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"THE ECONOMICS OF WATER SUSTAINABILITY MANAGEMENT FOR AGRICULTURE IN ITALY"

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Main introduction

Water management will soon be one of the most important issues on the international political agenda. Although various institutional efforts at international level have been undertaken in order to highlight how critical the management of water resources at global level is, water seems to be marginal in economics research - considering it not as crucial as other environmental topics such as air pollution, waste management, or climate change. The reasons why the debate over water was not of primary interest to economists are not easily understandable as water is a basic pillar of life. This was pointed out by Adam Smith through the diamond-water paradox, according to which

” *Even though life cannot exist without water and can easily exist without diamonds, diamonds are, pound for pound, vastly more valuable than water.* “

The lack of consideration of water in the economic literature is emblematic, and can be explained by: its intrinsic characteristics, such as its mutability of state (solid, liquid, and gas); its non-transportability as a classical commodity; and, its different forms of being both a private and a public good with different levels of rivalry, which make water very difficult to be classified as a standard economic good (Garrick et al., 2020).

Although scarcity is one of the key concepts on which economic science is founded, empirical works on water economics are still scarce in comparison to other topics of environmental and resource economics literature. One of the main reasons for the poor economic debate over water can be related to the general scarcity of data on water, and the significant difficulties in applying appropriate conventional empirical economic models. Other reasons could be hidden by the disconnection, in developed countries, between the high level of water needs satisfactions and users imaginary over real water endowments and water availabilities, which might lead to a false perception of an ever-lasting water abundancy (Praskievicz, 2019). Last (but not least), another explanation may be connected to some kind of political fear towards economists, seen as creatures able to commodify everything, even a recognized human right as water. This may have created a sort of “taboo” over water issues in economics.

In any case, water scarcity is endangering many areas of the world, affecting almost four billion people globally, and in the coming decades water-related problems will become one of the most crucial challenges for human development, environmental conservation, and food security (Unesco et al., 2019). Climate change will exacerbate this difficult situation, adding important unexpected stress on water resources and reducing its availability for both drinking and food production, with detrimental effects on economic growth and social stability. Moreover, increasing population, urbanization, and global affluence will converge in an exponential growth of water demand in a world that will face an even more erratic precipitation and variability of water supply. This will affect the global socio-economic and environmental systems in an unexpected way, because of the strong nexus which links water resources to energy and food production, health, rural and urban settlements, and natural ecosystems (World Bank, 2016). Price spikes as well as unexpected weather shocks such as droughts and floods will disproportionately impact the fragile components of societies, exacerbating the already existent inequities and social differences between rich and poor, potentially leading to mass migrations, strong social conflicts, and political turbulences (Homer-Dixon, 1999).

Agriculture is one of the biggest drivers of water diversion and water abstraction, which around the globe is accounted to be on average 70% of the total water withdrawals. Moreover, agricultural activities are one of the heaviest sources of pollution and contamination of water resources, due to extractive and industrial practices used as a main paradigm of rural development since the green revolution of the Sixties. A focus of socio-economic research activities on agricultural water management is therefore crucial, as this sector is the main nexus which links water with food-health-environment-energy issues.

The Mediterranean basin is one of the most vulnerable areas in terms of water scarcity, while at the same time being one of the most agricultural productive areas of the world. With a high level of probability, the changes in temperatures and precipitation levels will increase water stresses, thus hampering agricultural production and food security. In spite of a relative abundance of precipitations compared to other Mediterranean countries, Italy is characterized by a high-level annual precipitation, but with strong regional differences in terms of historical water scarcity, water management policies, and agricultural structure. Moreover, at national level, increased variability in rainfall and growing temperatures have been recorded in the last decades, increasing pressures on water resources for agricultural activities (Laureti et al., 2020). The latitudinal diversity within Italy in terms of geographic, climatic, socio-economic and productive contexts make Italy a good candidate for being a strategic geographical area of study for the whole Mediterranean basin, although Italian case studies have been only seldom tackled before.

Policies and economics are essential for the design of adequate interventions in the agricultural sector, well-suited to support structural changes towards more sustainable water management for guaranteeing food production, rural development, the safeguard of ecosystems, and the resilience of the farming sector to climatic shocks at the same time. The European Water Framework Directive (WFD) was a first step toward a structural change in water management in Europe which envisaged the transition of agriculture towards a more sustainable production model as a cornerstone for improving the conditions of European water resources. Even though many steps have been covered, the finish line is still far away, and the time for structural changes is running over.

Many open questions in agricultural water economics literature still persist, predominantly because of the scarcity of data available for strong empirical analysis. One of the main issues which are debated in the literature are related to irrigation technological innovations adoption from a farmer perspective. Some studies have analysed the main socio-economic and environmental determinants of adoption, but only to homogenous delimited areas, disregarding the intensity of adoption in terms of irrigated land. The effectiveness of sustainable irrigation adoption in terms of economic benefits for adopters has not been widely explored.

Considering these aspects, the first and the second main research questions of this dissertation are:

Research question 1.
What are the main determinants of sustainable irrigation technology adoption of Italian farmers at national level?

Research question 2.
What are the productive gains of farmers in adopting sustainable irrigation technologies?

Another important aspect, too often overlooked in water economics, is the analysis of water management policies and their effectiveness in guiding sustainable and conservation behaviours of farmers. Specifically, opinions are polarized over pricing policies effectiveness in driving agricultural water savings, as there is not a clear agreement over farmers' water demand elasticity; which involve discordances around whether farmers are responsive to price incentives as in general neoclassical economics framework (Scheierling et al., 2006). This implies uncertainties and high potential margins

of error for policy makers in setting suitable pricing policies (either market, taxes, or tariffs) towards water conservation goals.
In light of these aspects, the third and the fourth main research questions of this dissertation are:

Research question 3.
What is the short term water demand elasticity to price of Italian farmers?

Research question 4.
Can the use of pricing policies cause a reduction of water use in agriculture?

This PhD thesis aims at contributing with in-depth empirical analysis to the existing water economics literature and to the policy debate on water conservation in agriculture using Italy as a case study. The dissertation is composed of four interconnected empirical essays on water economics in Italy. The papers are based on the analysis of vast observational microeconomic datasets at national and provincial level.
In all the papers farm data have been combined with the main climatic variables such as accumulated precipitation, reference evapotranspiration, minimum and maximum temperatures, and aridity index.
The papers are focused mainly on two topics of water management in agriculture from the demand side. The first is the adoption of water conservation and saving technologies (WCST), studying the main determinants of adoption and the impacts in terms of production due to WCST. The second topic is linked to agricultural water conservation policies, and the reaction of farmers to pricing water on water consumption. Both topics are extremely important as there are not many other studies covering these issues using panel data econometric analysis at vast scale.

The evidence from the findings of this thesis can be of interest for both academics and policymakers, as they highlight some critical points in the water economics debate: the effectiveness of water pricing for incentivizing farmers to adopt water conservation strategies, a detailed measure of famers' water demand elasticity to price, the determinants and the intensity of WCST adoption, and the gains in terms of production due to the adoption of WCST.
The first paper "*What are the factors driving the adoption and intensity of sustainable irrigation technologies in Italy?"* authored with Prof. Sabrina Auci and Prof. Massimiliano Mazzanti analyses the main determinants of the intensity of WCST adoption at national level using farm panel data analysis combining binary choice and tobit models, to identify the main factors which could be used by policymakers to boost a sustainable transition through a wide use of WCST.
The second paper "*Innovation in Irrigation Technologies for Sustainable Agriculture: An Endogenous Switching Analysis on Italian Farms' Land Productivity*" written with Prof. Sabrina Auci is a novel application of the endogenous switching regression model, with the objective of considering differences in productive outcomes due to the adoption of WCST avoiding selection biases. This study analyses whether the gains in productive terms induced by the use of WCST could furtherly induce adoption of sustainable technologies considering it as a win-win solution for both famers and policymakers, as they result in higher profits and water saving at the same time.
The third paper "*Water Demand Elasticity in agriculture: the case of Emilia Centrale Irrigation Water Districts*" authored with Prof. Julio Berbel analyses the elasticity of farmers' water demand as a proxy of reactivity to water consumption to prices. The topic is widely debated in the literature and this contribution can be important as our analysis offers an application on different crops, technologies, and combinations of them with interesting empirical results.

The fourth paper "*The impact of volumetric water tariffs in the irrigated agriculture in Northern Italy*" authored with Prof. Julio Berbel studies the effect of the introduction of a volumetric tariff on farmers, analysing their change in water consumption. This study uses a novel application of the difference in differences method, adapting it to the empirical situation under analysis. The results of the study provide evidence of the effectiveness of water tariffs linked to the reduced farmers' water consumption even with small amount of charges. This empirical application demonstrates that famers react to water prices changing from a free public good behaviour to a private commodity inserting water in their cost functions.

These analyses are among the first studies in agricultural water economics literature with a strong microeconomic framework using observational data at farm level. To the best of my knowledge, no other in-depth empirical microeconomic works (using panel data econometrics) have been developed at national or regional level in Italy or in other Mediterranean countries before these studies. Moreover, this dissertation contributes to economic literature through the application of two novel empirical methods (Endogenous Switching Regression and Inverse Difference in differences) which can be replied in other policy analyses considering other topics.

The findings of this dissertation, even if are focused on just one nation, can be easily replicated in other countries if similar data are available. The results of this research can be easily translated into practical policy suggestions for institutions and public managers contributing to the international debate on water resource sustainable management.

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What are the factors driving the adoption and intensity of sustainable irrigation technologies in Italy?

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Abstract

This paper analyses the determinants of Italian farmers' adoption and intensity of sustainable irrigation technologies such as microirrigation (drips and sprinklers) and subirrigation. To improve farmers' water management, promoting incentivization for climate change adaptation should be encouraged. Italy, like other Mediterranean countries, has suffered the most from an increase in the frequency and intensity of droughts, higher temperatures and less precipitation. By applying innovative irrigation systems, water scarcity and water stress may be monitored if not overcome. Accurate analyses of the determinants of the adoption and intensity of these techniques are still scarce. Filling this gap, this study uses a microeconomic approach that combines farm data and climatic variables of Italian farmers. Based on an unbalanced panel dataset for the period 2012-2016, the determinants of a farmer's decision to adopt irrigation-saving technology are estimated by applying logit, probit and correlated random effects probit models, while tobit and correlated random effects tobit models are used for estimating the intensity of adoption. Our main findings confirm that farm size, crop typology, land tenure, age, insurance against farming risks, internal water sources, geographical and climate characteristics are all relevant factors that influence the choice of sustainable irrigation technology adoption as well as adoption intensity.

Keywords: Water conservation and saving technologies; Irrigation technologies; Technology adoption; Adaptation to climate change; Italian farmers

1. Introduction

Water scarcity and sustainable water management describe two crucial issues that humankind will face in the future (Wheeler et al., 2015). Water scarcity affects approximately four billion people and will represent the main shortcoming for many developing countries during sustainable development (De Angelis et al., 2017; Hoekstra and Mekonnen, 2016). Among all the exogenous problems, climate change (CC) and population growth are putting extraordinary pressures on water resources in arid and semiarid regions, which are already strongly affected by anthropic activities (Fischer et al., 2007). Water resource depletion is deeply related to agricultural activities, which may exacerbate global food security and social stability issues (FAO, 2012; Alexandratos and Bruinsma, 2012 FAO, IFAD and WFP, 2015).

The increasing global agricultural water demand is mainly due to intensive irrigation and the mass production of crops. In southern Europe, agriculture is responsible for almost 80% of freshwater withdrawals (Alcon et al. 2011). In the Mediterranean Basin, which is characterized by erratic and inconstant climates, water reservoirs have declined in quantity and quality, causing important environmental damage in recent years (AquaStat, 2018; Tilman et al., 2002; Fischer et al., 2007). Climate variability involving more frequent, extreme, and adverse climate conditions may increase the water demand for irrigation and farmers' needs (Huang et al., 2017; Lu et al., 2019) and exacerbate water shortages within water basins due to increasing demand peaks in drought periods (Mestre-Sanchís and Feijóo-Bello, 2009; Olsen and Bindi, 2002). Rising water withdrawals may intensify competition among alternative uses such as agricultural and civil services, as well as natural needs (Iglesias et al., 2009; Alcon et al. 2011).

Characterized by low levels of water efficiency, the agricultural sector wastes water resources due to evaporation, percolation and runoff losses (FAO, 2011; MEA, 2005). Under water scarcity conditions and climate variability, substantial efforts should be devoted to improving water efficiency. Crop production efficiency should be achieved with less water use and better water management (Chartzoulakisa and Bertaki, 2015). Promoting the adoption of water conservation and saving technologies (WCSTs), such as drip irrigation, low-pressure microsprinkling and subirrigation, may greatly contribute to reducing agricultural activity impacts on water resources in the context of water scarcity and water endowment variability (Green et al., 1996; Pfeiffer and Lin, 2014; Expósito and Berbel, 2019).

The ratio between irrigation water requirements and withdrawals is generally very low, suggesting a scarce irrigation efficiency. Applying innovative irrigation technologies such as WCSTs allows farmers to achieve water management improvements (Alcon et al., 2014; Frenken and Gillet, 2012; Chartzoulakisa and Bertaki, 2015) mainly through a reduction in the number of water applications that are poured directly onto crop roots, which lessens water stress (Pereira, et al. 2002; Schuck et al., 2005; Dasberg and Or, 1999); a decrease in the amount of water per unit of time consumed by crops that now receive with higher precision the exact amount of water required; and finally, a reduction of water loss due to less evapotranspiration (Taylor and Zilberman, 2017; Wheeler et al., 2010). The use of WCSTs may alleviate crop diseases due to over-irrigation, salinity and erosion effects (Skaggs, 2001; Alcon et al., 2019), thereby enhancing water productivity, i.e., the capability of producing more value with less water (Expósito and Berbel, 2019).

The adoption of a well-defined innovative irrigation system is related not only to interactions among institutions, scientists and farmers but also to how much knowledge and technology is spread in the economy (Horst, 1998; Turral et al., 2010). According to production theory, to maximize their own benefits, farmers should choose the right amount of production inputs based on their future expected values (Fleischer et al., 2011). Therefore, a farmer's choice should include the best adaptation strategies for climate change. Deciding to adopt new technology is mainly related to expectations about future outcomes, as well as perceptions and information received. Therefore, by considering different scenarios of climate change, a farmer may gain the maximum benefits, thereby lessening the exploitation of natural resources (Reidsma et al., 2010). Farmers' decisions regarding production and technology adoption may have an effect on natural resource management. Thus, analysing the determinants of a farmer's choices related to adopting sustainable water technologies may be important to prevent and mitigate water scarcity and droughts, as defined by the European Union (EU)'s Strategy for Water Scarcity and Droughts policy, whose main aim is to ensure access to good quality water in sufficient quantities. This may contribute to developing a water-efficient and water-saving economy.

While a relevant stream of literature on irrigation systems is still present (Caswell and Zilberman, 1985; Alcon et al. 2011; Alcon et al., 2014; Taylor and Zilberman, 2017; Alcon et al. 2019), a stream of WCST adoption literature has emerged in recent years (Shrestha and Gopalakrishnan 1993; Expósito and Berbel, 2019). Due to data availability, econometric studies are mainly based on case studies of specific sub-regional areas in developing countries (Skaggs, 2001; Shah et al. 2013; Getacher et al., 2014) and developed countries (Caswell and Zilberman, 1985; Expósito and Berbel, 2019) or on cross-sectional analyses (Shrestha and Gopalakrishnan, 1993; Kondouri et al 2006). However, both case studies and cross-sectional analyses present some drawbacks, such as not considering heterogeneity or endogeneity problems (Greene, 2003).

This paper fills this gap by collecting a detailed dataset at the farmer level for a well-developed country, namely, Italy. Thus far, this analysis represents a first attempt to examine the farm-level innovation drivers of WCST adoption and intensity. The determinants of farmers' decisions related to adopting water-saving technologies are estimated by applying three binary response models (logit, probit and correlated random effects probit models), while tobit and correlated random effects tobit models are used for estimating the intensity of adoption. Accurate analyses on the determinants of farmers' adoption and intensity of innovative irrigation techniques are still scarce even though the adoption of sustainable irrigation systems can optimize water requirements. Farm-level data representing 13,592 farmers for the period of 2012-2016 are merged with climatic indicators. This combined dataset allows us to use panel data methodologies to control for unobserved heterogeneity and endogeneity. The point of deepening the understanding of farmers' WCST adoption choices in Italy is mainly related to the diversified orographic and microclimatic areas. Dissimilarities among farmers are principally due to geographical, socioeconomic, productive, and climatic factors. All these factors make Italy an interesting case study within the Mediterranean Basin that shares similar climatic conditions and longitudinal positions.

As found in several previous studies that focused primarily on the determinants of micro-irrigation system adoption, socioeconomic and geographical factors contribute to affecting farmers' decisions to adopt WCSTs. To these factors, we add other determinants, such as environmental and climatic characteristics, which are selected on the basis of economic theory and researchers' perceptions (see Mango et al., 2018 for a review). Moreover, we also contribute to the literature by analysing those factors that may affect the intense distribution of WCSTs over the total amount of irrigated land. Due to a lack of detailed data, very few analyses have considered the intensity of irrigation technology adoption and its drivers (Arslan e al. 2014; Pokhrel et al., 2018).

The paper is organized as follows. Section 2 focuses on the literature regarding the technology adoption of WCSTs for irrigation. Section 3 develops background information on the Italian irrigation context. In Section 4, the empirical framework and data description are presented, while in Section 5, the results are shown and discussed. Finally, in Section 6, some main conclusions with policy implications are organized.

2. WCST adoption for sustainable irrigation

Technological innovation can be considered an improvement over past technologies and techniques used within a productive and socio-economic process with the aim of improving efficiency, effectiveness and higher values of outcomes. The innovation decision-making process can be defined as a dynamic process in which an economic agent (i.e., a farmer) passes through five steps (knowledge, persuasion, decision, implementation and confirmation) (Rogers, 1971).

Starting from a disequilibrium in which a farmer does not efficiently use the available resources means that information on new innovations is used to reach a new equilibrium. In a long-run equilibrium, the final adoption consists of deciding to use the new innovative technology (or process) after having considered all the potentials and drawbacks (Feder et al., 1985).

A relevant literature on technology adoption has emerged since the 1960s. Studies have explored the distinctive factors that may influence the decision to implement innovations (Jaffe et al. 2002). A growing branch of this literature has focused on the agricultural determinants of adopting innovation, such as agroecological constraints, farmers' characteristics, land features, seed supply constraints, risk preferences, or traditional values (Koundouri et al. 2006; Pannell et al, 2006; Arslan and Taylor, 2009; Arslan et al., 2014). This topic has started to gain interest, especially in the study of developing countries (among others Feder et al., 1985; Neupane et al., 2003; Sheikh et al., 2003; He et al., 2007; Arslan et al. 2014; Mango et al. 2018), where the focus is on the causes that determine the success or failure of agricultural innovations such as improved fertilizers, ploughing techniques and pest control (Feder and Umali, 1993; Baidu-Forson, 1999; Somda et al., 2002; Herath and Takeya, 2003).

Within the technology adoption literature, a specific branch is related to water technology adoption, which aims to improve water management and water conservation by applying both theoretical and empirical approaches (Taylor and Zilberman, 2017). In the empirical analyses, the focus on the main factors that may influence the adoption of WCSTs has been based on binary response models such as logit, probit and multinomial logit models. These methodologies are used to understand the probability of the adoption of a specific technology over the set of several technologies that are available. Very few studies (Arslan et al., 2014; Pokhrel et al., 2018) have used nested binary models, fractional methods or tobit models to study the intensity of adoption in terms of land under a specific technology. In Table 1, the main studies on WCST adoption are summarized, highlighting the methods applied in their analyses.

Among the seminal works on this field, we may recall the analyses of Caswell and Zilberman (1985), Shresta and Gopalakrishnan (1993), and Green et al. (1996), which focus mainly on farm production features (such as crop type, field size, expected yields), geographical aspects (such as type of soil, slope) and water resource characteristics (such as water sources, water price and irrigated land size). Subsequently, Skaggs (2001), Moreno and Sunding (2005), Schuck et al. (2005) and Foltz (2003) introduce farmers' characteristics such as age, education, years of experience, in-farm and off-farm income, expectations of water availability, access to information and extension services. More recently, other studies have enlarged the initial framework by adding further interesting factors such as electricity costs (Namara et al., 2007; Wheeler et al., 2010; Singh et al., 2015), farming production risks (Koundouri, 2006), social factors—being part of farmers' organizations, the imitation of adopting WCSTs by other colleagues, social networks, etc.—(Alcon, 2011; Salazar and Rand, 2016; Hunecke et al.) and mechanization levels within farms (Mohammadzadeh et al., 2014). The variables of financial aspects (Alcon, 2011), governmental incentives (Huang et al., 2017) and water measuring instruments used (Hunecke et al., 2017) have also been considered. All these abovementioned studies substantially agree in confirming that the main determinants of adoption are socioeconomic, technical, geographical and productive factors, even though the results are contradictory for some factors (Koundouri et al., 2006).

Finally, further studies have introduced climatic variables as having an effect on WCST adoption choice. Among the indicators used to capture these climate effects, we may recall evapotranspiration, rainfall, temperature (Negri and Brooks, 1990; Huang et al., 2015), frost-free days (Negri and Brooks, 1990; Moreno and Sunding, 2005) and drought aridity events (Schuck et al., 2005; Kondouri et al. 2006; Genius et al., 2014; Olen et al., 2015; Knapp and Huang, 2017). Moreover, Frisvold and Deva (2013) and Knapp and Huang (2017), which focus on climate and irrigation technology adoption, introduce climatic variables considering both different time spans (from 5 to 40 years) and the variations and intensities of climatic events.

The majority of the abovementioned studies, with just a few exceptions, rely on one-year case studies based on surveys related to case-specific productive agricultural areas. The use of cross-sectional data confines the analysis to the explanation of why a farmer chooses to adopt new technology in the particular period considered. This approach may reduce the reliability of theoretical dynamic models that focus mainly on farmers' dynamic processes for choosing technology adoption on different dates or for excluding time-related elements such as learning by doing, observation and information collection, productive strategy changes, macroeconomic events and the individual heterogeneity of farmers (Koundouri et al., 2006). By providing more robust and consistent estimates, the use of panel data models can substantially improve the results of an analysis by controlling for a dynamic pattern that is either endogenous or exogenous, the effects of time-specific events and unobserved individual effects (Greene, 2003). Only a few studies have used panel data in developing either continuous, fractional, multichoice or binary dependent variable models (Table 1). Moreover, most of the studies conducted in the WCST adoption literature have referred to countries and areas with important water problems, such as Israel, Iran, Greece, Spain, India, Tunisia, Chile, African countries, the United States and China (see Table 1 for references).

To the best of our knowledge, there are no relevant studies in this literature on Italian farmers. Italy represents an interesting case study since its agricultural production is mainly based on irrigation. The only studies that consider irrigation water issues are based on a different empirical setting. Irrigation water represents a relevant input for a producer's optimization problem in a specific zone of southwest Sardinia (Dono et al., 2011) or a strategic decision made under climate-related risk perception for all Italian farmers (Bozzola, 2014). As found in the analysis of Pino et al. (2017), which is based on a survey dataset, psychological aspects, such as favourable attitudes towards water-saving measures and farmers' innovativeness, or orientations of environmental associations may positively influence the adoption of water-saving measures. A more exhaustive analysis is that of Capitanio et al. (2015), who consider the effects of climate change and irrigation decisions over the Italian agriculture sector. Using the FADN dataset and applying a panel procedure, Capitanio et al. (2015) find that irrigated land (compared to rainfed land) is an important factor in producing agricultural income. Even if this study is interesting, it does not consider which are the main determinants for irrigation adoption. Thus, in the Italian agricultural sector, a deeper investigation of the drivers of WCST adoption is needed.

Table 1. Main studies on WCST adoption.

Authors	Year	Area	Country	Method
Caswell and Zilberman	1985	San Joaquim Valley (California)	United States	Multinomial logit
Shrestha and Gopalakirishnan	1993	Hawaii	United States	Probit model
Green et al.	1996	San Joaquim Valley (California)	United States	Multinomial logit
Skaggs	2001	New Mexico	United States	Logit model
Foltz	2003	Cap Bon	Tunisia	Probit model
Shuck	2005	Colorado	United States	Logit and multinomial logit
Moreno and Sunding	2005	Kern County (California)	United States	Nested logit model
Namara et al.	2007	Gujarat and Maharashtra regions	India	Logit model
Koundouri et al.	2007	Crete Island	Greece	Probit model
Wheeler et al.	2010	Alberta	Canada	Probit model
Alcon et al.	2011	Campo de Cartagena	Spain	Duration analysis
Mohammadzadeh et al.	2014	Urmia Lake	Iran	Logit model and ordinal logistic model
Singh et al.	2015	Dahod district (Gujarat)	India	Logit model
Salazar and Rand	2016	All regions	Chile	Probit model with sample selection and multinomial probit
Huang et al.	2017	Arkansas	United States	Logit and multinomial logit
Knapp and Huang	2017	Arkansas, Mississippi, Louisiana	United States	FE OLS regression
Hunecke et al.	2017	O'Higgins and Maule regions	Chile	Partial least squares -SEM model
Mango et al.	2018	Chinyanja Triangle	Zambia, Malawi, Mozambique	Logistic model and OLS
Pokhrel et al.	2018	Various states	United States	Probit model and multivariate fractional regression model

Source: Authors' elaboration

3. Water use in the agriculture sector in Italy

The issuing of European environmental directives has improved the Italian environmental legislation and institutional framework on water quality and use (Massarutto, 1999). In 2000, the European Union issued the Water Framework Directive (WFD) n. 2000/60/EC, which included the Strategy for Water Scarcity & Droughts policy and placed the basis for common sustainable water management within all European members. The main objective of this directive consisted of improving the quality of European water basins and their use by 2015 (WFD, 2000). The WFD particularly pointed out the importance of water conservation in both quantitative and qualitative terms and supported water-saving policies to reach a sustainable use of water resources in the long term (Zucaro, 2011). The multidimensional approach used in the WFD was based on the relevance of the ecosystem for the sustainable management of water (Berbel and Expósito, 2018).

Italian water policy is coherent with the common legislation, even if some delays in the development of an environmental policy put Italy well behind schedule (Massarutto, 1999). However, by the end of the selected timeframe, i.e., the year 2015, some European goals of the WFD were reached, while others were still far from being realized. Thus, relevant gaps must be filled for both water pollution and water withdrawals. For example, in many Mediterranean countries, water extractions persist at a higher level with respect to their natural rate of renovation (WFD Report, 2015; Berbel and Expósito, 2018). In the future, the continued lack of proper water management based on an efficient allocation of water endowments within agricultural activities would cause the failure of national and supranational water policies in achieving European sustainable development goals (Sauer et al., 2010; FAO, 2017; Bazzani et al., 2005). Since the 1970s, Italy has organized each region as being responsible for their own water abstractions and water policies. When a basin belongs to more than two regions, a basin authority has been established as the competent authority. For water quality controls, regional environmental agencies (ARPAs) have been placed in charge only recently (Massarutto, 1999).

In Europe, differences in water use withdrawals and water availability are substantial among countries. Southern countries' levels of water withdrawals are higher (60% of total water withdrawals) than those of northern countries, which exploit water resources mainly for energy production (Eea, 2009). Moreover, southern European countries present higher levels of water scarcity because of their climate variability. A forecasted increase in the frequency of drought spells and a reduction in precipitation frequency and intensity combined with higher temperatures have given rise to negative impacts on agricultural yields (Eu, 2011; Euc, 2012). For this reason, southern Europe represents an area exposed to climate variability where countries with similar geographical and pedoclimatic characteristics share similar problems and challenges related to food production and water provisions (Eea, 2018; AWRA, 2018; Milano et al., 2012). The Mediterranean Basin is thus highly dependent on water irrigation, and climate variability will definitely affect the agricultural production pattern by influencing both the supply and demand of food and increasing economic losses (Olsen and Bindi, 2002; Iglesias et al., 2009).

Italy, which is one of the major southern European countries, is heavily dependent on water demand for irrigation in agricultural production (Eurostat, 2019). After Spain, Italy's agriculture sector represents the second largest consumer of water in Europe; its irrigated land size is equal to 2.4 million ha of cultivated lands, and 11 million cubic metres is the amount of water it uses for irrigation, which represents 4,666 m3/ha on average (Istat, 2010). In Italy, the most water-intensive crop is rice (39.8% of total water used), followed by maize (27.9% of total water used), citrus and fruits (both 5.5% of total water used) and open-field horticultural crops (5.2% of total water used) (Istat, 2010). Italy is also characterized by highly disproportionate volumes of water used among macro regions, with the northern regions showing a higher intensity use of irrigation compared to that of the central and southern regions (6800 m3/ha compared to 3500 m2/ha, respectively) (Istat, 2010). These outcomes obviously depend on water consumption, but they also reflects important structural and historical differences in production patterns, irrigation systems and geographic conditions, which make Italy a highly diversified agricultural water user (Zucaro et al., 2011). In northern Italy, the more diffuse irrigation technique is that of using surface water as a source of agricultural water mainly distributed through gravity by consortium water basins, whereas the central and southern areas of the country are characterized by a reliance on groundwater and pressurized distribution (Zucaro et al., 2011; Istat, 2010).

Regional differences also emerge in agricultural water efficiency, in which the most water-using regions (in terms of water extracted volume) are the least efficient in terms of total production. The most evident examples are those of Lombardy and Piedmont, which are the highest agricultural water consumers at 42.2% and 16.6% of the total water withdrawn, respectively, with quite a low share of the crop production, 4.4% and 2.9% of the total harvested production, respectively (Auci and Vignani, 2020). The majority of the water distribution is made using low-efficiency irrigation systems. Approximately 62% of the total water withdrawn is distributed using traditional irrigation techniques, such as furrow irrigation (27.2%) and flood irrigation (34.8%), whereas sprinkling irrigation represents only 27% of the distribution. In terms of land, inefficient irrigation practices account for 79.1% of the irrigated lands, while only 9.6% of the total water withdrawn is distributed using an efficient system (such as drip irrigation). The land equipped with micro-irrigation systems is approximately 17.5% of the total cultivated land, which is mostly distributed in the centre and southern macro areas, especially along the Apennine Mountains and the two islands of Sicily and Sardinia (Istat, 2010).

4. Empirical strategy and data description

4.1 The econometric models

Several studies (among others, Skaggs, 2001; He et al., 2007; Wheeler et al., 2010; Afrankhteh, 2014; Singh et al., 2015; Namara et al., 2007; Foltz, 2003; Salazar and Rand, 2016; Trinh et al., 2018) have modelled the optimal choice of adopting a new irrigation technology system as the probability of farmers adopting or not adopting it. By using a binary discrete probability model, such as probit or logit, the actual relationship between farmers' observed choice and some explanatory variables, such as farmers' characteristics and socioeconomic, territorial and climatic factors, can be verified.

The decision about adopting environmentally friendly technologies by choosing among various feasible alternatives has been analysed using cross-sectional data and binary or multinomial probability models (Moser and Barrett, 2006; Schuck et al., 2007; Huang et al., 2017; Pokhrel et al., 2018) or panel data analysis and correlated random effects probit models (Arslan et al., 2014). As suggested by Feder et al. (1985), these two methodologies may capture only whether (or not) the adoption decision about the new irrigation technology is made, while not considering the intensity of the adoption as measured by the hectares of land dedicated and allocated to this innovative technology. In a cross-sectional analysis, Pokhrel et al. (2018) examine farmers' decision to adopt different irrigation technologies in different fractions of land, while in a panel data analysis, Arslan et al. (2014) identify which determinants affect farmers' intensity use of the prevalent conservation farming practices in Zambia. For the intensity of adoption estimation, a correlated random effects tobit model and a pooled fractional probit model are used (Arslan et al., 2014; Pokhrel et al., 2018).

In line with these two last studies, an analysis on adoption and intensity is proposed. First, the probability of adopting WCSTs by an Italian farmer is estimated by comparing clustered population averaged (PA) logit and probit models with a correlated random effects probit model. Second, the intensity of adopting WCSTs when the technology is used is estimated by comparing a random effects tobit model with a correlated random effects tobit model to consider censored solutions.

4.1.1 Farmers' Decisions to Adopt WCSTs

A farmer's discrete choice of whether to adopt WCSTs is based on a latent variable approach. Under the hypothesis of rationality, as in Caswell and Zilberman (1985), a farmer adopts an innovation if and only if the expected utility from adopting the new technology is higher than the expected utility of not adopting it (Feder et al., 1985; Huang et al., 2017). The latent utility of a farmer may be defined as follows:

$$Y_{it}^{*} = X_{it}\beta^{*} + v_i + \varepsilon_{it}^{*} \tag{1}$$

where Y_{it}^{*} is the latent net utility of the *i-th* farmer at time *t*, X_{it} is a vector of covariates that explicate the level of utility derived by the irrigation technology (farms, farmers, financial and institutional, water use, and geographical and climatic characteristics), β^{*} is a vector of parameters to be estimated including the intercept, ε_{it}^{*} is a random error uncorrelated with the explanatory variables that follows a normal distribution with zero mean and fixed variance, and v_i represents time invariant unobserved effects (Cramer, 2003; Greene, 2003; Wooldridge, 2010).

However, the utility function is not easily or directly observable. One may only infer the unobservable and latent utility function Y_{it}^{*} of the *i-th* farmer at time *t* by modelling the *ex-post* response status on the adoption of WCSTs (Cramer, 2003). Using a binary choice model, a farmer's observable decision on innovation Y_{it} is represented by a dummy variable as follows:

$$\begin{aligned} Y_{it} &= 1 \quad \text{if} \quad Y_{it}^{*} > 0 \\ Y_{it} &= 0 \quad \text{if} \quad Y_{it}^{*} \leq 0 \end{aligned} \tag{2}$$

Therefore, we may predict the likelihood of adopting WCSTs as follows:

$$Pr\ (Y_{it} = 1 | X_{it}, v_i) = \phi(X_{it}, v_i) \tag{3}$$

where $\phi(.)$ is the distribution function of ε_{it}^{*} and can be approximated by a logistic distribution or a normal distribution function. To estimate the parameters of interest, we focus on the unobserved effects logit and probit model. More specifically, random effect logit or probit models are preferred since the fixed effects logit or probit models are subject to incidental parameter problems in addition to computational difficulties. Thus, the main assumptions required to estimate these models are the strict exogeneity of the observed covariates, the conditional independence assumption of the predicted variable and the normality assumption (Wooldridge, 2010). These last strong assumptions imply independence between v_i and X_i and that v_i has a normal distribution as follows:

$$v_i | X_i \sim N(0, \sigma_v^2) \tag{4}$$

The conditional independence assumption of the predicted variable may be relaxed in two different ways. First, when the heterogeneity is averaged out, a population average model is run wherein the responses are independent conditional on only X_i. Second, when a particular correlation structure between the unobserved effects and the explanatory variables is assumed, a correlated random effects probit model based on the full conditional maximum likelihood approach (CMLE) is applied.

First, to avoid inconsistency in the estimated coefficients due to underestimated standard errors, a population averaged clustered approach is applied by using the generalized estimating equation (GEE) approach (Neuhaus et al., 1991; Neuhaus, 1992). The population average estimation allows no independence of observations among individuals, thus dealing with autocorrelation and heteroscedasticity problems. The interpretation of the estimators is related to the change in the mean population outcome related to the change in the independent variables within the specific cluster of the *i-th* individual (Hubbard et al., 2010). For the estimation of the population average model, clustered-robust standard errors are computed to let vary the standard error within clusters and to allow autocorrelation across them but not among them (Ullah and Gilles, 2011).

Second, when a particular correlation structure between the unobserved error and the explanatory variables is present, a correlated random effect (CRE) model based on Mundlak's (1978) devises is applied, and some drawbacks of the fixed and random effects models may be overcome. The fixed effects model is subject to incidental parameter problems that lead to inconsistency of the estimators; at the same time, it does not allow the use of time-invariant variables. Conversely, random effects estimation allows time-invariant estimators but is constrained to the very strong assumption of no correlation between the error terms and the independent variables, which often is not the case, thus leading to bias and inconsistency in the estimation results.

Using Mundlak's approach, the heterogeneity problem is addressed by relaxing the strict assumption of the random effects model ($Cov(X, \varepsilon) = 0$) and allowing unobservables to be correlated with some elements of X_i by assuming the following:

$$v_i|X_i \sim N(\psi + \bar{X}_i\xi, \sigma_a^2) \tag{5}$$

where $\bar{X}_i$ is the average of X_{it} in time, and σ_a^2 is the variance of a_i in equation $v_i = \psi + \bar{X}_i\xi + a_i$. From this model, we can consistently estimate the partial effects of the elements of X_i on the response probability at the average value of v_i (v_i= 0). This allows comparing the betas with those of the population average model, which represent the partial effects of X_i on the response probability at the average value of v_i. Testing the unconditional normality of v_i consists of verifying whether $\xi = 0$. We reject this hypothesis in all the specifications and use the CMLE approach in modelling adoption decisions (Wooldridge, 2010).

