlated random effects model is run considering the seasonal aridity indexes as exclusion restrictions. In the second step, in the output equation, the selection bias is addressed by adding generalized residuals. This equation represents the relationship between farmers' agricultural economic performance (productivity of land) and its main inputs such as, land, irrigation land, labour and capital as well as social and economic characteristics of farmers. If land is a continuous endogenous explanatory variable with external water sources and mixed soil texture as instruments, then a two-stage least squares (2SLS) model is estimated. Otherwise when all the variables are exogenous an Ordinary Least Squares (OLS) estimation is applied. Of interest is the impact analysis of irrigation adoption decision on farmers' land productivity, a counterfactual analysis is carried on. Estimating the average treatments effects on treated (ATET) allows considering the impact of irrigation adoption on farmers' performance for those firms that received the treatment which in this case is considered adopting WCST.

3. Methodology

Innovation activities may improve efficiency (resources used over results obtained) and effectiveness (objectives over results) over past technologies and techniques used. The decision of adopting innovations depends mainly on firms' ability and motivation as well as the expected value of farmers' benefits after the introduction of a new technology (Läpple and Thorne, 2019). The adoption process should be considered concluded only when the expected profits, obtained by new technology implementation, are at the maximum level (Feder, 1982; Feder et al., 1985; Shrestha and Gopalakrishnan, 1993). However, a bundle of observable and unobservable determinants may influence the choice of innovation and in turn the farmer's utility function (Foster and Rosenzweig, 2010; Rogers, 1971). So, isolating the effect of innovation on profits may be a challenging issue since farmers who innovate are self-selected (Läpple and Thorne, 2019).

In a cross-section context, several empirical studies have considered the strategy for adaptation to climate change. By analysing the impact of new technology adoption on farm outcome these studies have principally used an endogenous switching regression model (Abdulai and Huffman, 2014, 2014; Alene and Manyong, 2007; Di Falco et al., 2011; Fuglie and Bosch, 1995; Kassie et al., 2018), a multinomial endogenous switching regression model (Di Falco and Veronesi, 2013; Kassie et al., 2015; Teklewold et al., 2013) or a propensity score methodology (Kassie et al., 2011; Läpple and Thorne, 2019). However, to the best of our knowledge, there are only few studies that have considered the innovative behaviour of a farm using a longitudinal dataset. We, thus, focus on the WCST adoption decision by modelling adaptation to climatic variability as a selection process, where the expected benefits may drive the choice of a farm.

The interaction among all the observable and unobservable factors may affect benefits and costs perceived by a farmer who defines each option, compares them with all the other possible alternatives (new or old technologies) and ranks all the alternatives in a list. In line with the neoclassical economic theory, the final choice is based on the comparison of several alternatives with different levels of expected profits depending on intrinsic and extrinsic characteristics such as the innovative technology adoption. For example, if alternatives A and B represent two different technologies (an old or a new technology), a farmer will choose the one that will give the highest profit after having considered all the different technology characteristics (Baidu-Forson, 1999; Somda et al., 2002).

Differences in farmers' performances may be explained by their ability and motivation as well as technology innovation choices. Thus, innovative farmers may obtain higher performances than the less innovative ones independently by the decision of technology adoption. Explaining this difference considering only innovation efforts might overestimate innovation effects. For this reason, taking into consideration the potential selection effect and unobserved heterogeneity represents a precondition for the estimation of the WCST adoption impact on farmers' performance (Imbens and Wooldridge, 2009; Läpple and Thorne, 2019).

Since the selection process is based on a time-varying unobserved heterogeneity, standard regression techniques are biased and an endogenous switching regression model should be applied (Kassie et al., 2018; Wooldridge, 2010). In this model, the adoption decision is modelled on the basis of firm-level characteristics and climatic indicators while the relationship between the outcome variable and a set of explanatory variables may vary across the two discrete regimes (i.e., WCST adopting and non WCST adopting farms). A two-step approach based on the control function approach implies that the first stage estimation is a binary model i.e. the self-selection equation and the second stage is a linear estimation of the outcome equation dependent on the treatment effect i.e. adoption decision.

One of the advantages of applying a switching regression model regards the interaction between inputs and technology. An innovative choice may affect not only the intercept of the outcome equation but also the slope (Kassie et al., 2018; Murtazashvili and Wooldridge, 2016). Thus, even if the average values of farm characteristics may be the same, the adopter and the non-adopter farmer may differently affect the outcome variable (Wooldridge, 2010). Estimating the two different situations (adoption or non-adoption) allows us to determine the counterfactual effect on the outcome variable by considering adopters and non-adopters characteristics. Another advantage of the switching regression model is that allows the unconfoundedness assumption to be overcome. This methodology allows us to control for the systematic differences between adopters and non-adopters since we may control for unobservable characteristics (Abdulai and Huffman, 2014; Smith and Todd, 2005).

Following Murtazashvili and Wooldridge (2016), an endogenous switching regression model with endogenous explanatory variables is implemented. This model is based on two sources of endogeneity: the selection and endogenous explanatory variables. Combing the Mundlak's approach with control function method allows following a two-step procedure. In the first step, a selection equation is estimated by using a correlated random effects probit model (CRE probit) (Mundlak, 1978) while in the second, an outcome equation is estimated by applying a two-stage least squares (2SLS) model. In this outcome equation, thus, the selection bias is addressed by introducing generalized residuals and the continuous endogenous explanatory variable is included by considering the instrumental variables issue. For robustness checks, the outcome equation is estimated with no continuous endogenous explanatory variables and thus an Ordinary Least Squares (OLS) estimation is applied.

