Irrigation Practices, Water Effectiveness and Productivity Measurement

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Abstract

This paper develops a consistent theoretical framework for measuring irrigation water effectiveness and its impact on productivity growth rates by assuming a smooth transition process from traditional to modern irrigation technologies among individual farmers. The econometric model is based on a two-stage estimation procedure incorporating the transition process within a primal TFP decomposition framework. An empirical investigation addresses a panel of 56 small-scale greenhouse farms in Crete, Greece during the 2010-13 period. The results indicate that technical change driven by irrigation water techology improvement contributes significantly to total factor prodcutivity growth. Further, the impact of specific climatic and soil conditions do not allow farmers to fully explore the potential of the new irrigation technology delaying adoption rates.

Keywords: irrigation technology adoption and diffusion; irrigation effectiveness; productivity growth; translog-transition model; greenhouse farms
JEL Codes: *C41*, *O16*, *O33*, *Q25*.

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1 Introduction

The sustainability of ecosystems and its relationship to economic growth is intertwined with water management in both developing and developed nations. Water management issues in the agricultural sector often take a central role in controversies over how to allocate this resource that is becoming increasingly scarce in many arid and semi-arid areas around the world. With the agricultural sector being the largest user of freshwater, its use in this sector commands particular attention when it comes to discussions about conservation and sustainability of water in terms of both quantity and quality (Molden, 2007). While country-level estimates are available, estimates for freshwater withdrawals from irrigated agriculture and their impact are difficult to present on a worldwide basis. With an estimated 20 per cent of cultivated land being irrigated, this acreage accounts for 40 per cent of total agricultural production (Rosegrant *et al.*, 2013).

At the same time, there can be significant interregional competition for water use in agriculture (*e.g.*, Middle East or Sub-Saharan African countries) as well as intersectoral competition for water between agriculture, urban and environmental uses (*e.g.*, tourist areas in Southern Europe and North Africa). The value of water used in agriculture must be balanced against these competing uses (Rosegrant *et al.*, 2013). Improved irrigation technologies have contributed to rapid yield increases and to more effective irrigation practices in the two decades. But pumping groundwater for agricultural purposes can be unsustainable in areas where withdrawals exceed recharge. In addition to rapidly depleted groundwater reserves, excessive groundwater extraction can lead to both water scarcity and water quality concerns. Quality concerns arise from human-induced impacts such as salinization, excess nutrients, acidification, toxic waste, saltwater contamination, and eutrophication that are not irrelevant to agricultural water uses (Abdulai and Huffman, 2014).

The recent projections for food and agricultural production by 2050 have brought the agriculturally related water needs front and center (United Nations, 2015). Once climate change scenarios are factored into the discussions, water-need forecasts for agricultural, urban and environmental sectors have elevated the attention to calls for global water security.[1] Productivity is the measure of economic performance which is defined broadly as output per unit of input. The emergence of the *Blue Revolution* (Calder, 1999) and the *Kofi Annan Foundation* brought attention to the issue of water use in agriculture by promoting the tag line of *more crop per drop* (Annan, 2000); that is, focusing attention on water as a specific factor of production, and the practices and technological innovations that can increase agricultural output per unit of water applied (Mendelsohn and Dinar, 2003).

The reality of modelling and measuring agricultural productivity as *farm output per unit of input* must first acknowledge that any reasonable farm production situation involves multiple variable or quasi-fixed inputs producing a variety of crops. Agricultural water productivity (or *crop per*

[1] A wide range in internationally based institutions seek to address the sensitivity of water use in agriculture. These include the *Global Water Partnership*, the *World Water Council UN World Water Assessment Programme*, and the *World Bank* among others.

drop) is a partial productivity measure that focuses on a single input (irrigation water) similar to labor or land productivity that are often raised in farm production policy discussions. However, in a family-farming rural setting, both land and labor (usually family labor) are considered as quasi-fixed factors of production. Measuring their partial productivity growth rates or quasi-rents can provide useful insights about the use of farming technology and variable inputs utilization. However, irrigation water is a variable input in farm production impacted by the farmer's managerial capability, environmental conditions, the state of irrigation technology and more importantly by other variable inputs use (*e.g.*, fertilization practices). Therefore, proper measurement of agricultural water productivity should be focused on a total factor productivity setting accommodating farm's adjustments beyond the short run.