4.1.2 *Farmers' Intensity of adoption of WCSTs*

Since farmers can decide to only partially adopt the new technology, the intensity of WCST adoption is analysed to determine the relevant drivers. In the presence of a censored dependent variable, as in our case, a tobit model is preferred (Tobin, 1958). Since the intensity of adoption is represented by the amount of total irrigated land under WCSTs for each *i-th* farmer and is bounded by the range [0, 1], the dependent variable presents pileups at the corners and a continuous distribution in between (Arslan et al., 2014). Thus, a two-limit tobit model should be applied, meaning that farmers may behave in three different ways, namely, they may irrigate, not irrigate or irrigate only a fraction of their cultivated land with the WCSTs (Greene, 2003; Wooldridge, 2010; Wooldridge, 2013).

The censored dependent variable assumes the following form:

$$\begin{aligned} Y_{it} &= 0 && \text{if} \quad Y_{it}^* \leq 0 \\ Y_{it} &= Y_{it}^* && \text{if} \quad 0 < Y_{it}^* < 1 \\ Y_{it} &= 1 && \text{if} \quad Y_{it}^* \geq 1 \end{aligned} \tag{6}$$

where the random effects tobit model for panel data can be specified as follows:

$$Y_{it} = X_{it}\beta + v_i + \varepsilon_{it} \quad \text{where } \varepsilon_{it}|X_i, v_i \sim N[0, \sigma_\varepsilon^2] \qquad \text{when equation 6 is verified} \tag{7}$$

where Y_{it} is the ratio of the extension of land irrigated with sustainable irrigation technologies of the *i-th* farmer in the *t-th* period over the total irrigated lands in the same time; β represents the coefficients to be estimated; X_{it} represents the vectors of explanatory variables such as farms, farmers, financial and institutional, water use, and geographical and climatic aspects; v_i represent the unobserved effects considered as random; and ε_{it} is the error term with a zero mean and constant variance σ^2.

Accounting for the unobserved heterogeneity issue, a two-limit correlated random effect (CRE) tobit model, as in Arslan et al. (2014), is applied, allowing the unobservables to be correlated with some elements of X_{it}. By introducing Mundlak's devices, the mean in *t* of the explanatory variables, allows unbiased and consistent estimations of the β coefficients. The final specification of the two-limit CRE tobit model is as follows:

$$\begin{aligned} &Y_{it} = X_{it}\beta + \psi + \bar{X}_i\xi + a_i + \varepsilon_{it} \\ &\varepsilon_{it}|X_i, a_i \sim N[0, \sigma_\varepsilon^2] \\ &a_i|X_i \sim N[0, \sigma_a^2] \end{aligned} \tag{8}$$

All the continuous covariates used in the analysis (except for *Age*) are transformed in logarithmic form to smooth their distribution, thereby reducing heteroscedasticity problems (Greene, 2003). The estimated coefficients of the tobit model can be interpreted as the partial change due by each covariate in the fraction of irrigated land with WCST over the total irrigated. For this model, we test the unconditional normality of v_i and reject the null hypothesis that $\xi = 0$. Thus, we can apply the two-limit CRE tobit model in modelling the intensity of adoption (Wooldridge, 2010).

Finally, all the estimated econometric models include regional dummy variables to consider structural regional differences such as production patterns or different policies adopted at regional levels. Time dummy variables are also included to consider macroeconomic shocks or temporal breaks. For robustness checks, additional analyses at the regional level are performed for all the models examined.

4.2 Data Description

The dataset used in this study comes from the Italian database of the Agricultural Accounting Information Network (Rete di Informazione Contabile Agricola - RICA), which is the basis of the European Farm Accountancy Data Network (FADN), the data for which are collected randomly through the use of annual surveys over more than 10,000 farms. In this way, a representative sample is created for the Italian agricultural sector. Within the RICA datasets, very precise and detailed information on farms' economic, productive, environmental, geographical and social factors may be found. All the information that are included in separate datasets have been merged to study the relevant aspects of WCST adoption on farmers' decisions. Moreover, yearly datasets have been further merged to obtain a unique unbalanced panel dataset of 13,592 farms for five years spanning from 2012 to 2016 for a comprehensive database of 45,837 observations. The same database has been used by Van Passel et al. (2017) for Western European countries and Bozzola et al. (2019) for Italian farms, as in our case, but with a different time frame that used data from 2008 to 2011; both authors used FADN for analysing the lung-run relationship between climate and agricultural land value.

To test whether climatic and weather conditions influence sustainable irrigation technology adoptions, the assembled panel data from RICA have been combined with climatic data. These climatic data have been provided by the division of Impacts on Agriculture, Forests and Ecosystem Services (IAFES) of the Euro-Mediterranean Center for Climate Change with 0.5° x 0.5° grid cell spatial resolution (25 km^2). Extracted from the ERA-Interim dataset of the European Centre for Medium-Range Weather Forecasts (ECMWF), this dataset includes seasonal values of reference evapotranspiration (ET_0) (Allen et al., 1998) and accumulated precipitation (P). Finally, climatic data have been joined with the RICA dataset using the farms' georeferenced information included in this latter database.

Based on previous empirical studies on farmers' determinants of WCST adoption in developed and developing countries, two dependent variables and a set of explanatory variables were selected for the econometric analysis. The definition of each variable used in the models and their descriptive statistics are presented in the following.

Regarding the dependent variables, we consider a dummy for the adoption of innovative irrigation farming systems and the proportion of cultivated land under a given WCST practice for the intensity of adoption, as presented in Table 2. Figure 1 shows the geographical distribution of the WCST adoption choices and intensity in Italy for each farm in 2012.

Figure 1: Adoption of WCSTs (blue) with respect to traditional irrigation technology and intensity of WCST adoption (blue) over total irrigated land for each farm in 2012.

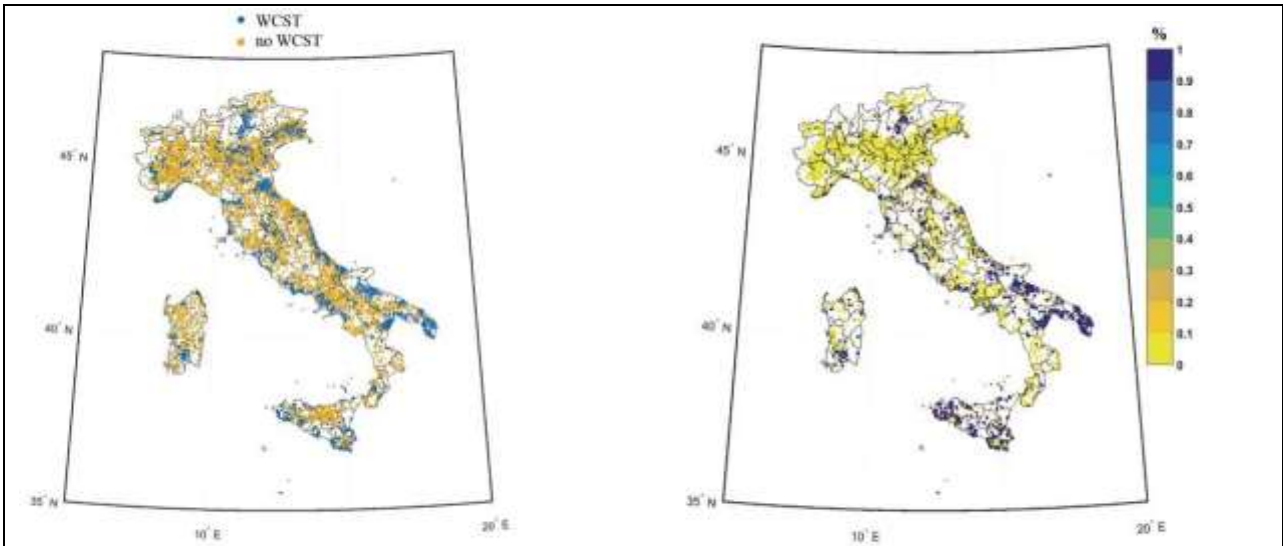

figure (a) figure (b)

Source: Authors' elaboration

Regarding the explanatory variables, we grouped them into five main characteristics, as shown in Table 2: 1) farms' characteristics, 2) farmers' characteristics, 3) financial and institutional characteristics, 4) water use characteristics and 5) geographical and climatic characteristics.

Table 2. Description of the variables specified in the adoption and intensity models.

Variable Acronym	Description	Measurement	Posited Sign	Supporting References
Dependent variable				
WCSTs dummy	Whether a farmer adopted irrigation farming systems or not	Dummy (1 if yes, 0 if no)		Arslan et al. 2014; Pokherel et al., 2018
WCSTs intensity	Proportion of cultivated land that is under a given WCSTs practice	Variable is bounded by the [0,1] interval		Arslan et al. 2014; Pokherel et al., 2018
Explanatory variables				
Farms' characteristics				
Hours worked	Labour input employed within a farm such as farm size and labour intensity.	The logarithm of total working hours spent in a farm (family or external work).	+	Boahene et al., 1996; He et al., 2007
Machine power	Capital input employed within a farm as technology ability.	The logarithm of the total machine power within a farm in kilowatts/hours.	+	Pokherel et al., 2018
Land size	Size of land available for cultivation within a farm.	UAA (Utilized Agricultural Area) in ha.	+	Trinh et al., 2018
Land value	Land monetary value as reported in the balance sheet of each farm.	The logarithm of the market value of agricultural lands in euro.	+	Moreno and Suning, 2005
Land Tenure	The amount of rented land used by farmers for cultivations.	The logarithm of the rented land size in ha.	-	Alcon et al., 2019; Doss and Morris., 2001; Moreno and Suning, 2005; Pokherel et al., 2018
High-value crops Mixed production Livestock	Farms are classified in three categories: - high-value crop production farms based on olive-growing, fruticulture, viticulture, horticulture and floriculture production; - mixed farms based on livestock farming and vegetables production; - livestock farms based on dairy and cattle farming.	Three separated dummies (1 if crop farming, or mixed farming or livestock farming, 0 otherwise)	+ high value, + mixed farms, - livestock	Green et al., 1996
Family Run	Whether a farm is prevalently run by the farmer and his/her relatives or not.	Dummy (1 if yes, 0 if no)	+	Koundouri et al., 2006
Organic	Farms producing certified organic products.	Dummy (1 if yes, 0 if no)	+	
Farmers' characteristics				
Female head	Gender of household head (farmer).	Dummy (1 if female, 0 if male)	+ or -	Asfaw et al., 2016; Somda et al., 2002
Age	Age of household head (farmer).	Years	+ or -	Alcon et al., 2011; Alcon et al., 2019; Skaggs, 2001; Salazar and Rand, 2016
High education	Educational background of the household head (farmer) such as technology skills.	Dummy (1 if farmer's education level is high school or above, 0 if farmer's education level is less).	+	Alcon et al., 2019, Moreno and Sunding, 2005; Salazar and Rand, 2016; Pokherel et al., 2018
External activities	Extra jobs of household head (farmer)	Dummy (1 if farmer is engaged in external activities, 0 if farmer is engaged only within the farm).	-	Afrakhteh et al., 2015; He et al., 2007; Weeler et al., 2010

Financial and Institutional characteristics				
EU Funds	Funds directly received from EU through the CAP program.	Log of funds received in euros	+	
No EU Funds	Funds received from other institutions no EU, as national and local governments.	Log of funds received in euros	+	
ROI	Return on investment (ROI), a performance measure, to evaluate the efficiency of an investment.	Log of operating revenues over total investments in euros	+	
Leverage	Indebtedness of a farm whether with a prevalence of own capital or third-party capital.	Log of total assets over own capital (equities) in euros	-	Alcon et al., 2016; Boahene et al., 1996
Insurance	Insurance from farming risks.	Log of total amount spent for insurance by a farmer in euros.	+	Rogers, 1971; Koundouri, 2006
Water use characteristics				
Internal water source	Area irrigated by water sources, internal to land ownership, such as access to water for irrigation purposes.	Log of area irrigated by internal wells, ponds and tanks	+	Alcon et al., 2011; Moreno and Sunding, 2005; Salazar and Rand, 2016
Energy, electricity and water costs	Energy, electricity and water costs within a farm.	Log of energy, electricity and water costs in euros.	+ for water – for energy and electricity	Moreno and Sunding, 2005;
Irrigated land	Land irrigated available for cultivation.	Log of irrigated area in ha.	+	Huang et al. (2017)
Geographic and Climatic characteristics				
Altitude avg.	The average altitude level of the farm fields.	Log of the average altitude level of a farm in metres.	-	
Field slope	The acclivity of farm fields measured by steep and very steep slope fields.	Log of the area with high acclivity within a farm in ha.	+	Afrakhteh et al., 2015; Alcon et al., 2019; Green and Sunding, 1997; Negri and Brooks, 1990; Sherestha and Gopalakrishan, 1993
Sandy soil	Fields' surface with loose-textured soil composed by sand and loamy sand soil.	Log of loose-textured soil within a farm in ha.	+	
Mixed soil	Fields' surface with medium-textured soil composed by loam and silty loam soil.	Log of medium-textured soil within a farm in ha.	-	Afrakhteh et al., 2015; Green et al., 1996; Moreno and Sunfing, 2005; Sherestha and Gopalakrishan, 1993
Clay soil	Fields' surface with fine-textured soil composed by silty-clay, sandy-clay and clay soil.	Log of fine-textured soil within a farm in ha.	-	
Aridity Index (AI)	Aridity is commonly quantified by comparing long-term average of water supply measured by seasonal accumulated precipitation (P) and long-term average of climatic water demand measured by seasonal reference evapotranspiration (ET_0). $AI \geq 0.65$ indicates humid areas, $AI < 0.65$ indicates arid areas.	Ratio between P and ET_0. It is calculated considering the moving average of the last 5 years in mm*day^{-1}.	-	CGIAR, 2019

Source: our elaboration

Farms' characteristics

Several farm production aspects are extremely important for the choice of WCST adoption. These aspects may be related to farm size, typology of production, ownership and management, and economic characteristics. Regarding farm size, the variables *hours worked* and *land size* were considered. The larger the farm size is, the wider the scale economies and the higher the investment or the odds of adopting new irrigation technologies. For the economic characteristics, we introduce two monetary values, *machine power* and *land value*, which embed the intensity of the capital used and the profitability of the agricultural activities employed. Both variables may positively influence the propensity to invest in new technology for irrigation (Moreno and Suning, 2005). Considering that landowners and family farmers are keen to invest in irrigation systems, ownership and management characteristics are captured by *land tenure*, which may negatively influence WCST adoption (Alcon et al., 2019; Doss and Morris., 2001; Moreno and Suning, 2005; Pokherel et al., 2018), and *family run*, which may have a positive effect on irrigation technology adoption. Additionally, the typology of production, meaning the farm's product specialization, may influence the WCST adoption. Prevalent farming production may substantially affect the water demand and water use of farms (Green et al., 1996). Therefore, three dummy variables indicating the prevailing farming production on the basis of RICA classification are defined. Farms are distinguished as *high-value crop* farms when their farming production is mainly based on olive-growing, fruticulture, viticulture, horticulture and floriculture. *Mixed production* farms consist of farming production that includes both livestock and vegetables, and *livestock* farms are farms where production is based on dairy and cattle farming. We also introduce the *organic* dummy variable, which captures the effect of the organic certification of farming products, since organic farmers may have a higher propensity for conservation and sustainable water management strategies than conventional farmers.

Farmers' characteristics

Distinctive farmers' factors may strongly influence irrigation strategies and WCST adoption. In several studies, household head gender (*female head*) has been identified as an important driver for innovation, especially in developing countries (Asfaw et al., 2016; Somda et al., 2002), whereas in developed countries, its effect is unclear. Even though farmer age is crucial for innovation adoption choice, the economic literature does not find a prevailing effect (Alcon et al., 2011; Alcon et al., 2019; Skaggs, 2001; Salazar and Rand, 2016). Education is another feature that may influence both the choice and propensity for innovation and the intensity of adoption. Several studies have highlighted that more educated farmers have a higher propensity to invest in new technologies (Alcon et al., 2019, Moreno and Sunding, 2005; Salazar and Rand, 2016; Pokherel et al., 2018). The propensity to adopt new technologies may depend even on a farmer's effort level spent working within the farm. Some authors have stated that extra jobs, as measured by *external activities*, may be considered a proxy for high risk aversion and generally reduce the choice of adopting new technologies (Afrakhteh et al., 2015; He et al., 2007; Weeler et al., 2010). We use a dichotomous variable to describe whether a farmer has an external working activity, which is different from distinguishing between in-farm and off-farm income, as in Skaggs (2001), Moreno and Sunding (2005), Schuck et al. (2005), Foltz (2003) and Koundouri et al. (2006).

Financial and institutional characteristics

Farms' financial structures and socio-political and institutional aspects may substantially influence their propensity and intensity to adopt WCSTs. Important elements are economic incentives and policies related to technological innovations and agricultural development. External funding may influence the adoption of technologies by incentivizing a farmer's behaviour that otherwise would not have been taken (Rogers, 1971). Lacking specific information on WCST funding, the total amount of funds from the European community, as well as from other sources, has been considered a proxy for farms' reliance on external funds. Two variables have been used for this purpose: *EU funds* (funds directly received from EU through the CAP program) and *no EU funds* (funds received from national and local institutions).

Farms' financial aspects are highly related to WCST adoption choice; thus, we focus on farms' profitability from their operating performance. We consider the return on investment (*ROI*) variable as a proxy for farms' profitability from new technology investments. Calculated as the level of operating revenues over the total investments of a farm, this indicator may represent the capability of a farmer to measure the efficiency of an investment in gaining high levels of returns. Farm debt size, as a *leverage* indicator, may suggest farm credit access availability, as well as the degree of farmer indebtedness, with respect to internal and external financial resources. This indicator is considered a proxy for a farm's financial strategy (Alcon et al., 2016; Boahene et al., 1996). Another important aspect is farmer risk aversion. Farming risk may influence farmers' decisions regarding whether to invest in WCSTs. As stated by Rogers (1971) and Koundouri et al. (2006), farmers' attitudes towards farming risks and the propensity to innovate are strictly related. Thus, to cover farming risks, the amount spent for insurance by a farmer is considered a proxy for farmer risk aversion. The higher the insurance level is, the higher the farmer's risk aversion; thus, the *insurance* variable may positively affect the adoption and intensity of WCSTs.

Water-use characteristics

Factors related to water use strictly affect irrigation strategies and technology used within a farm. Water costs may directly influence the amount of water demand and used within a farm, while energy and electricity costs may negatively affect WCST adoption, which is typically more energy-consuming than traditional irrigation systems (furrow and flood). Lacking water prices and tariff details, the *energy, electricity and water costs* variable is used as a proxy for water, energy and electricity consumption. The correlation may not be strictly defined because of the opposite effect of water costs with respect to energy and electricity costs.

Water sources may explain the different farmers' availability of water and may have an influence on the irrigation technology used within a farm. Water pressure, cleanliness, and differences in height among several sources may be relevant for the choice of WCST adoption (Alcon et al., 2011; Moreno and Sunding, 2005; Salazar and Rand, 2016). Moreover, different water sources, which imply different water quantity availability and water quality, may substantially influence the irrigation systems and technology used. We thus define *internal water* sources as access to water sources that are internal to a farm's own fields, such as water withdrawn from wells, artificial ponds and water tanks. This is considered in comparison to external water sources, such as water distributed by local authority services or pumped from superficial water bodies outside the farm. Finally, we introduce the irrigated land areas with the variable *irrigated land* because the higher the irrigated area is, the higher the adoption of more efficient irrigation technologies as the WCSTs.

Geographic and Climatic characteristics

Environmental and territorial contexts, as well as physical and qualitative aspects such as weather, altitude and acclivity (slope), may directly influence irrigation system strategies. One of the main aspects influencing WCST adoption is soil type. The soil texture, i.e., the combination of sand, silt and clay, may influence the water availability in the soil layers, i.e., the rate at which water can enter and move through soil and crop water needs. If the soil is mainly sandy, it should increase the probability of adopting WCSTs because of the reduced water soil retention and the inefficiency and ineffectiveness of traditional irrigation systems (such as flooding or furrow). Conversely, when the water soil retention is high, as in clay soil, the probability of adopting WCSTs should decrease. To consider the impact of soil texture on farmers' adoption decisions, we introduce a set of variables, *sandy soil*, *mixed soil* and *clay soil*, which distinguish among loose-, medium- and fine-textured soil, respectively. To capture the territorial context, we also introduce the variables of average altitude (*altitude avg*.) and the slope (*field slope*) of the fields of a farm (Afrakhteh et al., 2015; Green et al., 1996; Moreno and Sunfing, 2005; Sherestha and Gopalakrishan, 1993).

Climate and weather are also key factors influencing WCST adoption. Different studies consider climate and weather characteristics as the main drivers affecting farmers' adaptation strategies by using new irrigation technologies, but climatic or weather variables are often introduced as yearly averages or variances of temperature and rainfall (among others, Dell et al., 2014; Asfaw et al., 2016; Huang et al., 2017; Knapp and Huang; 2017). Similar to Kondouri et al. (2006), we introduce an aridity index to capture climate effects; however, differently from these authors, we compare the long-term average of water supply to the long-term average of climatic water demand. Specifically, we consider a more sophisticated indicator of the aridity index (AI), which captures the shortage of water in a particular region as developed by the United Nations Environmental Programme. This indicator is computed as the ratio of seasonal accumulated precipitation (P) and potential evapotranspiration[1] (ET_0) (CGIAR, 2019). AI is a measure of dryness of the climate at a given location based on how much water needs of crops have been satisfied by precipitation as follows:

$$AI_{season} = P/ET_0$$

(9)

If ET_0 is greater than P, meaning an AI < 0.65, then the climate is considered to be arid, and the precipitation does not satisfy the crop water needs. Conversely, if AI values are equal or greater than 0.65, then rainfalls do cover the crop water needs, and the climate is considered humid. Considering seasonal AI indexes implies that when water deficits occur over shorter periods, then a drought period is present. Following Mendelsohn et al. (1994), Bozzola et al. (2017) and Van Passel et al. (2017), seasonal aridity indexes for winter *AIJFM* (AI of January, February, March), spring *AIAMJ* (AI of April, May, June), summer *AIJAS* (AI of July, August, September), and autumn *AIOND* (AI of October, November, December) are computed on the basis of each farm's geographic ERA coordinates.

To consider short past weather conditions, seasonal moving averages of the AI index are used to test how weather conditions may influence farmers' water technology strategies. Based on the study of Woodill and Roberts (2018), a five-year moving average is applied for each seasonal

[1] Reference evapotranspiration (known also as potential evapotranspiration) (ET_0) is the evaporative demand of the atmosphere independent of crop type, crop development and management practices. Its value is independent of water abundance in the area to which is referred because it is only affected by climatic parameters. It is comparable in time and space with other ET_0 (Allen et al., 1998). It is measured in mm*day^{-1}. ET_0 is a measure of the evaporating power of the atmosphere from land surfaces in a specific area and time, independent from crop and soil characteristics. Its value represents the amount of water lost by evaporation and plant transpiration, and it is a proxy for water demand of crops to compensate natural water losses (Allen et al., 1998; Villalobos and Fereres, 2016). ET_0 is calculated through the Penman-Monteith method, which is based on a hypothetical grass reference crop, specific height, soil resistance in shadow and water standard conditions (Allen et al., 1998). The standard ET_0 considers solar radiation (sunshine), air temperature, humidity and wind speed from a dataset of standard climatological records. Therefore, it can be considered as a comprehensive index of weather conditions for plant water requirements (Allen et al., 1998).

AI index. To calculate the seasonal moving average indexes, 4 years back and the present year are included. The time frame of the climatic data considered is 2007-2016.

In Table 3, the descriptive statistics of the variables included in the estimations are reported. Notably, 19% of the farmers adopted WCSTs for irrigation, and 15% of the land was irrigated by using WCSTs, with respect to the total irrigated area in farm fields. The density distribution of the *WCST intensity* variable is characterized by two pileups at zero and one that represent the two limits of this fractional response variable, as shown in Figure A2 in Appendix A. Since the average farm size is 4.04 ha, and 86% of farms are family run, these outcomes confirm that in Italy, farmers are smallholders, and farms are managed mainly by families. The average age of the farmers is 55 years old, they are more often male, and they more often have a low level of education. The seasonal aridity indexes show that spring and summer are dry periods where the levels are well below the threshold. In contrast, winter and autumn correspond to the humid period; this is especially true for autumn, where the aridity index average value is equal to 1.44. In Appendix A, Figure A1 confirms that in spring and summertime, the aridity indexes remain stable with low variability and below the threshold of 0.5, meaning that those areas may be defined as semi-arid. In contrast, during winter and autumn, the aridity indexes are well above the threshold 0.65, and the land may be classified as non-drylands or humid.

Table 3. Descriptive statistics.

Variable	mean	p50	min	max	N
Dependent variable					
WCSTs dummy (d)	0.19	0	0	1	45824
WCSTs intensity (no)	0.15	0	0	1	45632
Explanatory variables					
Farms' characteristics					
Hours worked (h)	8.08	7.99	4.09	12.41	45826
Land size (ha)	4.04	3.87	3.51	7.06	45830
Family run (d)	0.86	1	0	1	45830
High-value crops (d)	0.40	0	0	1	45830
Mixed production (d)	0.09	0	0	1	45830
Livestock (d)	0.24	0	0	1	45830
Organic (d)	0.05	0	0	1	45830
Machine power (Kw)	4.79	4.82	0	8.13	44285
Land tenure (ha)	3.14	2.79	2.74	6.65	45830
Land value (€)	13.19	13.01	12.73	17.16	45830
Farmers' characteristics					
Age (years)	55	54	16	97	45830
Female head (d)	0.22	0	0	1	45830

External activities (d)	0.26	0	0	1	45830
Higher education (d)	0.30	0	0	1	45830
Financial and institutional characteristics					
Insurance (€)	7.78	7.55	7.38	13.00	45830
ROI (no)	11.97	11.97	11.93	12.66	45625
Leverage (no)	7.72	7.72	7.59	8.41	45786
EU Funds (€)	9.89	9.71	9.43	14.52	45830
No EU Funds (€)	8.37	8.00	8.00	13.57	45830
Water use characteristics					
Internal water source (d)	0.99	0.76	0.76	6.04	45823
Energy, electricity and water costs (€)	8.66	8.43	8.24	13.59	45830
Irrigated land (ha)	2.61	2.25	2.23	6.91	45632
Geographical and climatic characteristics					
Altitude avg. (m)	4.99	5.34	0	7.61	45830
Field slope (m^2)	2.06	1.84	1.84	7.28	45830
Sandy soil (ha)	1.83	1.63	1.63	7.26	45830
Mixed soil (ha)	3.82	3.65	3.32	7.64	45830
Clay soil (ha)	1.37	1.17	1.17	6.63	45830
AIJFM (no)	0.86	0.79	0.19	2.67	271354
AIAMJ (no	0.39	0.36	0.03	1.45	271354
AIJAS (no)	0.35	0.27	0.03	1.88	271354
AIOND (no)	1.44	1.40	0.29	4.43	271354

Note:(d) stays for dummy variable and (no) stays for unit less variable (e.g. indexes).

5. Main Results and Discussion

We estimate the probability and intensity of the adoption of innovative irrigation systems based on WCSTs. Based on the methodologies described, the results on the whole sample and on the macro areas of Italy[2] are described and discussed in the following sections. In Table 4, in the first three columns, the results for the probability of adopting micro-irrigation technologies based on the PA logit model (model 1), the PA probit model (model 2) and the CRE probit model (model 3) are reported, while in the last three columns, the results for the odds ratio of the PA logit model and the average marginal effects (AMEs) of models 1 and 2 are presented. Table 5 shows the estimation results for the intensity of WCST adoption based on the RE tobit model (model 1) and the CRE tobit model (model 2). In Appendix B, Tables B1 and B2 present the estimation results for the probability and intensity of adoption of WCSTs, splitting the sample by the four macro areas of Italy.

[2] Italy is usually split in four macro areas: northwest, northeast, centre, south and islands.

5.1 Results of the probability of adoption of WCSTs (Logit, Probit and CRE Probit model)

In Table 4, the estimation results for the probability of adopting WCSTs are based on binary response models estimating the whole sample of Italian farmers (13,054 farms) and accounting for serial correlation across time by computing robust White-Huber standard errors. In addition to the odds ratios for the logit model, the AMEs for the logit and probit models are analysed because they represent the change in the probability of adoption at the regressors' mean. Specifically, marginal effects or partial effects allow us to define the effects on the conditional mean of the dependent variable when a unitary change of a covariate occurs. In other words, the AMEs allow us to capture the change in the probability of adoption by, *ceteris paribus*, a unit change of a regressor (Greene, 2003; Wooldridge, 2010).

The statistical significance of the explanatory variable coefficients remains high and stable across all the different estimated models. The signs of all the coefficients seem to be reasonable and conform to our expectation; Italian farmers characterized mainly by having small and family run farms and by being climatic risk adverse farmers are more likely to adopt WCSTs than are other farmers.

Regarding farms' and farmers' characteristics, our findings show that neither *energy, electricity and water costs* nor *higher education* are significant in determining the adoption of WCSTs in any of the models. Therefore, investing in reducing energy and water costs as innovative capability (Moreno and Sunding, 2005) and in education as technology skills (Pokhrel et al., 2018) is not relevant for adopting new irrigation technologies.

Even if statistically significant only at 10%, the coefficient of the *family run* variable of the PA logit and CRE probit models provides weak evidence for managing constraints. As shown in Kondouri et al. (2006), the negative sign of these coefficients confirms that a family run farm is less likely to adopt new irrigation technologies as WCSTs than are non-family run farms. Since Italian farms are prevalently dominated by small and family run farms, this reduces the probability of WCST adoption.

The size of a farm as measured by *hours worked* and *land size* presents divergent results. While the coefficients of the workforce are highly statistically significant with a positive sign, the coefficients of *land size* show statistically significantly negative effects. In terms of AMEs, an increase in *hours worked* results, *ceteris paribus*, in an increase in the probability of adoption by 4.6 percentage points (for the logit model), 5.1 percentage points (for the probit model) and 2.4 percentage points (for the CRE probit model). In contrast, the partial effects of *land size* are -0.135 (logit) -0.147 (probit) and -0.157 (Cre probit); therefore, an additional hectare of land for cultivation negatively influences the probability of adoption of WCSTs by approximately 15 percentage points. Thus, an increase in the probability of WCST adoption when increasing the time spent on a farm is counterbalanced by a reduction in the probability of adopting WCSTs when land size increases. New irrigation systems are more likely to be observed on small and labour-intensive farms. This result is partially in contrast with those found in the literature on irrigation technology adoption, in which farm size matters positively for WCST adoption decisions (e.g., Green et al., 1996; Huang et al., 2017). However, the study of Knapp and Huang (2017), which finds a positive relationship between size and traditional irrigation methods but no effects with WCSTs, is very close to our results.

As expected, the coefficient signs of the three farming-type variables are statistically significant at 1% for all the models estimated. Both the *high-value crops* (olives, fruits, viticulture, horticulture farming specialization) and *mixed production* (animal and crop joint production) variables positively influence the probability of adopting WCSTs, whereas the *livestock* variable, i.e., farms specializing in cattle rearing (bovines and other herbivorous animals), are less likely to adopt WCSTs. The marginal effects are 0.087 (logit), 0.109 (probit) and 0.114 (CRE probit) for *high-value crops*; 0.046 (logit), 0.074 (probit) and 0.086 (CRE probit) for *mixed production*; and -0.137 (logit), -0.124 (probit) and 0.122 (CRE probit) for *livestock.* Livestock farms are less inclined to adopt new irrigation systems, and this type of farming production substantially reduces the likelihood of adopting by approximately 14 percentage points for the PA logit model and by 12 percentage points for the two probit models. In terms of odds ratio, for an average high-value crop farming production (an average mixed farming production), the odds of adopting WCSTs are estimated to be about two and a half times (one and a half times) as large as the odds of adopting innovative irrigation systems for an average low-value crop farming production (an average no-mixed or specialized production).

Similar to Moreno and Sunding (2005) and Salazar and Rand (2016), our results confirm a negative relationship between *land tenure* and the probability of WCST adoption, suggesting that sustainable irrigation systems are more likely to be observed when land is owned instead of rented. Owner farmers, in fact, are more likely to adopt new irrigation technologies that provide further benefits over the long term (Soule et al., 2000; Salazar and Rand, 2016). However, the magnitude of the rented land impact has a low marginal effect on the likelihood of WCST adoption. The partial effects are -0.025 (logit), -0.021 (probit) and 0.020 (CRE probit), meaning that renting land increases the probability of adopting micro-irrigation technologies by almost 2 percentage points for all the models.

Since the future profits from yields are incorporated into the monetary value of land, the *land value* variable should increase the propensity of adopting new irrigation technologies. This relationship is not confirmed by our results, as all the estimations show statistically significantly negative signs. This outcome implies that the higher the value of land is, the less likely it is that fields will be irrigated with WCSTs. Nevertheless, the marginal effects present quite low values (-0.016 for the logit model, -0.023 and -0.026 for the two probit models), suggesting that the *land value* impact is relatively less important in choosing WCSTs as the irrigation system of a farm.

Farmers' characteristics are also quite relevant in the choice of adopting WCSTs. While *age* is significant at the 1% level for only the PA logit and probit models, *female head* presents a different level of significance for each of the three models estimated. Younger and male farmers are more likely to adopt new irrigation technologies (Alcon et al. 2011; Asfaw et al., 2016), while participating in external activities is not statistically significant for the choice of engaging in a new irrigation system, except for in the CRE probit model (Alcon et al. 2011; Asfaw et al., 2016; Salazar and Rand, 2016). Regarding the AMEs of the *female head* and *age* variables, the impact on the probability of WCST adoption is very low. The *female head* variable's marginal effect is approximately 1 percentage point, whereas for *age*, the partial effect is paltry. In line with Alcon et al. (2019), Mango et al. (2018), Namara et al. (2007) and Huang et al. (2017), our findings confirm that being young is not a key driver for WCST adoption.

Concerning financial and institutional characteristics, it is worth noting that farms' debts (*leverage*) and the capability to generate an adequate return on investment (*ROI* index) are irrelevant for the choice of which is the best irrigation system to adopt. The estimated coefficient of the *insurance* variable, which is a proxy for farmers' perceived farming risk, is positive and differently statistically significant, suggesting that farmers are risk adverse. Sheltering from farming risks is an essential issue when choosing WCSTs, as seen in Koundouri et al. (2007) and Bozzola (2014). However, the magnitude of the impact is negligible; in fact, the *insurance* marginal effect is approximately 1 percentage point (0.013 for the logit model and 0.009 and 0.012 for the two probit models).

EU funds and *no EU funds* affect the probability of adopting new irrigation technologies in a different way. More specifically, the negative and statistically significant signs of *no EU funds* and the positive and statistically significant signs of *EU funds* seem to confirm a strong influence of national and local governments with respect to EU common agricultural policy. The marginal effects for these estimated coefficients are very low at -0.019 (logit) for *EU funds* and 0.012 (logit), 0.018 (probit) and 0.012 (CRE probit) for *no EU funds*. With the due differences, these results are in contrast with those of Huang et al. (2017), where local government programs offering financial assistance predict lower probabilities of utilizing sprinkler irrigation. This outcome could depend on the fact that fruits and horticulture, which use higher levels of WCSTs, are less supported by the EU Common Agricultural Policy funds than is the production of cereals and other arable crops, which conversely use conventional irrigation methods.

Among water-use characteristics, the *internal water source* and *irrigated land* coefficients show positive and statistically significant signs. As in the theoretical results of Caswell and Zilberman (1986) and the empirical findings of Green et al. (1996), Alcon et al. (2011), Moreno and Sunding (2005), Salazar and Rand (2016) and Huang et al. (2017), increasing the area irrigated by using internal water sources as wells, ponds and tanks, as well as the hectares of irrigated area for cultivation, has a positive impact on the likelihood of adopting WCSTs. Farmers who use irrigation water endowments for their land ownership have a higher probability of adopting WCSTs than do those who rely only on external sources. In addition, the larger the size of the irrigated land, the higher the benefit in terms of scale economies. The marginal effects analysis shows that *irrigated land*, whose values are 0.127 (logit) 0.121 (probit) and 0.116 (CRE probit), has a higher impact with respect to *internal water sources*, whose values are 0.038 (logit), 0.048 (probit) and 0.013 (CRE probit). This means that an additional hectare of irrigated land increases the probability of adopting WCSTs by almost 12 percentage points, while an additional hectare of area irrigated by an internal water source increases the probability of WCST adoption by almost 4 percentage points for the PA logit and probit models and only by 1 percentage point for the CRE probit model.