We model the impact of WCSTs adoption on farmers' benefits by assuming as an alternative to traditional irrigation systems the micro-irrigation ones. Under the risk-neutral assumption, a farmer may choose the innovative irrigation system which provides the maximum net benefits. Thus, if the net benefit of a farmer *i* in the period *t* from the adoption of WCSTs is $y_{it1}^{(1)}$ and the net benefit from the non-adoption is $y_{it1}^{(0)}$, we may specify the two regimes as:

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

where the vector of explanatory variables x_{it1} includes some exogenous explanatory variables (defined as z_{it1}) as farmers, farms, financial and institutional characteristics. Moreover, it contains a continuous endogenous explanatory variables (EEVs) the land value variable (defined as y_{it2}) as well as an intercept and a set of time dummies. As a panel estimation, time-constant individual-specific unobserved effects are introduced in both regimes and are c_{i10} and c_{i11} respectively. Finally, u_{it10} and u_{it11} are the idiosyncratic errors in both regimes which are strictly independent of the exogenous explanatory variables z_{it1}.

As in the panel data model developed by Murtazashvili and Wooldridge (2016), a panel switching regression model with constant coefficients which linearly combines the two regimes (0 and 1) is applied and an outcome equation may be represented as follows:

$$y_{it1} = (1 - y_{it3})y_{it1}^{(0)} + y_{it3}y_{it1}^{(1)} \tag{2}$$

where y_{it1} represents the outcome of interest, in our case land productivity, as a linear combination of the two regimes. y_{it3} is the endogenous switching variable, namely, the dummy variable which represents the choice of WCST adoption. Substituting the two regimes of Eq. (1) in Eq. (2), we may obtain:

$$y_{it1} = x_{it1}\beta_0 + y_{it3}x_{it1}\gamma_1 + c_{i10} + y_{it3}(c_{i11} - c_{i10}) + u_{it10} + y_{it3}(u_{it11} - u_{it10}) \tag{3}$$

where the endogenous switching variable y_{it3} interacts with both time constant and time-varying unobservable variables.

Applying the Mundlak's (1978) device, we allow for the correlation between individual-specific unobserved effects and the strictly exogenous variables which are assumed to be linearly related to the mean in time of the exogenous variables. Thus, the switching regression model with constant coefficients can be re-written as an outcome equation, as follows:

$$y_{it1} = x_{it1}\beta_0 + y_{it3}x_{it1}\gamma_1 + \underline{z}_i\rho_0 + y_{it3}\underline{z}_i\rho_1 + r_{it0} + y_{it3}r_{it1} \tag{4}$$

where the Mundlak's devices $\underline{z}_i$ are the mean of the exogenous variables $\underline{z}_i = T^{-1}\sum_{t=1}^{T} z_{it}$, and r_{it0} and r_{it1} are the error terms assumed to be independent of the exogenous variables and ρ_0 and ρ_1 represent the parameters to be estimated.

The endogenous switching variable y_{it3} may be represented in the following selection equation, where the endogenous switching indicator is modelled using the Mundlak's (1978) binary response correlated random effects model as follows:

$$y_{it3} = 1\left[k_{t3} + z_{it}\pi_3 + \underline{z}_i\delta_3 + v_{it} > 0\right], \text{ where } v_{it} \sim N[0,1] \tag{5}$$

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. Finally, v_{it} the usual error term normally distributed is independent of all the exogenous variables.

Taking the conditional expectation of eq. (5), the conditional mean of the error term can be written as a generalized residual function ($h(.)$) (Vella, 1998) as follows:

$$\begin{aligned} &E(v_{it}|y_{it3}, z_i) = h\left(y_{it3}, k_{t3} + z_{it}\pi_3 + \underline{z}_i\delta_3\right) \\ &= y_{it3}\lambda\left(k_{t3} + z_{it}\pi_3 + \underline{z}_i\delta_3\right) - (1 - y_{it3})\lambda\left(-k_{t3} - z_{it}\pi_3 - \underline{z}_i\delta_3\right) \end{aligned} \tag{6}$$

where $\lambda = \lambda(.)$ 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 that r_{it0} and r_{it1}, the unobservables error terms of equation (4) follow a linear function and combining the estimated generalized residual function (6) with the outcome equation (4), we may obtain the final and complete outcome equation as follows:

$$y_{it} = x_{it1}\beta_0 + y_{it3}x_{it1}\gamma_1 + \underline{z}_i\rho_0 + y_{it3}\underline{z}_{i_i}\rho_1 + \xi_0\hat{h}_{it3} + \xi_1 y_{it3}\hat{h}_{it3} + a_{it} \quad \text{with } E(a_{it}|y_{it3}, z_{it}) = 0 \tag{7}$$

where $\hat{h}_{it3}$ is the generalized residuals, which account for the endogeneity of the selection variable and x_{it1} also incorporates the continuous endogenous explanatory variable. Equation (6) is then estimated applying an instrumental variable 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 ξ_0 and ξ_1 should be tested by applying the Wald test.

In line with Fuglie and Bosh (1995), the adoption of a new technology is a dichotomous choice which results from the utility maximization of a farmer and affects other decisions such as agricultural yields. Thus, under the risk-neutral assumption, a farm may choose to follow an innovative behaviour if he/she may gain the maximum land productivity (agricultural yields per hectare) and the outcome equation represented in eq. (7) may be described as follows:

$$\begin{aligned}\frac{gross\ output_{it}}{hectare_{it}} = {} & \beta_0 + \beta_1 Farm\ characteristics_{it} + \beta_2 Farmer\ characteristics_{it} + \\ & \beta_3 Financial\ and\ Institutional\ characteristics_{it} + \gamma_2 Farm\ characteristics_{it} * Adoption_{it} + \\ & \gamma_2 Farmer\ characteristics_{it} * Adoption_{it} + \gamma_2 Financial\ and\ Institutional\ characteristics_{it} * \\ & Adoption_{it} + \rho_0 Mundlak's\ device + \rho_1 Adoption_{it} * Mundlak's\ device + \\ & \xi_0 Generalized\ residuals + \xi_1 Adoption_{it} * Generalized\ residuals + \delta_1 D\_year_t + \\ & \delta_2 Macro\ areas_i + a_{it}\end{aligned} \tag{8}$$

where all farm, farmer, financial and institutional characteristics and their interactions with the selection variable (*Adoption*) are included for each year t and farm i. Moreover, the Mundlak's device and the generalized residuals derived from the probit correlated random effect model and their interactions with the Adoption variable are also included.