In doing so, the definition of farm technology must address two important issues related to irrigation water use. First, the quantity of irrigation water applied deviates from the amount of water that is actually consumed by the crop. Second, the irrigation technology choice is not instantaneously mobilized by individual farmers, and its impact on individual productivity rates is ambiguous. The water engineering literature provides an extensive discussion of why applied irrigation water differs from effective water actually utilized by the crop (*e.g.*, Merriam and Keller, 1978; Clemmens, 1991). The farm technology should reflect this deviation to properly measure agricultural water productivity rates. Otherwise, measured farm productivity will misstate the true contribution of irrigation water use, leading to wrong decisions concerning the sustainability of water resources (*e.g.*, Dinar and Yaron 1992; Khanna *et al.*, 2002).

The transition between the alternative irrigation technologies, like any other technological decisions made by individual farmers, does not take place in a single time period. Farmers continuously revise their own perceptions about the effectiveness of each irrigation practice and when they are certain about the potential productivity improvements they move to the new technological regime. The development of new, more effective technologies is the result of innovations in irrigation practices combined with policy schemes to advance the diffusion process (*e.g.*, Dridi and Khanna, 2005; Genius *et al.*, 2014). However, policies intending to advance diffusion rates do not necessarily improve effectiveness; for example, risk averse farmers adopt technologies to hedge against the risk of adverse climatic conditions (Tsur *et al.*, 1990) or soil characteristics and climatic conditions favoring a traditional irrigation system may perform equally well in terms of irrigation water effectiveness (Caswell and Zilberman, 1986).

Taking this line of argument we assume that non-linearities may exist in the adoption of new irrigation technologies. Contrary to previous studies that assume only a single technological regime, we adopt the production function able to identify the different technological regimes that may exist (if any) among farmers. This transition-production function allows for a smooth transition between traditional and innovative irrigation technologies. In this approach the transition from one technological regime to the other depends on the conditional probability of farmers' gains from the adoption of new technologies. The case study addresses a farm-level panel of greenhouse vegetable producers in Crete, Greece. The decomposition of total factor productivity (TFP) growth is undertaken which separates the different technical change, irrigation effectiveness and scale effects. The next section presents the theoretical framework outlining the irrigation water effectiveness from an engineering perspective, the farmer's irrigation technology choice and how this technological framework incorporating the irrigation effectiveness measure and irrigation technology choice are embodied in the TFP growth decomposition. This is followed by the econometric framework, specified to implement this framework followed by the section describing the case study, its data and farmer choices. The next section presents the empirical results and their implications. The final section offers a set of concluding remarks and suggestions for future directions to investigate.

2 Theoretical Model

Irrigation Water Effectiveness

From a classical engineering perspective, irrigation water effectiveness (IWE) at the field level is defined as the proportion of applied water (*i.e.*, the water actually applied in the field) that is used by the crop beneficially (*i.e.*, effective water).[2] According to this engineering notion, innovative irrigation technologies increase this proportion, allowing less water to be applied for a given crop yield at the expense of increased capital. Hence, irrigation water effectiveness depends on the choice of irrigation technique, and it is defined from (Burt *et al.*, 1997):

$$IWE_k = \frac{\tilde{x}_k^w}{x_k^w} \in [0,1] \tag{1}$$

where, k indicates the state of irrigation technology applied in the field, $\tilde{x}_k^w$ is the amount of effective irrigation water (*i.e.*, the amount of water actually used by the crop), and x_k^w is the water actually applied to the crop by individual farmers. At the extreme, when $IWE_k = 0$ applied irrigation water is completely lost ($\tilde{x}_k^w = 0$), while when $IWE_k = 1$ the plant absorbs all applied water ($\tilde{x}_k^w = x_k^w$).