The last types of characteristics—geographical and climatic—are also relevant drivers for the probability of adopting sustainable irrigation technologies. Having a higher *altitude avg.*, as well as having a *mixed soil* type, reduces the probability of WCST adoption, while the seasonal aridity indexes present diversified signs depending on the season considered. In contrast to the literature (Moreno and Sunding 2005; Afrakhteh et al., 2015; Alcon et al., 2019), the slope of the field (*field slope*) is irrelevant for the irrigation system adoption choice.

Regarding the quality of the soil, Moreno and Sunding (2005) and Caswell and Zilberman (1986) underline that drip technologies are soil-quality augmenting. Our results confirm that farms having a mixed soil that is not intensive in regard to water consumption are less likely to adopt WCSTs (Kondouri et al. 2006). Similarly, *altitude avg.* negatively influences the probability of WCST adoption. For increasing altitude levels, where cultivated crops become less water intensive, the AMEs are approximately 3 percentage points. For mixed soil quality, the partial effects are -0.055 (logit), -0.041 (probit) and -0.037 (CRE probit). When the hectares of mixed soil increase, a farm is less likely to adopt WCSTs by approximately 5.5 percentage points for the logit model and 4.1 and 3.7 percentage points for the PA and CRE probit models, respectively.

From Sherestha and Gopalakrishan (1993) to more recent studies (Kondouri et al 2006; Bozzola, 2014; Asfaw et al., 2016; Salazar and Rand, 2016; Huang et al., 2017; Knapp and Huang; 2017), the effects of climate variability on the probability of adopting new irrigation systems are largely confirmed.

AI-estimated coefficients confirm the relevance of recent past climatic conditions in choosing to adopt WCSTs. Focusing on the coefficient signs, the four indexes are statistically significant in the logit model, while for the probit model, only summer AI is irrelevant, and for the CRE probit model, only the spring and autumn AIs are statistically significant at the 1% level.

While the growing season (*AIAMJ*) and summertime (*AIJAS*) findings present unexpected positive signs, for the winter and autumn periods, the negative expected signs are confirmed. The higher the level of the Ais is, the higher the humidity level, the lower the deficit of water for plant necessities[3], and the higher the probability of adopting WCSTs. Although this may appear puzzling, this result is in line with what the literature finds. From Figure A1 of Appendix A, it is evident that during spring and summer, the aridity index values remain substantially low, i.e., well below 0.65, suggesting a dry period that requires more intense irrigation independent of crop cultivation. In other words, spring and summer periods characterized by higher levels of dryness are more likely to require additional water for crops to reduce the production risk due to adverse climatic conditions such as droughts (Kondouri et al. 2006). The opposite occurs in the more humid periods (winter and autumn), where the probability of WCST adoption increases if the AIs are low. In making a decision regarding WCST adoption, farmers consider more the climatic variability in the humid seasons instead of that in the dry seasons. This is because in spring and summer, low levels of precipitation and high evapotranspiration are normal, and farmers are more accustomed to maximum temperature peaks or drought periods. Thus, farmers seem to be more reactive to the aridity indexes during cold seasons, since increasing temperatures and less precipitation are perceived as anomalous and dangerous for agricultural production. Moreover, since farmers are rational agents but limited, they have to decide on irrigation technologies on the basis of their own perception of climatic variations.

In terms of partial effects, the highest impact magnitude arises from the spring aridity index (*AIAMJ*), which increases the probability of adopting WCSTs by almost 15 percentage points for the logit model and 26 and 33 percentage points for the PA and CRE probit models, respectively. An increase in the winter and autumn aridity indexes implying more humidity is instead associated with a lower probability of adopting WCSTs by almost 2.6 percentage points and 4.5 percentage points for the logit model, respectively, and by 4.7 (2.5) percentage points and 6.3 (4.3) percentage points for the PA (CRE) probit model, respectively.

Only for robustness purposes, we carried out the same analysis but estimated only the CRE effects probit model for each Italian macro area: northwest, northeast, centre, south and islands (see Table B1 of Appendix). The results are confirmed in terms of coefficient signs and significance for farming production with *high-value crops*, with *mixed production* positively influencing WCST adoption probability and *livestock* negatively influencing adoption. Moreover, the effects of the seasonal AIs confirm that in winter and autumn, the higher the humidity is, the lower the probability of WCST adoption, while negative signs are present for the northeast and south areas of Italy in summer and the centre area in spring.

[3] This means that the need for water is covered by precipitation, reducing the perception of aridity.

Table 4. Estimation results for the probability of WCST adoption, odds ratio and AMEs of WCST adoption for PA logit and probit models.

VARIABLES	(1) PA Logit Model	(2) PA Probit Model	(3) CRE Probit Model	(4) PA Logit Model Odds Ratio	(5) AMEs of PA Logit Model	(6) AMEs of PA Probit Model	(7) AMEs of CRE Probit Model
Farms' characteristics							
Hours worked	0.505***	0.311***	0.145***	1.657***	0.0458***	0.0511***	0.0237***
	(11.57)	(10.83)	(2.832)	(11.57)	(11.60)	(10.92)	(2.833)
Land size	-1.488***	-0.894***	-0.962***	0.226***	-0.135***	-0.147***	-0.157***
	(-5.243)	(-5.098)	(-8.983)	(-5.243)	(-5.268)	(-5.149)	(-9.060)
Family run	-0.131*	-0.0642	-0.0475*	0.877*	-0.0121*	-0.0107	-0.00786*
	(-1.824)	(-1.461)	(-1.709)	(-1.824)	(-1.790)	(-1.438)	(-1.688)
High-value crops	0.917***	0.630***	0.658***	2.502***	0.0866***	0.109***	0.114***
	(14.13)	(16.19)	(24.51)	(14.13)	(13.72)	(15.31)	(23.38)
Mixed production	0.482***	0.413***	0.478***	1.620***	0.0463***	0.0737***	0.0859***
	(5.775)	(8.651)	(13.89)	(5.775)	(5.501)	(8.130)	(12.98)
Livestock	-1.956***	-0.918***	-0.903***	0.141***	-0.137***	-0.124***	-0.122***
	(-12.66)	(-11.16)	(-18.13)	(-12.66)	(-18.75)	(-15.37)	(-24.32)
Organic	0.123	0.0341	0.00749	1.131	0.0114	0.00565	0.00123
	(1.295)	(0.532)	(0.172)	(1.295)	(1.271)	(0.527)	(0.172)
Machine power	0.0001	-0.020	-0.0371***	1.000	0.00001	-0.0033	-0.00607***
	(0.00389)	(-0.952)	(-2.779)	(0.00389)	(0.00389)	(-0.952)	(-2.776)
Land tenure	-0.280***	-0.128**	-0.122***	0.756***	-0.0254***	-0.0211**	-0.0200***
	(-2.709)	(-2.052)	(-3.023)	(-2.709)	(-2.705)	(-2.053)	(-3.026)
Land value	-0.181**	-0.142***	-0.161***	0.835**	-0.0164**	-0.0233***	-0.0263***
	(-2.092)	(-2.859)	(-5.335)	(-2.092)	(-2.087)	(-2.853)	(-5.329)
Farmers' characteristics							
Age	-0.008***	-0.004***	0.001	0.992***	-0.0007***	-0.0007***	0.0001
	(-3.868)	(-3.535)	(0.229)	(-3.868)	(-3.873)	(-3.542)	(0.229)
Female head	-0.101*	-0.0681**	-0.0715***	0.904*	-0.00906*	-0.0111**	-0.0115***
	(-1.828)	(-1.986)	(-3.297)	(-1.828)	(-1.845)	(-2.007)	(-3.335)
External activities	-0.0693	-0.0511	-0.0481**	0.933	-0.00625	-0.00834	-0.00782**
	(-1.175)	(-1.374)	(-2.040)	(-1.175)	(-1.181)	(-1.382)	(-2.052)
Higher education	0.00303	-0.0176	-0.0189	1.003	0.000275	-0.00288	-0.00309
	(0.0515)	(-0.511)	(-0.895)	(0.0515)	(0.0515)	(-0.512)	(-0.897)
Financial and institutional characteristics							
Insurance	0.145***	0.056**	0.074*	1.156***	0.0132***	0.00917**	0.0120*
	(3.821)	(1.972)	(1.940)	(3.821)	(3.823)	(1.972)	(1.940)
ROI	0.547	0.336	0.143	1.728	0.0496	0.0552	0.0233
	(0.664)	(0.455)	(0.225)	(0.664)	(0.664)	(0.455)	(0.225)
Leverage	1.729	0.835	0.875	5.635	0.157	0.137	0.143
	(1.467)	(0.908)	(0.681)	(1.467)	(1.467)	(0.908)	(0.681)
EU Funds	-0.212***	-0.0434	-0.0222	0.809***	-0.0192***	-0.00713	-0.00362
	(-2.872)	(-0.902)	(-0.657)	(-2.872)	(-2.875)	(-0.902)	(-0.657)
No EU Funds	0.131***	0.107***	0.0745**	1.140***	0.0119***	0.0176***	0.0122**
	(3.649)	(4.072)	(2.003)	(3.649)	(3.647)	(4.074)	(2.003)
Water use characteristics							
Internal water source	0.416***	0.291***	0.0775**	1.517***	0.0378***	0.0479***	0.0127**
	(10.47)	(12.58)	(2.029)	(10.47)	(10.61)	(12.78)	(2.029)
Energy, electricity and	0.0236	0.0257	0.00454	1.024	0.00215	0.00421	0.0007

water costs							
	(0.500)	(0.873)	(0.0763)	(0.500)	(0.500)	(0.874)	(0.0763)
Irrigated land	1.399***	0.739***	0.712***	4.050***	0.127***	0.121***	0.116***
	(17.33)	(14.77)	(9.479)	(17.33)	(17.96)	(15.48)	(9.554)
Geographical and climatic characteristics							
Altitude avg.	-0.339***	-0.189***	-0.183***	0.712***	-0.0308***	-0.0310***	-0.0300***
	(-13.08)	(-12.49)	(-18.81)	(-13.08)	(-13.41)	(-12.67)	(-18.99)
Field slope	-0.0525	-0.0125	0.0130	0.949	-0.00477	-0.00206	0.00212
	(-0.488)	(-0.206)	(0.356)	(-0.488)	(-0.488)	(-0.206)	(0.356)
Sandy soil	-0.00823	0.0221	0.0280	0.992	-0.000747	0.00362	0.00457
	(-0.0863)	(0.386)	(0.773)	(-0.0863)	(-0.0863)	(0.386)	(0.773)
Mixed soil	-0.604***	-0.252**	-0.225***	0.547***	-0.0548***	-0.0414**	-0.0367***
	(-2.849)	(-2.037)	(-2.779)	(-2.849)	(-2.855)	(-2.038)	(-2.782)
Clay soil	-0.121	-0.0551	-0.0495*	0.886	-0.0109	-0.00904	-0.00808*
	(-1.508)	(-1.173)	(-1.662)	(-1.508)	(-1.509)	(-1.173)	(-1.663)
AIJFM	-0.288**	-0.290***	-0.154	0.750**	-0.0261**	-0.0475***	-0.0251
	(-2.231)	(-3.329)	(-1.414)	(-2.231)	(-2.231)	(-3.330)	(-1.414)
AIAMJ	1.608***	1.571***	2.069***	4.994***	0.146***	0.258***	0.338***
	(3.742)	(5.327)	(7.624)	(3.742)	(3.738)	(5.302)	(7.622)
AIJAS	0.746**	0.0125	-0.0520	2.109**	0.0677**	0.00206	-0.00850
	(2.027)	(0.0505)	(-0.239)	(2.027)	(2.031)	(0.0505)	(-0.239)
AIOND	-0.498***	-0.384***	-0.264***	0.608***	-0.0452***	-0.0630***	-0.0432***
	(-5.609)	(-5.574)	(-3.054)	(-5.609)	(-5.620)	(-5.568)	(-3.054)
Constant	-17.01	-9.564	-7.625	0.000			
	(-1.201)	(-0.816)	(-0.606)	(-1.201)			
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mundlak's devices			Yes				Yes
Observations	43,917	43,917	43,917	43,917	43,917	43,917	43,917
Number of ID	13,054	13,054	13,054	13,054	13,054	13,054	13,054

*Note: z-statistics with robust adjustment are reported in parentheses, * p-value <0.10; ** p-value <0.05; *** p-value <0.01*

5.2 Results for the intensity of WCST adoption (tobit random effects and CRE tobit)

In the intensity of adoption analysis, the measure of how much irrigated land is dedicated to WCSTs by an innovative farmer is estimated. This process allows us to capture how widespread the innovation of irrigation systems is in farmers' lands (Arslan et al., 2014). In Table 5, we report the estimated coefficients of the WCST adoption intensity based on the whole sample of Italian farmers by applying the RE tobit and the CRE tobit models. In Table B2 of Appendix B, for robustness checks, we present the analysis of WCST adoption intensity for each macro area of Italy by applying only the CRE tobit model.

Most of the drivers considered are statistically significant and adhere to the expected signs, as in the case of the WCST adoption decision. Several farm characteristic variables are significant at 1% in both models. Although *family run* was not significant in determining adoption decisions, this variable decreases the intensity of adoption in both models at the 1% level of significance, confirming the relevance of managing constraints. Again, *hours worked* and *land size* present divergent signs, indicating that while labour constraints do not play a role in farmers' decisions on

WCST adoption, land does. Both *high-value crops* and *mixed production* show positive quite high magnitude[4], while *livestock* has the highest negative magnitude, followed by *land size*.

As in Arslan et al. (2014), *female head* and *external activities* present negative effects on WCST adoption intensity, meaning that being male and being engaged in only farming activities are relevant for increasing the intensity of innovative irrigation systems. As in Pokhrel et al. (2018), *irrigated land* increases the adoption intensity of WCSTs, presenting the highest magnitude of the estimations. However, among the typology of soils, only *mixed soil* shows a negative and statistically significant sign, which is surprising since we would expect that a water-intensive soil that easily absorbs water such as *sandy soil* would increase the adoption intensity of WCSTs.

Regarding climatic variables, similar to the case of WCST adoption choice, the two periods with more aridity (spring and summer) represent a stimulus in intensifying irrigation using drip or sprinkler systems. In the spring season, the AI estimated coefficients are high and positive, indicating that an increase in AIs leads to a more than proportional adoption of WCSTs in terms of WCST adoption intensity. In summer, the negative sign for the CRE model confirms the necessity of intensifying the adoption of innovative irrigation systems. The magnitude is higher for spring AI, with values of 1.335 (RE tobit) and 3.693 (CRE tobit), than for summer AI, with values of 0.559 (RE tobit) and -0.693 (CRE tobit).

The CRE tobit model was also used to analyse the effects on the intensity of WCST adoption for Italian macro areas. The overall results respect the above findings for the whole sample. Some differences are related to some specific areas. For example, *land size* is significant in the northwest and south areas and in the islands of Italy, suggesting that land is a stringent constraint in farmers' decisions on WCST adoption. For climatic impacts, the results confirm that the higher the winter and autumn AIs are, the lower the intensity of innovative irrigation systems, while the higher the spring and summer AIs are, the higher the intensity of WCST adoption. The only exception is in regard to the negative sign of *AIJAS* for the northeast and *AIAMJ* for the centre of Italy.

Table 5. Estimation results for the intensity of WCST adoption.

VARIABLES	(1) RE Tobit Model	(2) CRE Tobit Model
Farms' characteristics		
Hours worked	0.366***	0.239***
	(11.44)	(0.010)
Land size	-1.318***	-1.685***
	(-7.805)	(0.000)
Family run	-0.292***	-0.152***
	(-4.659)	(0.003)
High-value crops	0.637***	1.342***
	(15.24)	(0.000)
Mixed production	0.232***	0.908***
	(4.502)	(0.000)

[4] We consider strong the values that are higher than 0.5.

Livestock	-1.562***	-1.680***
	(-16.28)	(0.000)
Organic	0.124	-0.095
	(1.633)	(0.249)
Machine power	0.0138	-0.120***
	(0.476)	(0.000)
Land tenure	-0.0252	-0.256***
	(-0.345)	(0.000)
Land value	-0.108*	-0.328***
	(-1.681)	(0.000)
Farmers' characteristics		
Age	-0.00517***	0.004
	(-2.868)	(0.568)
Female head	-0.103**	-0.094**
	(-2.217)	(0.025)
External activities	-0.0992*	-0.116**
	(-1.911)	(0.011)
Higher education	-0.0295	-0.040
	(-0.580)	(0.319)
Financial and institutional characteristics		
Insurance	0.0720***	0.091
	(3.027)	(0.177)
ROI	0.391	0.941
	(0.450)	(0.411)
Leverage	3.445	2.255
	(1.123)	(0.605)
EU Funds	-0.140***	-0.029
	(-2.655)	(0.619)
No EU Funds	0.0556**	0.109*
	(2.176)	(0.092)
Water use characteristics		
Internal water source	0.317***	0.159**
	(12.43)	(0.031)
Energy, electricity and water costs	0.0305	-0.033
	(0.883)	(0.753)
Irrigated land	0.858***	1.124***
	(17.90)	(0.000)
Geographical and climatic characteristics		
Altitude avg.	-0.418***	-0.341***
	(-17.97)	(0.000)
Field slope	-0.0310	0.036
	(-0.450)	(0.534)
Sandy soil	0.0587	-0.002
	(0.952)	(0.970)
Mixed soil	-0.256**	-0.461***
	(-1.983)	(0.003)
Clay soil	-0.0597	-0.084
	(-1.076)	(0.132)
AIJFM	-0.186*	-0.409*
	(-1.808)	(0.051)
AIAMJ	1.335***	3.693***
	(4.202)	(0.000)
AIJAS	0.559**	-0.693*
	(2.022)	(0.096)
AIOND	-0.359***	-0.547***
	(-4.570)	(0.001)
Constant	-29.08	-26.569
	(-1.128)	(0.460)
Regional dummies	Yes	Yes
Time dummies	Yes	Yes

Mundlak's devices		Yes
Observations	43,917	43,917
Number of ID	13,054	13,054

*Note: z-statistics with robust adjustment are reported in parentheses, * p-value <0.10; ** p-value <0.05; *** p-value <0.01*

6. Conclusions

Our study represents the first attempt to estimate the main determinants of the decision to engage in sustainable irrigation technology adoption and intensity at the farm level for Italy. The variety of geographical, socioeconomic, productive, and climatic factors makes Italy an interesting case study, whose findings may contribute to deepening the water scarcity management knowledge within the Mediterranean Basin areas that collectively suffer from the same problems.

Our main findings confirm that farm size, crop typology, land tenure, insurance against farming risks, internal water sources, geographical and climate characteristics are all relevant factors influencing the choice of sustainable irrigation technology adoption and intensity. Farmers with a high probability of adopting WCSTs are male and own their land, which is usually small in size and with an internal water source. Education is not a key farmer characteristic in choosing to adopt WCSTs. Highly specialized farms with high-value crops and mixed production are more likely to adopt WCSTs.

The innovative farmers prefer to dedicate themselves to internal farming activities and present a risk-averse attitude by covering their activities with increasing insurance. Farmers receive low levels of EU funds but high levels of local funds. Farmers who adopt WCSTs are more sensitive to the effects of the recent seasonal climatic conditions. Because spring and summer are characterized by higher dryness, and winter and autumn are characterized by higher humidity, farmers, in making their decisions about WCST adoption, focus more on climatic variability in humid seasons instead of dry seasons. More specifically, climatic characteristics may influence the strategic decision patterns of a farmer in determining their adoption of WCSTs. This is because in spring and summer, farmers are more accustomed to maximum temperature peaks or drought periods, while during cold seasons, increasing temperatures and less precipitation may be perceived as anomalous and dangerous factors for agricultural production. Farmers are quite sensitive to the aridity indexes, which seem to be good indicators of climate conditions since they combine precipitation (P) and evapotranspiration (ET_0).

Our analysis may suggest to policy-makers some relevant incentives to be applied to spread the adoption of WCSTs among farmers. Moreover, it should be easy to enlarge this analysis to include other similar countries if more data were available. This analysis places the basis for future analyses on the main drivers of sustainable technology adoption in irrigation within the southern part of Europe, which suffers the most from droughts. This may strongly help such areas to cope with important challenges that the agricultural sector will face in the future due to climate change and water resource scarcity.

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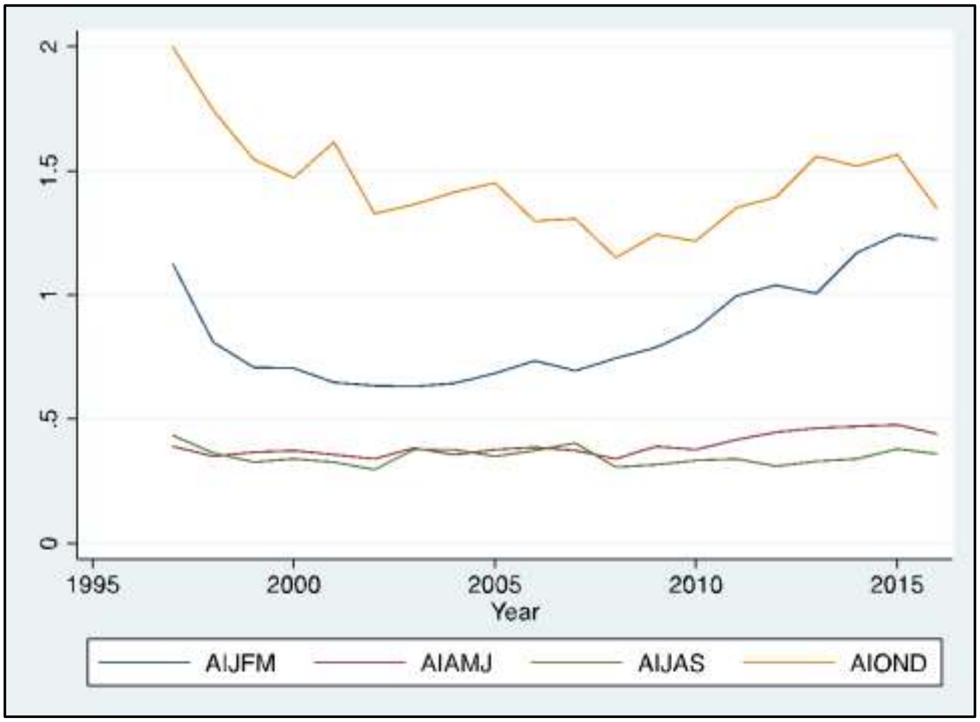
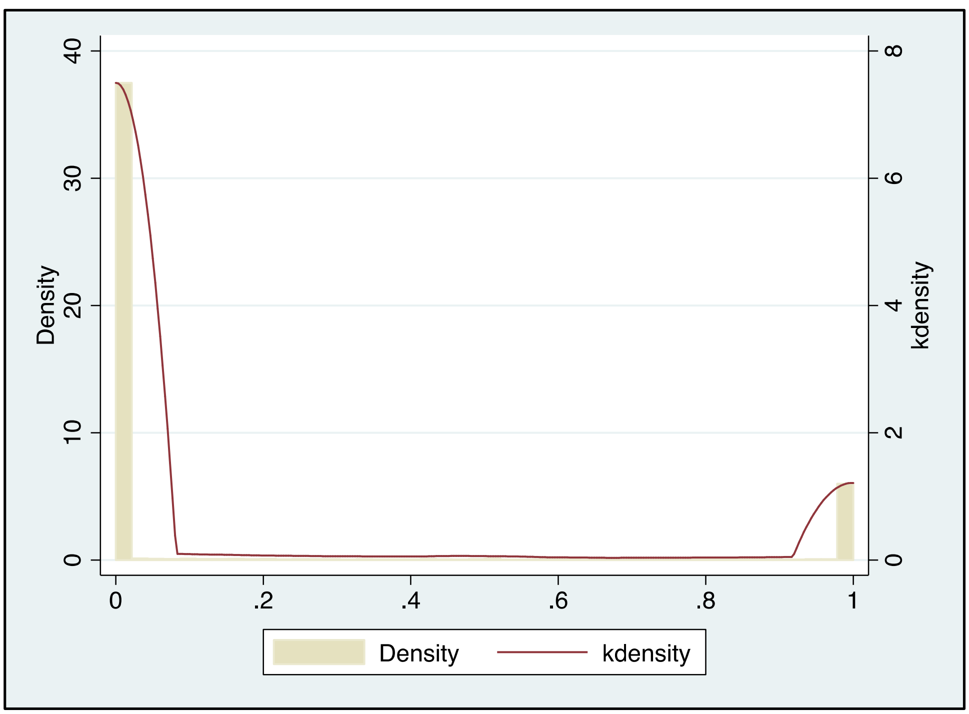
Appendix A

Figure A1. Tendencies of the seasonal aridity indexes



Source: Authors' elaboration

Figure A2. Density and Kernel density of WCST adoption intensity



Source: Authors' elaboration

Appendix B

Table B1. Estimation results for the probability of adoption of WCST for macro-areas of Italy

VARIABLES	(1) CRE Probit Model North-West	(2) CRE Probit Model North-East	(3) CRE Probit Model Centre	(4) CRE Probit Model South and Islands
Farms' characteristics				
Hours worked	0.026	0.039	0.217**	0.156***
	(0.728)	(0.527)	(0.023)	(0.004)
Land size	-0.967**	-0.425	-0.086	-1.338***
	(0.031)	(0.227)	(0.852)	(0.000)
Family run	-0.254*	0.154	0.207*	-0.151**
	(0.063)	(0.189)	(0.086)	(0.019)
High-value crops	1.023***	1.041***	0.360***	0.514***
	(0.000)	(0.000)	(0.000)	(0.000)
Mixed production	0.742***	0.876***	0.114	0.417***
	(0.000)	(0.000)	(0.255)	(0.000)
Livestock	-0.496**	-0.437***	-1.124***	-1.182***
	(0.013)	(0.002)	(0.000)	(0.000)
Organic	0.253	0.337	0.024	-0.149
	(0.293)	(0.127)	(0.859)	(0.103)
Machine power	0.059	0.004	-0.178***	-0.010
	(0.207)	(0.936)	(0.000)	(0.816)
Land tenure	-0.001	-0.118	-0.406***	0.031
	(0.996)	(0.405)	(0.009)	(0.780)
Land value	-0.209**	-0.184**	-0.496***	0.008
	(0.023)	(0.028)	(0.001)	(0.949)
Farmers' characteristics				
Age (head)	0.009	-0.003	-0.001	-0.001
	(0.246)	(0.525)	(0.836)	(0.777)
Female head	0.027	-0.101	-0.069	-0.040
	(0.768)	(0.233)	(0.319)	(0.481)
External activities	0.152	-0.071	-0.151*	-0.030
	(0.136)	(0.370)	(0.055)	(0.641)
Higher education	-0.032	-0.025	-0.025	-0.010
	(0.708)	(0.749)	(0.725)	(0.860)
Financial and institutional characteristics				
Insurance	0.220***	0.041	0.073	0.005
	(0.002)	(0.249)	(0.370)	(0.928)
ROI	-2.690	-1.485	-0.478	0.805
	(0.361)	(0.355)	(0.803)	(0.558)
Leverage	-3.319	5.109	9.048	-2.138
	(0.553)	(0.672)	(0.138)	(0.840)
EU Funds	-0.338**	-0.327***	-0.002	-0.124*
	(0.039)	(0.001)	(0.987)	(0.083)
No EU Funds	0.222***	0.120***	0.052	0.002
	(0.003)	(0.001)	(0.284)	(0.945)
Water use characteristics				
Internal water source	0.145	0.007	-0.010	0.233***
	(0.158)	(0.899)	(0.911)	(0.002)
Energy, electricity and water costs	0.098	0.041	-0.099	0.052
	(0.267)	(0.603)	(0.295)	(0.311)
Irrigated land	0.262	0.641***	0.928***	0.918***
	(0.273)	(0.000)	(0.000)	(0.000)

Geographical and climatic characteristics				
Altitude avg.	-0.247***	-0.055*	-0.199***	-0.256***
	(0.000)	(0.099)	(0.000)	(0.000)
Field slope	0.186	0.161	-0.170	0.072
	(0.188)	(0.153)	(0.149)	(0.493)
Sandy soil	-0.170	-0.053	-0.272*	0.248***
	(0.253)	(0.613)	(0.077)	(0.007)
Mixed soil	-0.881***	-0.196	-0.443	0.335*
	(0.002)	(0.361)	(0.207)	(0.093)
Clay soil	-0.301**	0.001	-0.041	0.062
	(0.034)	(0.987)	(0.725)	(0.380)
AIJFM	-1.805***	1.531***	-1.452***	-4.854***
	(0.000)	(0.000)	(0.000)	(0.000)
AIAMJ	0.197	7.219***	-3.249***	4.235***
	(0.778)	(0.000)	(0.003)	(0.000)
AIJAS	1.216*	-4.445***	1.776*	-2.346**
	(0.062)	(0.000)	(0.092)	(0.040)
AIOND	-0.993***	-1.131***	-0.163	-1.853***
	(0.002)	(0.000)	(0.578)	(0.000)
Constant	64.185	-19.556	-60.056	8.093
	(0.238)	(0.839)	(0.279)	(0.919)
Regional dummies	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes
Mundlak's devices	Yes	Yes	Yes	Yes
Observations	9,955	9,903	9,877	14,182
Number of ID	2,645	2,874	3,260	4,275

*Note: z-statistics with robust adjustment are reported in parentheses, * p-value <0.10; ** p-value <0.05; *** p-value <0.01*

Table B2. Estimation results for the WCST adoption intensity for macro-areas of Italy

VARIABLES	**(1) CRE Tobit Model North-West**	**(3) CRE Tobit Model North-East**	**(5) CRE Tobit Model Centre**	**(7) CRE Tobit Model South and Islands**
Farms' characteristics				
Hours worked	0.007	0.019	0.436	0.375*
	(0.961)	(0.903)	(0.110)	(0.075)
Land size	-0.914**	-0.261	-0.186	-3.462***
	(0.017)	(0.394)	(0.788)	(0.000)
Family run	-0.266***	0.177	0.495***	-0.564***
	(0.009)	(0.108)	(0.002)	(0.000)
High-value crops	1.316***	1.875***	0.952***	1.488***
	(0.000)	(0.000)	(0.000)	(0.000)
Mixed production	0.887***	1.504***	0.313*	1.068***
	(0.000)	(0.000)	(0.060)	(0.000)
Livestock	-0.573***	-0.654***	-2.447***	-2.955***
	(0.000)	(0.000)	(0.000)	(0.000)
Organic	0.134	0.355**	0.168	-0.485***
	(0.437)	(0.044)	(0.471)	(0.002)
Machine power	0.044	-0.005	-0.455***	-0.050
	(0.206)	(0.919)	(0.000)	(0.415)
Land tenure	-0.093	-0.225*	-0.909***	0.031
	(0.463)	(0.058)	(0.000)	(0.840)
Land value	-0.315***	-0.314***	-1.145***	0.183
	(0.000)	(0.000)	(0.000)	(0.304)
Farmers' characteristics				
Age (head)	0.013	-0.005	-0.000	0.000
	(0.275)	(0.690)	(0.982)	(0.997)

Female head	-0.003	-0.087	-0.156	-0.007
	(0.966)	(0.286)	(0.165)	(0.942)
External activities	0.202***	-0.143**	-0.400***	-0.036
	(0.009)	(0.044)	(0.003)	(0.727)
Higher education	-0.017	-0.092	-0.081	-0.015
	(0.791)	(0.200)	(0.455)	(0.866)
Financial and institutional characteristics				
Insurance	0.160*	0.058	0.049	-0.016
	(0.083)	(0.487)	(0.837)	(0.942)
ROI	-2.335	-3.051	-3.317	2.316
	(0.261)	(0.301)	(0.470)	(0.334)
Leverage	-8.976	14.441	24.452	-4.929
	(0.475)	(0.648)	(0.153)	(0.857)
EU Funds	-0.295**	-0.599***	0.045	-0.417***
	(0.028)	(0.000)	(0.805)	(0.000)
No EU Funds	0.154	0.192*	0.131	-0.022
	(0.146)	(0.057)	(0.489)	(0.888)
Water use characteristics				
Internal water source	0.226*	-0.012	-0.031	0.729***
	(0.051)	(0.907)	(0.880)	(0.001)
Energy, electricity and water costs	0.057	0.083	-0.263	0.006
	(0.713)	(0.613)	(0.334)	(0.985)
Irrigated land	0.033	0.850***	1.950***	1.800***
	(0.892)	(0.000)	(0.000)	(0.000)
Geographical and climatic characteristics				
Altitude avg.	-0.265***	-0.090***	-0.432***	-0.715***
	(0.000)	(0.005)	(0.000)	(0.000)
Field slope	0.226**	0.261**	-0.444**	0.163
	(0.047)	(0.010)	(0.017)	(0.222)
Sandy soil	-0.190	-0.075	-0.790***	0.493***
	(0.129)	(0.484)	(0.001)	(0.000)
Mixed soil	-0.996***	-0.455*	-1.099*	0.743**
	(0.001)	(0.052)	(0.057)	(0.035)
Clay soil	-0.298**	0.006	-0.135	0.180
	(0.011)	(0.948)	(0.459)	(0.145)
AIJFM	-2.457***	2.770***	-4.059***	-14.128***
	(0.000)	(0.000)	(0.000)	(0.000)
AIAMJ	-0.001	12.313***	-6.427***	10.237***
	(0.998)	(0.000)	(0.001)	(0.000)
AIJAS	1.672***	-7.457***	3.529*	-8.521***
	(0.002)	(0.000)	(0.084)	(0.000)
AIOND	-1.481***	-1.623***	-0.533	-5.715***
	(0.000)	(0.000)	(0.432)	(0.000)
Constant	105.996	-71.420	-140.846	16.277
	(0.287)	(0.771)	(0.305)	(0.938)
Regional dummies	Yes	Yes	Yes	Yes
Time-dummies	Yes	Yes	Yes	Yes
Mundlak's devices	Yes	Yes	Yes	Yes
Observations	9,955	9,903	9,877	14,182
Number of ID	2,645	2,874	3,260	4,275

*Note: z-statistics with robust adjustment are reported in parentheses, * p-value <0.10; ** p-value <0.05; *** p-value <0.01*

Innovation in Irrigation Technologies for Sustainable Agriculture:
A Panel Endogenous Switching Analysis on the Italian Farms' Land Productivity

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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. By applying a panel endogenous switching regression model, 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.

Keywords: Water scarcity, Innovation, Micro irrigation, Sustainable agriculture, Italian farms

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 one of the main constraints 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 that in many cases is highly inefficient, with most of the water lost through evaporation, percolation, and runoff (EEA, 2019; MEA, 2005). In Europe, the water used in agriculture account for around 24% of total water use. However, this share may vary substantially, reaching up to 80% in the southern countries of Europe (EEA, 2019, 2009; UN-Water, 2018). Since the ’70s of the last century, the climate change (CC) and its extremizations have contributed to intensifying the water demand for irrigation in agriculture putting additional pressures on water resources. Local water authorities will have to face the challenge of maintaining the balance between water demand and supply, i.e. available natural water resources (Rosenzweig and Tubiello, 1997; UNESCO and UN-Water, 2020).

Water shortage and agricultural water use will represent important issues affecting the European agricultural activities in terms of both the agricultural production level and capability of assuring a good level of food security. In Europe, a clear north-south divide in terms of water stress is projected with global warming, with southern countries that will suffer the most. Water requirements are foreseen to increase across Europe with peaks in the southern European countries (EEA, 2019; European Commission. Joint Research Centre., 2020). This pressure on water resources is and will be 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; EEA, 2019; European Commission. Joint Research Centre., 2020).

Many Italian regions have experienced warmer and drier weather conditions with an increase of extreme events and have suffered from water scarcity during these last decades beyond being at risk of future water crises due to CC (Brunetti et al., 2004; Senatore et al., 2011; Toreti et al., 2009). Moreover, meaningful structural differences in water endowments among Italian regions are continuously increasing, making the national agricultural production more fragile and outstandingly dependent on water irrigation, especially in water-scarce regions (Auci and Vignani, 2020; Tubiello et al., 2000).

Small farms are particularly affected by CC events as they present a less capacity for adaptation to climatic extreme conditions (EEA, 2015 and 2019). Therefore, the whole Italian agricultural sector is intensely at risk to the adverse CC scenarios, as it is mainly composed of small farms with low land extensions, run at the family level, and with low levels of diversification. (Eurostat, 2016). One strategy that small farmers can undertake is the adoption of technological innovation to allow adaptation of agricultural activity to new climatic scenarios.

Understanding the relationship between innovation in the irrigation system and agricultural yields is an important issue for analysing the sustainability of the agricultural sector as a whole. Indeed, innovation within the agricultural sector can be considered as a strategy for adaptation to climate challenges and water scarcity issues. Therefore, understanding 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 essential to design suited adaptation policies to influence farmers behaviour toward more conservative water uses (Bozzola and Swanson, 2014).

Innovations and the use of water conservation saving technologies (WCSTs) may reduce the impacts of agricultural activities on water resources and have important effects on the improvement of agricultural productivity in a context of uncertainties due to climatic adversities (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.