Since land value may also be endogenously determined, we develop two models. In model A (our principal model), the presence of an endogenous variable (land value) allows us to apply a pooled instrumental variable (IV) estimation based on the two stage least squared (2SLS) procedure. In model B (used for robustness check) where land value is considered as exogenous, a pooled OLS estimation is run. In the first case (model A), the endogenous variable equation of land value with the following exclusion restrictions may be written as follows:

$$land\ value = \alpha_0 + \alpha_1 external\ sources_{it} + \alpha_2 mixed\ soil\ texture_{it} + \varepsilon_{it} \tag{9}$$

where in addition to the instrumental variables, all the other exogenous variables with their interactions with the adoption variable as well as Mundlak's device and the generalized residuals of the selection equation are included.

Regarding the choice among technology alternatives, the adopted technology depends on the comparison between the expected utility of adoption and the utility of non-adoption. Only if the difference is positive then the adoption occurs. The selection equation based on technology adoption can then be modelled as a CRE panel probit model as follows:

$$P(Adaptation = 1|z_{it}) = \alpha_0 + \alpha_1 Winter\ AI_{it} + \alpha_2 Spring\ AI_{it} + \alpha_3 Summer\ AI_{it} + \alpha_4 Autumn\ AI_{it} + \alpha_5 z_{it} + \rho_0 Mundlak's\ device + \delta_1 D\_year_t + \delta_2 Macro\ areas_i + v_{it} \tag{10}$$

where in addition to climatic variables measured by the seasonal aridity indexes, which captures the soil humidity through the evapotranspiration and rainfalls, all the other variables of the outcome equation such as farm, farmer, financial and institutional characteristics (z_{it}) and the Mundlak's device are included. It is worth to note that when the Land value variable is assumed endogenous, it is replaced by its instrument of eq. (8).

4. Counterfactual analysis and treatment effects

The advantage of the endogenous switching regression model involves comparing the different impact of the decision of adopting innovative technology on land productivity. By using the counterfactual analysis, we may assess the expected agricultural yields in the two regimes. More specifically, the expected value of agricultural yields of the farms who adopted may be compared to the counterfactual hypothetical case of the same farmers, if they had not adopted. This can be examined by first specifying the expected agricultural yield values of farmers that adopted WCST (Abdulai and Huffman, 2014; Di Falco and Veronesi, 2013; Fuglie and Bosch, 1995).

For an adopter of WCSTs with all the characteristics already defined, the expected value of the outcome, the land productivity, is given as:

$$E\left(y_{it1}^{(1)}|y_{it3}=1\right)=x_{it1}\beta_1+\underline{z}_i\rho_1+\xi_1\hat{h}_{it3} \tag{11}$$

By introducing the last term, that is the generalized residual, we may consider unobserved heterogeneity in the choice of adopting the new irrigation technologies and thus we may correct for a selection bias in the outcome equation. Because of unobserved heterogeneity the farmer who adopted WCSTs behave differently from a farmer with the identical characteristics but that had chosen not to adopt WCSTs.

Thus, we derive the expected land productivity value of farmers that adopted WCSTs in the counterfactual hypothetical case that they had chosen not to adopt as follows:

$$E\left(y_{it1}^{(0)}|y_{it3}=1\right)=x_{it1}\beta_0+\underline{z}_i\rho_0+\xi_0\hat{h}_{it3} \tag{12}$$

Following Heckman *et al*. (2001), Di Falco and Veronesi (2013), Abdulai and Huffman (2014) and Imbens and Wooldridge (2009), we may calculate the average treatment effect on treated firms (ATET). In other words, we may assess the impact of WCST adoption decision on land productivity for those farms that receive the treatment as the difference between the expected outcomes in both regimes for the treated agricultural firms. Combining equations (11) and (12), we obtain:

$$ATET=E\left(y_{it1}^{(1)}|y_{it3}=1\right)-E\left(y_{it1}^{(0)}|y_{it3}=1\right)=x_{it1}(\beta_1-\beta_0)+\underline{z}_i(\rho_1-\rho_0)+\hat{h}_{it3}(\xi_1-\xi_0) \tag{13}$$

which represents the effect of an innovating behaviour induced by climatic variability on agricultural yield per hectare that actually choose to innovate. It is worth to note that if selection is based on comparative advantage, then innovating strategy may give higher benefits in terms of land productivity (Abdulai and Huffman, 2014).

5. Data description

In this analysis, the data used are a combination of cross-section datasets of the Italian FADN (Farm Accountancy Data Network): a European survey, in the agricultural sector, which collects yearly data on socio-economic, demographic, geographic and sustainable water management aspects at the farm level (RICA, 2020). Climatic data, from the Era-Interim Climate dataset of the European Centre for Medium-Range Weather Forecasts (ECMWF, 2020) with 0.25° x 0.25° grid cell spatial resolution, have been merged to FADN database using georeferenced specification in order to obtain a unique unbalanced panel dataset at the farm level. Among the climatic variables, quarterly accumulated reference evapotranspiration (ET0) and accumulated precipitation (PC) are included. These two variables have been used to calculate seasonal Aridity Indexes at the farm level[1] as a backward-looking rolling means with lag length of 5 years not including the current year (Henderson et al., 2017; Woodill and Roberts, 2018). The final unbalanced panel dataset includes 13,592 farms over a yearly time frame between 2012 and 2016 with 44,083 observations.

As dependent variable of the outcome equation, we consider the gross farm productivity of land expressed as the real gross output per hectare (euro/ha). It has been considered in natural logarithm term in order to smooth its distribution and to give a normal shape form.