Using this engineering notion of irrigation water effectiveness the furrow irrigation system is generally 65-75% efficient, where gravity is used to distribute water across the field. In contrast, conventional center pivot irrigation systems, where specific equipment (*e.g.*, tubes, emitters) and pressure are used to distribute water uniformly throughout the field, increase efficiency to 80-90%, while other types of dropped nozzle irrigation systems are 95-98% efficient (Howell, 2003). While advanced irrigation technologies enhance irrigation effectiveness and therefore farm profitability, we do not observe a uniform distribution of irrigation technologies among homogeneous populations of farmers. Irrigation water effectiveness varies with environmental and soil conditions influencing

[2] In some cases, a portion of irrigation water applied is available for other users via runoff, or recharges the underground aquifer via deep percolation (*i.e.*, infiltrated water which moves below the root zone). In these instances, the spatial measure of irrigation water efficiency at the basin level assumes that effective water is equal to the applied water minus this return flow. Its difference from the definition at the field level is the amount of irrigation water reuse through runoff or percolation (Huffaker, 2008).

adoption decisions for advanced irrigation technologies by individual farmers (New and Fipps, 1990; Pfeiffer and Lin, 2014).

Soil is a dynamic system which acts as a reservoir and buffer against plant dehydration. Whether enough water is stored into soil layers depends on soil characteristics such as texture, salinity and depth. These combined soil characteristics are summarized by Caswell and Zilberman (1986) under the term *water holding capacity.* Obviously, soils that are relatively porous (*e.g.*, sandy soils) or plots that are steep have a lower irrigation effectiveness than a well-drained levelled plot. A furrow irrigation system applied to a well-drained levelled plot may perform equally well in terms of irrigation water effectiveness with a drip irrigation system applied to a steep sandy soil. The same is true for the general environmental conditions like air temperature or rainfall that affect evapotranspiration in the field. Evapotranspiration is the combined process of evaporation from soil and transpiration from plants. The combined evapotranspiration process is controlled or influenced by atmospheric factors. Hence, farms cultivating in areas with a higher annual precipitation and lower air temperature are faced with reduced transpiration and therefore exhibit higher irrigation water effectiveness.

For a given choice of irrigation technology, irrigation water effectiveness may be defined as a general function of the form (Dinar *et al.*, 1992; Khanna *et al.*, 2002):

$$IWE_k = g_k\left(q, d, s; k\right) \tag{2}$$

where $q \in \Re_+$ denotes soil water holding capacity, $d \in \Re_+$ is a general aridity index capturing micro-climate changes, and $s \in \Re_+$ represents the slope of the plot. The function $g_k\left(q, d, s; k\right) \in [0, 1]$ is a positive valued function representing the percentage of applied irrigation water that is actually beneficial for the crop. Accordingly, $1 - g_k\left(q, d, s; k\right)$ is the percentage of applied irrigation water lost during application due to deep percolation, runoff and non-beneficial evapotranspiration. The irrigation water efficiency function is non-decreasing and concave in soil water holding capacity $(\partial g_k(\cdot)/\partial q \geq 0, \partial^2 g_k(\cdot)/\partial q^2 \leq 0)$, and non-increasing and convex in adverse weather conditions $(\partial g_k(\cdot)/\partial d \leq 0, \partial^2 g_k(\cdot)/\partial d^2 \leq 0)$. The slope of the field is characterized by $(\partial g_k(\cdot)/\partial s \leq 0, \partial^2 g_k(\cdot)/\partial s^2 \leq 0)$.

For any given choice of irrigation technology, soil and micro-climatic conditions at the field level exhibit a given level of irrigation water effectiveness that lies within the $[0, 1]$ interval. Let $k = 1$ denote innovative irrigation technology and $k = 0$ a traditional one. Following Caswell and Zilberman (1986), we can assume that modern irrigation technology augments water effectiveness of any given plot with specific soil characteristics and atmospheric conditions:

$$g_1\left(\bar{q}, \bar{d}, \bar{s}; 1\right) \geq g_0\left(\bar{q}, \bar{d}, \bar{s}; 0\right)$$

for which it holds that $g_1\left(\cdot\right) = 1$ if $g_0\left(\cdot\right) = 1$ and $g_1\left(\cdot\right) = 0$ if $g_0\left(\cdot\right) = 0$. Further, we assume that the effectiveness of modern irrigation technology is increasing at a decreasing rate. This implies that if soil characteristics and micro-climatic conditions are favorable a traditional irrigation system may perform equally well with a modern irrigation technology.