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). Whereas only some studies focus primarily on innovation within the agri-food sector (Ghazalian and Fakih, 2017; Harvey et al., 2017; Materia et al., 2017) and 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).

This paper wants to contribute to the current debate on how innovation in irrigation systems 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' WCST adoption choices, as a strategy to cope with climate variability, may have a different effect on land productivity to adopters compared to non-adopters. The novelty of our paper is principally in the application of the control function approach using panel data as developed by Murtazashvili and Wooldridge (2016). We implement a two-stage switching regression model with an endogenous switching and an endogenous explanatory variable with constant coefficients combining the Mundlak–Chamberlain approach for unobserved heterogeneity. This method allows us to consider two different sources of endogeneity: the selection indicator and an endogenous explanatory variable.

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. Then, a counterfactual analysis has been computed in order to corroborate whether adopting WCSTs for land irrigation will lead to differences in farmers' land productivity performance. Estimating the average treatments effects on treated (ATET) allows evaluating the effects of the treatment, i.e. the decision of adopting WCSTs for irrigation (Imbens and Wooldridge, 2009).

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. Section 4 introduce the dataset used in the analysis, section 5 presents the main results which are discussed in section 6. Finally, some conclusions are drawn in section 7.

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

An effective strategy to obtain sustainable irrigation at the high scale level consists of improving water use on the demand side (farmers), therefore individual decisions over irrigation technologies may influence pressures on water resources at higher scales (EEA, 2009). 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 knowledge of a farmer regarding the application of a new technology (Levidow et al., 2014).

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 their intrinsic and extrinsic characteristics (Baidu-Forson, 1999; Somda et al., 2002). The primary motivation is related to the choice of increasing marginal benefits within a profit maximization procedure or more generally, to the improvement of adopter's economic conditions. But, there are other elements that might also be considered in the innovation decision process which are not always observable such as social networks, cultural factors, shared ideas, implementation costs or the ease of innovation adoption (see Pronti et al., 2020).

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 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 a farmer's intrinsic characteristics as well as farm structure i.e., motivations and ability, adaptability to changes or green aptitudes. This may determine systematic differences between farmers which do adopt and those that do not. 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, selection bias should be considered properly in order to obtain unbiased and consistent estimates.

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 on land productivity in Ethiopia. Abdulai and Hoffman (2014) have analysed the effect on land productivity and returns of soil and water conservation technique adoption among rice producers in Ghana.

Other empirical works have applied a ESRM approach 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 have 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. Anyway, all of them relied on cross-sectional data structures.

At the best of our knowledge, no previous studies attempted to apply a ESRM for technological innovation in the Italian agriculture using panel data. The only study is that of Teklewold and Mekonnen (2017) which have 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.

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 a cross-section ESRM for testing the effectiveness of an extension program on profits for dairy farmers in Ireland. Moreover, in terms of agricultural water management, the only authors analysing specifically this issue with a cross-section ESRM were Da Cunha et al. (2015) and Abdulai and Hoffman (2014). Our study represents the first attempt in addressing the WCSTs innovation issue in terms of land productivity at the national level in a western country using a panel data ESRM proposed by Murtazashvili and Wooldridge (2016).

3. Methodology

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).

The interaction among all the observable and unobservable factors may affect farmers' benefits and costs given all the technological alternatives that may influence the decision of adopting WCSTs[5]. Unobserved structural differences in farmers' performances may be explained by their ability and motivations as well as their technology innovation choices. Thus, innovative farmers may obtain higher performances than the less innovative ones independently by the decision of technology adoption. Explaining these differences 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 ESRM should be applied (Kassie et al., 2018; Wooldridge, 2010). In this model, the adoption decision is modelled considering 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., farmers' WCST adoption and non-adoption). A two-step approach, based on the control function method, implies that in the first stage a binary model (i.e. the self-selection equation) is estimated while in the second stage an outcome equation conditional on the treatment effect that is the adoption decision is estimated.

One of the advantages of applying a ESRM 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 farms' 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 determining the counterfactual effect on the outcome variable by considering adopters and non-adopters characteristics. Another advantage of the ESRM is that allows the unconfoundedness assumption to be overcome (Abdulai and Huffman, 2014). This methodology allows controlling 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 ESRM with an endogenous explanatory variable is implemented. This model is based on two sources of endogeneity: the selection indicator and an endogenous explanatory variable. Also, the unobserved heterogeneity is controlled through Mundlak's devices. Applying the control function methodology, the two-step procedure implies that the selection equation is estimated by using a correlated random effects probit model (CRE probit) (Mundlak, 1978) while the outcome equation, when an endogenous continuous explanatory variable is present, is estimated by applying a two-stage least squares (2SLS) model with Mundlak's devices. In this way, the selection

[5] The farmer compares all the possible alternative technologies (new and old) and ranks all of the them in terms of overall expected utilities and her/his final choice is based on their comparison. 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 expected utility after having considered all the different technology characteristics (Baidu-Forson, 1999; Somda et al., 2002).

bias is addressed by introducing the generalized residuals in the outcome equation. For robustness check, no continuous endogenous explanatory variable assumption is introduced, and the standard estimation applies.

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

$$y_{it}^{(0)} = x_{it}\beta_0 + c_{i0} + u_{it0}$$
$$y_{it}^{(1)} = x_{it}\beta_1 + c_{i1} + u_{it1} \qquad \forall\, i = 1, \dots, N \text{ and } t = 1, \dots, T \qquad (1)$$

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

Following Murtazashvili and Wooldridge (2016), the panel ESRM linearly combines the two regimes and the outcome equation may be represented as follows:

$$y_{it} = (1 - AD_{it})y_{it}^{(0)} + AD_{it}y_{it}^{(1)} \qquad (2)$$

where y_{it} represents the outcome of interest i.e., farmers' land productivity, as a linear combination of the two regimes. AD_{it} is the endogenous switching indicator that is 1 when a farmer chooses of adopting WCSTs and 0 otherwise. Substituting the two regimes of Eq. (1) into Eq. (2), we obtain:

$$y_{it} = x_{it}\beta_0 + AD_{it}x_{it}\gamma_1 + c_{i0} + AD_{it}(c_{i1} - c_{i0}) + u_{it0} + AD_{it}(u_{it1} - u_{it0}) \qquad (3)$$

where $\gamma_1 = \beta_1 - \beta_0$ and the endogenous switching variable AD_{it} interacts with the time-varying endogenous and exogenous explanatory variables (x_{it}) and time constant unobservable variables (c_{i0} and c_{i1}) as well as with the error term. Assuming that the correlation between farmer-specific unobserved effects and exogenous variables is not left unspecified but is linearly related to the mean in time of the exogenous variables, we introduce the Mundlak's devices in the outcome equation, as follows:

$$y_{it} = x_{it}\beta_0 + AD_{it}x_{it}\gamma_1 + \bar{z}_i\rho_0 + AD_{it}\bar{z}_i\rho_1 + r_{it0} + AD_{it3}r_{it1} \qquad (4)$$

where the Mundlak's devices $\bar{z}_i$ are the mean of the exogenous variables $\bar{z}_i = T^{-1}\sum_{t=1}^{T} z_{it}$, 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.

Given that farmers choose to adopt WCSTs to increase land productivity, the decision to adopt may be represented as an endogenous dichotomous choice. This implies estimating a correlated random effects probit model as follows:

$$AD_{it} = 1[k_{t3} + z_{it}\pi_3 + \bar{z}_i\delta_3 + v_{it} > 0], \text{where } v_{it} \sim N[0,1] \qquad (5)$$

where the vector z_{it} contains all the exogenous variables. This implies that z_{it} includes the exogenous variables of the outcome equation, and any instrumental variables that may affect the endogenous and the selection variable. $\bar{z}_i$ is the mean in time of all the variables and 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), we obtain the conditional mean of the error term as a function of the generalized residuals ($h(.)$) (Vella, 1998):

$$\begin{aligned} E(v_{it}|AD_{it}, z_i) &= h(AD_{it}, k_{t3} + z_{it}\pi_3 + \bar{z}_i\delta_3) \\ &= AD_{it}\lambda(k_{t3} + z_{it}\pi_3 + \bar{z}_i\delta_3) - (1 - AD_{it})\lambda(-k_{t3} - z_{it}\pi_3 - \bar{z}_i\delta_3) \end{aligned} \quad (6)$$

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:

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

where $\hat{h}_{it3}$ is the estimated generalized residuals, which account for the endogeneity of the selection variable and x_{it} also incorporates the continuous endogenous explanatory variable. Equation (7) 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 productivity. 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 specified as follows:

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

where all farm, farmer, financial and institutional characteristics and their interactions with the selection variable (AD_{it}) 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 AD 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 net benefits of adopting and non-adopting. 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 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 instruments of eq. (8).

3.1 Counterfactual analysis and treatment effects

The advantage of the ESRM involves comparing the different impact of the decision of adopting innovative irrigation 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 farmers 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 WCSTs (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:

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

By introducing the generalized residuals, we may capture the choice of adopting new irrigation technologies and thus we may correct for the selection bias in the outcome equation. This is useful to distinguish a farmer who adopted WCSTs that behaves 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:

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

Following Heckman *et al*. (2001), Di Falco and Veronesi (2013), Abdulai and Huffman (2014) and Imbens and Wooldridge (2009), we may compute 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 farmers. Combining equations (11) and (12), we obtain:

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

which represents the effect of an innovating behaviour induced by climatic variability and other observable characteristics 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).

4. Data description

In this panel data analysis, we combined in a longitudinal database all the 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 variables, coming 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, were merged with the FADN database using georeferenced specifications 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 compute seasonal Aridity Indexes (AIs) at the farm level[6] 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.

Table 1 presents the statistics description of all the variables used in the estimation models for adopters and non-adopters. In Appendix, Table A1 reports the description of the variables and the descriptive statistics for all the sample[7]. Structural differences between WCST adopters and non-adopters are evident from descriptive statistics as shown in Table 1 and the Wald test on the mean difference confirms a systematic difference between the two groups. As dependent variable of the outcome equation, we consider the productivity of land measured by the ratio between the real profit and loss value and cultivated land hectares (euro/ha). The average land productivity for adopters of WCSTs is 20,933,65 euro/ha while for non-adopters is quite low and equals to 7,965.13 euro/ha. The mean difference between the outcome of adopters and no-adopters is very high and equals to 12,968.5 that in percentage change

[6] 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).

[7] For a more detailed description of all the variables considered see Pronti et al. (2020).

terms represents 162.82%. This suggests that adopting WCSTs for irrigation may play a significant role in increasing land productivity for the Italian farmers.

As regards the independent variables of the model, we distinguish among production inputs, further inputs, farms' characteristics, farmers' characteristics, other incomes and financial and accounting characteristics. We also add the macro-areas in which Italy is sub-divided.

The production inputs that affect the most the agricultural production activity are the total level of working hours spent within the farm (Working *hours*), the total machine power available in the farm (*Machine power*) and the market value of the farms' land (*Land value*) all expressed in logarithmic term. As underlined by Timmins (2006), land value should be considered as an endogenous variable[8]. Thus, we develop two different models. In Model A we overcome the endogeneity of land value by introducing a valid set of instrument variables. Following Timmins (2006), we consider three non-climate attributes, as instruments for the land value variable. Specifically, we introduce the *average altitude* of the farm fields, as a proxy for land location, the *mixed soil texture* for capture soil quality, and the *external water source* as a measure of access to irrigation water availability from consortium, river and natural and artificial lakes. In Model B, instead, we assume that land value is exogenous, and thus, we estimate land productivity considering land value as an input in the outcome equation.

We also consider further exogenous inputs, as the annual costs of energy, electricity and water and the amount spent on insurance to cover from production risks. As control variables, we introduce farms' characteristics such as farm specialization in producing crops exclusively of high value and family-run management of a farm. The *High value crop* dummy variable 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 while a family-run management suggests a small farm size. We comprise famers' characteristics such as the age of the head of the farm and other two dummies indicating if the farm's head is female, or the farmer holds at least a secondary school education. Further, we control for farmers' other incomes by considering EU funds and no-EU funds as well as external activities and for financial characteristics such as return on investments (ROI) and leverage (indicating the dimension of external financial resources over the resource generated internally). 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 the geographic heterogeneity and some exogenous macroeconomic shocks.

WCST adopters which show higher levels of land productivity, present a higher figure of working hours suggesting more working-intense activities and less capital and land value compared to the non-adopting farmers. Moreover, they bear an higher insurance cost as well as higher energy, electricity and water costs. In addition, adopting farms are specialized in high value crops and are not family-run. Farmers who choose to adopt WCSTs are younger, male, more educated compared to non-WCST adopters. The adopters have fewer funds both from EU and national level and are fonder of their own activities without searching for incomes coming from other activities.

[8] Timmins (2006) refers to endogeneity of land value within a Ricardian model, but it can be extended to other models as ours in which land value is considered as an explanatory variable. 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 its range of available alternatives, in which the wider alternative land uses are the more severe the estimation bias is.

This first mean comparison underlines how the differences between the adopter and the non-adopter in terms of land productivity is relevant but is not enough to explain the adoption of WCST decision across the sample famers. Since the process of WCST adoption could depend on farmers unobserved heterogeneity we should account for the self-selection issue based on the ease of adopting WCSTs by farmers who find these technologies more useful than those who do not adopt by applying a panel ESRM.

Table 1. Descriptive statistics

	Variable	Adopters (n=8227)		Non-Adopters (n=35849)		Diff.
		mean	std	mean	std	
Outcome variable	Land productivity (€/ha)	20,933.65	81,326.14	7,965.13	62,657.28	12,968.5***
Instruments for Land value when is considered as an endogenous variable	External water source (d)	5.45	16.35	7.22	28.85	-1.766***
	Mixed soil texture (%)	44.73	32.32	58.34	59.84	-13.61***
	Altitude avg. (m)	174.05	194.98	302.24	286.11	-128.2***
Production inputs	Working hours (h)	5,744.46	9,650.80	4,021.25	4,218.35	1,723.2***
	Machine power (Kw)	157.25	168.87	188.63	202.12	-31.38***
	Land value (€)	270,638.20	550,722.60	292,077.80	772,073.40	-21,439.6*
Further inputs	Energy, electricity and water costs (€)	4,919.01	20,417.87	3,632.73	11,416.46	1,286.3***
	Insurance (€)	2,594.30	10,675.00	1,445.71	5,105.74	1,148.6***
Farms' characteristic	High value crop (d)	0.78	0.41	0.32	0.47	0.464***
	Family run (d)	0.74	0.44	0.89	0.32	-0.146***
Farmers' characteristics	Age (years)	53.51	13.24	55.10	13.68	-1.586***
	Female head (d)	0.20	0.40	0.21	0.41	-0.0126*
	High education (d)	0.34	0.47	0.29	0.45	0.0454***
Other incomes	EU Funds (€)	8,244.64	22,764.86	13,866.22	41,361.35	-5,621.6***
	No EU Funds (€)	5,173.33	11,456.52	6,204.37	9,797.57	-1,031.0***
	External activities (d)	0.24	0.43	0.25	0.44	-0.0112*
Financial and accounting characteristics	ROI (no)	346.20	3,356.09	186.71	1,932.01	159.5***
	Leverage (no)	1.35	5.37	1.26	12.19	0.0882
Macro-areas	North-west (d)	0.13	0.34	0.25	0.43	-0.114***
	North-east (d)	0.23	0.42	0.22	0.42	0.01*
	Centre (d)	0.16	0.37	0.24	0.43	-0.077***
	South (d)	0.33	0.47	0.20	0.40	0.130***
	Islands (d)	0.14	0.35	0.09	0.29	0.05***

*Note: * p<0.05, ** p<0.01, *** p<0.001;in the units of measurement (d) stays for dummy variable and (no) stays for unit less variable (e.g. index).*

Table 2: Climatic variability descriptive statistics

	Variable	Description	Micro-irrigation=1 (n=8228)		Micro-irrigation=0 (n=35855)		Diff.
			mean	std	mean	std	
Climate variables (instruments for the selection indicator: Micro-irrigation)	AIJFM	Winter Aridity Index	1.041	0.325	1.156	0.281	0.114***
	AIAMJ	Spring Aridity Index	0.442	0.319	0.491	0.252	0.0492***
	AIJAS	Summer Aridity Index	0.346	0.365	0.368	0.299	0.0223***
	AIOND	Autumn Aridity Index	1.376	0.708	1.556	0.596	0.180***

*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. * p<0.05, ** p<0.01, *** p<0.001*

In the selection equation as dependent variable a variable indicating the adoption of WCST technologies in each year has been used. This dummy variable assume the value of 1 if a farmer irrigates using drip, micro-sprinklers and sub-irrigation system and 0 otherwise. In the CRE probit model, as climate variables, seasonal AIs are introduced. These represent the exclusion restrictions of the selection indicator to account for the endogeneity of the famer's choice of adopting WCSTs (Murtazashvili and Wooldridge, 2016). In Table 2, we present the descriptive statistics of climate variability distinguishing for adopters and non-adopters, while in Table A2 of Appendix A, we report the descriptive statistics for all the sample. 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-adopters. In the selection model, all the exogenous explanatory variables used in the outcome equation are also added to the exclusion restrictions as described in Murtazashvili and Wooldridge (2016).

5. Empirical results

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 land productivity value 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 while land value is considered exogenous. Within each model, two alternative estimations are presented. The first estimation is based on all farmers of the Italian agricultural sector (first two columns for Model A and B), while the second estimation regards only a restricted sample i.e. farmers who cultivate only crops excluding livestock productions (the second two columns for Model A and B).

Table 3 shows the results of the binary choice model which estimated 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?

Dep. Var.: Micro-irrigation adoption	**Model A**		**Model B**	
	Endogenous Land value		**Exogenous Land value**	
	All farmers	**Only crop farmers**	**All farmers**	**Only crop farmers**
AIJFM	-0.719***	-0.686***	-0.861***	-0.735***
	(0.064)	(0.072)	(0.063)	(0.073)
AIAMJ	3.722***	4.224***	2.679***	3.414***
	(0.170)	(0.195)	(0.170)	(0.197)
AIJAS	-1.166***	-1.293***	-1.291***	-1.418***
	(0.118)	(0.140)	(0.117)	(0.142)
AIOND	-0.217***	-0.625***	-0.149*	-0.219**
	(0.084)	(0.055)	(0.083)	(0.096)
External water source	0.240***	0.184***		
	(0.046)	(0.021)		
Mixed soil texture	-0.345***	-0.475***		
	(0.027)	(0.035)		
Altitude avg.	-0.239***	-0.254***		
	(0.007)	(0.009)		
Land value			0.008	-0.011
			(0.018)	(0.022)
Constant	-37.029	-0.494	-47.272	-15.638
	(36.015)	(14.367)	(33.939)	(34.438)
Control variables	Working hours; Machine power; Energy electricity and water costs; Insurance; High-value crops; Age; Age^2; Female head; Family run; High education; EU Funds; No EU Funds; External activities; ROI; Leverage.			
Dummy Year	Yes	Yes	Yes	Yes
Macro Regional Dummy	Yes	Yes	Yes	Yes
Mundlak device	Yes	Yes	Yes	Yes
Observations	44,083	27,565	44,083	27,565
Wald Chi-squared	7918	5045	7141	4477
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

Dep. Var.: Land productivity	Model A Endogenous Land value				Model B Exogenous Land value			
	All farmers		Only crop farmers		All farmers		Only crop farmers	
	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters
Land value	-0.753***	-1.246***	-0.537***	-1.35***	-0.015***	-0.113***	0.008	-0.138***
	(0.065)	(0.146)	(0.092)	(0.154)	(0.005)	(0.015)	(0.005)	(0.018)
Working hours	0.032**	0.064	0.020	0.072	0.060***	0.118**	0.040***	0.12***
	(0.014)	(0.045)	(0.015)	(0.044)	(0.011)	(0.029)	(0.012)	(0.030)
Machine power	-0.024***	-0.169***	-0.061***	-0.181***	-0.080***	-0.226***	-0.101***	-0.237***
	(0.007)	(0.013)	(0.008)	(0.015)	(0.003)	(0.009)	(0.004)	(0.010)
Energy, electricity and water costs	0.075***	0.055	-0.025	-0.046	0.082***	0.072	0.062**	0.075
	(0.025)	(0.062)	(0.028)	(0.071)	(0.019)	(0.044)	(0.024)	(0.044)
Insurance	-0.004	0.002	0.006	0.023	0.011	0.026	-0.006	0.019
	(0.017)	(0.037)	(0.014)	(0.037)	(0.010)	(0.022)	(0.011)	(0.024)
High-value crops	0.006	0.015	-0.142***	-0.228	0.018	0.022	-0.052***	-0.096
	(0.019)	(0.044)	(0.019)	(0.060)	(0.012)	(0.029)	(0.015)	(0.036)
Age	0.000	0.006	0.000	0.005	0.001	0.007	-0.003	0.002
	(0.005)	(0.015)	(0.005)	(0.015)	(0.003)	(0.010)	(0.004)	(0.010)
Age2	-0.0001	0.0001	0.0001	0.0001	-0.0001	0.0001	0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female head	-0.024***	-0.073**	-0.026***	-0.08**	-0.018***	-0.037	-0.013**	-0.024
	(0.006)	(0.021)	(0.007)	(0.021)	(0.005)	(0.015)	(0.006)	(0.016)
Family run	-0.099***	-0.023***	-0.040**	-0.02	-0.026***	0.007**	0.019**	0.029
	(0.015)	(0.028)	(0.016)	(0.027)	(0.009)	(0.017)	(0.008)	(0.017)
High education	0.016**	0.024	0.010	0.04	-0.031***	-0.063	-0.024***	-0.052
	(0.008)	(0.022)	(0.009)	(0.024)	(0.005)	(0.013)	(0.006)	(0.015)
EU Funds	0.051**	0.118	-0.030	0.183***	-0.169***	-0.282***	-0.147***	-0.245***
	(0.022)	(0.050)	(0.023)	(0.054)	(0.007)	(0.019)	(0.008)	(0.023)
No EU Funds	-0.010	-0.017	0.003	-0.003	-0.003	-0.024	-0.006	-0.027
	(0.011)	(0.041)	(0.013)	(0.046)	(0.005)	(0.016)	(0.007)	(0.022)
External activities	0.016**	-0.095***	0.016*	-0.104***	-0.001	-0.078***	-0.011*	-0.091***
	(0.007)	(0.022)	(0.010)	(0.023)	(0.005)	(0.014)	(0.006)	(0.014)
ROI	0.953	0.781	0.542	0.873	0.573	0.697	0.350	0.645
	(0.876)	(1.412)	(0.706)	(1.261)	(0.858)	(1.213)	(0.751)	(1.188)
Leverage	-0.314	3.159	-0.408	2.493	-0.274	2.819	-0.463	2.952
	(2.761)	(8.879)	(2.418)	(7.429)	(2.033)	(5.888)	(2.190)	(5.062)
North-west	0.157***	0.325***	0.191***	0.361***	0.164***	0.268***	0.186***	0.309***
	(0.008)	(0.041)	(0.009)	(0.039)	(0.006)	(0.029)	(0.007)	(0.030)
North-east	0.279***	0.384**	0.212***	0.414***	0.128***	0.059***	0.093***	0.058
	(0.017)	(0.051)	(0.025)	(0.052)	(0.006)	(0.023)	(0.007)	(0.029)
South	-0.088***	-0.434***	-0.156***	-0.517***	-0.019***	-0.317***	-0.132***	-0.425***
	(0.008)	(0.032)	(0.011)	(0.034)	(0.007)	(0.029)	(0.009)	(0.032)
Islands	-0.088***	-0.513***	-0.270***	-0.64***	-0.076***	-0.371***	-0.270***	-0.497***
	(0.010)	(0.035)	(0.014)	(0.036)	(0.009)	(0.030)	(0.015)	(0.036)

Generalised residuals	-0.559***	-0.353***	-0.577***	-0.437***	-0.138***	0.07***	-0.484***	-0.132***
	(0.032)	(0.030)	(0.029)	(0.032)	(0.041)	(0.023)	(0.041)	(0.025)
Constant	79.339**		42.042		-64.092***		-53.675**	
	(35.832)		(61.040)		(20.320)		(21.516)	
Dummy Year	Yes		Yes		Yes		Yes	
Mundlak device	Yes		Yes		Yes		Yes	
Observations	44,076		27,562		44,076		27,562	
Underidentification test	925.6		159.5					
p-value	0		0					
Weak identification test	157.3		25.17					
p-value	0		0					

*Note: Results in extended form are available in appendix in which data are presented using the analytical notation in which the coefficients γ of the interactions between the treatment variable (WCST) and the other covariates represent the difference between the coefficient of adopters (β_1) and non-adopters (β_0), in which $\gamma = \beta_1 - \beta_0$. In this table the coefficient of the two groups are shown directly with the adopters' equal to the non-adopters coefficient plus the γ ($\beta_1 = \gamma + \beta_0$). 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 (not for crop growers subsample) and, to a lesser extent, *high-value crops*, Energy, electricity and water costs (only for crop growers), *external activities* (only for model A), machine hours (at the 5% and 10% level of significance), *no EU funds* (only at 10% level of significance) and *external activities*. As in other empirical work, among others Green et al. (1996) and Huang et al. (2017), new irrigation systems are more likely to be observed on labour-intensive farms. The total amount of labour force measured as total *working hours* can be considered as proxy of the economic size of a farm, thus higher levels of adoption are more likely in large farms than in small ones. 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 (not for all the farms sample in Model A). This result is contrary to the main 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 Centre while farms in the northern-west and east (for Model A) parts of Italy are more likely to adopt.

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 (Model A), 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 and this effect is stronger if a farmer who does innovate. This confirms that controlling for endogeneity allows land value to have a higher negative impact on land productivity if farmers innovate than if they do not. Considering labour intensity, the coefficient is statistically significant only for non-adopters (only for the full sample with livestock), but not for adopters. Therefore, labour does not influence land productivity if adopting WCST, whereas for non-adopters each hour spent working in the farm affect positively land productivity[9].

Energy, electricity and water costs can be considered as a proxy of energy and water intensity, they are significant and positive for non-adopters, but not for adopters. This could be explained as the adoption of WCST does not put any additional gains in terms of land productivity considering EEW intensity. The dummy indicating high-value crops is negatively significant for non-adopters considering the subsample of crop growers, this variable is not significant for adopters. This can be interpreted as that high value crops have a negative effect on land productivity for non-adopters and that conversely the adoption of WCSTs does not involve any incremental negative effect on that.

The dummies for female head and family run farms are negative and statistically significant indicating a negative effect on land productivity for non-adopters (both sample) and adopters (only full sample). Age is not statistically significant in any model. Education of the farmer is significant, but with a low magnitude for non-adopters considering the full sample, whereas it does not seem a determinant of land productivity for WCST adopters. The coefficient indicating external activity of the farmer, as a proxy of his/her involvement in running the farm, is positive for non-adopters (in both samples used) whereas it is negative for WCST adopters. This may indicate that a less enthusiasm in farming activities requested for WCST adopters can be detrimental in terms of economic results, conversely additional income from external activities increases land productivity for non-adopters.

Receiving EU subsidies increase land productivity for both, adopters (only crop growers) and no-adopters (full sample), whereas receiving other types of funds (*No EU Funds*) seems to be not determinant in influencing land productivity for both groups.

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. This suggests that considering land value as endogenous is extremely relevant in terms of reducing the bias of the results.

Excluding livestock production farms from the sample produces similar results in terms of sign and magnitude of the coefficients of most of the explanatory variables as for the whole sample indicating robustness of our estimations. Considering land value as an exogenous variable (Model B), and therefore performing a OLS instead of 2SLS produces similar results for all the explanatories apart of the exception of *higher-education*, *Eu Funds*, *working hours*, *family run* and *external activities*. However, the most important difference regards *land value* which shows an important lower magnitude than in Model A and, for WCST no-adopters, a statistically insignificant coefficient in the case of the full sample. Again, this suggests the presence of endogeneity between land productivity and land value. Thus, the more appropriate approach is the ESRM with a continuous endogenous explanatory variable which implies the use of the 2SLS method in the estimation of the outcome equation. Furthermore, even in this case the Wald tests on generalized residuals confirm endogeneity in the selection process showing that sample

[9] 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 per hectare of productive land.

selection bias would be present, if the outcome equation has been estimated without considering the irrigation adoption decision. The Wald tests on Mundlak's devices also confirm the correctness in the use of this strategy to cope with individual heterogeneity.

5.1 Results on the counterfactual analysis

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 differences of the two groups (adopters and non-adopters) which has the disadvantage of confounding the impact of WCST adoption on land productivity due to the influence of other characteristics, the 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 in the case they had not adopted WCSTs on the basis of a counterfactual analysis (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	26,894.98	8,430.97	18464.01	56.05	219.00
	Model B	23,754.51	15,712.30	8,042.21	51.85	51.18
Only crop farmers	Model A	29,742.07	8,272.85	21,469.22	50.91	259.51
	Model B	24,555.00	8,997.99	15,557.01	77.48	172.89

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

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 26,894.98 euro/ha for adopters who adopt WCSTs compared to the counterfactual case in which the same farmers had not adopted (8,430.97 euro/ha). This corresponds to a difference in the economic performances of land between the case of WCST adoption with the counterfactual hypothesis of non-adoption of the adopters of almost 219%. Considering only crop growers the ATET value is even higher 29,742.07 euro/ha. In this case the percentage differences in land productivity between WCST adopters and their outcome in the hypothetical case of non-adoption is even higher than before and equal to 259.51%. In the case of Model B, the value of ATET is 23,754.51 euro/ha and 24,555 euro/ha respectively, for all type of farms and only crop growers. This implies a percentage change of adopters compared to non-adopters of respectively 51.18% (full sample) and 172,89% (only crops 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.

6. Discussion and concluding remarks

The overall CC impacts on Italian agriculture are not easily foreseeable. In fact, even if in the short term the 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; Feyen et al., 2020), in the long term, the impact on national agricultural production will be strongly negative (Bocchiola et al., 2013; Bozzola et al., 2018; Toreti et al., 2009; Tubiello et al., 2000; Van Passel et al., 2017; EEA, 2019) influencing impressively the Italian socio-economic system as a whole (such as less food security, more unemployment, less protection of the environment and worse conditions of public health).

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 farms' 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).

How an agricultural system may react to the different negative CC scenarios may depend mainly on what management practices farmers will follow for adapting to the extremization of the climate and increasing their resilience to weather fluctuations (Tubiello et al., 2000). Climate policies will have potentially significant impacts on the agricultural sector and in particular on the innovation within agriculture. Removing distortions and barriers would foster farm-level innovation and facilitating investments in new sustainable technologies (OECD, 2013; EEA, 2019; Feyen et al., 2020). Thus, it is worth to consider the role that technological change may have as a key element which can contribute to solve long-term environmental problems as CC (Popp, 2005).

Our findings confirm the importance of new agricultural technologies adoption in the improvement of farm productivity (OECD, 2013; EEA, 2019; Feyen et al., 2020) 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. In terms of policy suggestion, our analysis confirms the relevant role of innovation in the irrigation systems and the fact that more productive farmers are those that adopt WCSTs. A policy-maker oriented toward water conservation policies for the agricultural sector should take into consideration the wide effect of WCST adoption on production performances as an incentive for supporting large scale conversions toward more efficient irrigation technologies. 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.

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.

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Appendix A

Table A1. Variable names, definitions, and descriptive statistics for the whole sample

	Variable	Description	All the Sample (n=44076) mean	std
Outcome variable	Land productivity	Real profit and loss value per hectare (euro/ha).	10,385.77	66,731.24
Instruments for Land value when is considered as an endogenous variable	External water source	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 (ha).	6.89	26.97
	Mixed soil texture	Agricultural area with mixed soil texture (ha).	55.80	55.99
	Altitude avg.	Average altitude level of a farm (metre).	278.31	275.99
Production inputs	Working hours	Total working hours of labour (hour).	4,342.90	5,683.90
	Machine power	Total machine power within a farm (Kwh).	182.77	196.72
	Land value	Real market value of agricultural lands (euro).	288,076.00	735,871.00
Further inputs	Energy, electricity and water costs	Total costs of water, fuel and energy consumed (euro).	3,872.82	13,567.06
	Insurance	Total amount spent on insurance by a farmer (euro).	1,660.10	6,532.32
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.	0.40	0.49
Farmers' characteristics	Age	Age of household head (farmer) (year).	54.80	13.62
	Female head	Dummy = 1 if a farm is managed by a woman and 0 by a man.	0.21	0.41
	Family run	Dummy =1 if a farm is family run and 0 otherwise.	0.86	0.35
	High education	Dummy = 1 if a farmer has at least a secondary degree or above and 0 otherwise.	0.30	0.46
Other incomes	EU Funds	Total amounts of funds directly received from EU through the CAP program (euro).	12,816.92	38,638.74
	No EU Funds	Total amounts of Funds received from other institutions no EU, as national and local governments (euro).	6,011.92	10,135.69
	External activities	Dummy =1 if a farmer is engaged in external activities and 0 if a farmer is engaged only within the farm.	0.25	0.43
Financial and accounting characteristics	ROI	Return of investment (ROI) (euro)	216.48	2,267.59
	Leverage	Farms' leverage (euro)	1.28	11.24
Macro-areas	North-west	Dummy=1 if regions are Piedmont Liguria Lombardy and Aosta Valley	0.23	0.42
	North-east	Dummy=1 if regions are Emilia-Romagna, Veneto, Friuli-Venezia-Giulia, Trentino-Alto-Adige	0.23	0.42
	Centre	Dummy=1 if regions are Tuscany, Umbria, Marche, and Latium	0.22	0.42
	South	Dummy=1 if regions are Basilicata, Calabria, Campania, Molise, Puglia	0.22	0.42
	Islands	Dummy=1 if regions are Sicily and Sardinia	0.10	0.30

Table A2: Climatic variability descriptive statistics

	Variable	Description	All the Sample (n=44083)	
			mean	std
Climate variables (instruments for the selection indicator: Micro-irrigation)	AIJFM	Winter Aridity Index	1.134	0.293
	AIAMJ	Spring Aridity Index	0.482	0.267
	AIJAS	Summer Aridity Index	0.364	0.312
	AIOND	Autumn Aridity Index	1.523	0.622

Appendix B

Table B1. First-stage probit coefficient estimates: What factors determine micro-irrigation adoption?

Dep. Var.: Micro-irrigation adoption		Model A		Model B	
		Endogenous Land value		Exogenous Land value	
		All farmers	Only crop farmers	All farmers	Only crop farmers
Climate variables	AIJFM	-0.719***	-0.686***	-0.861***	-0.735***
		(0.064)	(0.072)	(0.063)	(0.073)
	AIAMJ	3.722***	4.224***	2.679***	3.414***
		(0.170)	(0.195)	(0.170)	(0.197)
	AIJAS	-1.166***	-1.293***	-1.291***	-1.418***
		(0.118)	(0.140)	(0.117)	(0.142)
	AIOND	-0.217***	-0.625***	-0.149*	-0.219**
		(0.084)	(0.055)	(0.083)	(0.096)
Instruments for Land value	External water source	0.240***	0.184***		
		(0.046)	(0.021)		
	Mixed soil texture	-0.345***	-0.475***		
		(0.027)	(0.035)		
	Altitude avg.	-0.239***	-0.254***		
		(0.007)	(0.009)		
Production inputs	Working hours	0.216***	0.250***	0.133***	0.150***
		(0.017)	(0.019)	(0.045)	(0.050)
	Machine power	-0.022*	-0.021	-0.014	-0.030**
		(0.011)	(0.013)	(0.011)	(0.012)
	Land value			0.008	-0.011
				(0.018)	(0.022)
Further inputs	Energy, electricity and water costs	0.007	0.446***	0.035	0.074
		(0.054)	(0.027)	(0.052)	(0.063)
	Insurance	0.069*	0.029	0.078**	0.096**
		(0.036)	(0.020)	(0.036)	(0.039)
Farms' characteristic	High-value crops	0.085	0.705***	0.095	0.314***
		(0.065)	(0.027)	(0.064)	(0.069)
	Family run	-0.228***	-0.126***	-0.235***	-0.113***
		(0.025)	(0.027)	(0.024)	(0.027)
Farmers' characteristics	Age	0.004	-0.003	0.001	0.005
		(0.017)	(0.005)	(0.017)	(0.020)
	Age^2	-0.000	-0.000	-0.000	-0.000

		(0.000)	(0.000)	(0.000)	(0.000)
	Female head	-0.059***	-0.039*	-0.074***	-0.061***
		(0.020)	(0.023)	(0.020)	(0.022)
	High education	0.003	-0.050**	-0.035*	-0.099***
		(0.019)	(0.022)	(0.019)	(0.021)
Other incomes	EU Funds	-0.247***	-0.257***	-0.313***	-0.384***
		(0.025)	(0.029)	(0.022)	(0.027)
	No EU Funds	0.059*	0.007	0.053*	0.051
		(0.032)	(0.020)	(0.030)	(0.035)
	External activities	0.039*	0.053**	0.032	0.033
		(0.022)	(0.025)	(0.022)	(0.024)
Financial and accounting characteristics	ROI	-0.091	-0.703	-0.112	-0.120
		(1.028)	(0.697)	(1.039)	(1.182)
	Leverage	0.516	0.981	0.431	0.356
		(1.547)	(1.535)	(1.472)	(1.551)
Macro-areas	North-west	-0.512***	-0.569***	-0.319***	-0.340***
		(0.040)	(0.043)	(0.038)	(0.043)
	North-east	-0.392***	-0.426***	0.096**	0.131***
		(0.042)	(0.048)	(0.039)	(0.044)
	South	0.305***	0.484***	0.211***	0.397***
		(0.032)	(0.037)	(0.030)	(0.037)
	Islands	0.369***	0.751***	0.132***	0.456***
		(0.047)	(0.056)	(0.045)	(0.054)
	Constant	-37.029	-0.494	-47.272	-15.638
		(36.015)	(14.367)	(33.939)	(34.438)
	Dummy Year	Yes	Yes	Yes	Yes
	Mundlak device	Yes	Yes	Yes	Yes
	Observations	44,083	27,565	44,083	27,565
	Wald Chi-squared	7918	5045	7141	4477
	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 B2. Results of the outcome equations of Table 4 in the extended form.