Among the independent variables, we first introduce those production inputs that affect the most the agricultural production activity, namely the total level of working hours spent within a farm (*Working hours*), the total machine power available in a farm (*Machine power*) and the market value of the farm land (*Land value*) all transformed in logarithmic term. As underlined by Timmins (2006), land value

[1] *For each season the **Aridity index is measured** as:* AI_{season} *= Accumulated Pricipitation (PC)/ Accumulated reference Evapotranspiration (ET0)* (Allen and FAO, 1998). Seasons have been divided quarterly Winter (January, February, March), Spring (April, May, June); Summer (July, August, September); Autumn (October, November, December).

should be considered as an endogenous variable within a Ricardian model. The author argues that land value can be influenced by many unobservable determinants and only in part by climate conditions. Moreover, unobserved determinants of land value may differ with land use and the range of available alternatives, which the wider are the more severe is the estimation bias. Thus, to overcome this problem, a valid set of instrument variables are required. Following Timmins (2006), we consider three non-climate attributes, as instruments for land value. More specifically, we introduce the *average altitude* of the farm fields, the *mixed soil texture* for capture soil type and, for our specific purpose, *external water source* as a measure of access to water from consortium, river and natural and artificial lakes for irrigation. Only for robustness analysis, we estimate land productivity considering land value as an exogenous variable.

We also consider further inputs, as exogenous variables, such as the annual cost of energy, electricity and water and the amount spent on insurance to cover from production risks. As control variables, other exogenous explanatory variables are included in the model. We introduce, as farm characteristic, the farm specialization by considering a high value crop dummy variable, where it takes the value of 1 if a farm cultivates olives, fruits, vegetables and grapes and 0 otherwise. This allows us to consider the technical-economic orientation of a farm. As famer characteristics, we include the age of the head of the farm and three dummies indicating if the head of the farm is female, the farm is family-run or the farmer holds at least a secondary school education. As financial characteristics, return on investments (ROI) and leverage (indicating the dimension of external financial resources over the resource generated internally) are considered. Finally, to take into consideration other sources of income, we include EU funds and no-EU funds as well as external activities. All the monetary variables are deflated and converted to 2000 euros before logged. Moreover, macro regional and year dummies are included in order to consider geographic heterogeneity and exogenous macroeconomic shocks.

In the case of land value as an endogenous variable, the three instruments – the *mixed soil texture* of land as a proxy for soil quality, the *average altitude* as a proxy for land location and the *external water source* as a measure of water withdrawn from an external source have been used for controlling for endogeneity of the continuous explanatory variable in the first stage of a 2SLS regression model (Model A) (Murtazashvili and Wooldridge, 2016). While, in the case of land value as an exogenous variable, the instruments are not included in the outcome equation (Model B).

Table 1. Descriptive statistics

	Variable	Description	Micro-irrigation=1 mean	Micro-irrigation=1 N	Micro-irrigation=0 mean	Micro-irrigation=0 N
Dep. Var. of outcome equation	Productivity of land	Real gross output per hectare (euro/ha).	31,478.68	8227	18,510.15	35849
Instruments for Land value when is considered as an endogenous variable	External water source	Log of area irrigated by water sources, external to land ownership, such as access to water from water consortium, river and natural and artificial lake for irrigation purposes.	2.26	8228	2.20	35855
	Mixed soil texture	Log of the agricultural area with mixed soil texture (ha).	3.68	8228	3.86	35855
	Altitude avg.	Log of the average altitude level of a farm (metre).	4.44	8228	5.11	35855
Production inputs	Working hours	Log of total working hours of labour (hour).	8.28	8228	8.06	35855
	Machine power	Log of total machine power within a farm (Kwh).	4.66	8228	4.83	35855
	Land value	The logarithm of the real market value of agricultural lands (euro).	13.03	8228	13.02	35855
Further inputs	Energy, electricity and water costs	Log of total costs of water, fuel and energy consumed (euro).	8.76	8228	8.64	35855
	Insurance	Log of total amount spent on insurance by a farmer (euro).	7.91	8228	7.76	35855
Farm characteristic	High value crop	Dummy = 1 if a farm cultivates olives, fruits, vegetables and grapes and 0 if a farm cultivates other crop types or rears farm animals.	0.78	8228	0.32	35855
Farmers' characteristics	Age	Age of household head (farmer) (year).	3.95	8228	3.98	35855
	Female head	Dummy = 1 if a farm is managed by a woman and 0 by a man.	0.20	8228	0.21	35855
	Family run	Dummy =1 if a farm is family run and 0 otherwise.	0.74	8228	0.89	35855
	High education	Dummy = 1 if a farmer has at least a secondary degree or above and 0 otherwise.	0.34	8228	0.29	35855
Other incomes	EU Funds	Log of total amounts of funds directly received from EU through the CAP program (euro).	9.76	8228	9.93	35855
	No EU Funds	Log of total amounts of Funds received from other institutions no EU, as national and local governments (euro).	8.25	8228	8.39	35855
	External activities	Dummy =1 if a farmer is engaged in external activities and 0 if a farmer is engaged only within the farm.	0.24	8228	0.25	35855
Financial and accounting characteristics	ROI	log of return of investment (ROI) (euro)	11.97	8228	11.97	35855
	Leverage	log of farms' leverage (euro)	7.72	8228	7.72	35855
Macro-areas	North-west	dummy=1 if regions are Piedmont Liguria Lombardy and Aosta Valley	0.13	8228	0.25	35855

	North-east	dummy=1 if regions are Emilia-Romagna, Veneto, Friuli-Venezia-Giulia, Trentino-Alto-Adige	0.23	8228	0.22	35855
	South	dummy=1 if regions are Basilicata, Calabria, Campania, Molise, Puglia	0.33	8228	0.20	35855
	Islands	dummy=1 if regions are Sicily and Sardinia	0.14	8228	0.09	35855