Using relations (1) and (2) we may define effective irrigation water with the following multiplicatively separable structure:

$$\tilde{x}_k^w = x_k^w g_k\left(q, d, s; k\right) \tag{3}$$

for which it holds that $\partial \tilde{x}_k^w / \partial x_k^w \geq 0$ and $\partial^2 \tilde{x}_k^w / \partial x_k^{w2} = 0$, that is, a linear relationship. It also holds that $\tilde{x}_k^w = 0$ *if* $x_k^w = 0$.

Under this general setup, we are able now to describe farm technology using irrigation application method k in period t from the following closed, non-empty production possibilities set:

$$T(t,k) = \left\{ \left(\mathbf{x}_k^v, x_k^w, q, d, s, y_k\right) : \left(\mathbf{x}_k^v, x_k^w\right) \text{can produce } y_k \text{ for a given level of } (q,d,s) \right\}$$

where $y \in \Re_+$ is crop output, and $\mathbf{x}_k^v \in \Re_+^j$ is the vector of j variable inputs the utilization of which is affected by the choice of irrigation water application. Changes in irrigation technology affect the use of variable inputs as different water applications require new equipment, different methods of fertilization or labor hours on the field.

Using (3), the farm's crop technology may be now described as:

$$T(t,k) = \left\{ \left(\mathbf{x}_k^v, x_k^w, q, d, s, y_k\right) : y_k \leq f\left(\mathbf{x}_k^v, \tilde{x}_k^w, t\right), \tilde{x}_k^w = x_k^w g_k\left(q, d, s; k\right) \right\} \tag{4}$$

where $f\left(\mathbf{x}_k^v, \tilde{x}_k^w, t\right) : \Re_+^{j+2} \to \Re_+$, is a continuous and, strictly increasing, twice differentiable concave production function, representing maximal farm output from variable inputs, irrigation water given exogenous farm characteristics and irrigation technology choice.

Finally, assuming strictly positive farm crop ($p \in \Re_{++}$), irrigation water ($w^w \in \Re_{++}$), and variable input ($\mathbf{w}^v \in \Re_{++}^j$) prices, the associated short-run profit function $\pi_k\left(p, \mathbf{w}^v, w^w, q, d, s, t\right) : \Re_+^{j+2} \times \Re_+^4 \to \Re_+$ for the representation of farm technology in (4) and using irrigation application method k is given:

$$\begin{aligned}
\pi_k\left(p, \mathbf{w}^v, w^w, q, d, s, t\right) &\equiv \max_{\mathbf{x}_k^v, x_k^w, y_k} \left\{ p y_k - \mathbf{w}^v \mathbf{x}_k^v - w^w x_k^w : y_k \leq f\left(\mathbf{x}_k^v, \tilde{x}_k^w, t\right), \tilde{x}_k^w = x_k^w g_k\left(q, d, s; k\right) \right\} \\
&\equiv \max_{\mathbf{x}_k^v, x_k^w} \left\{ p f\left(\mathbf{x}_k^v, x_k^w g_k\left(q, d, s; k\right), t\right) - \mathbf{w}^v \mathbf{x}_k^v - w^w x_k^w \right\}
\end{aligned}$$

By standard results, $\pi_k\left(p, \mathbf{w}^v, w^w, q, d, s, t\right)$ is *sublinear* (positively linearly homogeneous and convex) in crop, variable input and irrigation water prices, non-decreasing in p, and non-increasing in $\mathbf{w}^v$ and w^w (Chambers, 1988, Chapter 4).