	Model A Endogenous Land value		**Model B Exogenous Land value**	
	All farmers	**Only crop farmers**	**All farmers**	**Only crop farmers**
Land value	-0.753***	-0.537***	-0.015***	0.008
	(0.065)	(0.092)	(0.005)	(0.005)
Working hours	0.032**	0.020	0.060***	0.040***
	(0.014)	(0.015)	(0.011)	(0.012)
Machine power	-0.024***	-0.061***	-0.080***	-0.101***
	(0.007)	(0.008)	(0.003)	(0.004)
Energy, electricity and water costs	0.075***	-0.025	0.082***	0.062**
	(0.025)	(0.028)	(0.019)	(0.024)
Insurance	-0.004	0.006	0.011	-0.006
	(0.017)	(0.014)	(0.010)	(0.011)
High-value crops	0.006	-0.142***	0.018	-0.052***
	(0.019)	(0.019)	(0.012)	(0.015)
Age	0.000	0.000	0.001	-0.003

	(0.005)	(0.005)	(0.003)	(0.004)
Age2	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Female head	-0.024***	-0.026***	-0.018***	-0.013**
	(0.006)	(0.007)	(0.005)	(0.006)
Family run	-0.099***	-0.040**	-0.026***	0.019**
	(0.015)	(0.016)	(0.009)	(0.008)
High education	0.016**	0.010	-0.031***	-0.024***
	(0.008)	(0.009)	(0.005)	(0.006)
EU Funds	0.051**	-0.030	-0.169***	-0.147***
	(0.022)	(0.023)	(0.007)	(0.008)
No EU Funds	-0.010	0.003	-0.003	-0.006
	(0.011)	(0.013)	(0.005)	(0.007)
External activities	0.016**	0.016*	-0.001	-0.011*
	(0.007)	(0.010)	(0.005)	(0.006)
ROI	0.953	0.542	0.573	0.350
	(0.876)	(0.706)	(0.858)	(0.751)
Leverage	-0.314	-0.408	-0.274	-0.463
	(2.761)	(2.418)	(2.033)	(2.190)
North-west	0.157***	0.191***	0.164***	0.186***
	(0.008)	(0.009)	(0.006)	(0.007)
North-east	0.279***	0.212***	0.128***	0.093***
	(0.017)	(0.025)	(0.006)	(0.007)
South	-0.088***	-0.156***	-0.019***	-0.132***
	(0.008)	(0.011)	(0.007)	(0.009)
Islands	-0.088***	-0.270***	-0.076***	-0.270***
	(0.010)	(0.014)	(0.009)	(0.015)
Generalised residuals	-0.559***	-0.577***	-0.138***	-0.484***
	(0.032)	(0.029)	(0.041)	(0.041)
WCST adoption	237.184**	238.642**	185.837***	167.078***
	(98.702)	(101.528)	(57.583)	(57.264)
Land value * WCST adoption	-0.493***	-0.813***	-0.098***	-0.146***
	(0.146)	(0.154)	(0.015)	(0.018)
Working hours * WCST adoption	0.032	0.052	0.058**	0.080***
	(0.045)	(0.044)	(0.029)	(0.030)
Machine power * WCST adoption	-0.145***	-0.120***	-0.146***	-0.136***
	(0.013)	(0.015)	(0.009)	(0.010)
Energy, electricity and water costs * WCST adoption	-0.020	-0.021	-0.010	0.013
	(0.062)	(0.071)	(0.044)	(0.044)
Insurance * WCST adoption	0.006	0.017	0.015	0.025
	(0.037)	(0.037)	(0.022)	(0.024)
High-value crops * WCST adoption	0.009	-0.086	0.004	-0.044
	(0.044)	(0.060)	(0.029)	(0.036)
Age * WCST adoption	0.006	0.005	0.006	0.005
	(0.015)	(0.015)	(0.010)	(0.010)
Age2 * WCST adoption	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Female head * WCST adoption	-0.049**	-0.054**	-0.019	-0.011
	(0.021)	(0.021)	(0.015)	(0.016)
Family run * WCST adoption	0.076***	0.020	0.033**	0.010

	(0.028)	(0.027)	(0.017)	(0.017)
High education * WCST adoption	0.008	0.030	-0.032**	-0.028*
	(0.022)	(0.024)	(0.013)	(0.015)
EU Funds * WCST adoption	0.067	0.213***	-0.113***	-0.098***
	(0.050)	(0.054)	(0.019)	(0.023)
No EU Funds * WCST adoption	-0.007	-0.006	-0.021	-0.021
	(0.041)	(0.046)	(0.016)	(0.022)
External activities * WCST adoption	-0.111***	-0.120***	-0.077***	-0.080***
	(0.022)	(0.023)	(0.014)	(0.014)
ROI * WCST adoption	-0.172	0.331	0.124	0.295
	(1.412)	(1.261)	(1.213)	(1.188)
Leverage * WCST adoption	3.473	2.901	3.093	3.415
	(8.879)	(7.429)	(5.888)	(5.062)
North-west * WCST adoption	0.168***	0.170***	0.104***	0.123***
	(0.041)	(0.039)	(0.029)	(0.030)
North-east * WCST adoption	0.105**	0.202***	-0.069***	-0.035
	(0.051)	(0.052)	(0.023)	(0.029)
South * WCST adoption	-0.346***	-0.361***	-0.298***	-0.293***
	(0.032)	(0.034)	(0.029)	(0.032)
Islands * WCST adoption	-0.425***	-0.370***	-0.295***	-0.227***
	(0.035)	(0.036)	(0.030)	(0.036)
Generalised residuals * WCST adoption	0.206***	0.140***	0.208***	0.352***
	(0.049)	(0.049)	(0.067)	(0.062)
Constant	79.339**	42.042	-64.092***	-53.675**
	(35.832)	(61.040)	(20.320)	(21.516)
Observations	44,076	27,562	44,076	27,562
Dummy Year and its interaction with AD	Yes	Yes	Yes	Yes
Mundlak devices and its interaction with AD	Yes	Yes	Yes	Yes
Underidentification test	925.6	159.5		
p-value	0	0		
Weak identification test	157.3	25.17		
p-value	0	0		

*Note: The γ coefficients of the interaction between treated (WCST adopters) and the covariates in this case indicate the gap between adopters and non-adopters. 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*

Water Demand Elasticity in agriculture: the case of Emilia Centrale Irrigation Water Districts

With:

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Abstract

The elasticity of irrigation water demand is estimated based on a large panel dataset in an Irrigation District in Emilia-Romagna region, one of the most important areas for agricultural production in Italy. An econometric analysis is applied to the level of irrigation technologies, crops and to combinations of both variables by controlling for autocorrelation and heteroscedasticity by using a log-log model with a fixed effect and a Feasible General Least Squares regression. Results generally show a marked heterogeneity of demand elasticity for irrigation water for a variety of crops and irrigation systems. The main finding is the fact that water price elasticity increases with the level of system efficiency (i.e., it is more elastic with drip vs. furrow irrigation), which implies that response to water pricing in the context of our analysis (short-term and full irrigation context) is less effective with traditional irrigation technologies.

Keywords: Agricultural water management, Water Demand Elasticity, Water use response to price, Emilia-Romagna.

Introduction

Water scarcity is one of the most crucial challenges in terms of both environmental conservation and food security that humankind is facing in the near future (Unesco et al., 2019). Many areas of the world are suffering from structural water scarcity and water-resource-related problems. Climate change and increasing demand for food worldwide are intensifying pressures on water resources for both household access and industrial production activities with unpredictable effects on public health, the economy, and on society as a whole (Steduto et al., 2012). Agriculture constitutes one of the main causes for pressure on water resources, principally in the form of crop irrigation, which accounts on average for 70 % of total water withdrawal across the globe (Koohafkan, 2011). Agricultural policies towards the conservative use of water can provide effective instruments of adaptation to water scarcity and climate change issues, thereby contributing towards sustainable development.

The international debate on pricing water as a measure to cope with water scarcity started in 1992 with the Dublin principles during the United Nation International Conference on Water and the Environment (United Nations, 1992) in which water was declared as a social commodity whose intrinsic economic value should be managed sustainably (Savenije and van der Zaag, 2002; Somanathan and Ravindranath, 2006). In the last three decades, economic measures have started to be implemented as a tool for environmental policies in water resource management based on the polluter-pays and the user-pays principles (Lago et al., 2015; Renzetti, 2002).

Water pricing is an economic tool that stimulates farmers to reduce water use and optimise its allocation (Wheeler et al., 2015). Volumetric tariffs can lead to the modification of a farmer's water strategies, such as crop substitution (Varela-Ortega et al., 1998) and technological change (Pronti et al., 2020), that reduce over-exploitation by assigning opportunity cost to water as an input and guiding water allocation towards the greatest economic return (Ward and Michelsen, 2002). Additionally, the price of water plays a major financial role in creating revenues for the supplier (Saleth and Dinar, 2005) and in implementing cost recovery principles (Dinar and Mody, 2004; Rogers, 2002).

Assigning a price to each volume of water demanded can also reduce the cost of setting and controlling the policy effect, since profit-maximising farmers should consequently adapt water demand to their own real cost function (Dinar and Mody, 2004; Massarutto, 2003). Irrigators adapt to changes in water prices by basing their calculations on their own marginal adjustment costs, thereby reducing the aggregate cost of the policy more than with regulatory instruments which target farmers indiscriminately. Moreover, economic tools create permanent incentives for the application of technological innovation more than do regulation methods, which provide incentives to innovate only until compliance is achieved (Lago et al., 2015). Volumetric tariffs had been used as a principal economic measure towards sustainable water management, but with ambiguous results in terms of real water consumption with major differences between the various cases of application (Cooper et al., 2014; Dinar and Mody, 2004; Molle and Berkoff, 2007).

Effectiveness of water pricing depends upon the demand characteristics and specifically on water price elasticity. Price elasticity of demand is a measure of the change in the quantity demanded of a product in relation to its change in price (Olmstead et al., 2007). Water price elasticity is extremely important for policy-making in agricultural water management in terms of responsiveness of farmers to institutional incentives in water use for crop production (Somanathan and Ravindranath, 2006; Wheeler et al., 2008). An erroneous assessment of water demand elasticity can lead to pricing policy failures due to either overpricing water, thereby lowering farmers income due to high water costs, or under-pricing water, thereby assigning excessively low opportunity costs which incentivize over-irrigation (Molle, 2009).

The effect of water price elasticity on the total quantity of water demanded remains unclear in the literature due to the heterogeneous results of empirical analysis, which depend on a variety of local conditions linked to water systems and on other aspects, such as socio-economic, geographical, and institutional factors (Scheierling et al., 2006). Very little applied research has been carried out related to this aspect which influences the availability of effective analysis on the outcomes and impacts of water policies (Massarutto, 2003).

The objective of this paper is to analyse the water demand elasticity of farmers by considering the heterogeneity of agricultural production and irrigation systems through an empirical analysis using a large observational panel dataset at plot level of an Irrigation Water District (IWD) in northern Italy. Various econometric models were employed to assess water demand elasticity to price by considering different technologies, different crops and their combination, while controlling for weather conditions and other heterogeneities between observations.

Panel data econometric methods can partially account for unobserved factors with estimates that are not deterministic but instead are based on the stochastic process. There are examples of water demand elasticity based on various econometric analyses, although all of them share data scarcity mainly based on cross-section analysis (Scheierling et al., 2006). To the best of our knowledge, our study is one of the widest-spanning analyses in terms of datasets and variety of crops and technologies considered using a panel data approach at plot level.

The paper is structured as follows: In Section 2, a brief state of the art is presented of the literature on water demand elasticity; in Section 3, materials and methods are discussed; in Section 4, the results of the analysis are presented; Section 5 introduces a discussion of the main findings; and the paper finishes with the concluding remarks of Section 6.

The price elasticity of water demand in agriculture

The main element of uncertainty in water pricing interventions in agriculture is linked to the response of farmers to the policy which principally depends on their reactions to changes in the price of water. Ascertaining water demand elasticity is fundamental for the effectiveness of water pricing policies and for the formulation of ad hoc actions in order to improve water use efficiency by reducing pressure on water resources, while considering the overall effects on farmers' incomes and the revenues raised by such policies (Iglesias et al., 1998).

Agricultural water demand largely depends on the physical productivity of water, farmers' incomes, local environmental conditions, and market structure while other factors that are not directly observable may also influence water demand, such as social, institutional, and behavioural aspects (Massarutto, 2003). These elements vary widely across countries and regions, depending on their geographic, socio-economic, financial, political, and infrastructural conditions, by constraining considerations on water demand and elasticity to single case-by-case studies (Dinar and Mody, 2004; Molle and Berkoff, 2007).

Scheierling et al. (2006) review the elasticity of irrigation water demand and reveal that the variability of estimates depends mainly on factors of the case study and find an average elasticity of water demand to price of -0.48, which indicates that water demand is, on average, inelastic. However, these authors also found a relatively large standard deviation of 0.53 whose range in absolute terms lies between 0.001 and 1.97. Zuo et al. (2015) confirmed these results with a contingent evaluation in Australia estimating a water demand elasticity of -0.57 considering long-term water entitlements. Conversely, considering the same area, Zuo et al. (2016) found farmers' water demand to be elastic to water prices which ranged from 0.73 to 3.23 with differences between geographical, demographic, and productive farm characteristics. The main differences in the two studies is that, in the latter, elasticity is calculated by considering willingness to accept the price threshold to trigger the abandonment of farming, which can substantially differ from real water demand elasticity to price.

What emerges in agricultural water demand elasticity is unclear: there are no totally convergent visions, since the results depend heavily on intrinsic low external validity and methodological choices. Several scholars claim that water demand is totally inelastic (Hendricks and Peterson, 2012; Massarutto, 2003; Moore et al., 1994; Ogg and Gollehon, 1989), others that water demand is elastic (Schoengold et al., 2006), or that it is elastic only for underground water, but not for furrow irrigation using gravity irrigation (Nieswiadomy, 1985).

Other studies found that water demand is elastic only after a certain price threshold, and remains inelastic below that point (Expósito and Berbel, 2016; Varela-Ortega et al., 1998). Wheeler et al. (2008) estimated an average elasticity for water demand of -1.5 by considering the Australian water markets and a time-series of total water market allocations, and they highlighted significant fluctuations within the irrigation season (-1.71 to -4.14). They had estimated a short-term elasticity to have a mean of -0.52, and of -0.89 for that of the long-term. In a recent study of de Bonviller et al. (2020) based on Australian groundwater markets, a unitary elasticity of -1.05 was found. They also highlighted that price is not the only major cause of water demand, but that drought, price of products, season, other inputs related to irrigation (such as diesel prices and electricity), and type of crop may also influence farmers' demand (de Bonviller et al., 2020; Wheeler et al., 2008). Inelastic water demand has also been found in earlier prominent studies (Caswell et al., 1990; Zilberman, 1984).

In general, empirical studies presented in the literature indicate that water demand is inelastic for both major and minor changes in the price of water and that, in the main, the water demand curve is not strongly respondent to water pricing policies owing to a general low water demand elasticity of farmers (Dinar and Mody, 2004; Molle and Berkoff, 2007). Moreover, for the water price to provoke an effective response, it should be fixed at excessively high levels, which would incur a greater effect on agricultural incomes than its possible positive effects on the environment and water savings (Expósito and Berbel, 2016;de Fraiture and Perry, 2007). Conversely, other studies state that, despite structural levels in which water demand is inelastic, water prices can be effective due to the high elasticity of water demand segments (Gómez-Limón and Riesgo, 2004). Water demand elasticity is affected by threshold effects: for low ranges of water prices, water demand does not respond to higher prices:, for medium price ranges, changes in water demand do respond to prices due to farmers' strategies that involve changing to water conservation and saving technologies (WCST) (Berbel et al., 2018; Pronti et al., 2020) or to crops with low water needs; whereas for high price ranges, water demand is again inelastic owing to the abandonment of the market by the farmer (de Fraiture and Perry, 2007; Gómez-Limón and Riesgo, 2004).

In a low level of prices, threshold effects depend on technical substitution effects (of technology and crops) which reflect changes in input composition within the farmer production function. Those changes determine the elasticity of the demand curve which represents substitutions of water with capital and labour as a strategy adopted by the farmer to cope with the increasing price of water (Renzetti, 2002). At certain price levels, the demand curve again becomes inelastic due to the end of input substitution possibilities and increasing disadvantages in agricultural production due to the excessively high opportunity cost of water (Berbel and Gómez-Limón, 2000; de Fraiture and Perry, 2007; Expósito and Berbel, 2017). Therefore, no complete agreement exists in the literature regarding the effect of pricing water on water demand, and consequently there is no complete agreement on the effect of tariff policy on farmers' irrigation decisions (de Fraiture and Perry, 2002; Molle and Berkoff, 2007).

In empirical works, water demand elasticity has been derived using a variety of methods. Those studies that are present in the literature are divided principally into Mathematical Programming (MP), Experimental Studies, and Econometric analysis. One of the main problems in this field of study involves the very low level of reliable information on both water prices and water demand. The absence of observations over a range of different prices has encouraged scholars to use MP methods (linear, quadratic, and stochastic approaches) to derive water demand elasticity using the simulation of optimisation models (Bontemps and Couture, 2002). The principal means for the extraction of elasticity measures with MP is through the derivative of the dual solutions, which can be considered as the water shadow prices (Elbakidze et al., 2017; Howitt et al., 1980). Mathematical Programming has frequently been employed to estimate water demand, whereby the first examples have assumed profit maximisation. More recently, however, MP has integrated more realistic assumptions in an effort to adapt to observed decisions, such as PMP and MCDM, so that a better representation of irrigation can be considered as a stochastic process and not completely deterministic (Antle and Hatchett, 1986; Wheeler et al., 2015). Mathematical Programming research relies on strong assumptions and strong constraints on irrigation technology (Mieno and Brozović, 2017). Conversely, field experiments link agronomic concepts with economic production function studies and use of statistical methods to estimate the marginal effects of the application of water on yields in order to modify water demand to obtain the best value of output, while still leaving a little room for water demand adjustments that lead to structural inelastic demands (Mieno and Brozović, 2017; Scheierling et al., 2006).

Econometric methods rely on real and observational data in order to find statistical inferences of various factors on water demand, and use specific marginal effects of the logarithm of the variable of interest in order to find elasticities. The principal problems related to econometric approaches include those of measurement errors caused by using proxies of water costs when real prices are not observed (such as energy or extraction costs), spatially aggregated data (Mieno and Brozović, 2017), and of unobserved heterogeneity, which leads to endogeneity biases and problems of consistency of the estimations (Havranek et al., 2018). Due to the limitations on agricultural water data, most of the econometric analysis present to date in the literature is largely cross-sectional and aggregated at a higher level than that of the plot which can lead to the under-estimation and unreliability of results of water elasticity (Bontemps and Couture, 2002).

To the best of our knowledge, only the work of Schoengold et al. (2006) on surface water and that of Hendricks and Peterson (2012) on underground water deal with the estimation of water demand elasticity and they use a panel data approach to endogeneity problems. We contribute to the current empirical literature by adding an econometric analysis; by using real price data applied at plot level; and by exploring the effect on different technologies, varieties of crops, and combinations of crops and irrigation systems while controlling for different factors.

Material and methods

3.1 Case study and data description

In Italy, the lowest institutional level of agricultural water management is held by the Irrigation Water Districts (IWD) (*Consorzi di Bonifica* in Italian). These districts are private-public institutions which started up as irrigators associations in the beginning of the last century (Bazzani et al., 2005). Over time, IWD has taken on increasing institutional importance in the national water management system, and has been entrusted by national law (*Gazzetta Ufficiale della Repubblica Italiana*, 2006) to address the WFD at local level (Dono et al., 2019). Nowadays, IWDs are responsible for the implementation, development, maintenance, and management of the irrigation systems serving the farms located in their assigned area (Dono et al., 2019; El Chami et al., 2011). There are approximately 500 IWDs in Italy, with many differences in management systems, dimensions, and tariff systems. In accordance to regional laws, these IWDs must set the price of water services to their users (Berbel et al., 2019). Of the water withdrawn for agriculture, 63% comes from IWDs, (34%

with a rotation system and 29% with service on demand), with the remaining 37% from groundwater (18%) and private superficial sources (15%) (Istat, 2014).

The Emilia-Romagna Region (ERR) holds the largest share of irrigated land in Italy, and the agricultural sector of ERR constitutes one of the major productive areas of the country (Pérez-Blanco et al., 2016). In 2017, the value added of agriculture in ERR was 11% of the national value with a total value of production of 4.8 billion euros (ERR, 2019a, 2019b; Fanfani and Pieri, 2018). The role of irrigation is crucial for the regional production system, and, during recent decades, agricultural development has strongly increased the pressure on water resources (Pérez-Blanco et al., 2016). Moreover, ERR has been affected by major repeated extreme events due to severe droughts during the harvest season since 2003 (Vezzoli et al., 2015).

The ERR regional government implemented several policies based on incentives and regulations for the improvement of the conservation of water resources thereby boosting improvements in irrigation efficiency and reduction of pollutants, for which a major role has been taken by the introduction of pricing instruments for irrigation guided by the Cost Recovery Principle (El Chami et al., 2011).

The database employed in this study comes from water prices and water distribution of the Central Emilia Irrigation Water District (CEWD) (in Italian, *Consorzio di Bonifica dell'Emilia Centrale*) in the provinces of Reggio-Emilia and Modena in the Emilia-Romagna region (Italy).

The area served by the CEWD has the highest level of regional production value (ERR, 2019a), in which many important high-value certified agri-food products are produced (such as Parmigiano-Reggiano cheese, Balsamic Modena Vinegar, Lambrusco wine, and crops with Protected Geographical Indication) (ERR, 2019b). The CEWD is in charge of the water distribution of local farmers with a complex infrastructural network that diverts water from the rivers Po, Secchia, and Enza, and serves thousands of farmers annually (CEWD, 2017, 2015). The most important crops cultivated in the area include: Alfalfa, Maize, Meadows, Vineyard, and Orchards (principally Pear and a minority of Apple, Peach, and others). Other crops grown are: Soya, Sugar Beet, Tomato, and Watermelon. The principal irrigation system adopted is of the sprinkler type, whereas for specific crops, drip irrigation is used (Watermelon, Vineyard, and Orchards), and for other crops, furrow is the main irrigation system (Meadows, Orchards and Vineyard). In Table 1, the average values per crop and irrigation system of observations, water used, water tariffs, and irrigated land within the CEWD are summarised.

Farmers served by the CEWD do not possess large farms and the dimension of each plot on average is small. By considering a farm as an agglomeration of single irrigated plots managed by the same user, then the average farm dimension is 4.9 ha (SD 6.41 ha) with 99 % of the population observed holding less than 29 Ha. However, by considering single irrigated plots, the average surface is 3.7 ha (SD 4.04 ha).

Table 1. Mean Irrigated areas and water price considering Crops and Irrigation systems.

Crop	Irrigation system	Irrigated Area (ha)	Water Volume (m^3 per ha)	water tariff (€)	n obs.
Alfalfa	Drip	3.61	775.82	0.0238	10
Alfalfa	Furrow	3.53	1225.51	0.0253	235
Alfalfa	Sprinkler	4.74	1023.30	0.0226	3339
Maize	Drip	1.82	1184.19	0.0204	49
Maize	Furrow	2.53	3575.39	0.0321	99
Maize	Sprinkler	3.60	1298.57	0.0230	3947
Meadows	Drip	5.18	1686.91	0.0222	1
Meadows	Furrow	4.92	1277.90	0.0245	5895
Meadows	Sprinkler	6.48	1199.32	0.0244	150
Orchards	Drip	2.40	7695.00	0.0000	817
Orchards	Furrow	2.70	4604.92	0.0258	225
Orchards	Sprinkler	2.82	2234.76	0.0220	1511
Soya	Drip	3.67	1469.49	0.0284	2
Soya	Furrow	1.96	2854.30	0.0289	18
Soya	Sprinkler	2.96	1977.25	0.0278	405
Sugar Beet	Drip	1.73	888.83	0.0248	2
Sugar Beet	Furrow	5.14	1430.06	0.0236	20
Sugar Beet	Sprinkler	5.36	1010.33	0.0253	796
Tomato	Drip	2.65	334.09	0.0274	80
Tomato	Furrow	6.20	996.45	0.0273	5
Tomato	Sprinkler	5.63	849.53	0.0260	486
Vineyard	Drip	6.25	341.22	0.0251	1578
Vineyard	Furrow	3.74	1259.20	0.0238	3031
Vineyard	Sprinkler	5.85	846.79	0.0261	6178
Watermelon	Drip	8.30	1504.83	0.0249	236
Watermelon	Furrow	4.65	4188.69	0.0249	3
Watermelon	Sprinkler	6.64	1886.76	0.0246	73

General descriptive data shows that, for the same crop, the water use is usually lower with drip and higher with furrow, with sprinkler use calibrated somewhere in the middle; this is an expected result of the water saving achieved by increased precision in irrigated systems. Irrigation demand is made directly by farmers to the CEWD, which calculates the total amount of water to be diverted to the plot by considering an irrigation plan compiled annually by the farmer with details on the irrigation system and the crop plan. Therefore, water demand is not controlled by the farmer in the flows, which are optimised by the CEWD supply, but instead in the number of times they ask for irrigation during the year. Direct water metering is impossible in the area since water is served principally through open canal systems. Each water supply is therefore measured indirectly by considering the canal flow rate, the capacity of the water structure, and the duration of the delivery (CEWD, 2017).

Over the years, the CEWD has experimented with various tariff schemes. The CEWD was established in 2009 by the fusion of two previous IWDs present in the area (the *Consorzio di*

Bonifica Parmigiana Moglia Secchia and *Bentivoglio-Enza*) in which irrigators were faced with different water tariff schemes (flat and two-part tariffs), which were not modified until 2015. In 2016, in conformity with its own sustainability aims, which are in line with those of the WFD, the CEWD implemented a new pricing plan based on a two-part tariff scheme for all its users in order to reduce over-irrigation and to gather financial resources to cover operational and maintenance costs using a cost recovery approach. The new two-part tariff scheme is composed of a fixed fee to cover the general service of the CEWD, and a volumetric part based on a baseline price (BP) multiplied by an economic multiplier calculated with a variety of coefficients, which consider different types of service costs, water intensity of the crop, and rivalry on water resources. The new two-part tariff scheme is synthetized and shown in Equation 1. All the tariffs applied in the CEWD during the years of the study are presented in Table 2.

$$WP = BP * (RIV * SER * MOM * WI) \qquad \text{(Eq.1)}$$

where:

- WP is the water price of the two-part tariff applied within the CEWD since 2016 to each water request.
- BP is baseline price of 0.025 €/m^3 in 2016, and 0.027€/m^3 in 2017 and 2018.
- RIV is the coefficient for rivalry for the water resources. It is applied in areas of the Secchia and Enza water basin in which droughts have a high probability of arising, with limited water flows in peak demand periods. The coefficient increases the price by a level of 1.15 BP. If no rivalry occurs, then RIV is equal to 1.
- SER is the service coefficient and it works as a recovery of the operational and maintenance costs in areas where water withdrawal is more energy intensive (in certain areas of the Enza water basin). The coefficient increases the price by 1.2 BP. If the user is located in a normal area, then SER is equal to 1.
- MOM is the momentum coefficient which considers the out-of-season provision of services to recover operational costs when the all the water irrigation systems of the CEWD is not still fully operational. The coefficient increases the basic price by a range between of 1.2 and 1.5 BP. If the request is made during in-season periods, then MOM is equal to 1.
- WI is the crop-water intensity coefficient which considers the crop-water intensity in its production cycle. It ranges from 1.1 for crops of a medium water intensity (such as watermelon, apples, maize) to 1.3 for crops of high water intensity (such as peaches, rice, and kiwis). Neutral water-intensity crops have a WI equal to 1.

Table 2. Tariff schemes in the CEWD over the years with frequencies and water basin.

Period	Tariff scheme	Price € per m3	Frequency	Water Basin
2009-2015	Flat tariff	0	2,570	Po
2009-2015	Volumetric	0.0248358 €	4,596	Po, Secchia
2009-2015	Volumetric	0.025080 €	7,266	Po, Secchia
2009-2015	Volumetric	0.0436944 €	255	Enza
2009-2015	Volumetric	0.0441389 €	399	Enza
2016-2018	Two-part	0.02508 € * cost-recovery coefficients	5,125	Po, Secchia, Enza
2016-2018	Two-part	0.027 € * cost-recovery coefficients	10,232	Po, Secchia, Enza

The many different price tariffs imposed over the years resulted in a varied range of prices applied to volumetric water use from 0 to 0.0489€. This is a small price range, but can be employed in the analysis of water-use behaviour of farmers in the short-term to build a water demand curve with a good level of details for both different irrigation schemes and crops. The water demand curves were used for the analysis of water demand elasticities to price using real observational data of water provision directly released by the CEWD with panel-data econometric methods. The observations of the CEWD dataset represent the water demand managed by the CEWD in the area for surface irrigation. Water requests have been aggregated at a yearly level by considering the total amount of water demanded for the plot during the year. Water prices are calculated as the average volumetric water price paid for irrigation of the plot in the year while considering differences in price formation as explained above. The final panel is unbalanced; it considers a timeframe of six years from 2013 to 2018 with a total of 28,738 observations and 9,097 different plots. Data has been aggregated at yearly level.

External climatic data has been merged by considering georeferenced data of the municipality where the plot was located using the ERA-Interim dataset of the European Centre for Medium-Range Weather Forecasts (ECMWF) with 25km^2 grid cell spatial resolution. Various weather variables have been included at seasonal level (maximum and minimum temperatures, accumulated precipitation, and reference evapotranspiration) (ECMWF, 2020). Unlike Hendricks and Peterson (2012), who used climatic variables separately, we created a seasonal aridity index (AI) for each plot as the ratio between accumulated precipitation and reference evapotranspiration (Steduto and Food and Agriculture Organization of the United Nations, 2012) in order to consider the relative contribution of rain to potential water needs.

3.2 Theoretical framework and methodological approach

Elasticity can be defined as the percentage change of the dependent variable of a function caused by a unitary change of one of its independent variables. The demand elasticity of a commodity to price measures the responsiveness of the demand function to its price;, it indicates the relative change in the quantity demanded due to a unitary change of price and it can be interpreted as a measure of responsiveness of the demand function to price changes

(Varian, 1990). Elasticity is often defined as the ratio between the percentage variation of the quantity demanded and the percentage variation of the price (Equation 2).

$$\varepsilon_d = \frac{\Delta q/_q}{\Delta p/_p} = \frac{\Delta_q}{\Delta_p} * \frac{p}{q} \qquad \text{(Eq.2)}$$

Elasticity can be thought as the ratio between the slope of the demand curve and the relationship between price and quantity (Varian, 1990). At a single point, elasticity can be well approximated by the partial derivative of the demand function with respect to price, or by the ratio between the marginal function and the average function of the demand function (Equation 3) (Chiang and Wainwright, 2013).

$$\varepsilon_d = \frac{\partial Q}{\partial P} = \frac{dy}{dx} \Big/ \frac{q}{p} \qquad \text{(Eq.3)}$$

The value of price elasticity is usually negative, since the relationship between quantity and price is negative (for anon-inferior commodity), whereas its magnitude indicates the level of responsiveness of the function to a unitary change of the dependent variable. It is well established that: an elasticity value of 1 in absolute terms indicates constant elasticity with a proportional reaction of q for a change of x in 1 unit; a value higher than 1 in absolute terms indicates that the curve is elastic, which suggests a more than proportional response of q to unitary changes of x; and a value lower than 1 in absolute terms indicates an inelastic curve which suggests a less-than-proportional response of q to unitary changes of x (Chiang and Wainwright, 2013). The values of elasticity change along the curve and therefore in analysing the overall elasticity of a function, we should refer to the average elasticity of the curve (Iglesias et al., 1998). Geometrically, water demand elasticity can be regarded as the reciprocal of the slope of the water demand curve. Steep demand curves will have small changes in water demand due to their low elasticities; conversely, flat water demand curves will experience great reactions to water price changes (either increases or decreases) owing to their high elasticities (Olmstead et al., 2007).

Various econometric models have been developed in order to capture water demand elasticity in agriculture using real observed data. The basic models employed to capture elasticity with econometrics are log-log models, which fit the rate of change of the dependent variable well due to a change in the covariates (Greene, 2018). Log-log models are defined using the logarithm of the dependent variable and the logarithm of the independent variable of interest, while controlling for other factors. Although these are basic econometric approaches, they are very effective in approximating the partial effect of an independent variable on the dependent variable (Wooldridge, 2010).

In a stochastic framework, the partial effect of an explanatory variable x_j can be considered as the effect of the conditional expectation on the dependent variable $E(Y|X)$ by an infinitesimal change of x_j while holding the remaining variables constant. In linear models, this is expressed by the estimated parameter of the coefficients of each variable in the econometric equation (Wooldridge, 2010). Elasticity in a linear regression model can be defined as the change in the average values of the dependent variable Y as each single independent variable changes, and it can be approximated by the partial derivative of the independent variable of interest while holding the remaining X variables constant, as in Equation 4.

$$\Delta E(Y|X) = \frac{\partial \mu(x)}{\partial x_j} * \Delta x_j \qquad \text{(Eq.4)}$$

where the change of the conditional expectation value of Y on X is the partial derivative of μ with respect to x multiplied by the change in x , and where it is assumed that μ is a differentiable function which determines the realisation of Y , and x_j is a continuous variable (Wooldridge, 2010). Elasticity is a particular case of partial effect. By considering the variables of the model as random, elasticity can be defined as in Equation 4 by interpreting it as the approximation of the percentage change in $\Delta E(Y|X)$ due to a unitary change of x_j , which can also be defined through the use of logarithms (Equation 5).

$$\frac{\partial E(y|x)}{\partial x_j} * \frac{x_j}{E(y|x)} = \frac{\partial \mu(x)}{\partial x_j} * \frac{x_j}{\mu(x)} \cong \frac{\partial log[\mathrm{E}(y|x)]}{\partial \log(x_j)} \text{ (Eq.5)}$$

Therefore, the estimated parameter coefficient β in the econometric model, specified in the form as $\log(Y) = \beta \log(X) + \varepsilon$, releases the elasticities of the dependent variable Y in terms of each X explanatory variable (Wooldridge, 2010).

In this analysis, the Log-Log specification is employed to take advantage of a vast panel dataset available at plot level. Through the application of plot-level data, many problems can be solved related to biases that arise from macro-geographical aggregations (Mieno and Brozović, 2017) and to biases due to problems of endogeneity that arise from the output decisions of farms regarding output mix and input use (Hendricks and Peterson, 2012). Moreover, the application of a fixed-effect method helps in the consideration of unobserved heterogeneity which could otherwise cause endogeneity problems (Wooldridge, 2010). Our baseline model is a linear regression fixed-effect model (Equation 6) that uses the logarithm of the total yearly water demand at plot level as its dependent variable, and, as its independent variable of interest, the logarithm of the yearly average price of water for each cubic metre (m^3) of water consumed under several controls:

$$Log(y_{i,t}) = \beta Log\ (x_{i,t}) + \gamma Z_{i,t} + \tau_t + \delta_i + \varepsilon \qquad \text{(Eq.6)}$$

where:

$y_{i,t}$ is the volume of water demanded per hectare for each plot i at time t; $x_{i,t}$ is the water price per m^3 of water used for the plot; $Z_{i,t}$ is a set of control variables. There are numerous control variables: the seasonal aridity index (AI) for the plot; the type of crop cultivated on the plot (dummy); the irrigation system used for the plot (dummy); and the water basin specified for different sub-zones (dummy). τ_t is a year dummy variable for the year when macroeconomic exogenous effects are absorbed; and δ_i is the individual fixed effect at plot level for the consideration of individual unobserved heterogeneity (such as unobserved characteristics of the farmer, the farm as the ability of the farmer, and the soil quality), which could cause bias and inconsistent estimations of the coefficients (Hendricks and Peterson, 2012); ε is the idiosyncratic error with zero mean; and σ^2 is the variance (Wooldridge, 2010).