Table 2: Climatic variability descriptive statistics

	Variable	Description	Micro-irrigation=1		Micro-irrigation=0	
			mean	N	mean	N
Climate variables (instruments for the selection indicator: Micro-irrigation)	AIJFM	Winter Aridity Index	1.04	8228	1.16	35855
	AIAMJ	Spring Aridity Index	0.44	8228	0.49	35855
	AIJAS	Summer Aridity Index	0.35	8228	0.37	35855
	AIOND	Autumn Aridity Index	1.38	8228	1.56	35855

*Note: The Aridity Index is the ratio between P and ET_0 and it is calculated considering the moving average of the last 5 years in mm*day^{-1}. If $AI \geq 0.65$ indicates humid areas, $AI < 0.65$ indicates arid areas.*

In the selection equation (the probit model) as dependent variable a dummy indicating the adoption of WCST technologies (namely drip, micro-sprinklers and sub-irrigation) in each year has been used. In the probit model the climate characteristics, seasonal AIs, have been introduced as exclusion restrictions in order to reduce the bias due to the endogeneity of the selection indicator related to the famer's choice of adopting WCSTs (Murtazashvili and Wooldridge, 2016). In Table 2, we present the descriptive statistics of climate variability measured by the seasonal AIs. In spring and summer period, the mean values show that Italy suffers for dryness since the period should be classified as semi-arid, while in winter and autumn season, the AIs measure a degree of humidity in line with the climatic zone. This difference is confirmed even when we distinguish between adopters and non-adopeters. In the selection model, all the exogenous explanatory variables used in the outcome equation are added to the exclusion restrictions as described in Murtazashvili and Wooldridge (2016).

All the variables used in the estimation models independently if they are exogenous, endogenous or instruments are presented in Table 1, in which descriptive statistics are reported. For a more detailed description of all the variables considered see Pronti et al. (2020). Structural differences between WCST adopters and non-adopters are evident from descriptive statistics as shown in Table 1. Adopters have higher levels of productivity of land, they have more work intense activities and use less capital. Moreover, they are younger, more educated, they spent more on insurance, energy, electricity and water and cultivate higher value crop compared to non WCST adopters. This evidence emphasizes how the process of WCST adoption could depend on unobserved differences among the two groups such as the ease of adopting WCSTs by farmers who find these technologies more useful than those who do not adopt. Due to self-selection, a direct comparison between the behaviour of adopters and non-adopters is not feasible. A simple naïve comparison of the outcome variable using POLS without ESRM could lead to biased estimates.

6. Empirical results and Discussion

Results of the empirical analysis are reported in Table 3 and 4. In Table 3, the main results of the selection equation based on the CRE probit model where the dependent variable is the adoption of WCSTs are summarized. In Table 4, the estimated coefficients of the outcome equation are reported where the natural logarithm of gross land productivity represents the dependent variable. In both tables, the results are presented distinguishing between two different models. The first model (Model A) is based on the estimation of the switching regression model considering two different endogenous sources: an endogenous explanatory variable due to land value and an endogenous switching indicator due to micro-irrigation system. The second model (Model B) instead considers only one endogenous variable: the switching indicator representing the farmer's choice in adopting WCSTs (whereas land value is considered exogenous). Within each model, two alternative estimations are presented. The first estimation is based on all the farmers of the Italian agricultural sector (column 1 for Model A and 3 for Model B), while the second estimation regards only a restricted sample i.e. farmers who cultivate only crops excluding livestock productions (column 2 for Model A and 4 for Model B).

Table 3 shows the results of the binary choice model which estimates the coefficients of the main determinants of WCST adoption where the seasonal AIs are considered as exclusion restrictions. More specifically, the probability of adopting WCSTs decreases when the *AIs* for winter, summer and autumn increase. This confirms that a significant reduction of rainfalls over evapotranspiration needs increases water scarcity and thus influences farmers in choosing to adopt WCSTs. Nevertheless, other factors may affect the decision of adopting WCSTs.

Table 3. First-stage probit coefficient estimates: What factors determine micro-irrigation adoption?

	Model A		Model B	
	All farmers	Only crop farmers	All farmers	Only crop farmers
Dep. Var.	Micro-irrigation adoption		Micro-irrigation adoption	
	Endogenous Land value		Exogenous Land value	
AIJFM	-0.840***	-0.807***	-0.652***	-0.589***
	(0.000)	(0.000)	(0.000)	(0.000)
AIAMJ	3.514***	4.258***	2.788***	3.515***
	(0.000)	(0.000)	(0.000)	(0.000)
AIJAS	-1.141***	-1.209***	-1.338***	-1.416***
	(0.000)	(0.000)	(0.000)	(0.000)
AIOND	-0.474***	-0.491***	-0.285***	-0.294***
	(0.000)	(0.000)	(0.000)	(0.000)
External water source	0.237***	0.282***		
	(0.000)	(0.000)		
Mixed soil texture	-0.343***	-0.458***		
	(0.000)	(0.000)		
Altitude avg.	-0.240***	-0.255***		
	(0.000)	(0.000)		
Land value			0.005	-0.011
			(0.796)	(0.594)
Working hours	0.141***	0.150***	0.135***	0.148***
	(0.001)	(0.003)	(0.002)	(0.003)
Machine power	-0.025**	-0.013	-0.015	-0.030**
	(0.032)	(0.330)	(0.174)	(0.018)
Energy, electricity and water costs	0.014	0.040	0.034	0.073
	(0.788)	(0.513)	(0.502)	(0.222)
Insurance	0.072**	0.085**	0.078**	0.094**