Choice of Irrigation Technology

We incorporate the farmer's decision whether or not to adopt a new innovative irrigation technology into this model. This decision can be modeled as a binary choice, where the farmer can choose to adopt an innovative irrigation technology ($k = 1$) or not ($k = 0$). For each irrigation technology, the producer's short-run problem is to choose variable inputs to maximize profit. Hence, the maximization problem faced by adopters is given by (*e.g.*, Dridi and Khanna, 2005; Genius *et al.*, 2013):[3]

$$\pi_1\left(p, \mathbf{w}^v, w^w, q, d, s, t\right) \equiv \max_{\mathbf{x}_1^v, x_1^w} \left\{pf\left(\mathbf{x}_1^v, \tilde{x}_1^w, t\right) - \mathbf{w}^v \mathbf{x}_1^v - \frac{w^w}{g_1\left(q, d, s; 1\right)} \tilde{x}_1^w\right\}$$

whereas non-adopters

$$\pi_0\left(p, \mathbf{w}^v, w^w, q, d, s, t\right) \equiv \max_{\mathbf{x}_0^v, x_0^w} \left\{pf\left(\mathbf{x}_0^v, \tilde{x}_0^w, t\right) - \mathbf{w}^v \mathbf{x}_0^v - \frac{w^w}{g_0\left(q, d, s; 0\right)} \tilde{x}_0^w\right\}$$

Assume now that future profit flows after adoption of the innovative irrigation technology are not known with certainty due either to ignorance of the exact performance of the new irrigation technology or to the higher probability of committing errors in the use of this technology. Moreover, buying the new irrigation technology entails sunk costs characterized by some irreversibility in the decision and difficulty to sell used equipment. These arguments imply that additional information may possess a positive value (Dixit and Pindyck, 1994; Baerenklau, 2005). Farmers may prefer to delay adoption to gain the opportunity to gain more information on the new equipment. Consequently, farmers will adopt the innovative irrigation technology if the following inequality holds (Koundouri *et al.*, 2006):

$$E\left[\pi_1(p, \mathbf{w}^v, w^w, q, d, s, t) - \pi_0(p, \mathbf{w}^v, w^w, q, d, s, t)\right] \geq VI \tag{5}$$

where $VI \geq 0$ represents the expected value of new information for the representative farmer, which should depend on the level of uncertainty related to the use of the new technology and the farmer's own characteristics.

Irrigation Effectiveness and Productivity Measurement

A primal TFP decomposition framework using the definition of farm technology in (4) is developed to analyze the impact of changes in irrigation water effectiveness on farm productivity levels. Taking logarithms of both sides of the production function, $f\left(\mathbf{x}_k^v, \tilde{x}_k^w, t\right)$, allowing irrigation technology adoption (k) to be represented as a continuous variable, totally differentiating with respect to time, and using relation (3), yields (where a dot over a variable indicates its time rate of change):[4]

$$\frac{\partial \ln y}{\partial t} = \sum_j \frac{\partial \ln f(\cdot)}{\partial \ln x_{kj}^v} \dot{x}_{kj}^v + \frac{\partial \ln f(\cdot)}{\partial \ln \tilde{x}_k^w} \frac{\partial \ln \tilde{x}_k^w}{\partial \ln x_k^w} \dot{x}_k^w + \frac{\partial \ln f(\cdot)}{\partial \ln \tilde{x}_k^w} \frac{\partial \ln \tilde{x}_k^w}{\partial \ln d} \dot{d} + \left[\frac{\partial \ln f(\cdot)}{\partial t} + \frac{\partial \ln f(\cdot)}{\partial \ln \tilde{x}_k^w} \frac{\partial \ln \tilde{x}_k^w}{\partial k}\right]$$

[3] We assume that farmers are not affecting crop, irrigation water and variable inputs prices by changing irrigation water application method. There is a world market price for the crops considered whereas input supply is perfectly elastic.