The aridity index is used as a synthetic dimension of several weather variables, as in Kounduri et al. (2006), and it is calculated following CGIAR (2019). Quarterly AIs for different seasons[10] have been employed as a climatic variable of control and are computed as the ratio of the value of the accumulated precipitation (measured in mm) of a specific season and reference accumulated evapotranspiration (measured in mm) (Allen and FAO, 1998; Villalobos et al., 2016) for each season, which results in a unit-less proxy measure of the water requirement of the crop that is satisfied by seasonal rainfall (Allen and FAO, 1998; CGIAR, 2019). The data used is from the ERA-Interim dataset of the European Centre for Medium-Range Weather Forecasts (ECMWF) with a definition at cell level of 25km^2 spatial resolution (ECMWF, 2020). Values of AI lower than 1 indicate that precipitation in the considered period fails to satisfy the water requirement of the crop, while a value greater than 1 indicates that the accumulated rainfall for the period is higher than the accumulated reference evapotranspiration (CGIAR, 2019). Levels of AI less than 0.65 indicate arid areas (CGIAR, 2019).

Crop types have been divided into main macro categories present in the area and are divided into: Alfalfa, Maize, Meadows, Pear, Soya, Sugar Beet, Tomato, Vineyard, and Watermelon. Other crops with low and negligible observations or with generic definitions that cover various crops (e.g., “Orchards” and “Vegetables”) have been omitted. Irrigation systems have been divided into macro categories of irrigation used on the plots, such as Drip, Sprinkler, and Furrow. Both crops and irrigation technology are fixed for the crop for one year, but may be changed from year to year.

We test for heteroscedasticity and autocorrelation of the data using the White test and the Wooldridge test, both of which indicate that the data is heteroscedastic and serially correlated, respectively (Wooldridge, 2010). In order to solve this problem and attain consistent estimations, clustered robust standard errors are employed at plot level (Bertrand et al., 2004; Gehrsitz, 2017; Mieno and Brozović, 2017), which relaxes the assumption of homoscedasticity and allows for cross-section change in the individual variance and for correlation within individual groups (Hansen, 2007a). This leads to consistent estimations when the dimension of the panel is large and there are a sufficient number of clusters (Hansen, 2007b). Moreover, to verify robustness, the model is run while using a Feasible General Least Squares (FGLS) regression, which relies on first-order autoregressive disturbance terms, by producing unbiased, robust, and consistent estimation with disturbances in the variance-covariance matrix (Hansen, 2007a).

The baseline econometric and the FGLS models have been applied to the whole sample and then to various subsamples in order to analyse several patterns of elasticities among irrigation

[10] Aridity indexes have been calculated as AI_{season}= *AccumPricip/ ET0* for each season. Seasons have been divided as Winter (January, February, March), Spring (April, May, June), Summer (July, August, September), and Autumn (October, November, December).

technologies and crops. Moreover, the same analysis has been carried out for subsamples of the most representative combinations of crop and irrigation technologies.

In order to retain information on the whole demand curve and to prevent the truncation and deletion of data, water prices with zero values (occurring when flat tariffs have been applied for certain plots) have been transformed as the logarithm of zero is not defined (Weninger, 2003). In order to reduce bias, the transformation follows other empirical studies that have dealt with logarithmic functions by adding a very small quantity to zero values (Friedlaender et al., 1983; Gilligan and Smirlock, 1984; Kim, 1987). Those studies suggest adding a value in the order of 0.001 or 10 % of the sample mean in order not to alter the data distribution and consequently the logarithmic transformation (Bellégo and Pape, 2019). The zero values in our datasets represent 8.5% of the total, and although they constitute a residual part of the data, they were transformed in order not to do truncate our sample. Since our analysis deals with prices close to 0, we checked the effect of the transformation on the logarithmic function with different simulations. The addition of 10 % of the minimum value in the distribution was chosen to reduce the noise in the data caused by the transformation. Finally, sensitivity checks were made regarding the robustness of the transformation and the avoidance of any change in the structure of the model (Bellégo and Pape, 2019) by examining the kernel density estimation of the within transformation distribution of both the estimated dependent and the independent variable, which fit a normal distribution.

Results

We found general water demand to be inelastic to price, since the values of the estimated coefficients are all below one, which indicates the demand for water is disproportionately responsive to changes in water price. By considering the whole sample analysed, in which a variety of crops and technologies are present, a change of 1 % in the water price induces an average reduction of 0.27 % in the water demanded at plot level. This result is consistent with previous studies, which indicate a generally inelastic water demand in agriculture, such as the meta-analysis by Scheierling et al. (2006), who find an average price elasticity of -0.48. The results of the model estimations for the whole sample and sub-samples of irrigation technologies are presented in Table 3, results for sub-samples of crops in Table 4, and results for a representative combination of irrigation technologies and crops are laid out in Table 5. In each table, the estimation of the elasticities are highlighted for both the main log-log model and for the FGLS used for robustness control. The results of the estimations are very similar for the two econometric models, which indicates that our econometric estimations are robust. Only slight differences in the estimations of the two models arose for Pear and Sugar beet.

Although water demand has been estimated as inelastic in general, a few differences do arise between technologies and crops. When considering sub-samples of irrigation technologies (Table 3), furrow irrigation systems are the most inelastic with a coefficient of -0.208. Sprinkler and drip irrigation systems show a slightly higher responsiveness to change in water price, with coefficients of -0.326 and -0.435, respectively (Table 3). In the Discussion section below, we therefore strive to find an explanation for this result, which deviates from past studies.

By considering single crops, it can be observed that water elasticities change (Table 4). Cattle-grazing crops (Alfalfa and Meadows), which are irrigated principally with furrow irrigation, are strongly inelastic. Sugar beet and Maize also have a strongly inelastic water demand curve although their main irrigation system is that of sprinklers. Conversely, Watermelon (drip irrigation) and Tomato (sprinkler irrigation) are more responsive to price and their water demand curve is therefore less inelastic, with -0.5 of elasticity. This could partially depend on the high water intensity of vegetables compared to grazing crops and on the higher marginal value of productivity of water as an input in vegetable production. In fact, Alfalfa and Meadows are principally cultivated as an input for dairy farms, which in this area produce Parmesan cheese (*Parmigiano Reggiano*). In the value chain of this cheese, water costs represent a negligible part of the total cost of production, while for fruit and vegetables (such as Tomato and Watermelon), which are sold directly on the market, the cost of water, as a proportion of the final cost of the product, is higher. Therefore, the water demand function of Tomato and Watermelon (as for other fruit and vegetables) should be more elastic than that of cattle-grazing crops, since the embedded value of water in the final product is higher (Renault, 2002).

The water demand function for the Vineyard category is generally inelastic, and, in this case, when considering irrigation technology, that of furrow irrigation (-0.273) is more inelastic than it is for the sprinkler method (-0.382), whereas the coefficient for drip irrigation is not statistically significant. The explanation may lie in the high value of wine where water is an essential input and the cost is a small share of the total cost of the end product.

Pear crops yield puzzling results. These have no statistically significant estimated coefficients for the log-log model, whereas for the FGLS, the estimated coefficients indicate elastic water demand to price with a 10% significance for total sample of irrigation systems and 5% for drip irrigation. The elasticity of Pear crops was expected since these are both high value and have a high demand for water. This difference in the results of the estimations in the two models means that these results should be viewed cautiously. Even though the main findings reveal a generally inelastic water demand, our estimations indicate that the response of water use to price does in fact change according to the particular irrigation system and crop, especially if we take into consideration that the level of prices used in this study is low (0.00-0.048). Moreover, differences with other models may be explained by the fact that simulations in mathematical programming and analytical methods use higher prices and make general assumptions regarding the knowledge held by farmers and consider them to be perfect profit maximisers (Elbakidze et al., 2017), which is often far from their real behaviour.

Table 3. Estimation of water elasticity to price for the whole sample and for sub-samples of irrigation technologies

VARIABLES	(1) Total Sample	(2) Drip	(3) Sprinkler	(4) Furrow
Dependent Variable				
Log (Water m^3 per ha)				
OLS				
Log (Water price)	-0.268***	-0.435***	-0.326***	-0.208***
	(-25.54)	(-5.649)	(-17.92)	(-16.01)
FGLS				
Log (Water price)	-0.276***	-0.417***	-0.354***	-0.215***
	(-24.91)	(-6.293)	(-17.88)	(-17.03)
OLS				
Constant	5.254***	7.074***	4.947***	5.105***
	(17.35)	(5.788)	(11.10)	(8.773)
Observations	28,738	2,670	16,726	9,342
R-squared	0.230	0.245	0.228	0.273
Individual demands per plot	9,097	817	6,284	2,495
Robust S.E. (Clustered)	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Aridity Index	Yes	Yes	Yes	Yes
Irrigated Area	Yes	Yes	Yes	Yes
Crop Type	Yes	Yes	Yes	Yes
Irrigation Technology	Yes	Yes	Yes	Yes

Robust t-statistics are given in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Estimation of water elasticity for sub-samples of different crops

VARIABLES	(1) Alfalfa	(2) Maize	(3) Meadows	(4) Pear	(5) Vineyard	(6) Watermelon	(7) Tomato	(8) Sugar Beet	(9) Soya
Dependent Variable									
Log (Water m^3per ha)									
OLS									
Log (Water price € per m^3)	-0.287***	-0.295***	-0.192***	-0.141	-0.329***	-0.555***	-0.565***	-0.299***	-0.280
	(-11.37)	(-7.841)	(-13.12)	(-0.674)	(-5.347)	(-5.305)	(-7.578)	(-3.357)	(-1.340)
FGLS									
Log (Water price € per m^3)	-0.586***	-0.278***	-0.219***	-1.079***	-0.342***	-0.527***	-0.371*	-0.693***	0.412
	(-16.55)	(-6.227)	(-16.42)	(-2.902)	(-8.614)	(-4.357)	(-1.782)	(-3.884)	(1.166)
OLS									
Constant	6.214***	9.635***	142.4	73.13	-80.82	-584.0	-1,432	-43.96	-494.0
	(36.57)	(7.977)	(1.157)	(0.286)	(-1.131)	(-0.709)	(-1.324)	(-0.0962)	(-0.632)
Observations	3,584	4,095	6,046	2,100	10,787	312	571	818	425
R-squared	0.162	0.224	0.298	0.371	0.211	0.297	0.311	0.236	0.122
CHECK Individual demands per plot	1,925	2,185	1,523	454	2,895	129	348	569	327
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aridity Index	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Irrigated Area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Irrigation Technology	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Estimation of water elasticity to price for sub-samples of representative combinations of irrigation technologies and crops.

VARIABLES	(1) Alfalfa Sprinkler	(2) Alfalfa Furrow	(3) Maize Sprinkler	(4) Meadows Furrow	(5) Pear Drip	(6) Pear Sprinkler	(7) Tomato Sprinkler	(8) Watermelon Drip	(9) Sugar Beet Sprinkler	(10) Vineyard Drip	(11) Vineyard Sprinkler	(12) Vineyard Furrow
Dependent variabl Log (Water m^3pe ha)												
OLS												
Log (Water price)	-0.311***	-0.127	-0.304***	-0.190***	-0.0690	-0.836	-0.533***	-0.523***	-0.291***	-0.145	-0.382***	-0.273***
	(-10.18)	(-0.519)	(-8.030)	(-12.91)	(-0.447)	(-0.701)	(-7.457)	(-4.576)	(-3.179)	(-0.427)	(-3.753)	(-4.304)
FGLS												
Log (Water price)	-0.324***	0.381	-0.282***	-0.217***	- 1.020**	-0.741	-0.425**	-0.494***	-0.694***	-0.00640	-0.502***	-0.247***
	(-6.995)	(0.805)	(-6.128)	(-16.32)	(-2.103)	(-1.351)	(-2.355)	(-3.832)	(-3.837)	(-0.0397)	(-8.462)	(-4.688)
OLS												
Constant	151.4	419.8	332.2**	139.6	-363.5	260.5	-629.0	-318.8	-24.19	36.95	-61.57	7.659
	(0.784)	(0.459)	(2.058)	(1.140)	(-0.755)	(0.875)	(-0.856)	(-0.353)	(-0.0526)	(0.158)	(-0.592)	(0.0622)
Observations	3,339	235	3,947	5,895	712	1,352	486	236	796	1,578	6,178	3,031
R-squared	0.217	0.175	0.233	0.306	0.339	0.438	0.418	0.311	0.242	0.245	0.198	0.254
CHECK Individua demands per plot	1,802	137	2,113	1,456	173	322	306	91	553	470	1,834	841
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aridity Index	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Irrigated Area	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Irrigation Technology	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust t-statistics are given in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Discussion

Many previous studies found water demand inelastic to price. In an expansive review, Scheierling et al. (2006) found that less elastic estimates are found in the presence of high-value crops, which is also confirmed by our results, although our findings additionally highlight a difference in the level of responsiveness between both crops and irrigation technology. These findings are relevant for policy-makers since they reveal that farmers in the CEWD have a low response to water prices, and imply that water tariffs can be effective strategies to cope with over-irrigation issues only if actual water prices are increased significantly. Although water demand is generally inelastic it does not necessarily mean that farmers remain impervious to pricing policies, but it does indicate that they are responding less than proportionally to price changes. It should be borne in mind that the elasticities in our estimations are average elasticities that consider actual prices which are very low and are placed at the lowest part of the demand curve. In the aforementioned review by Scheierling et al. (2006), the elasticity is higher in the long-term at lower prices, and is more inelastic in the short-term at higher prices. The interpretation of our results should consider that, for higher prices and longer timeframes, the results may differ.

Our most interesting finding is related to the differences in water demand elasticities between irrigation technologies and crops. Our estimated elasticity that considers all technologies and all crops suggests that drip irrigation is more elastic than sprinkler irrigation, and that sprinkler system is more elastic than furrow irrigation systems, which is slightly in contrast with certain theoretical models, such as that by Berbel et al. (2018), which indicates the opposite findings. Our results also diverge from other empirical work, such as that by Hendricks and Peterson (2012), Caswell et al. (1990), and Zilberman (1984), which state that a higher level of precision in irrigation reduces water use, thereby causing an inelastic demand, in other words, the demand elasticity for precision irrigation systems (drip and sprinkler) should theoretically be lower than that of traditional systems (such as furrow).

Our models on crops and on combinations of crops and technologies confirm the pattern in which drip and sprinkler technologies are more reactive to water price than is furrow irrigation technology. This result can be justified as a matter of climate uncertainty and risk in farmers' irrigation decisions. Farmers are strongly affected by crop response to climate and the uncertainty regarding water efficiency and crop response to irrigation doses may explain the higher use of water in the case of less controllable technologies.

Our argument suggests that the greater controllability of drip and sprinkler irrigation systems results in sharper reactions to price changes. In contrast, furrow irrigation, which has a lower level of controllability, is more inelastic to price due to the higher yield loss (and foregone profits) when water crop requirements are not covered compared to the low cost of over-irrigation. This conclusion is the opposite to that drawn by Berbel et al. (2018) and Berbel and Mateos (2014), which was based on an analytical model under certainty, whereby farmers predict lower elasticity for higher precision systems with standard efficiencies (E) for furrow (E=0.60), sprinkler (E=0.85), and drip (E=0.95) irrigation systems. The elasticities have an inverse correlation with to the level of water control in the form of drip (the most elastic), sprinkler, and furrow (the least elastic).

The explanation of our results is consistent with the “just in case” model of Babcock (1992) for the use of agricultural inputs. The author stated that for a risk-averse farmer, when agricultural yields are difficult to predict and their variations depend strongly on the application of a specific input (for Babcock, this was nitrogen fertilisation), farmers tend to over-use that input with the aim of reducing the risk of yield loss. This effect is amplified when the variance of yields increases due climatic factors, such as precipitation and temperature (Babcock, 1992). Our findings are in line with this theory, since the lower the level is of control of the irrigation system (e.g., furrow irrigation), the higher the risk of yield loss becomes when water application remains below the maximum technical level of irrigation, and therefore the higher the level of water over-use becomes. This explains why water price elasticity increases from furrow (less elastic) to sprinkler and drip (more elastic). Our reasoning is that the higher the control is of the irrigation system, the higher the reaction to price changes becomes; this largely depends on the ease and level of certainty for the farmer in reaching the maximum technical level of irrigation.

Other findings in our research refer to differences in elasticity for crops where demand is a function of the marginal value of production. For high-value crops where water costs are a negligible part of the total cost, water demand is more inelastic, whereas for products in which its cost is a sizeable proportion of the final costs, water demand is more elastic, which coincides with the majority of the findings by Scheierling et al. (2006). This reflects the value of water used in production as an input over the total value of the final product.

We have found differences between crops as a function of the yield-water relationship, with herbaceous crops, such as livestock feed, reacting faster to water stress compared with vegetables or orchards where the marketable product (fruit) constitutes a small share of the total biomass. Therefore, this hypothesis could also justify why high-value crops are more elastic to water prices than are low-value crops, which contradicts what the theory says. Additionally, in market-oriented products (such as fruit and vegetables), the higher price for higher product quality may prove to be a more profitable strategy than that of increasing production yield (Geerts and Raes, 2009).

Our results highlighted that pricing policies for the reduction of over-irrigation should be tailored from the current system in the CEWD of a two-part tariff in which the baseline price (0.027€ per m^3) considering that crops with more inelastic water demand characterised by high levels of over-irrigation, such as Meadows, Vineyard, and Maize, could receive additional components of water price in order to stimulate a more conservative usage of water. Furthermore, the introduction of any additional parameters related to the irrigation system could strengthen the efficacy of the pricing policy of the CEWD with increasing coefficients proportional to their elasticity (higher coefficients for furrow and sprinkler systems). This could improve the effectiveness of pricing policies by incentivising a more conservative use of water for sustainable irrigation.

Our study works with average elasticity and considers the whole irrigation season: no different levels of seasonal elasticities are considered, as they are in Allen and FAO (1998), who state that the flourishing and growing stages should be more inelastic, while and the mature phase of the crop should be more elastic. Furthermore, our study did not consider the possible non-linear effect of price on water demand for the analysis of the diminishing effects of pricing policies or threshold effects, and therefore different non-linear and segmented demand curves should be included in future studies. Further studies could analyse the possible evidence of the non-linearity of water demand curves.

Conclusions

In our paper, a panel data set is used on water demand and prices with thousands of observations at plot level over different years. Observational data of this dimension is not common in the literature and it offered us the opportunity to analyse the agricultural water district in the Emilia Romagna region, which is of strategic importance for national production. Our findings show that, as previous empirical work in this field have found, water demand is inelastic to price, but we also increase the knowledge regarding differences between the various irrigation systems and crops. Surprisingly, we found that precision systems (drip and sprinkler) have a more elastic demand compared to traditional systems (furrow), which is the opposite of that predicted by previously published models. This is an interesting case study since it is based on extensive observed real data with an econometric analysis, which gives us the chance to compare our findings based on deterministic studies with other empirical econometric work. A log-log model with fixed effect was employed, as was an FGLS for robustness of the estimations. Our results highlight the importance of setting ad-hoc water tariffs and of treating water prices, technologies, and crops differently in order to boosting effective strategies for conservative water use in agriculture. This could be carried out by the management of the CEWD through the modification of the setting of the parameters used for the calculation of the two-part tariff, and by introducing an increasing coefficient related to water elasticity levels of the various irrigation technologies.

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The impact of volumetric water tariffs in irrigated agriculture in Northern Italy.

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Abstract

The impact of water-pricing policy in irrigated agriculture in Emilia Romagna (Italy) is evaluated through the analysis of farmers' water use whereby a flat-rate tariff (2013-2015) is replaced by a two-part scheme composed of a flat rate plus a volumetric tariff (2016-2018). The policy assessment is performed by an application of the Difference in Differences method considering the period of policy intervention in a reversed form. The results indicate that farmers reacted to volumetric pricing by reducing water use per hectare. The high responsiveness may be explained by the combined impact of volumetric metering itself and the small price increase from the previous flat rate (zero marginal price) to a moderate volumetric tariff (from 0.025 to 0.044 €/m^3).

Keywords

Difference in Differences, Water pricing, Policy assessment, Irrigation Water Management, Emilia-Romagna.

1 Introduction

The state of global water resources is crucial for food production and global food security (UN, 2020). Water scarcity constitutes one of the main environmental global problems (Wheeler et al., 2015) and will become even more important in the near future due to climate change (Misra, 2014). Agricultural activities are one of the main determinants of pressures on water resources and are the principal consumers of water resources: they account for 70% of total water withdrawal around the world (FAO, 2012). Agricultural water use is strictly related to problems with food security, public health, and economic growth (UN, 2015, 2006), and with the direct and indirect production of ecosystem services (Costanza et al., 1997).

One of the main problems in agricultural activity involves over-irrigation which can be defined as the application of water in greater amounts than the crop water requirement (Steduto et al., 2012). Over-irrigation has manifold negative impacts on the environment as soil erosion, groundwater leaching, salinization, transportation of nutrients and pollutant in downstream waterbodies (Trout, 2000). Excessive irrigation in a river basin can have a reduced impact in quantitative terms if the excess water returns to the hydrologic systems in the form of return flow, although the impact in qualitative terms can be highly relevant if the return flows exports nutrients and chemicals which are many times linked also to over-fertilization (since the N and P that are partly lost via return flows should be replaced) affecting further diffuse pollution through an increase in the export of nutrients and salt from agricultural soils downstream.

Over-irrigation depends largely on the technology adopted, but also to farmers' expectations and economic behaviour. Therefore, the information available to the farmer are extremely important, such as that regarding soil properties, weather, biology, expected yield, and other agronomic and productive aspects. The price of water, however, presents a crucial aspect in affecting over-irrigation.

In the European Union, the approval of the Water Framework Directive (WFD) established a comprehensive integrated approach towards attaining a good status of all water masses in the EU (EU Commission, 2000). The WFD uses economic science (economic analysis, cost-benefit analysis, cost-effectiveness analysis) and economic instruments (water pricing) as their core discipline to reach the environmental goals that constitute the principal objective of the directive. Article 9 promotes cost recovery and water pricing as a guiding principle in the Directive that should be implemented in national legislation (EU Commission, 2000), by indicating pricing policies as suitable instruments to incentivize efficient water use, thereby contributing towards the improvement of environmental conditions (Kejser, 2016).

The response to an increase in water pricing depends upon the characteristics of the demand curve, with mixed evidence regarding elasticities, which, in the case of irrigation, depend on crop profitability, environmental conditions, and farmer characteristics (Berbel and Expósito, 2020). An extensive review of residential water elasticity by the European Environmental Agency reported '*in some of the case studies, price does not appear to be a significant determinant of water demand (..) water pricing still remains a key instrument in achieving cost recovery for water services to ensure the maintenance and financing of existing and future water infrastructure'* (European Environment Agency, 2017). Unresponsiveness of water demand to water price is a key issue also in agriculture (Scheierling et al., 2006). This fact has been claimed as one of the main determinants of underusing water pricing as a correcting policy instead of basing water tariffs unlinked to water consumption (Lago et al., 2015).

In the case of a no-tariff policy for water, farmers can consider water as a non-constraining input and a free commodity. Conversely, if water is priced, it enters into the farmers' cost function, who then have to pay a certain fee for each quantity of water consumed in their productive activity. Demand-side policies, which apply prices to water used for irrigation through volumetric tariffs, can internalize issues and externalities regarding public goods (Hardin, 1968) by reducing over-irrigation and directing farmers towards the more efficient use of water resources (Cooper et al., 2014; Rogers, 2002; Wheeler et al., 2015).

Economic policy measures operate via incentives, motivation, and voluntary choices rather than via complying with prescriptions as do command and control measures. These policies tend to be reasonably flexible because they can be adapted to various contexts regarding the motivation of individual farmers (Lago et al., 2015) and/or the reduction of problems arising from asymmetric information (Johansson, 2002). The pricing of water assigns a marginal cost to each amount of water consumed thereby transforming water into a binding input in farmers' productive strategies and influencing the selection and allocation of both crops and irrigation technologies.

Despite pricing instruments gaining acceptance as a tool towards achieving sustainability in water management, the literature remains divided on the effectiveness of tariff policies on agricultural water use. Several scholars claim that water pricing alone cannot lead to improvements in water-use efficiency due to the many additional aspects that should be considered, such as institutions, physical infrastructures, costs, benefits, equity, and transparency (Cooper et al., 2014; Dinar and Mody, 2004; Molle and Berkoff, 2007). Moreover, the most important aspect in influencing farmers' irrigation responses to policies is water-demand elasticity to water price whose effect remains unclear from empirical analysis (Scheierling et al., 2006) with many contrasting evidences in the literature (Hendricks and Peterson, 2012; Schoengold et al., 2006; Wheeler et al., 2008). Elasticity to water price represents the responsiveness of the water demand function to changes in the price of water and it indicates the relative change in water demanded due to a unitary change of water price (Berbel and Pronti, 2020). Elasticity is defined as the ratio between the percentage variation of the quantity demanded of water and the percentage variation of the price of water (Varian, 1990). For a more detailed focus on water elasticity see Berbel and Pronti (2020), Hendricks and Peterson (2012) and Scheierling et al. (2006).There is still a relevant gap in the literature on agricultural water management regarding the evaluation of economic measures (especially that of pricing) due to the lack of ex-post evaluations that arises from important data limitations (Lago et al., 2015).

This paper strives to test the impact of a policy change from a flat rate to a volumetric two-part tariff using a natural experiments approach with a backward application inverting the two period of analysis commonly used in difference in differences(DiD) framework. This paper employs data observed in the Central Emilia Irrigation Water District (CEWD) in north eastern Italy and analyses the effect of the application of a volumetric tariff as a policy strategy for the improvement of water use by local farmers. The results enrich the knowledge regarding the farmers' response to the introduction of a volumetric water tariff based on water use. The main findings of this study show that the application of a volumetric tariff contribute to the change in water use of farmers that had a flat tariff before the policy converging to a more parsimonious use and similar to other farmers who already dealt with volumetric tariffs.

The paper is structured as follows: in Section 2, a brief introduction to institutional background of the case study is presented; in Section 3, material, methods, and our empirical strategy are described; Section 4 presents the main results, which are then discussed in Section 5; finally, Section 6 offers the concluding remarks.

2 Background on the case study

2.1 Agricultural Water Management in Italy

Italy is classified as a Mediterranean country, whose high annual precipitations (although the annual rainfall is 942mm, which is greater than that in France) are more evenly distributed throughout the year than all the other Mediterranean countries. Anyway, recently there has been an increase variability in local water availability and increasing stress on local ecosystems due to reduced precipitations and increasing temperatures have been recorded (Laureti et al., 2020). Despite that, natural environment implies a certain abundance in water resources, with hydropower as the dominant use of regulated water in Italy, mainly in the Northern regions. Table 1 compares the Italian irrigated sector with the large EU Mediterranean countries. The ratio of “Estimated” vs. “Registered” is defined as Relative Irrigation Supply (RIS)[11] (Playán and Mateos, 2006) and it can be observed that is close to 2.0 in Italy suggesting a serious over-irrigation situation at least compared with its neighbouring EU countries.

Table 1. Estimated and reported irrigation water demand in selected EU countries.

	Irrigated Area[1] (th.ha)	Reported[2] irrigation abstractions (hm^3)	Irrigation demand[2] (hm^3)	Reported irrigation[2] (mm/yr)	Calculated irrigation requirement (mm/yr)[1]	RIS [1,3]
Spain	3.700	21.763	35.919	679	1.120	0.61
France	1.500	4.872	6.349	311	405	0.77
Greece	1.159	7.600	12.776	656	1.102	0.60
Italy	2.866	38.360	22.381	1.565	913	1.71
Sum	9.225	72.595	77.425	866	923	0.94

Source: (1) Authors' own (2)(Wriedt et al., 2008) (3) Reported irrigation/Calculated

Italy has the higher share of irrigated land over total agricultural land (ISTAT, 2019) with important regional differences and with northern regions presenting the highest values of irrigation (Istat, 2014). The general over irrigation taking place in Italy is probably cause of a general water stress (EEA, 2020) observed in many regions. Water scarcity is becoming structural beyond the events of extreme weather conditions and recurring droughts (Auci and Vignani, 2020; Brunetti et al., 2006; Bucchignani et al., 2016).
Since the beginning of the last century the needs for an institutionalized management of water resources in Italy triggered the creation of the Reclamation and Irrigation Board (RIB) (in Italian ‘*Consorzio di Bonifica e Irrigazione*’), which was initially focused only on the drainage of temporarily or annually flooded areas, while water supply distribution was gradually integrated later for industries, urban areas, and irrigation. Nowadays, RIBs are responsible for the implementation, development, maintenance, and management of the irrigation systems serving the farms located in their assigned area (Dono et al., 2019; El Chami et al., 2011). There are approximately 500 RIBs in Italy, with many differences

[11] RIS is the ratio between irrigation water requirements and effective irrigation, it indicates how much water application is close to crop water requirements. If it close to 1 water application is equal to water requirements, if it is > than 1 it indicates over-irrigation if it is < than 1 it indicates deficit irrigation (Playán and Mateos, 2006).

in management systems, dimensions, and tariff systems. In accordance to regional laws, these RIBs must set the price of water services to their users (Berbel et al., 2019). Of the water withdrawn for agriculture in Italy, 63% comes from RIBs, (34% with a rotation system and 29% with service on demand), with the remaining 37% from groundwater (18%) and private superficial sources (15%) (Istat, 2014).

During time RIBs assumed increasing institutional importance in the national water management system, and has been entrusted by national law (Gazzetta Ufficiale della Repubblica Italiana, 2006) to address the European water framework directive (WFD) at local level with the aim of introducing policies for water conservation (both qualitative and quantitative) (Dono et al., 2019). The main tool recommended in the WFD is the introduction of water pricing in compliance of the user-pay principle and the use of water recovery costs in order to both boost more efficient uses of water and recover its operational and maintenance costs (Berbel and Expósito, 2018).

In accordance to WFD, the Italian Government decided to implement a suitable tariff systems at national level for all water users considering environmental costs and the full cost of the resource as defined by the Decree of the Ministry of Environment no. 39/2015 (Italian Ministry of the Environment, 2015). Previously, tariffs were defined on a per-area basis according to the water needs of irrigated land and crops, for further details see Zucaro et al.(2011). The introduction of agricultural water tariffs had the aim to boost sustainable water use and incentive a more efficient irrigation behaviour through technological improvement and the cultivation of low water demanding crops. Local RIBs were entrusted by the national government for the implementation of this deep transformation.

2.2 The case of Central Emilia Water District

The case study is located in the Emilia-Romagna Region (ERR), in the northeast of Italy. This region has the largest share of irrigated land, and its water courses have been highly modified for agricultural and drainage purposes since the 17^{th} century (Pérez-Blanco et al., 2016). The agriculture in the ERR constitutes an important dynamic sector at both national and European level, the value-added was $3.4\ 10^9$ € (year 2017) with irrigation playing a major role (ERR, 2019a; Fanfani and Pieri, 2018).

In recent decades, the ERR has been experiencing major increasing pressures on water resources due to extreme drought seasons, reduced precipitation, and increasing temperatures, which led to a declaration of the state of emergency for the years 2003, 2006, 2007 and 2015 (Pérez-Blanco et al., 2016; Vezzoli et al., 2015). The ERR government has been at the forefront of the implementation of the WFD at regional level with a series of regulations and economic instruments in order to reduce pressures on bodies of water by incentivizing technological irrigation efficiency and the reduction of water losses and waste. Numerous regional policies have been affected by the introduction of pricing instruments for irrigation guided by the Cost Recovery Principle (El Chami et al., 2011).

We studied the case of the Central Emilia Irrigation Water District (CEWD, in Italian *Consorzio di Bonifica dell'Emilia Centrale*) in the provinces of Reggio-Emilia and Modena in the Italian Emilia-Romagna region, which is the most important agricultural area in the region. The area is famous for being the district of Parmigiano-Reggiano cheese, Balsamic Modena Vinegar, Lambrusco wine, and of other agro-food products with the Protected Designation of Origin (PDO) or Protected Geographical Indication (PGI), such as watermelon, cherries, and pears (ERR, 2019b) with a share of 14.5% of the regional total agricultural added value (ERR, 2019a).

The CEWD is in charge of the management and distribution of surface water with a specific focus on the protection of water bodies, defence against floods, and the distribution of water for agricultural and environmental purposes in compliance with the WFD (CEWD, 2017). The CEWD has a complex infrastructural network of 3,500 km of canals covering 120,000 ha and serving an agricultural area of 24,000 ha that encompasses three river basins: Po (average withdrawal 142,7hm^3), Secchia (average withdrawal 29,2 hm^3), and Enza (average withdrawal 10,4 hm^3) (CEWD, 2015).

Farmers annually provide their crop plans and their irrigation systems to the CEWD and indicate the size of the irrigated area at plot level. Irrigation water demand from each user is made directly by phone. The amount of water to be delivered is calculated directly by the CEWD, which considers the canal flow rate, the capacity of the water structure, and the duration of delivery. To this end, the CEWD takes into account the irrigation technology used by the farmers and their crop water needs in order to lessen the information requirements from the farmer, since there is only a partial presence of a direct metric pressurized water structure with prevalence of open canal systems. Therefore, farmers cannot ask directly for an amount of water, which is calculated by the CEWD based on the crop/technology scheme, but they can request water whenever their needs arise. At the end of the irrigation scheme, farmers receive a report of their irrigation activities and the relative costs to be paid before the next season in order to continue to receive the irrigation services (CEWD, 2017).

The CEWD is a public entity established in 2009 by the fusion of two previous RIBs present in the area (the *Consorzio di Bonifica Parmigiana Moglia Secchia* and *Bentivoglio-Enza*). In the years immediately after the creation of the CEWD (2009-2015), water users had inherited their previous tariff schemes from the former IWDs. A minority of users coming from the *Consorzio di Bonifica Parmigiana Moglia Secchia* in which flat-rate tariffs were applied continued to pay only an annual fee for general services and not for the amount of consumed water. However, users from *Consorzio Bentivoglio-Enza* already had a two-part tariff scheme whose volumetric price lay between 0.024€/m^3 and 0.025€/m^3.

In 2016, in accordance with its own sustainability aims, the CEWD implemented a new pricing plan based on a two-part tariff scheme in order to both reduce over-irrigation and to gather financial resources to recover operational and maintenance costs as stated by the WFD. The two-part tariff scheme is composed of a fixed fee to cover the general service of the CEWD together with a volumetric part. The latter involves the basic price of 0.025 EUR per m^3 (increased to 0.027 EUR per m^3 in 2017) multiplied by an individual multiplier which considers: the existence of rivalry regarding the water resources (for Secchia and Enza water basin which are water scarce in the dry season); the recovery of operational and maintenance costs per area in which water withdrawal is more energy intensive, out-of-season provision services; and the water intensity of the crop.

3 Material and Method

3.1 Empirical strategy

The Difference in Differences (DiD) approach is one of the most used method of policy analysis used in economic literature which was extensively applied for policy assessment in many different fields (Imbens and Wooldridge, 2009; Lechner, 2010). Recently the DiD method has also been introduced for the evaluation of agricultural water policies, although applied works on agricultural water issues are still scarce principally due to the limited access to water micro-data in agriculture. Drysdale and Hendricks (2018), Smith et al. (2017) and Smith (2018) studied the effect of water regulations on agriculture related to groundwater management using DiD in Kansas and in Colorado, respectively, and found, in both locations, that the introduction of economic incentives is effective for the reduction of agricultural water use. In China, the DiD framework has been used to assess both the causal effect of surface water pollution due to the excessive use of rice pesticides derived from a national program that incentivizes agricultural development (Lai, 2017), and the effect on the subjective quality of life of participatory water management activities (Pan and Guo, 2019). To the best of our knowledge, no other studies related to water resources for agriculture have been carried out using the DiD approach.

Our analysis focuses on the effectiveness of the new imposition of water pricing on the behaviour regarding water use of irrigators passing from a flat-rate tariff to a volumetric scheme. This situation occurred in the CEWD as a natural experiment in which, from 2013 to 2015, two separate tariff schemes (flat-rate and volumetric) were applied, whereas from 2016 to 2018, all the users were on the same tariff scheme (volumetric).

The intuition under this analysis is that farmers were facing different types of decision patterns regarding their water consumption depending on their perception of water costs. Farmers who were already on the volumetric tariff should have previously incorporated water costs into their cost functions by considering water as a scarce factor and managing it in accordance with its marginal cost and its marginal benefit. Conversely, farmers who initially faced flat-rate tariff plans considered water as an unlimited input and used it as a free public commodity; this implied an almost zero marginal water cost, which encouraged them to over-irrigate. We can therefore test whether the application of a water-pricing scheme to farmers who previously had a flat-rate tariff scheme can be an effective policy in encouraging a reduction in water use.