	(0.031)	(0.022)	(0.018)	(0.010)
High-value crops	0.092	0.315***	0.097*	0.317***
	(0.104)	(0.000)	(0.082)	(0.000)
Age	0.005	0.010	0.002	0.007
	(0.792)	(0.606)	(0.886)	(0.727)
Age^2	-0.000	-0.000	-0.000	-0.000
	(0.852)	(0.669)	(0.921)	(0.748)
Female head	-0.058***	-0.038*	-0.070***	-0.060***
	(0.004)	(0.095)	(0.000)	(0.008)
Family run	-0.228***	-0.106***	-0.238***	-0.116***
	(0.000)	(0.000)	(0.000)	(0.000)
High education	0.003	-0.051**	-0.034*	-0.095***
	(0.891)	(0.019)	(0.068)	(0.000)
EU Funds	-0.243***	-0.236***	-0.315***	-0.386***
	(0.000)	(0.000)	(0.000)	(0.000)
No EU Funds	0.059**	0.060*	0.051*	0.050
	(0.049)	(0.088)	(0.080)	(0.148)
External activities	0.044**	0.053**	0.038*	0.037
	(0.043)	(0.032)	(0.080)	(0.129)
ROI	-0.078	-0.053	-0.075	-0.081
	(0.936)	(0.957)	(0.935)	(0.933)
Leverage	0.604	0.484	0.686	0.569
	(0.786)	(0.816)	(0.762)	(0.787)
Constant	-37.523	-20.874	-41.724	-14.740
	(0.341)	(0.576)	(0.298)	(0.698)
Dummy Year	Yes	Yes	Yes	Yes
Macro area dummy	Yes	Yes	Yes	Yes
Mundlak's device	Yes	Yes	Yes	Yes
Observations	44,083	27,565	44,084	27,565
F-test	11014	7690	9565	6568
p-value	0.000	0.000	0.000	0.000

*Note: The entire results for the reported regressions are available upon request. Bootstrapped standard errors for the CF approaches are shown in parentheses and *** p<0.01, ** p<0.05, * p<0.1*

Table 4. Final-stage coefficient estimates: the IV and the pooled-OLS regressions

	Model A		Model B	
	All farmers	Only crop farmers	All farmers	Only crop farmers
Dep. Var.:	Productivity of land		Productivity of land	
	Endogenous Land value		Exogenous Land value	
Land value	-0.752***	-0.530***	-0.014***	0.008
	(0.000)	(0.000)	(0.001)	(0.121)
Working hours	0.041***	0.037**	0.061***	0.040***
	(0.007)	(0.016)	(0.000)	(0.000)
Machine power	-0.025***	-0.063***	-0.081***	-0.102***
	(0.000)	(0.000)	(0.000)	(0.000)
Energy, electricity and water costs	0.074***	0.059**	0.083***	0.062***
	(0.003)	(0.034)	(0.000)	(0.007)
Insurance	-0.003	-0.009	0.012	-0.005
	(0.856)	(0.570)	(0.248)	(0.611)
High-value crops	0.006	-0.064***	0.018	-0.054***
	(0.720)	(0.001)	(0.110)	(0.000)
Age	0.001	-0.003	0.001	-0.004
	(0.869)	(0.571)	(0.828)	(0.342)
Age^2	-0.000	0.000	-0.000	0.000
	(0.939)	(0.605)	(0.653)	(0.587)
Female head	-0.025***	-0.026***	-0.019***	-0.013**
	(0.000)	(0.000)	(0.000)	(0.024)
Family run	-0.102***	-0.042***	-0.029***	0.020**
	(0.000)	(0.003)	(0.001)	(0.016)
High education	0.016**	0.012	-0.031***	-0.025***
	(0.042)	(0.178)	(0.000)	(0.000)
EU Funds	0.048***	-0.030	-0.172***	-0.147***
	(0.010)	(0.177)	(0.000)	(0.000)
No EU Funds	-0.010	-0.008	-0.002	-0.006
	(0.363)	(0.475)	(0.631)	(0.359)
External activities	0.016**	0.016*	-0.001	-0.011**
	(0.017)	(0.085)	(0.852)	(0.046)
ROI	0.900	0.329	0.569	0.316
	(0.254)	(0.667)	(0.502)	(0.691)
Leverage	-0.250	-0.356	-0.194	-0.459
	(0.926)	(0.845)	(0.927)	(0.843)
Micro-irrigation	245.272**	248.695***	188.284***	169.792***
	(0.013)	(0.001)	(0.002)	(0.003)
Land value * Micro-irrigation	-0.519***	-0.857***	-0.101***	-0.149***
	(0.000)	(0.000)	(0.000)	(0.000)
Working hours * Micro-irrigation	0.044	0.060	0.054*	0.077**
	(0.284)	(0.190)	(0.050)	(0.018)
Machine power * Micro-irrigation	-0.143***	-0.120***	-0.144***	-0.133***
	(0.000)	(0.000)	(0.000)	(0.000)