[4] Soil water holding capacity and the slope of the plot remain constant over time.

or in elasticity form

$$\dot{y} = \sum_j e_j^x \dot{x}_{kj}^v + e^w \dot{x}_k^w + e^d \dot{d} + (TC + ITC) \tag{6}$$

where a dot over a variable indicates its time rate of change. $e_j^x = \dfrac{\partial \ln f(\cdot)}{\partial \ln x_{kj}^v}$ and $e^w = \dfrac{\partial \ln f(\cdot)}{\partial \ln \tilde{x}_k^w} \dfrac{\partial \ln \tilde{x}_k^w}{\partial \ln x_k^w}$ are the output elasticities of the variable inputs and irrigation water input, respectively, and $e^d = \dfrac{\partial \ln f(\cdot)}{\partial \ln \tilde{x}_k^w} \dfrac{\partial \ln \tilde{x}_k^w}{\partial \ln d}$ is the output elasticity of general environmental conditions (*i.e.*, climatic effect). The last term in brackets is the overall rate of technical change that comprises two components: i) $TC = \dfrac{\partial \ln f(\cdot)}{\partial t}$ is the primal rate of autonomous technological changes measuring how technical change shifts the productive component of farm technology (*i.e.*, *output enhancing tecnical change*), and ii) $ITC = \dfrac{\partial \ln f(\cdot)}{\partial \ln \tilde{x}_k^w} \dfrac{\partial \ln \tilde{x}_k^w}{\partial k}$ measures how changes in irrigation water application method impact the irrigation effectiveness portion of farm technology (*i.e.*, *rate of irrigation effectiveness technical change*).[5]

Following Chan and Mountain (1983) it can be shown that the cost shares can be related to the scale elasticity as follows: $s_j^x = \dfrac{e_j^x}{E}$, and $s^w = \dfrac{e^w}{E}$ where $E = \sum_j e_j^x + e^w$ is a primal measure of returns to scale. Using these cost share relations into the conventional *Divisia* index of TFP growth (*i.e.*, $\dot{TFP} = \dot{y} - \sum_j s_j^x \dot{x}_{kj}^v - s^w \dot{x}_k^w$), substituting it into (6) results, after slightly rearranging terms yields:

$$\dot{TFP} = \left(\frac{E-1}{E} \right) \left(\sum_j e_j^x \dot{x}_{kj}^v + e^w \dot{x}_k^w \right) + e^d \dot{d} + (TC + ITC) \tag{7}$$

Under the assumptions made on farms' production technology, the TFP decomposition shows that the calculated TFP growth is a biased measure of technical change captured by the last term in (7). The most familiar source of this bias is the scale component that must be disentangled from observed growth in variable inputs and irrigation water use. The scale component of the technology is captured by the first term. Scale bias vanishes for constant returns to scale (*i.e.*, $\sum_j e_j^x + e^w = 1$) or if variable factors of production and irrigation water use do not change over time. It is positive (negative) under increasing (decreasing) returns to scale as long as inputs increase over time and *vice versa*.

A less familiar source of bias in measured TFP growth emerges from how changes in environmental conditions through changes in irrigation effectiveness affect output growth (the second term in (7)). Intertemporal changes in the micro-climatic conditions on-farm cause changes in observed crop output that are not due to variable factor growth or traditional scale concerns. Instead they reflect how changes in irrigation effectiveness affect crop yield. If climatic conditions change over time, measured TFP growth will misstate the amount of technical change that is occuring by con-

[5] In essence it constitutes the irrigation water biased component of technical change in a traditional *Hicksian* sense.

flating it with intertemporal output changes caused by intertemporal changes in climatic conditions. Alternatively, if environmental conditions are constant over time or if they do not impact crop yield, this term vanishes from observed TFP growth rates.

Even if all of these biases are removed, measured TFP growth will misstate the true effect of technological changes if the rate of irrigation effectiveness technical change is not taken into account. Changes in irrigation technology are affecting output growth by enhancing the farm's soil characteristics and atmospheric conditions and not directly through irrigation water application. Its effect on measured TFP growth rate will be zero if changes in irrigation technology have no effect on irrigation effectiveness, through their effect on the soil's water holding capacity and on the adverse effects of climatic conditions and plot's slope *i.e.*, $g_k(\bar{q}, \bar{d}, \bar{s}; k) = 0$ or $g_k(\bar{q}, \bar{d}, \bar{s}; k) = 1$.