We consider the CEWD case study as a natural experiment in which the effect of the volumetric policy on the farmers who had a flat-rate tariff before 2016 can be tested as a treated group using farmers who had had a volumetric tariff since 2013 as the control group. In classic DiD applications, analysts compare two groups of units that are similar in the pre-treatment period and become different in the post-treatment (policy implementation) period (Angrist and Pischke, 2009; Frondel and Schmidt, 2005).

The empirical problem in this specific case study is that data is available in the converse form of the classic application used for DiD (Cerulli, 2015). Before policy implementation, there were two different groups: one which maintain flat rate until 2016; and another group already paying by volume as early as 2013. Conversely, in the post-policy application periods, there are two homogeneous groups of farmers who are both under the same water-pricing scheme.

Our main interest is focused on the average effect in water demand for those farms which experienced a change in their billing policy. Therefore, those farms which did not receive the policy (the volumetric tariff) in the pre-treatment period are considered as treated farms, contrary to the normal application of the DiD method. We called this approach "inverse DiD".

One can imagine a classic natural experiment as a medical experiment, in which the effectiveness of a drug application is measured as the difference in the average health status between the two sub-groups of patients: those who receive the drug (the treatment) and those who receive the placebo. In this same context, the "inverse DiD" can be considered as a medical experiment, in which, at the beginning of the experiment, both groups of patients receive the same drug, then that drug is removed from only one group and the measure of the drug effect is measured as the difference in the average health status of the two groups of patients.

We apply this idea going backwards in time, starting with the analysis from 2018, the year in which all the farms received the water-pricing policy, to 2013, the year in which the farms had different tariff schemes. Our treatment status is that of being subject to a volumetric tariff scheme. The aim of the analysis is to measure the effect of removing the treatment (the pricing policy) from our units of interest in the second stage of the experiment, and to measure the average effect on farmers' water demand. Doing this, our first stage of analysis is the period in which both types of units had a volumetric tariff (2016-2018), while our second stage is the previous period in which the two groups had different type of tariff (2013-2015). We make our analysis backward in time, in figure 1 our method is depicted for simplicity of the readers.

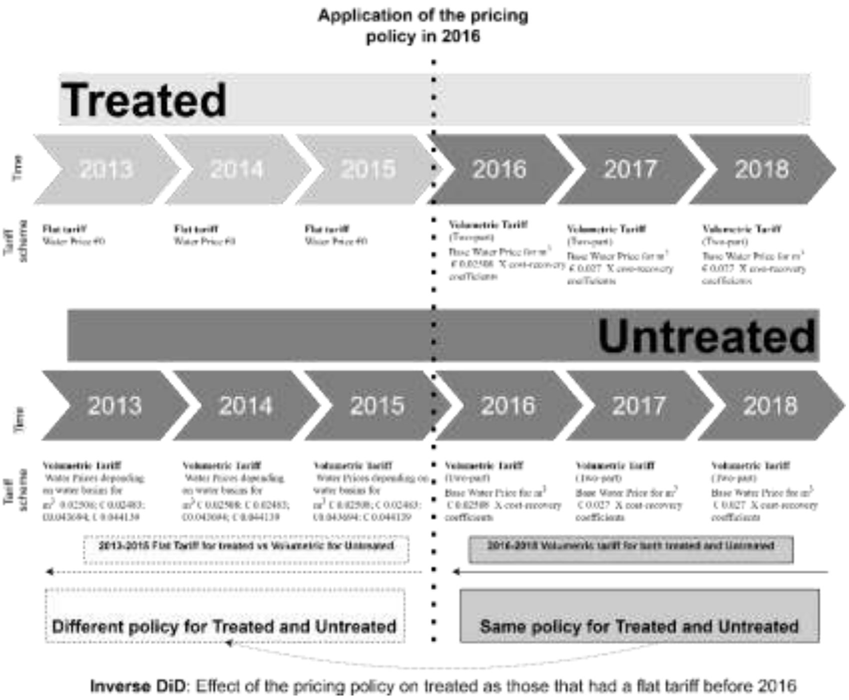


Figure 1. Representation of the empirical Strategy adopted.

3.3 Data description

The data used in this study is composed of a sample of water demand data in the CEWD for the provinces of Reggio-Emilia and Modena. Water demands are recorded in the CEWD dataset immediately following the irrigator's requests, which are made by phone. The database employed includes all the information at plot level for: the total amount of water delivered in m^3, crop cultivated, irrigated area, water basin, municipality, and irrigation technology used. The CEWD indirectly calculates the amount of water delivered in m^3 as the multiplication of the duration of opening the channel, the flow of water, and the capacity of the channel.

The data used in this analysis is aggregated yearly and at plot level. No data on yields, productivity and no other demographic farmers' information is available. Climatic data of seasonal accumulated precipitation and seasonal average minimum temperature at municipal level is merged into the principal dataset. Climatic data is from the ERA-Interim dataset of the European Centre for Medium-Range Weather Forecasts at 25 km^2 grid level (ECMWF, 2019). In table 2 the descriptive statistics for the main variables used.

Table 6. Summary statistics.

	Full sample				Treated		Untreated	
Num of observations	12604				3909		8695	
Variable	**Mean**	**Min**	**Max**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Water Use (M3/Ha)	2668.576	1.183	49356.000	1540.000	3934.436	2592.000	2099.484	1316.250
Inv DiD	0.158	0.000	1.000	0.000	0.509	1.000	0.000	0.000
Size higher than 10 Ha (Dummy)	0.204	0.000	1.000	0.000	0.166	0.000	0.222	0.000
Post policy time trend	0.315	0.000	3.000	0.000	1.016	0.000	0.000	0.000
Year 2013 (Dummy)	0.179	0.000	1.000	0.000	0.169	0.000	0.184	0.000
Year 2014 (Dummy)	0.160	0.000	1.000	0.000	0.169	0.000	0.156	0.000
Year 2015 (Dummy)	0.171	0.000	1.000	0.000	0.171	0.000	0.171	0.000
Year 2017 (Dummy)	0.191	0.000	1.000	0.000	0.178	0.000	0.197	0.000
Year 2018 (Dummy)	0.123	0.000	1.000	0.000	0.139	0.000	0.115	0.000
Accumulated Precipitation JFM	157.321	70.316	237.986	168.760	155.506	165.272	158.137	168.760
Accumulated Precipitation AMJ	154.384	93.506	236.310	147.420	153.601	139.909	154.736	147.420
Accumulated Precipitation JAS	144.905	105.012	222.359	129.242	144.073	129.242	145.279	133.620
Accumulated Precipitation OND	143.120	98.822	188.072	149.771	141.786	153.999	143.719	149.771
Minimum Temperature JFM	4.363	2.328	6.765	4.449	4.259	4.301	4.409	4.449
Minimum Temperature AMJ	15.896	14.502	16.931	15.904	15.835	15.901	15.924	15.944
Minimum Temperature JAS	20.925	19.027	21.947	21.146	20.840	20.902	20.964	21.146
Minimum Temperature OND	8.032	6.732	10.051	7.964	7.899	7.775	8.091	8.137
Drip irrigation (Dummy)	0.027	0.000	1.000	0.000	0.041	0.000	0.021	0.000
Furrow irrigation (Dummy)	0.445	0.000	1.000	0.000	0.532	1.000	0.406	0.000
Sprinkler irrigation (Dummy)	0.528	0.000	1.000	1.000	0.427	0.000	0.573	1.000
Alfalfa (Dummy)	0.182	0.000	1.000	0.000	0.163	0.000	0.191	0.000
Forage (Dummy)	0.019	0.000	1.000	0.000	0.012	0.000	0.022	0.000
Maize (Dummy)	0.222	0.000	1.000	0.000	0.157	0.000	0.251	0.000
Meadows (Dummy)	0.421	0.000	1.000	0.000	0.525	1.000	0.374	0.000
Melons (Dummy)	0.019	0.000	1.000	0.000	0.021	0.000	0.018	0.000
Other arable crops (Dummy)	0.035	0.000	1.000	0.000	0.017	0.000	0.043	0.000
Sylviculture (Dummy)	0.012	0.000	1.000	0.000	0.007	0.000	0.014	0.000
Tomato (Dummy)	0.031	0.000	1.000	0.000	0.053	0.000	0.021	0.000
Vegetables (Dummy)	0.060	0.000	1.000	0.000	0.046	0.000	0.066	0.000

The farm plot is assumed as our statistical unit. This can reduce major problems that would otherwise arise due to the underestimation of water-demand elasticity caused by data aggregation (Bontemps and Couture, 2002). We used an unbalanced dataset over the overall period (years between 2013 to 2018) with 12,604 statistical units related to 3,075 plots. The farm plots within the dataset are divided into the treated, considering farm plots that had a flat tariff before 2016, and the control group as the farm plots which already had a volumetric tariff before 2016. We have 3,909 treated and 8,695 untreated units, all of them are included at least once in both periods of pre and post policy application in order to cope with problems due to attrition (Lechner et al., 2016). Irrigation techniques and crops are fixed within one year, but can change among different years. Farmers cultivate different crops and use different types of irrigation technologies classified in three groups: furrow, sprinkler, and drip systems (Table 3). Most of the treated farmers in the sample produce meadows, which is used as input for Parmesan Cheese (a local high-value product). In the untreated group, meadows are the main cultivated crops, but also other crops are present.

The statistical units considered in the sample using the unbalanced panel represent 40.4% of the total CEWD farm plots served between 2013 and 2018 (the total number of plots served is 31,174). We chose to use an unbalanced panel in order to have an extended source of data to cope with problems of non-over lapping in the characteristics of treated and untreated units therefore improving the robustness of our results and deepen the analysis focusing in both specific crops and irrigation systems thanks to a higher statistical variety of observed units.

For robustness check of our results we extent our analysis using a balanced panel of 4,050 (275 Treated plots totally 1,650 units and 400 Untreated plots totally 2,400 units) observations for the same period 2013-2018 (675 farm plot units per year observed for 6 years). In this second case in each farm plot, only one unchanged irrigation technique during all the time frame has been used, whereas crops can differ over the years due to crop rotations. We did this in order to consider the price effect while constraining the dataset to units without technological change. Even if reducing the dataset in a balanced form might have limited statistical units overlapping as a large number of observations would be dropped12. In table 3 are shown the number of observations of the two panels divided by irrigation system and crop. Table 4 shows the average of yearly water demand for both groups. From simple data analysis in both panels of data, there is an evident reduction of water demand for treated units in the years immediately following the application of the cost-recovery tariff scheme, and an evident decrease in the difference between the two groups in both the average water use and the average water requests (Table 4).The evidence of water-demand reduction induced by volumetric tariff Table 4 is the starting point for a more developed analysis based upon a revised version of DID, that is described in the next section.

Table 3. Number of observations per type of irrigation technology and crop for Treated and Untreated farms in the two samples analysed (Balanced and Unbalanced).

				Balanced Panel				
			Treated				**Untreated**	
Crops	*Drip*	*Furrow*	*Sprinkler*	**Total**	*Drip*	*Furrow*	*Sprinkler*	**Total**
Alfalfa	0	0	58	**58**	0	14	178	**192**
Forage	0	0	3	**3**	0	0	21	**21**
Fruits	6	0	0	**6**	30	0	2	**32**
Maize	0	1	70	**71**	6	1	223	**230**
Meadows	0	1469	0	**1469**	0	1773	5	**1778**
Other Arable Crops	0	0	2	**2**	0	0	28	**28**
Sylviculture	0	6	0	**6**	0	30	0	**30**
Tomato	0	0	5	**5**	0	0	12	**12**
Vegetables	18	0	12	**30**	6	12	59	**77**
Total	**24**	**1476**	**150**	**1650**	**42**	**1830**	**528**	**2400**
				Unbalanced Panel				
			Treated				**Untreated**	
Crops	*Drip*	*Furrow*	*Sprinkler*	**Total**	*Drip*	*Furrow*	*Sprinkler*	**Total**
Alfalfa	0	17	620	**637**	3	140	1517	**1660**
Forage	0	0	45	**45**	0	5	188	**193**
Maize	18	13	582	**613**	17	63	2101	**2181**
Meadows	1	2015	35	**2051**	0	3190	61	**3251**
Melon	75	0	9	**84**	114	1	41	**156**
Other Arable Crops	0	3	62	**65**	1	18	356	**375**
Sylviculture	0	26	1	**27**	11	89	19	**119**
Tomato	43	1	164	**208**	16	1	165	**182**
Vegetables	25	3	151	**179**	22	22	534	**578**
Total	**162**	**2078**	**1669**	**3909**	**184**	**3529**	**4982**	**8695**

[12] The statistical units considered in this case the sample using the balanced panel represent 26% of the total CEWD farm plots served over the periods considered.

Table 4. Average of the yearly water demand per ha and number of water requests and differences between Treated and Untreated units over the years (both unbalanced and balanced panel).

		balanced						*unbalanced*					
		T (1)	U (2)	T (3)	U (4)	T-U (1-2)	T-U (3-4)	T (5)	U (6)	T (7)	U (8)	T-U (5-6)	T-U (7-8)
	Year	water use m3/ha	water use m3/ha	water requests n	water requests n	Δ in water use m3/ha	Δ in water requests n	water use m3/ha	water use m3/ha	water requests n	water requests n	Δ in water use m3/ha	Δ in water requests n
Pre policy	2013	7,600	4,486	3.60	3.04	3,114	0.56	5,280	2,512	2.90	2.30	2,767	0.60
Pre policy	2014	6,410	2,662	3.16	1.88	3,748	1.28	4,505	1,675	2.56	1.62	2,831	0.94
Pre policy	2015	7,565	3,385	3.70	2.30	4,180	1.40	5,236	1,989	2.99	1.92	3,247	1.07
Post policy	2016	4,743	3,458	2.99	2.33	1,285	0.66	2,950	2,058	2.63	1.82	892	0.81
Post policy	2017	5,215	4,515	3.55	3.25	701	0.30	3,193	2,347	3.10	2.37	846	0.73
Post policy	2018	2,894	2,493	2.17	1.84	401	0.32	2,183	1,820	2.21	1.78	363	0.43
		Average values over the two periods						**Average values over the two periods**					
Pre policy	2013-2015	7,192	3,511	3.48	2.41	3,681	1.08	5,006.78	2,058.56	2.82	1.95	2,948.22	0.87
Post policy	2016-2018	4,284	3,489	2.90	2.47	796	0.43	2,774.99	2,074.87	2.65	1.99	700.12	0.66

Legend: T=treated U=Untreated, Δ=difference. Source: Authors' elaborations.

3.4 Description of the method of analysis "The Inverse DiD"

The DID will assume as treated farms those with flat tariff in the pre-treatment period (2013-2015) meanwhile the control group are farms that already had a volumetric tariff from 2013 onwards: As in the classical DiD framework the relevant variable is the interaction between the treated group and the period of interest for the policy impact, which in our case is the pre-treatment period (2013-2015) (Angrist and Pischke, 2009).
The model applied to test the policy impact include several variables to make allowance for other confounding factors influencing water use and hiding the policy effect, such as climatic aspects at seasonal level (accumulated precipitations and average minimum temperature), type of crop, irrigation technology, and plot size. A trend variable for the post treatment period has also been inserted into the models in order to control for structural patterns in the data. Furthermore, lagged and lead variables of order one and two have been employed to incorporate anticipatory and forward effects (Angrist and Pischke, 2009; Cerulli, 2015). Individual and year fixed effects have been employed to consider respectively the unobserved heterogeneity and the external shocks which could bias the estimates.
The econometric model is:

$$y_{it} = \delta + \omega_i + \tau_t + \alpha_{it} Flat_{it} * PrePolicy_{it} + \beta_{it} X_{it} + \varepsilon_{it} \qquad (1)$$

where: y_{it} is the volume of water demanded per ha by the farmer for the plot *i* in time *t*; ω_i is the individual fixed effect; τ_t is the year's fixed effect, which captures macroeconomic and exogenous shock factors; α_{it} is the coefficient of the inverse DiD estimator, (our variable of interest) composed of (a) the interaction term of $Flat_{it}$, which is a dummy variable indicating whether the unit is treated (equal to 1 if it had a flat-rate tariff before 2016), and of (b) $PrePolicy_{it}$, which is a dummy variable indicating the pre-policy period (equal to 1 for periods before 2016); β_{it} is a vector of a set of coefficients of the X_{it} confounders. X_{it}includes: 1) a dummy variable indicating whether the farm considering all its plot is higher than 10 ha (which is the value under the 90 percentile), 2) a set of dummies indicating the crop type cultivated in the plot (namely Alpha-Alpha, Forage, Melon, Maize, Meadows, Other Arable crops, Sylviculture, Tomato and Vegetables), 3) a set of dummy indicating the irrigation system implemented in the plot (namely furrow, sprinkler, drip), and 4) the level of seasonal accumulated precipitation and minimum temperature. The climatic variables are expressed in seasonal terms: winter (January, February and March), spring (April, May and June), summer (July, August and September), and autumn (October, November and December). δ is the intercept and ε_{it} is the idiosyncratic error term assumed to have zero mean and variance σ^2 (Greene, 2008).
Despite the impressive numbers of DiD applications in the applied economics literature, Bertrand et al. (2004) point out the major weakness of many applications due to serial correlation problems, which imply strongly biased outcomes in many DiD studies (Bertrand et al., 2004). We test for heteroscedasticity and autocorrelation of the data using a White test and a Wooldridge test, respectively, and indicate that the data is both heteroscedastic and serial-correlated (Greene, 2018). To solve this, clustered standard errors were used at individual level (plot level) as in the applied works of Malina and Scheffler (2015) and Gehrsitz (2017), This option has the same effect as Feasible General Least Squares (FGLS) on serial correlation problems, but without limiting the size of the

dataset. Bertrand et al. (2004) and Hansen (2007) propose as rule of thumb the number being greater than 42[13] and we include 3,075 that should cope with serial correlation. Finally, in order to give greater robustness to our results, an additional analysis was performed on subsamples of irrigation systems (Furrow, Drip, and Sprinkler) and the subsets of most relevant cultivated crops (Meadows, Alpha-Alpha, Melon, Vegetables and Tomato) in order to consider whether differences arise in the effect of the policy among them. All the additional models are applied to both datasets following the baseline specification of the baseline model. In all models in which the number of observation were enough, trend, and the anticipatory and delaying effect of the policy are controlled for with fixed-effect estimation (Cerulli, 2015; Greene, 2018).

3.5 Identification assumptions

The classical DiD approach with panel data in which the coefficient interaction term between the treatment indicator dummy (which indicates whether the unit *i* is part of the treated group) and the period of treatment is defined as the DiD estimator (Cerulli, 2015; Imbens and Wooldridge, 2009). Under specific assumptions the DiD estimator can provide a consistent estimation of the average treatment effect on treated unit (ATET) as the average difference of the expected value of the outcome variable between the period after the treatment and before the treatment (Angrist and Pischke, 2009; Blundell and Dias, 2009). Following Frondel and Schmidt (2005), Blundell and Dias (2009), Lechner (2010), and Cerulli (2015) the main DiD assumptions are:

- Stable Unit Treatment Value Assumption (SUTVA). One and only one potential outcome is observable for each member of the population; there is just one rule for the assignment of treatment and non-treatment, and there is no interaction between units that can influence the treatment assignment.
- Common support Assumption (COSU). This embodies two sub-assumptions: first, that both treated and untreated units are observable; and second, that for each treated unit there is a comparable untreated unit with similar observed characteristics of confounders *X*.
- Exogeneity of the control variable assumption (EXOG). The confounders *X* are not influenced by the treatment.
- Non-effect of treatment on the pre-treatment population in the pre-treatment period (NEPT). This assumption is imposed in order to avoid distortions due to the anticipatory effect on the variable under study.
- Common Trend Assumption (CT). This assumes that the differences in the expected potential non-treatment outcomes (conditioned to the confounders vector *X*) are unrelated to whether or not the treatment is received, and that both sub-populations experience the same trend in the pre-treatment period. This implies that if the treatment did not occur then the two groups would have experienced the same trend. Therefore, this means that changes occurring in the outcome variable depend solely on the effect of the treatment (such as the effect of the policy).

[13] Only in two cases using subsamples of the balanced panel we have a less number of clusters considering drip irrigation as subsample of irrigation system and vegetables as subsample of cropping system.

If the above assumption holds the DiD coefficient is a consistent estimator of the policy effect on the treated group while considering the effect of other observable confounders. Conversely, if the assumptions are violated the estimation of DiD is biased and inconsistent and therefore it can give misleading suggestions regarding the policy effects. All the above listed DiD assumptions were verified. The assumptions in SUTVA and COSU hold due to the nature of the data as farm plots are static and farmers do not interact much amongst them for irrigation decision, but they follow their previous knowledge and expectations on crops water needs. EXOG and NEPT also hold since the treatment assignment is completely exogenous and depends on pre-existing conditions which cannot be influenced by any characteristic of the farms. Self-selection of the treated farms and spill-over effects due to treatment are excluded because the type of farming is not influenced by water costs, which are simply a residual part of production costs. Moreover, migrations of farmers among properties between the areas of treatment and the areas of the counterfactuals are also excluded due to the assumption that local farmers usually use the same lands for generations. In order to control for this migration effect, the plot is regarded as a statistical unit. The possibility that farmer change crop patterns as a response to water pricing is controlled by using the types of crop cultivated on the plot as a possible confounder.
Furthermore, in order to take possible anticipatory or lead effects related to the NEPT assumption into account, lags and leads of order one and two (and order three for lags) as interactions of the treatment dummy with each years before and after the application of the policy have been also included. We also control for specific structural trend in water demand using the interaction of the linear post-trend period and the dummy of treatment. The addition of interactions of single years and post-period trend with the treatment dummy allows testing the CT assumption as an empirical strategy following Autor (2003), Besley and Burgess (2004), Reber (2005) and Furman and Stern (2011). This strategy is a standard empirical method used with the aim of avoiding distorted findings taking into account the structural differences in groups trends. These methods consider the statistically insignificance of trend in the pre-treatment periods and the treatment dummy interaction coefficients for testing the CT assumption (Mora and Reggio, 2019). The full specification used for testing CT assumption used lags and leads of order one and two for the treated units, linear and quadratic trend in the pre-policy period for the treated units and interactions of dummies for the irrigation technology (drip used as reference) using both time invariant and year fixed effects and a full set of confounding factors using the unbalanced panel as shows equation 2 that illustrates the specification of the model considering lags, leads, and trend:

$$y_{it} = \delta + \omega_i + \tau_t + \alpha_{it} Flat_{it} * PrePolicy_{it} + \sum_{\tau=1(2018)}^{T=3(2016)} \theta_{it}\, \tau * Flat_{it} + \sum_{n=2013}^{N=2015} \gamma_{in}\, \omega_{in} * Flat_{it} + \sum_{m=2017}^{M=2018} \delta_{im}\, \omega_{im} * Flat_{it} + \rho_{it} Furrow_{it} * Flat_{it} + \pi_{it} Sprinkler_{it} * Flat_{it} + \beta_{it} X_{it} + \varepsilon_{it} \qquad \text{eq. (2)}$$

All the coefficients and variables in eq. 2 are the same as those in the base model in eq. 1, with the sole additions of the coefficients γ_{in} for lags (order 1, 2 and 3) and δ_{im} for the leads (order 1 and 2) as interaction terms of the policy treatment dummy $Flat_{it}$ with both the dummy ω_{in} for the specific years before the policy (lags years 2013, 2014, 2015) and the dummy ω_{im} for the years after the policy (leads years 2017, 2018). Moreover, the coefficient θ_{it} of the time trend for the post-policy period[14] has been added as suggested

14 In standard empirical works the CT assumption is tested using the interaction of the trend in the pre-policy period with the treatment dummy and the lags of the DiD estimators as the single years before the

by Cerulli (2015) and Mora and Reggio (2019). It can be seen that eq.1 is expanded by adding ρ_{it} and π_{it} as estimators of the interaction between irrigation technology dummies and the treatment dummy in order to consider time variant effect due to technology change for the treated group. The specification in eq. 2 will be used throughout the models without the interaction term of the treatment dummy with irrigation technologies, but using dummies for irrigation technology as a classical confounder for the whole sample.
Appendix 1 shows complete results of the analysis with the result that all coefficients of the interaction of the trend θ_{it} and the leads δ_{it} with the treatment dummy turn to be insignificant., Additionally, a robustness test following Lenhart (2017) and Hangoma et al. (2018) who dealt with the same problem is done by applying Mora and Reggio (2019, 2015) robustness check model which allow for testing CT assumption using a fully flexible model alternative to standard econometric strategies. The results of the full flexible approach of Mora and Reggio (2015) are shown in appendix 2.
Both tests suggest that our analysis do not violate the CT assumptions considering the treatment periods in a reversed way as no evident structural different tendency arose among the two group in the post treatment period whereas in the pre-treatment period statistically significant differences are present. Therefore, we can consider the tariff scheme as the explanatory factor behind the differences within both groups in the pre-treatment period. Therefore, the model analyses whether the policy (water tariff) determines changes in water demand.
Another test on CT assumption in water demand between the two groups has been verified by considering the parallel trends in the periods after the application of the policy using a graphical analysis (Figure 2 and Figure 3) by checking for CT in the periods after the application of the policy (Blundell and Dias, 2009; Lechner, 2010). The graphical analysis of values of the means of the two groups show parallel trends for treated and untreated units after the policy application (in 2018, 2017 and 2016), but that they have different paths before the policy (2013, 2014 and 2015). Between the two periods of analysis, there is an evident difference in water consumption of the treated farms in the pre-policy, with higher water use pre-treatment (2013 – 2015) than in the post-treatment period (2016 – 2018). The graphical analysis on the CT has been carried out using both the balanced and the unbalanced dataset.
The difference in means of the two groups reveals a parallel trend after the implementation of the policy and a relevant structural break can be seen graphically in Figure 4 and Figure 5 between the years 2016-2015 during the introduction of the policy with different water use patterns. The same graphical verification was carried out using subsamples of the three different irrigation technologies and similar results were found for the CT assumption (from Figure 6 to Figure 10 in Appendix). Thus, while the CT assumption holds, the effect of the policy can be considered as the only element influencing the differences in the trends of the two groups.

policy. In our case as we want to reverse our analysis we used to test the CT assumption the interaction of the trend after the policy introduction (τ=1 with 2018, τ=2 with 2017 and τ=3 with 2016) with the treatment dummy and leads of the DiD estimator as the interactions of the years dummies after policy introduction (2017 and 2018) with the treatment dummy.

Figure 2. Trends of average values of water use by Treated and Untreated units using a balanced panel.

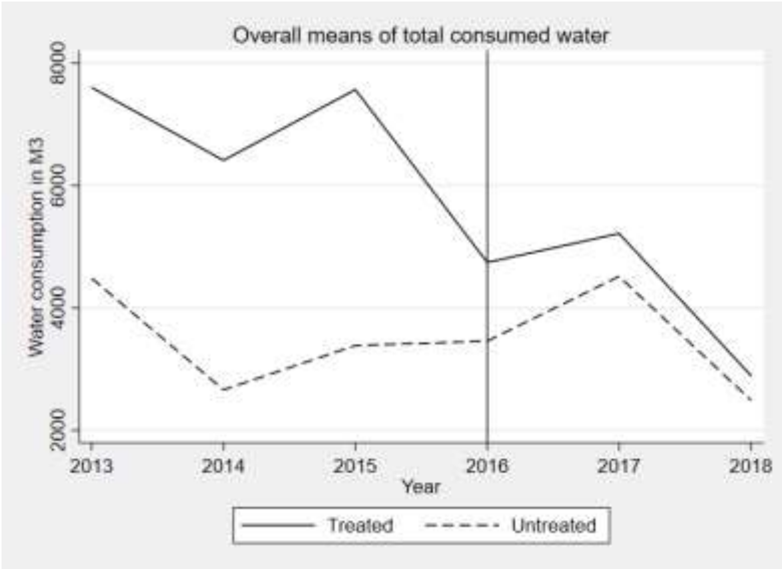


Figure 3. Trends of average values of water use by Treated and Untreated units using an unbalanced panel.

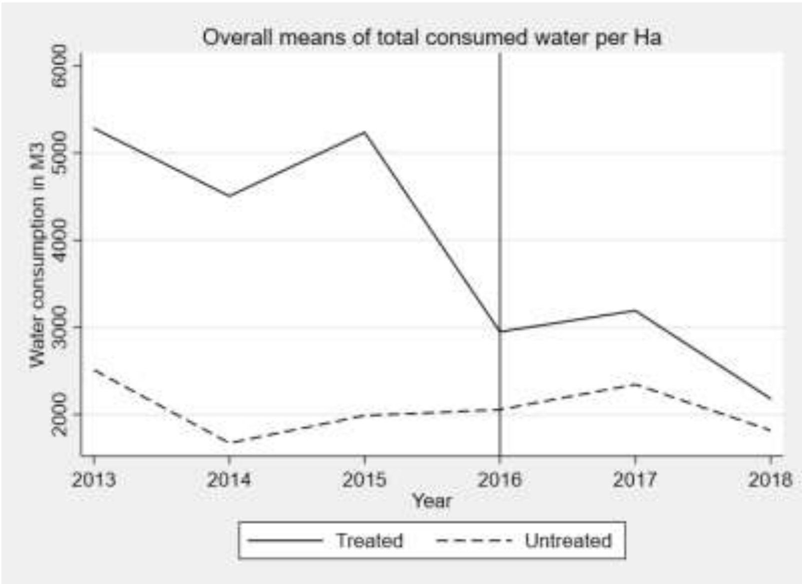


Figure 4. Difference in means over the whole period (from 2013 to 2018) between Treated and Untreated units using a balanced panel.

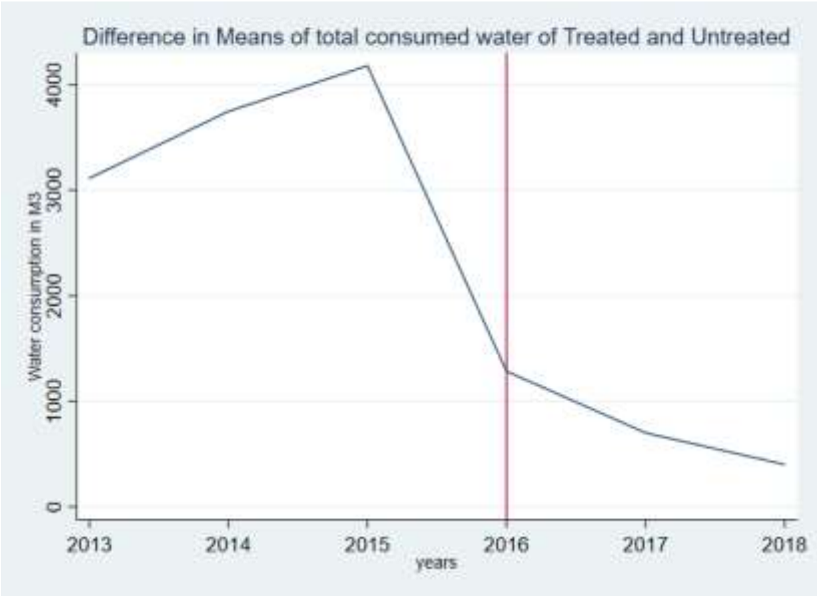
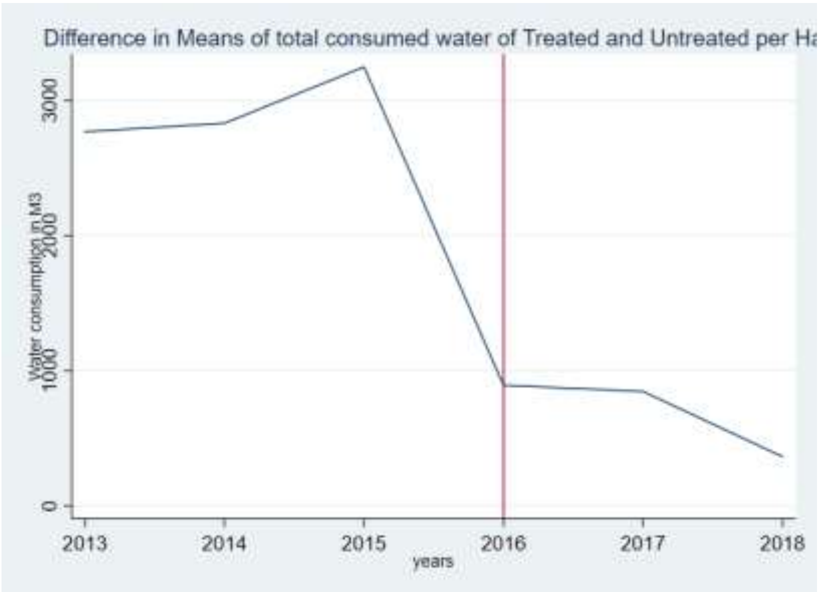


Figure 5. Difference in means over the whole period (from 2013 to 2018) between Treated and Untreated units using an unbalanced panel.



4 Results

In all the models, the coefficient of the inverse DiD estimator is significant (0.01 significance level) with a positive sign a part of the model using the sprinkler subsample in which the estimator is not significant with opposite sign. This indicates that, considering the whole sample, in the pre-treatment period, water demand for treated farms was consistently higher than the farms with volumetric tariffs. The water saving after policy implementation in the farms with flat tariff was 2.533 m^3 per ha . The specification of the model does not influence the statistical significance of the inverse DiD coefficient. Indeed, the leads and the time trend (as interactions of the treatment variable with the time trend of the post policy period) do not modify the sign nor the magnitude of the coefficient of the inverse DiD estimator. The results of the general econometric models using the unbalanced panel are shown in Table 5, in column 3 the model is fully specified highlighting that CT assumption on the whole unbalanced panel holds. Considering irrigation technology sub-samples differences among irrigation systems are evident, but in general it is not statistically evident a general difference in trend patterns considering the two groups of farms (treated and not treated). The time trend is significant only for furrow irrigation when using subsamples of irrigation technology and the balanced panel. Including policy delaying effects and the structural trend pattern, the coefficient of the inverse DiD is still significant and positive, which indicates that our regression models considering both dataset are robust. The results of our analysis consequently suggest that a change in water-use behaviour occurred in the treated farms principally due to the introduction of the water-pricing policy.

Furrow irrigation systems shows a higher impact as the reduction from the pre-policy period is important (decreasing 4,263 m^3 per ha after policy implementation), with lower reduction for drip irrigation (1,869 m^3 per ha lower after the policy application) (Table 5 columns from 4 to 6). Using the unbalanced panel, the inverse DiD estimator is not significant in the case sprinkler subsample.

The analysis using balanced panel release similar findings (Table 6), but in this case all the irrigation technology sub samples have statistical significant inverse DiD estimators with different levels of magnitudes (Table 6 columns from 4 to 6). Using the balanced panel Furrow and Drip irrigation systems are similarly the most affected by the policy (with respectively ATET of 3,860 m^3 per ha and 3,436 m^3 per ha), whereas the inverse DiD estimator for sprinkler irrigation systems turn to be significant indicating a difference 1,469 m^3 per ha between the pre and post policy periods. Furthermore, in this case, the time trend is significant giving evidence that some differences on pattern trend arise using different subsamples (in sprinkler and drip time trend is not significant).

Similarities of results using both balanced and the unbalanced panel datasets give robustness to our analytical approach. Moreover, this suggests that the effect of the policy is evident both considering good fit of the observable characteristics (unbalanced panel) of treated, and untreated groups and removing the effect of technological change during time (balanced panel).

The analysis using different crop systems highlights positive effects in terms of water use reduction for most of the crops, but with heterogeneous effects (Table 7 and 8). Meadows seems to be the more sensitive crop with a mean difference between the two periods of 4,174 m^3 per ha and 3,886 m^3 per ha using respectively the unbalanced and balanced panel, tomato shown an ATET[15] of 3,024 m^3 per ha (only unbalanced panel), Alfalfa ATET is 820.4 m^3 per ha (unbalanced) and 1,707 m^3 per ha (balanced), melons 1,809 m^3 per ha (only unbalanced panel) and maize 2,234 m^3 per ha (balanced, not significant with unbalanced dataset). Even in this case, considering different crop systems, the results confirm that the water-pricing policy was effective on the treated sample with the inverse DiD coefficients positive and in most of the cases with high statistically significance.

[15] ATET in the DiD framework is coefficient of the DiD estimator.

Table 5. Results of the econometric models using the unbalanced panel dataset. Columns 1-3 consider the general specification of the model adding leads of order 1 and 2 and group time trend in the post-policy period. In columns 4-6 irrigation technology subsample are considered.