Energy, electricity and water costs * Micro-irrigation	-0.023	-0.001	-0.015	0.009
	(0.718)	(0.986)	(0.690)	(0.842)
Insurance * Micro-irrigation	0.007	0.017	0.014	0.027
	(0.868)	(0.693)	(0.491)	(0.239)
High-value crops * Micro-irrigation	0.003	-0.051	-0.004	-0.053
	(0.946)	(0.342)	(0.881)	(0.122)
Age * Micro-irrigation	0.005	0.005	0.006	0.007
	(0.753)	(0.769)	(0.546)	(0.501)
Age^2 * Micro-irrigation	-0.000	-0.000	-0.000	-0.000
	(0.799)	(0.819)	(0.643)	(0.597)
Female head * Micro-irrigation	-0.052**	-0.058**	-0.018	-0.012
	(0.015)	(0.011)	(0.249)	(0.403)
Family run * Micro-irrigation	0.077***	0.015	0.047***	0.014
	(0.004)	(0.580)	(0.009)	(0.409)
High education * Micro-irrigation	0.008	0.030	-0.033**	-0.026*
	(0.686)	(0.218)	(0.012)	(0.055)
EU Funds * Micro-irrigation	0.070	0.217***	-0.099***	-0.088***
	(0.128)	(0.000)	(0.000)	(0.000)
No EU Funds * Micro-irrigation	-0.005	-0.005	-0.022	-0.022
	(0.892)	(0.903)	(0.248)	(0.287)
External activities * Micro-irrigation	-0.112***	-0.120***	-0.077***	-0.078***
	(0.000)	(0.000)	(0.000)	(0.000)
ROI * Micro-irrigation	-0.228	0.348	0.145	0.349
	(0.860)	(0.808)	(0.893)	(0.748)
Leverage * Micro-irrigation	3.461	3.343	3.041	3.420
	(0.661)	(0.638)	(0.589)	(0.529)
Constant	81.859***	42.407	-62.747***	-54.962**
	(0.009)	(0.110)	(0.002)	(0.011)
Dummy Year	Yes	Yes	Yes	Yes
Macro area dummy	Yes	Yes	Yes	Yes
Mundlak's device	Yes	Yes	Yes	Yes
General residuals	Yes	Yes	Yes	Yes
Observations	44,076	27,562	44,076	27,562
Underidentification test	931.8	564.5		
p-value	0.000	0.000		
Weak identification test	158.4	95.81		
Wald test on Mundlak's device	32.58	26.17	572.41	327.35
p-value	0.000	0.000	0.000	0.000
Wald test on general residuals	443.13	312.05	7.82	139.66
p-value	0.000	0.000	0.005	0.000

*Note: The entire results for the reported regressions are available upon request. Bootstrapped standard errors for the CF approaches are shown in parentheses and *** p<0.01, ** p<0.05, * p<0.1*

The most important characteristics which positively affect the adoption of WCSTs are *working hours*, *insurance* against agricultural risks (at the 5% of significance) and, to a lesser extent, *high-value crops*, *no EU funds* and *external activities*. The positive relationship of *working hours* by labour force, which may measure even the size of a farm, means that the greater is the farm size the more likely is the adoption of WCSTs by farmers. New irrigation systems are more likely to be observed on labour-intensive farms (Green et al., 1996; Huang et al., 2017 and Pronti et al., 2020). As regards *insurance*, farmers' risk aversion increases the adoption of irrigation technologies to reduce agricultural production risk confirming the main findings of Fuglie and Bosch (1995) and Feder et al. (1985).

Conversely, there are other factors which affect negatively the adoption of WCSTs. *High-education* has a negative impact on the probability of adopting WCSTs, the coefficient is statistically significant at the 1% only for the Model B and the crop farmers sample of Model A. This result is in contrast with the literature that has found an opposite and significant sign (Alcon et al., 2019; Moreno and Sunding, 2005; Pokhrel et al., 2018; Salazar and Rand, 2016). Moreover, if the head of a farm is a female, the farm is run at the family level, and the funds come mainly from the EU institutions, it is less likely to adopt WCSTs. As regards the geographical variables, the signs of the coefficients confirm the descriptive analysis where the WCST distribution over the country is dominant in the South and Island macro-areas. Farms placed in the southern part of Italy or in the two islands are more likely to adopt WCSTs compared to those farms located in the northern-west part of Italy where the probability of adoption is less.

In the hypothesis of the presence of a continuous endogenous variable as land value, the instrumental variables – *External water source, Mixed soil texture* and *Altitude average* – show significant coefficients meaning that these variables are important determinants in the choice of WCST adoption. More specifically, the use of *external water source* positively influences the adoption of WCSTs, whereas the quality of soil (*mixed soil texture*) and the average height of fields (*Altitude avg.*) negatively affects the adoption of WCSTs. Thus, having a higher *average altitude.*, as well as a *mixed soil texture* type, reduces the probability of WCST adoption. For a deeper discussion of the marginal effects and elasticities of the different characteristics of the WCST adoption within the selection equation, one may refer to the analysis of Pronti et al. (2020).

By considering the outcome equation results as reported in Table 4, findings on land productivity for WCST non-adopters are compared to WCST adopters. The relevance of general residuals, confirmed by the Wald test, indicates that, in all the models, the self-selection is present and the use of WCSTs can improve substantially land productivity. When assuming land value as an endogenous variable, the effect of *land value* and *machine power* on land productivity is predicted to be statistically different for non-adopters with respect to adopters. The effect of the intense use of capital (*machine power*) and *land value* is negative for both types of farmers. This confirms that controlling for endogeneity allows land value to have a negative impact on land productivity if farmers innovate. This result is the opposite for labour input where only for WCST non-adopters it is possible to achieve higher performances for each hour spent working in a farm. Those findings, the negative effect of capital intensity and the positive effect of labour intensity on farm productivity, can be explained by the fact that farm productivity (our dependent variable) is normalized per hectare (unit of measure is € per Ha). Therefore, the results do not say that capital is negative for productivity, but that considering unitary level of land productivity the increase of machinery usage level reduces productivity outcomes. Conversely, labour intensity increase productivity per hectare of agricultural land. Then, capital intensity can be seen as an effective strategy considering high extensions of land used, conversely work intensity can increase productivity with small agricultural fields.

The findings also indicate that a man, not so well-educated whose farm is family run who adopts WCSTs would gain in terms of land productivity. Whereas, for non-innovative farmers, being a male that runs a non-family farm with higher education as in Model A (with no higher education as in Model B) would improve land productivity.

Receiving EU subsidies increase (decrease) land productivity for both, adopters and no-adopters for Model A (for Model B), whereas receiving additional income from external activities reduce land productivity for WCST adopters and conversely increases land productivity for non-adopters for Model A but the significance decreases dramatically. The *high education level* coefficient is positive (negative) and statistically significant at 5% (1%) level for non-adopters for Model A (for Model B), whereas it is not significant for adopters for Model A while is negative but statistically significant only at 5% for Model B.