3 Econometric Model

In an empirical setting, we usually observe farmers in a unique situation: adoption or non-adoption of the new irrigation technology. However, the switch between the alternative irrigation technologies is not instantaneous. From relation (5), it is evident that individual farmers each year revise their own perceptions about the profitability of the new technology and once they pass a certain threshold they move to the new irrigation application practice. Therefore, the transition from the traditional to the innovative irrigation technology is smooth and it does not take place in a single time period. We estimate the model in two stages to incorporate this smooth transition process into our decomposition framework. In the first stage we estimate a simple probit model to analyze the factors affecting individual adoption decisions for the new irrigation technology. Then, the calculated individual probabilities are used in the second stage to approximate a *translog-transition* production function that takes into account the dynamic process of switching among irrigation technology regimes.

Starting from the first stage, farmers will choose to adopt the modern irrigation technology if the following inequality holds:

$$Y_{it}^* \equiv E\left[\pi_1(\cdot)\right] - E\left[\pi_0(\cdot)\right] - VI \geq 0$$

where Y_{it}^* is an unobservable random index for farmer i that defines his/her propensity to adopt the new irrigation technology at year t. Since we observe individual farmers in a unique situation we cannot estimate this structural equation. Instead, we estimate a reduced form of this equation and we focus on the most important farm-specific characteristics to explain the adoption decision. For purposes of estimation, let

$$Y_{1it}^* = h_1\left(\mathbf{z}_{1it}; \alpha_1\right) + e_{1it}$$

denote the profits of farmer i at year t if he/she is an adopter, and

$$Y_{0it}^{*} = h_0\left(\mathbf{z}_{0it};\alpha_0\right) + e_{0it}$$

denote the profits if he/she is not an adopter utilizing the traditional irrigation practice. The vector $\mathbf{z}_{kit} \in \Re_{+}^{l}$ includes farm-specific characteristics affecting the farm's profitability and information set where α_k are the associated parameters, and $e_{kit} \sim N\left(0,\sigma_k^2\right)$ are normally distributed error terms.

From the above relations, the probability of farmer i adopting modern irrigation technology at time t is given by the following probability model:

$$\begin{aligned} Pr[Y_{it}^{*}=1] &= Pr\big[Y_{0it} - Y_{1it}\big] \\ &= Pr\big[e_{it} < h\left(\mathbf{z}_{it};\alpha\right)\big] \\ &= \Phi\big[h\left(\mathbf{z}_{it};\alpha\right)\big] \end{aligned} \tag{8}$$

where $e_{it} = e_{0it} - e_{1it}$, $\mathbf{z}_{it} = \mathbf{z}_{0it} - \mathbf{z}_{1it}$, $\alpha = \alpha_0 - \alpha_1$, and $\Phi[\cdot]$ is the cumulative of the normal distribution. The model is estimated as a simple probit model taking into account the panel structure of the data.

For the approximation of true farm technology, we assume that the transition production function takes the following modified, transcendental logarithmic (*translog*) form:[6]

$$\ln y_{it} = \beta_0 + \beta^t t + \sum_j \beta_j^v \ln x_{jit}^v + \beta^w \ln \tilde{x}_{it}^w + \sum_j \beta_j^{vt} \ln x_{jit}^v t + 0.5 \sum_j \sum_m \beta_{jm}^{vv} \ln x_{jit}^v \ln x_{mit}^v + v_{it} \tag{9}$$

where i subscripts correspond to the i^{th} farm, t subscripts to the t^{th} year, j,m stands for variables inputs used in farm production, β are the parameters to be estimated, and $v_{it} \sim N\left(0,\sigma_v^2\right)$ is a normally distributed error term.