VARIABLES	(1) Model 1. General	(2) Model 2. General	(3) Model 3. General	(4) Model 4. Furrow	(5) Model 5. Sprinkler	(6) Model 6. Drip
Dep. variable **Water Use (M3/Ha)** ***(Unbalanced Panel)***						
Inv DID	2,339***	3,033***	2,533*	4,263***	-302.0	1,869***
(Treatment x pre policy period)	(17.48)	(14.18)	(1.894)	(3.183)	(-0.273)	(3.100)
Post policy time trend		345.4***	125.5	778.5*	-605.3	-73.66
(inverse time trend from 2018 to 2016 x Treated		(4.779)	(0.279)	(1.729)	(-1.643)	(-0.357)
Inv DID Lead1			253.0	206.1	-662.9*	-15.28
(Year 2017 x Treated)			(0.557)	(0.427)	(-1.736)	(-0.0350)
Inv DID Lead2			-520.0	69.36	-1,097	
(Year 2018 x Treated)			(-0.583)	(0.0780)	(-1.474)	
Constant	47,901***	5,939	10,341	-36,704	-4,516	-3,512
	(4.975)	(0.298)	(0.522)	(-0.967)	(-0.250)	(-0.0291)
Observations	12,604	12,604	12,604	5,607	6,651	346
R-squared		0.214	0.216	0.286	0.171	0.256
Number of Farm Plots	3,075	3,075	3,075	1,181	1,955	123
Robust	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Plot	Plot	Plot	Plot	Plot	Plot
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Lags	No	No	No	No	No	No
Leads	No	No	Yes	Yes	Yes	Yes
Trend	No	No	Yes	Yes	Yes	Yes
Controls						
Dimension > than 10 Ha	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Min. Temp.	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Acc. Precip.	Yes	Yes	Yes	Yes	Yes	Yes
Irrigation Technology	Yes	Yes	Yes	Yes	Yes	Yes
Crop Type	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Results of the econometric models using the balanced panel dataset. Columns 1-3 consider the general specification of the model adding leads of order 1 and 2 and group time trend in the post-policy period. In columns 4-6 irrigation technology subsample are considered.

VARIABLES	(1) **Model 1. General**	(2) **Model 2. General Time trend**	(3) **Model 2.1 General Time trend and Leads**	(4) **Model 3. Furrow**	(5) **Model 4. Sprinkler**	(6) **Model 5. Drip**
Dep. variable Water Use (M3/Ha) ***(Balanced Panel)***						
Inv DID	2,673***	3,890***	4,013***	3,860***	1,469***	3,436**
(Treatment x pre policy period)	(10.71)	(13.10)	(13.43)	(10.37)	(3.197)	(3.116)
Post policy time trend		654.9***	657.0***	828.3***	-62.13	270.3
(inverse time trend from 2018 to 2016 x Treated		(6.390)	(6.417)	(6.445)	(-0.500)	(1.127)
Inv DID Lead1			349.0*	-252.4	-49.75	862.0
(Year 2017 x Treated)			(1.758)	(-0.958)	(-0.168)	(1.702)
Constant	66,574*	34,229	41,714	9,385	115,208***	-443,474
	(1.684)	(0.891)	(1.072)	(0.177)	(2.863)	(-1.406)
Observations	4,050	4,050	4,050	3,306	678	66
R-squared	0.320	0.325	0.325	0.352	0.237	0.504
Number of ID_Plot	675	675	675	551	113	11
Robust	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Plot	Plot	Plot	Plot	Plot	Plot
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Lags	No	No	No	No	No	No
Leads	No	Yes	Yes	Yes	Yes	Yes
Trend	No	Yes	Yes	Yes	Yes	Yes
Controls						
Dimension > than 10 Ha	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Min. Temp.	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Acc. Precip.	Yes	Yes	Yes	Yes	Yes	Yes
Irrigation Technology	No	No	No	No	No	No
Crop Type	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Results of the econometric models considering single cropping systems using the unbalanced panel dataset.

VARIABLES	(1) Model 1. Meadows	(2) Model 2. Maize	(3) Model 3. Tomato	(4) Model 4. Alfalfa	(5) Model 5. Vegetables	(6) Model 6. Melon
Dep. variable						
Water Use (M3/Ha)						
(Unbalanced Panel)						
Inv DID	4,174***	-1,017	3,024**	820.4***	687.0	1,809***
(Treatment x pre policy period)	(3.259)	(-0.671)	(2.456)	(2.876)	(0.943)	(2.936)
Post policy time trend	865.4**	-926.1*	-69.48	-133.2	-374.5**	-319.6
(inverse time trend from 2018 to 2016 x Treated	(2.005)	(-1.848)	(-0.177)	(-1.152)	(-1.969)	(-1.083)
Inv DID Lead1	-206.7	-1,341**	-741.1	-77.59	-776.6	-88.66
(Year 2017 x Treated)	(-0.441)	(-2.456)	(-0.892)	(-0.449)	(-1.429)	(-0.211)
Inv DID Lead2	71.95	-1,873*				
(Year 2018 x Treated)	(0.0847)	(-1.809)				
Constant	-53,667	10,425	155,380	-27,730	-26,635	-21,219
	(-1.314)	(0.263)	(0.992)	(-0.932)	(-0.452)	(-1.140)
Observations	5,302	2,794	390	2,297	757	240
R-squared	0.297	0.173	0.305	0.137	0.171	0.237
Number of ID_Plot	1,070	1,166	200	894	389	73
Robust	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Plot	Plot	Plot	Plot	Plot	Plot
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Lags	No	No	No	No	No	No
Leads	Yes	Yes	No	No	No	Yes
Trend	Yes	Yes	No	No	No	Yes
Controls						
Dimension > than 10 Ha	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Min. Temp.	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal Acc. Precip.	Yes	Yes	Yes	Yes	Yes	Yes
Irrigation Technology	Yes	Yes	Yes	Yes	Yes	Yes

Table 8. Results of the econometric models considering single cropping systems using the balanced panel dataset.

VARIABLES	(1) Model 1. Meadows	(2) Model 2. Maize	(3) Model 3. Alfalfa	(4) Model 5. Vegetables
Dep. variable				
Water Use (M3/Ha)				
(balanced Panel)				
Inv DID	3,886***	2,234**	1,707**	-1,481
(Treatment x pre policy period)	(10.31)	(2.186)	(2.007)	(-0.595)
Post policy time trend	880.2***	-81.23	-29.16	-915.8
(inverse time trend from 2018 to 2016 x Treated	(6.754)	(-0.327)	(-0.117)	(-1.318)
Inv DID Lead1	-335.9	19.60	-22.34	477.0
(Year 2017 x Treated)	(-1.241)	(0.0315)	(-0.0501)	(0.660)
Constant	-14,084	99,913	56,103	172,176
	(-0.260)	(1.312)	(0.780)	(1.350)
Observations	3,247	301	250	107
R-squared	0.356	0.292	0.295	0.310
Number of ID_Plot	544	76	58	28
Robust	Yes	Yes	Yes	Yes
Cluster SE	Plot	Plot	Plot	Plot
Year FE	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Lags	No	No	No	No
Leads	Yes	Yes	No	No
Trend	Yes	Yes	No	No
Controls				
Dimension > than 10 Ha	Yes	Yes	Yes	Yes
Seasonal Min. Temp.	Yes	Yes	Yes	Yes
Seasonal Acc. Precip.	Yes	Yes	Yes	Yes
Irrigation Technology	No	No	No	No
Crop Type	No	No	No	No

The new tariff policy was effective on the treated farms for all the irrigation systems of the CEWD and most of the crop systems analysed, but with marked heterogeneities of the effect of the water pricing policy. In fact, the analysis of the magnitude of the coefficients by irrigation system show that furrow system is the most responding to the application of a volumetric tariff in terms of water demand reduction. As expected furrow irrigation system is the most sensitive system to water pricing as it is the most inefficient method of water applications. Drip is unexpectedly more responsive to water tariff introduction than sprinkler and this can depend by the fact that drip irrigation can give a higher level of control to the farmer on water applications increasing their capacity to price changes adaptation. Sprinkler is the last irrigation system term of in responsiveness to price introduction (for unbalanced panel inverse DiD estimator is not significant with balanced panel is significant at 0.01, but with a minor magnitude compared to the others). This finding is counterintuitive as sprinkler should be higher responsive than drip, this could depend by the fact that some irrigation technologies are more linked to specific crops and this could influence the water demand elasticity (Berbel et al., 2018). Unfortunately, our analysis cannot be deepen running econometric models on subsamples of specific crops by each irrigation technologies due to excessive reductions of the unit of analysis. The effect of the introduction of the volumetric tariff within the treated group, is highlighted in Table 9 in which the ATET of each model is shown divided for cropping and irrigation systems.

Table 9: Average irrigation use differences between the pre-policy and the post policy periods (m3/ha)

ATET (m^3/Ha)	Unbalanced panel	significance	Balanced panel	significance
All sample	2,533	0.10	4,013	0.01
		Irrigation systems		
Furrow Irrigation	4,263	0.01	3,860	0.01
Sprinkler Irrigation	n/a	n/a	1,469	0.01
Drip Irrigation	1,869	0.01	3,436	0.05
		Cropping systems		
Meadows	4,174	0.01	3,886	0.01
Maize	n/a	n/a	2,234	0.01
Tomato	3,024	0.01	n/a	n/a
Alfalfa	820.4	0.01	1,707	0.01
Vegetables	n/a	n/a	n/a	n/a
Melon	1,809	0.01	n/a	n/a

Note: $1m^3$/ha =0.1mm

Both all irrigation technologies and all crops (a part of vegetables) show a marked response to the policy change in at least one model using either the unbalanced or the balanced panel. Table 9 shows that the response to policy is greater for Meadows, Tomato and Maize than Alfalfa and Melons. Vegetables (sugar beet, onion, potato, and mixed horticulture) seems to be not responsive to the water pricing policy. This may be explained by the fact that vegetables are highly water intensive crops with high value embedded as most of them are final product for markets flattening the elasticity of water demand to water price and that water stress reduces product quality affecting seriously to the price.

5 Discussion

Agriculture, especially in Europe, has been considered traditionally as a strategic sector protected through governmental support (Abu-Zeid, 2001). This has also occurred in the irrigation sector since the cost of water services frequently remain unrecovered (Massarutto, 2003). Without cost recovery or distorting tariff structures such as a flat-rate tariff, farmers can operate structurally with low levels of marginal water costs, below the level of marginal water benefits. This leads to a situation of undervaluing the natural resource in the farmers' production function and in their decisions regarding water allocation schemes (Cooper et al., 2014), where water is considered as a public commodity with problems of over-exploitation and resource misallocation (Hardin, 1968). Therefore, in the absence of suitable incentives aimed at internalizing the full cost of water resources, management methods can become inefficient (Rogers, 2002) with major externalities due to over-withdrawal and over-irrigation (Dinar and Mody, 2004; Wheeler et al., 2015).
Pricing policies for water have been advocated since 1992, with the Dublin declaration in which water was recognized as a social commodity with an intrinsic economic value, and where water pricing was identified as a good measure for the internalization of externalities due to over-irrigation (Dublin Statement, 1992). Transaction costs related to

design, implementation of metering infrastructures, and to the costs of control and enforcing the policy constitute possible drawbacks of water-pricing policies (Johansson, 2002). Moreover, there is uncertainty with the outcomes and heterogeneity of the impacts, which are case specific, and difficulties arise in creating best-practices and generalizations (Lago et al., 2015; Molle and Berkoff, 2007).

The findings of our study highlight the effectiveness of the pricing policy applied by the CEWD as an effective tool for encouraging the efficient use of water by farmers in order to sustain water conservation programs. In most of the specifications of the models, the coefficients of the application of the inverse DiD are significant and positive, which confirms that the introduction of the policy was effective, with reductions between 2,533 m^3per ha and 4,013 m^3per ha considering respectively an unbalanced and a balanced panel for the analysis. Therefore, our findings highlight that volumetric pricing act as a signal of scarcity to the farmer to induce efficient resource use. In our case, farmers reduced their water demand even if the water tariff is small, which indicates that simply passing from a quasi-zero to a non-zero water price can consistently reduce free-rider attitudes, thereby internalizing externalities. Another relevant factor is that we should consider that even if water tariff is zero (flat tariff), water use in irrigation bears certain costs, such as labour, information, energy, management, and other opportunity costs to the farmer, some explicit and others implicit.

Our study confirms the findings of Smith et al. (2017), Drysdale and Hendricks (2018), and Smith (2018) regarding groundwater, in which they indicate that the introduction of economic incentives and water quota restrictions consistently reduces water consumption and water saving behaviours. Following those studies, the introduction of a tariff reduced the amount of agricultural water extraction by 33% in Colorado (Smith, 2018; Smith et al., 2017) and 26% in Kansas (Drysdale and Hendricks, 2018). In our analysis, a 50% (unbalanced panel) and 55.8[16]% (balanced panel) average reduction of water demand due to the policy was found, which is in line with their findings, but slightly higher. Part of the differences in the results to previous studies can be explained by the ex-ante context, since groundwater should be pumped so that farmers pay the internal cost of energy, while surface water in the CEWD was almost free before the policy implementation. Furthermore, there are obvious differences between the agricultural systems of US states and those of northern Italy, although in both cases farmers are responsive to economic measures in water demand.

As mentioned earlier, the context before the policy change involved over-irrigation (see comments regarding Table 1), which from the hydrological point of view implies that excess water is not ‘lost ‘ for the basin since it returns to the system (Berbel and Mateos, 2014) and can be reused downstream, but the quality is deteriorated because it removes nutrients (e.g., N, P, K) in the form of chemicals and salts that are exported from the field, and therefore generates diffuse pollution externalities within the basin and into the sea and coastal ecosystems. The coastal area of the ERR is highly sensitive to anthropic pressures, especially nutrient loads from agriculture. Recently, the run-off of the Po river (Enza and Secchia river are tributaries of the Po) caused a significant growth of algae in the Northern Adriatic Sea and incurred major damage in terms of ecosystem impacts that consequently also affected regional tourism and the fishing sector (Russo et al., 2009). Diffuse pollution from the Po river has been estimated to be responsible for at least of 50% of the eutrophication in the Adriatic sea (de Wit and Bendoricchio, 2001). As farmers reduce water use, they are simultaneously improving water quality of return flows and therefore environmental conditions downstream in all the related ecosystems of Po

[16] Values calculated as the ratio between the ATET (Table 9) for the baseline model and the average use of water in the pre-policy period (Table 4 8th row 1st and 5th column) using both datasets.

river basin. The increase in the efficiency of water use induced by water conservation techniques improves water quality by reducing this significant externality of agricultural activities in the ERR (Berbel, Expósito et al. 2019).

One interesting point which arises from the results show a different response in water saving considering different irrigation systems. Furrow is the most responsive to the policy being the most inefficient, but our findings highlighted that in this study drip irrigation systems reacted to the introduction of the water pricing policy more than sprinkler irrigation (which was not significant with the unbalanced panel). This is counterintuitive according to analytical models of farmer response (Berbel et al., 2018). One hypothesis to be tested in the future is considering in the analysis the initial cost due to energy use required by irrigation systems[17] and the type of cultivated crops by irrigation systems as these two elements may explain the unresponsiveness of sprinkler systems to the policy. Anyway we consider unobserved heterogeneities between the units using a fixed effects approach as a ceteris paribus condition between plots, therefore our models take into accounts different initials energy prices and different endowments between plots.

The relevancy of this research is the in-depth econometric analysis on a large sample of plot level observations including information regarding the irrigation system and crop. One limitation of our approach is related to the unobservability of the effect of metering as a distinct element to the price effect. In residential water use there are evidences of the impact of just metering water and of information-sharing among users in influencing the reduction of water use as a behavioural response (Ferraro and Price, 2013). This can easily apply to the agricultural sector (Wallander, 2017), therefore, water metering can have an impact by its own on farmers response to water pricing policies without, but this element is difficult to be considered in our analysis (Wallander, 2017).

In our study, reliable metering was introduced since the 2013-2015 in the pre-policy phase, however, the metering information remained unused for water use by farmers who pay a flat tariff scheme. The farmers' perception and their behavioural responses to the change of paradigm (metering vs. non-metering) is not totally measurable, due to the difficulties in splitting the total impact of the policy change between the two components: a marginal water-pricing increase and water metering by itself. In our study we observe the total effect of two components, further studies might focus on considering the separated effects of metering and pricing water. Furthermore, the elasticity of water use is difficult to measure with our data for this combined effect of metering and marginal price, therefore a different methodology should be undertaken to estimate elasticity of water demand, for further details see Berbel and Pronti (2020).

6 Conclusion

The findings of this study indicate that volumetric water pricing is an effective strategy for inducing water saving in irrigation also in the case of water abundant regions such as North Italy. The case study of the CEWD shows that volumetric pricing triggers an increase in water-use efficiency even with a low water price (below 0.05 EUR/m^3). Volumetric tariffs render marginal costs of water higher than zero, thereby introducing a

[17] Initial energy costs of irrigation systems can be different even with flat rate tariff due to different use of pressurized water and water distribution to plants. Espinosa-Tasón et al. (2020) show important differences of energy costs for sprinkler and drip being respectively 0.21 kwh/m^3 and 0.12 kwh/m^3.

non-zero value of water resources into the cost function of the farmers, who therefore start to use the resource as a private commodity instead of a public commodity.
The overall effect of the policy is positive and this has been demonstrated by the huge reduction of water use. However, in our work, a combination of ‘metering’ and ‘small price increase’ is introduced almost simultaneously and the individual impact of each instrument cannot be easily differentiated. The transition from a zero marginal cost (common commodity) to a priced and measured input has been demonstrated to be highly effective in our case where instances of ‘over-irrigation’ in the behaviour of farmers was previously evident.

Finally, the inverse-DiD methodological proposal is a novel application of a simple and robust method that can be used to test policy innovations. The inverse DiD method relies strictly on the classic DiD application, but extends the domain of policy cases in which the application of this econometric tool can be applied. The proposed approach enables the standard DiD method to be expanded for use in environments other than those required by the original method. We hope that future applications of the inverse DiD method will demonstrate the utility of this empirical application.

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Appendix 1

Robustness check and verification of the Common Trends assumption using different models

Table 10. CT test using standard econometric methods adding interactions of dummies for the irrigation systems, years and post treatment trend with the treated dummy.

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8
Dep variable **Water Use (M3/Ha)**								
Year 2013 (Dummy)	420.3***	506.3***	484.1***	478.5***	478.5***	548.8***	-3,144**	-3,144**
	(7.995)	(9.857)	(9.304)	(9.193)	(9.193)	(10.79)	(-2.577)	(-2.577)
Year 2014 (Dummy)	-571.6***	-486.8***	-507.5***	-513.7***	-513.7***	-472.9***	7,518**	7,518**
	(-11.79)	(-10.31)	(-10.74)	(-10.87)	(-10.87)	(-10.63)	(2.105)	(2.105)
Year 2015 (Dummy)	0.766	87.15*	67.02	59.48	59.48	-53.48	-6,405***	-6,405***
	(0.0157)	(1.814)	(1.386)	(1.235)	(1.235)	(-1.194)	(-4.885)	(-4.885)
Year 2017 (Dummy)	449.5***	542.5***	484.9***	467.4***	467.4***	467.1***	-10,390***	-10,390***
	(9.991)	(12.22)	(10.28)	(10.10)	(10.10)	(10.08)	(-5.623)	(-5.623)
Year 2018 (Dummy)	-794.2***	-590.5***	-588.3***	-570.8***	-570.8***	-571.0***	-5,054***	-5,054***
	(-14.11)	(-11.06)	(-11.13)	(-10.98)	(-10.98)	(-10.98)	(-3.125)	(-3.125)
InvDID (Treatment x pre policy period)	2,274***	2,905***	3,648***	2,573*	2,573*	2,307*	2,422*	2,860**
	(18.57)	(14.01)	(8.881)	(1.865)	(1.865)	(1.655)	(1.759)	(2.090)
Post policy time trend (inverse time trend from 2018 to 2016 x Treated)		301.4***	1,122***	162.2	-318.5	-357.8	119.4	-646.8
		(4.219)	(2.778)	(0.351)	(-0.173)	(-0.193)	(0.259)	(-0.353)
Post policy time trend^2			-203.0**		160.2	170.3		255.4
			(-2.077)		(0.348)	(0.367)		(0.558)
DID_F1 (Year 2017 x Treated)				108.6	429.1	439.0	327.6	838.3*
				(0.232)	(0.908)	(0.923)	(0.705)	(1.767)
DID_F2 (Year 2018 x Treated)				-320.5			-510.8	
				(-0.348)			(-0.558)	
DID_L1 (Year 2015 x Treated)						592.5***	438.4***	
						(3.926)	(2.842)	
DID_L2 (Year 2014 x Treated)						118.1	-194.9	-633.4***
						(0.828)	(-1.257)	(-4.548)
DID_L3 (Year 2013 x Treated)								-438.4***
								(-2.842)
Crop 1							-538.4*	-538.4*
							(-1.856)	(-1.856)
Crop 2							-124.1	-124.1
							(-0.400)	(-0.400)
Crop 3							-265.2	-265.2
							(-0.938)	(-0.938)
Crop 4							1,139**	1,139**
							(2.521)	(2.521)
Crop 5							-161.0	-161.0
							(-0.449)	(-0.449)
Crop 6							-434.2	-434.2
							(-1.514)	(-1.514)
Crop 8							929.7***	929.7***

							(3.110)	(3.110)
Crop 9							-377.1	-377.1
							(-1.355)	(-1.355)
Min Temp JFM							-3,542***	-3,542***
							(-5.137)	(-5.137)
Min Temp AMJ							3,971***	3,971***
							(4.182)	(4.182)
Min Temp JAS							-2,074***	-2,074***
							(-3.675)	(-3.675)
Min Temp OND							-1,114*	-1,114*
							(-1.664)	(-1.664)
Acc Precip JFM							-41.75***	-41.75***
							(-4.397)	(-4.397)
Acc Precip AMJ							17.07***	17.07***
							(2.801)	(2.801)
Acc Precip JAS							-44.28***	-44.28***
							(-5.162)	(-5.162)
Acc Precip OND							-34.87***	-34.87***
							(-3.727)	(-3.727)
Furrow (Furrow Irrigation Type (Dummy) x Treated)			808.3					
			(1.291)					
Sprinkler (Sprinkler Irrigation Type (Dummy) x Treated)			-1,318***					
			(-3.504)					
Constant	2,337***	2,055***	1,894***	2,186***	2,186***	2,195***	25,014	25,014
	(69.90)	(31.16)	(10.93)	(5.097)	(5.097)	(5.085)	(1.277)	(1.277)
Observations	12,604	12,604	12,604	12,604	12,604	12,604	12,604	12,604
R-squared	0.194	0.196	0.202	0.197	0.197	0.199	0.215	0.215
Number of ID_Plot	3,075	3,075	3,075	3,075	3,075	3,075	3,075	3,075
Robust	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	YES	YES	Yes	Yes	Yes	Yes	Yes	Yes
Lags and Leads	No	No						
Trend	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trend^2	No	No	No	No	Yes	No	No	No
Lags			No	No	No	Yes	Yes	No
Leads			No	Yes	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In our case lags, leads and post treatment trend must be considered conversely for the interpretation of anticipatory and post policy effects and parallel trends among groups. In fact, we are considering the convergence effect of imposing a pricing tariff to farmers without that imposition with farmers that already experienced that policy.

Appendix 2

Robustness check and verification of the Common Trends assumption using the fully flexible model of Mora and Reggio (2019)

The approach of Mora and Reggio (2019) deals with the untestable assumption of common trends (CT), which is fundamental in the application of the DiD approach for ensuring unbiased and consistent results. As discussed in the paper, the authors use a different approach to classic econometric analysis used in empirical works for evidencing structural differences between the two groups under analysis (treated and control groups), such as the inclusion in the models of the interactions between year dummies and post-policy trends with the treatment dummy.

The authors defined an alternative approach using a family of different parallel (*q*) assumptions with *q* indicating the maximum period of pre-treatment (*q* ranges from 1 to the number of pre-treatment periods). They assume that in absence of treatment the average *q*-differences in the outcome variable between the two tested groups are equal. In other words, they consider that in the absence of treatment, average changes (and the speed of the change) in the outcome among treated are equal to the average changes among comparable controls (Mora & Reggio, 2015).

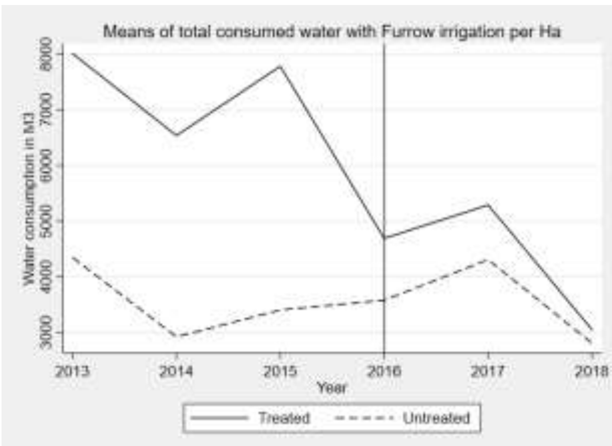
The model they propose is fully flexible to group specific dynamics with less restrictions to standard econometric test to identify CT assumption. We applied their approach for robustness check of our analysis on CT assumption made with the standard empirical approach (see Appendix 1). For a deeper understanding of the econometric approach and of the method used in this appendix see Mora and Reggio (2015, 2019). Further details are also available in Hangoma et al. (2018), which uses a similar analysis for robustness check of their DiD method.

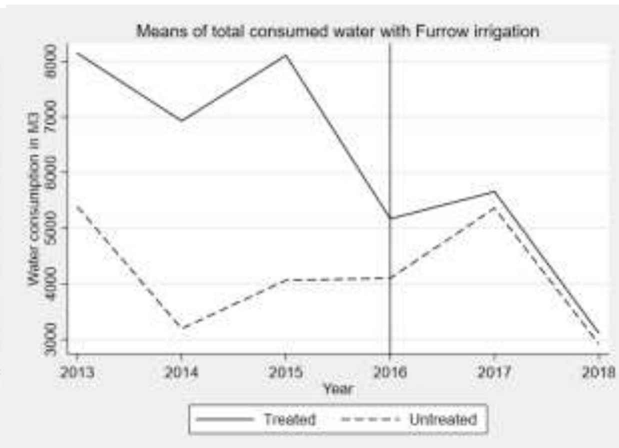
We used the *didq* STATA package implemented by Mora and Reggio (2015) for testing the CT assumption using the fully flexible model. We inverted the timeframe of our dataset in order to test the CT assumption in the post treatment period of policy application (such as 2018 = t1; 2017 =t2, 2016=t3) and the differences in trends in the pre-treatment periods (2015=t4, 2014=t5, 2013=t6). We used the OLS model adding the controls used in the baseline model to improve the accuracy of the test (a set of dummies for the type of Crop, seasonal minimum temperature, seasonal accumulated precipitations, size of the plot higher than 10 ha, interaction of the treated dummy with furrow and sprinkler irrigation technology). The CT test used by Mora and Reggio is a Wald test on the joint equivalence of parallel-*q* pre-treatment periods (in our case post-treatment) in which H_0 is the hypothesis of CT assumption. In our case, the H_0 is strongly not rejected in all the cases, therefore we cannot state that there is no CT for our period of analysis, which corresponds to the years after the application of the water pricing policy. Therefore, CT assumptions in our case hold and our analysis can be considered unbiased and reliable. In table 11 all the results of the tests.

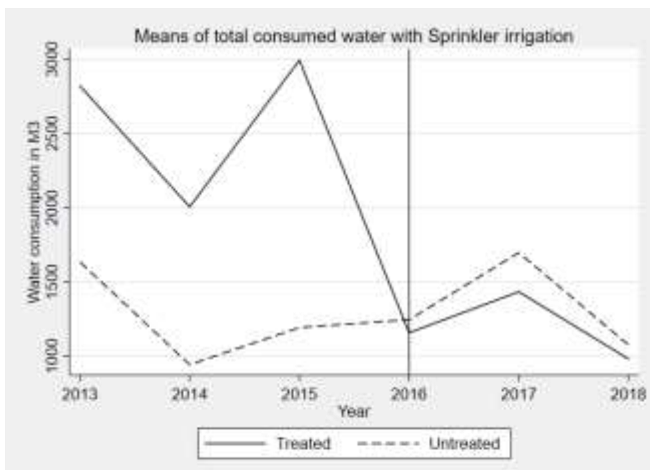
Table 11. CT test using the fully flexible model of Mora and Reggio (2015,2019). H0 is the hypothesis of common trends between treated and controls.

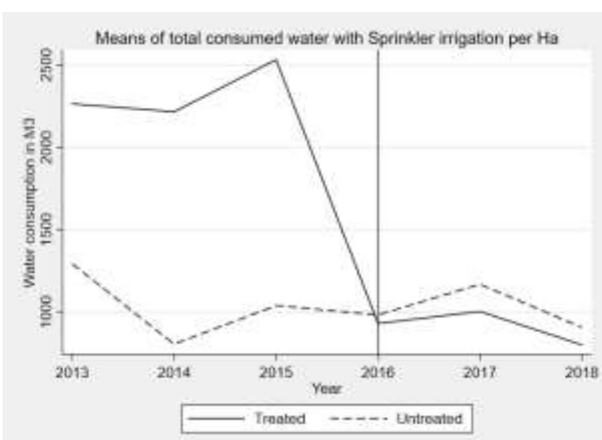
Conditional Fully Flexible Model						
Output: Water Volume (m3/ha)			Number of obs = 12604			
Sample Period: 1(2018):6(2013)			H0: Common Pre-dynamics = 44.54			
Treatment Period: 4(2015):6(2013)			p-value = 2.1e-10			
Robust Standard Errors						
	H0:q=q-1		H0:s=s-1			
	z	P> z	F	Prob>F		
q=1			8.062788	0.01775		
q=2	-72.1109	0.598647	4.186339	0.123296		
q=3	-892.929	0.000181	14.49448	0.000712		
Parallel-1						
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
s=1	2480.781	200.4117	12.38	0	2087.982	2873.581
s=2	1889.536	193.7183	9.75	0	1509.855	2269.217
s=3	1986.308	205.1566	9.68	0	1584.208	2388.407
Parallel-2						
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
s=1	2552.892	287.3826	8.88	0	1989.633	3116.152
s=2	2033.758	396.331	5.13	0	1256.963	2810.552
s=3	2202.64	512.932	4.29	0	1197.312	3207.969
Parallel-3						
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
s=1	3445.821	471.8645	7.3	0	2520.984	4370.658
s=2	4712.544	1044.926	4.51	0	2664.527	6760.562
s=3	7560.213	1842.713	4.1	0	3948.562	11171.86

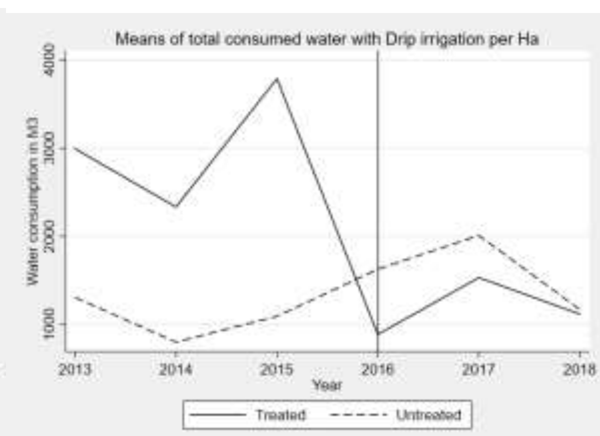
Graphical analysis of Common Trends among Treated and Untreated for different irrigation technologies











Main conclusions

The essays in this PhD thesis highlight different important aspects related to water management, with several policy implications.

The main message of the first two papers is that an important role for water conservation policies in agriculture is played by farmers' approaches related to irrigation technology adoption. Both the determinants and the intensity of adopting sustainable technologies do matter in boosting water conservation policies, and those elements should be taken seriously into consideration by policymakers for tailoring ad-hoc actions to increase the success of the interventions. Moreover, the additional gain in terms of economic outcomes, through a general increase in production, obtained by adopters of WCST may furtherly expand the policy effect at higher scales (regional and national), due to the higher profitability of sustainable irrigation technologies compared to traditional ones. Policymakers should consider the additional profitability of WCST adoption for farmers and employ it as a further basis for incentivizing high scale transitions toward sustainable irrigation strategies.
The adoption of WCST can improve the general level of sustainability of water use in the agricultural sector and a key element is the attitude of the farmer over innovation and new technologies. Therefore, demand side policies can have higher chances of success if the measures consider all the heterogeneities among farmers as economic agents and all the aspects which influence their potential response to technological changes. Tailored incentives, technical standards or rules on water use will have higher possibilities of success than general and homogenous approaches. Moreover, the economic benefits of technological changes might drive farmers to more efficient water-consuming irrigation technologies with a double gain for both the productive sector (lower water costs per unit produced) and the socio-ecological system as a whole (reduced abstraction of water for agriculture). Thus, technological/technical changes and the focus of environmental policies on them are crucial for a sustainable transition of the agricultural sector toward water conservative schemes.

Other key features for sustainable water management in agriculture have been identified by the last two papers, in which farmers' responses to prices have been analysed in depth. The case of Central Emilia Water District highlighted that farmers react to price as an economic incentive reducing their water consumption, considering water resources in presence of tariffs (even if very low) a finite and costly input in their producing patterns. Moreover, agricultural water demand elasticity to price resulted to be diverse and related to crop water needs and the market value of the final product (as the value of each drop of water spent for growing varies among crops). In addition, another relevant aspect in the responsiveness of farmers to water prices is the level of control that each irrigation system provides to the farmer. This last point is slightly in contrast with other theoretical studies on irrigation which claimed the opposite (i.e. the higher the level of control of the irrigation system the lower the water demand elasticity).

The main message is that, even if water demand is inelastic to prices in general, farmers do react to price changes, and therefore volumetric tariffs can be strategic for driving conservative use of water. This is confirmed by the analysis of the introduction of a volumetric tariff in the CEWD case study, which demonstrates the total change in the behaviour of farmers when shifting from a flat to a volumetric tariff, even with very small amounts of money spent for each cubic meter of water consumed. This implies that after the introduction of the policy farmers start to integrate water as a variable cost in their cost functions, changing their strategies towards water and their approach to its use from a public to a private good framework. In our case, the tariff introduced a cost of less than 4 cents per m^3, whereas in some irrigation districts in the south of Italy this costs up to 50 cents (ten times more than the CEWD); therefore, there is ample room for introducing water specific and non-detrimental pricing policies.

Furthermore, in the analysis of the last two papers the heterogeneity of irrigation technologies and crops have drawn attention to the diverse reactions to water pricing of each system. This underlines the importance of adopting ad-hoc interventions in order to achieve effective results in environmental terms while not lowering farmers' income excessively. Therefore, water pricing policies are effective, but in order to improve their impact in terms of water conservation, pricing schemes should discriminate among different producing systems, taking into account that different crops and irrigation system lead to different elasticities. To reiterate, this highlights the importance of considering the heterogeneities between different types of productions to increase the effectiveness of water conservation policies, which should be designed taking into consideration the different propensity to react to water prices of both different crops grown and irrigation systems.

With these essays, I contribute to water economics literature in several ways. Firstly, I provide different empirical analyses at national and regional level using observational micro data adding climatic variables in the econometric models. Moreover, Italian irrigation system has not been explored widely before and this area was not covered by previous empirical studies. The main findings of this PhD thesis – although limited to one country - can apply to other Mediterranean countries which have similar productive, geographical and socio-economic conditions to Italy. Secondly, I introduce some novel analytical approaches, such as the use of correlated random effect models, the inverse Did and the endogenous switching regression models with panel data; which represents the first application in agricultural and environmental economics literature of the control function approach model of Murtazashvili and Wooldridge (2016) for considering two sources of endogeneity. Thirdly, the findings contribute to current debates in water economics literature, especially to those in which the absence of empirical analysis was an important gap, such as the literature on elasticity and on the effectiveness of water pricing policies. Moreover, considering the literature on WCST adoption, the use of Italy as a national case study adds strong evidence to studies concerning the main drivers of adoption and intensity with important multidimensional heterogeneity among farms.

I would like to underline that the analyses conducted were difficult and challenging as in all empirical works, but with the additional complication of the structural lack of data in agricultural water management studies, on at least two levels. One obstacle was the absence of water databases accessible for consultation, as oftentimes these are either private or very difficult to access. As a consequence, one of the main difficulties has been the strong effort needed for data mining since the beginning of the research. Another obstacle, related to the former, was the lack of empirical studies on agricultural water economics using econometrics in the Mediterranean area, which made it difficult to compare and frame the research with other relevant studies in the same area.

To conclude, this set of empirical works constitutes a significant contribution to agricultural and environmental economics in water issues, which I regard as a first step towards more in-depth analysis of an extremely crucial issue which could mine global living conditions. Other issues on water economics should be extensively explored, such as the rebound effect of WCST adoption, the effect of droughts on the agricultural sector, the social effects of water pollution due to agricultural activities on public health, and virtual water trade exchanges for the efficient use of water for agricultural activities. The South of Europe and the Mediterranean area will become a critical hotspot for water issues and agricultural water management in the near future. Therefore, it is essential to continue on this line of research expanding the current knowledge on agricultural water management with the fundamental contribution of economics and social sciences jointly linked to sustainability, ecology, and natural sciences in a systemic and holistic way. I hope that this PhD thesis may positively contribute to further research on water economics in Italy.

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