Since all the estimated coefficients of the models can be interpreted as elasticities, one may observe that no evident differences arise among the models and between the two regimes of adoption (adopters and non-adopters). Most of the coefficients show low elasticities of land productivity with respect to the explanatories (they are mainly lower than 0.5), only land value shows very high level of elasticities, but only for Model A which considers the variable as endogenous.

Excluding livestock production farms from the sample produces the same results as for the whole sample. The WCST adopters' coefficients of the different explanatory variables do not show different impact with respect to the all farmers sample, thus indicating the robustness of our results.

Considering land value as an exogenous variable, and therefore performing a OLS instead of 2SLS, as in Model B, produces similar results for all the explanatories, with some exception as we already discuss. However, the most important difference regards *land value* which shows a lower magnitude and, for WCST no-adopters, a statistically insignificant coefficient in the case of only crop farmers. This suggests the presence of endogeneity between land productivity and land value. Thus, the more appropriate approach is the ESRM with an continuous endogenous explanatory variable which implies the use of the 2SLS method in the estimation of the outcome equation. Even in this case the Wald tests on generalized residuals confirm endogeneity in the selection process showing that sample selection bias would be present if the outcome equation has been estimated without considering the irrigation adoption decision. Moreover, running the model as a POLS considering WCSTs only as a exogenous dummy variable would have led to biased and inconsistent estimations (Di Falco and Veronesi, 2011). The Wald tests on Mundlak's devices also confirm the correctness in the use of this strategy to cope with individual heterogeneity.

Main differences in productive performances are more evident by estimating the average treatment effects of WCST adoption as in Table 5 (Abdulai and Huffman, 2014; Di Falco and Veronesi, 2013; Fuglie and Bosch, 1995). Differently from the analysis of a simple mean difference of the two sub-samples (adopters and non-adopters) which has the disadvantage of confounding the impact of WCST adoption on land productivity with the influence of other characteristics, these ATET estimates allow selection bias to be taken into account. This implies that the systematically difference between adopters and non-adopters is controlled by applying the ESRM. Estimating the average treatment effect on treated (ATET) implies to compute the difference in means between the outcome of the treated sample that actually adopted WCSTs and the mean of potential outcome of the same sample if they had not adopted WCSTs. (Angrist and Pischke, 2009).

Table 5. Impact of WCST Adoption on Land Productivity

		Mean outcome			
		Adopters	Non-Adopters	ATET	t-value
All farmers	Model A	26,900.71	8,688.549	18,212.16***	55.60
	Model B	23,315.31	16,100.17	7,215.14***	42.65
Only crop farmers	Model A	29,144.35	7,878.947	21,265.4***	47.9
	Model B	24,541.73	8,988.56	15,553.17***	78.70

*Note: ATET, average treatment effect on the treated; values are expressed in euro. *** Coefficient significant at the 1% level.*

The results suggest that the adoption of WCSTs significantly increase land productivity of adopters and that WCSTs potentially could improve productive performance of non-adopters either. By focusing on the ATET values, they are all highly statistically significant in both Models and in either all the farmers or only crop farmers sample. In the case of all farmers, Model A presents an ATET value of land productivity equals to 18,212.16 (€ per Ha) for adopters who adopt WCSTs with respect to the counterfactual case in which the same farmers had not adopted. Considering only crop growers the ATET value is even higher 21,265.4 (€ per Ha). In the case of Model B the value of ATET is 7,215.14 (€ per Ha) and 15,553.17 (€ per Ha) respectively for all type of farms and only crop growers. This further confirms that considering endogeneity of land value can release sensibly higher level of expected outcome for treated units. The counterfactual analysis on treatment effects shades light on the positive effect of WCST adoption on the productive performance of a farmer who adopts.

These findings confirm the importance of the adoption of new technologies within agriculture due to the improvement of farm productivity (Abdulai and Huffman, 2014) and the role of innovation policies to achieve an economically sustainable expansion of the agricultural sector in Italy. By boosting the adoption of WCSTs, it should be feasible to reduce the impact of agricultural activities on water resources through the improvement of the efficient use of scarce natural resources. This in turn may produce an increase in land productivity of Italian farmers. A policy maker oriented toward more conservative policies in the use of water in the agricultural sector should take into consideration the wide effect of WCST adoption on production performance when an incentive for supporting the adoption of WCSTs should be decided. Policies that boost more efficient use of water resources may therefore reach a double aim i.e. improving the economic values for the adopting farmers and reducing the negative impact on water resources.

7. Conclusions

In this paper, we addressed an important issue in agricultural water management using a novel application of the theoretical econometric model of Murtazashvili and Wooldridge (2016) dealing with two sources of endogeneity in the selection models. Differently from previous applications, we exploited a panel data approach considering the case study of Italian farmers which are characterized by geographical, socio-economic and environmental diversity. Our estimation released robust results and some statistical tests evidenced that the adoption WCSTs is an endogenous and self-selective process. By using common econometric methods, we would have biased and inconsistent results. The climatic variables used in the selection equations indicate that weather variability is an important factor in the WCST adoption choice. Other elements based on the literature are included and confirm the probability of adopting the new irrigation technologies in the agricultural sector. Differences in the outcome equations between adopters and non-adopters are significant and the counterfactual analysis highlight that adoption of WCSTs as a strategy to cope with water scarcity increase the overall farm productivity.

In terms of policy suggestion, our analysis confirm the relevant role of innovation in the irrigation systems and the fact that more productive farmers are those that adopt WCSTs. Therefore, following a policy through the spread of innovation in the irrigation systems among all farmers may be an effective strategy for reducing pressures on water resources from the demand side with remarkable positive economic effects for WCST adopters. In the next future, when climate variability and water scarcity will be substantially more stringent, increasing irrigation issues, the strategy of boosting farmers' technological improvements to enhance water productivity and water efficiency might be of crucial importance for sustainable agriculture.

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