This *translog*-transition production function is converted to estimable form by using (3) and making the following substitution:

$$\ln \tilde{x}_{it}^w = \ln x_{it}^w + \ln g_{it} \tag{10}$$

where irrigation water effectiveness function takes the following form:

$$\ln g_{it} = -\left[\left(\beta_0^q q_{it} + \beta_0^d d_{it} + \beta_0^s s_{it}\right) + \left(\beta_1^q q_{it} + \beta_1^d d_{it} + \beta_1^s s_{it}\right) F(\hat{k}_{it};\gamma,\delta)\right] \tag{11}$$

[6] We have tried to econometrically fit a complete *translog* specification of the transition production function including interaction terms between effective irrigation water and variable inputs, but due to the non-linearity of the g-function it was impossible. Also the quadratic term of time turned to non-significant parameter estimate and it was excluded from the final specification.

with

$$F(\hat{k}_{it};\gamma,\delta) = \left(1 - \exp\left[-\gamma(\hat{k}_{it}-\delta)^2\right]\right) \tag{12}$$

being an exponential smooth transition function bounded between 0 and 1. It reflects a dynamic smooth transition between the two irrigation technology regimes rather than an abrupt jump from the one technology to the other. The parameter $\gamma > 0$ represents the speed of transition between the irrigation technologies, δ is the location parameter, and $\hat{k}_{it}$ is the transition variable which in our case is the estimated individual farm probability of adoption of the new irrigation technology obtained from the econometric estimation of (8) as:

$$\hat{k}_{it} = \frac{\exp(\mathbf{z}'_{it}\alpha)}{1+\exp(\mathbf{z}'_{it}\alpha)}$$

The lower the value of γ, the slower the farm moves to the improved technology regime. If $\gamma \to 0$, then $F(\hat{k}_{it};\gamma,\delta) \to 0$, while when $\gamma \to \infty$ the transition function $F(\hat{k}_{it};\gamma,\delta)$ approaches a heavy-side function, taking the value of one if $(\hat{k}_{it}-\delta) < 0$ and zero if $(\hat{k}_{it}-\delta) > 0$, resulting in an instantaneous transition from the one regime to the other. These extreme values are associated with the regression coefficients $B_0 = \beta_0^d + \beta_0^q + \beta_0^\varepsilon$ and $B_1 = (\beta_0^d + \beta_1^d) + (\beta_0^q + \beta_1^q) + (\beta_0^\varepsilon + \beta_1^\varepsilon)$.

For the identification of the transition (γ) and location (δ) parameters, a grid search procedure was employed following relevant studies (*i.e.*, Holt and Craig, 2006; Christopoulos and Leon-Ledesma, 2008; Balagtas and Holt, 2009) as the log likelihood function of a transition model may have many local maxima (Van Dijk *et al.*, 2002). Specifically, the value of γ was estimated over the range $[0.1, 4.0]$ while that for δ over $[0.1, 1]$ using an 0.01 increment during the grid search for both parameters. Then, the remaining parameters of the *translog*-transition production function were estimated using a simple OLS procedure conditional on γ and δ. The smallest sum of squared residuals are used to obtain $\hat{\gamma}$ and $\hat{\delta}$.

Using the parameter estimates of the translog-transition production function we can identify all terms appearing in the decomposition formula in (7). First, the output elasticities of variable inputs:

$$e_j^x = \beta_j^v + \sum_m \beta_{jm}^{vv} \ln x_{mit} + \beta_j^{vt} t \tag{13}$$

The *translog*-transition production function specification in (9) leads to the output elasticity of irrigation water coinciding with the parameter estimate of β^w. Then, the irrigation water effectiveness output elasticities of soil water holding capacity, climatic conditions and land slope are generated, respectively by:

$$\begin{aligned} e^q &= (\beta^w\beta_0^q)\, q_{it} + \beta^w\beta_1^q\left(1 - \exp\left[-\gamma(\hat{k}_{it}-\delta)^2\right]\right) q_{it} \\ e^d &= \left(\beta^w\beta_0^d\right) d_{it} + \beta^w\beta_1^d\left(1 - \exp\left[-\gamma(\hat{k}_{it}-\delta)^2\right]\right) d_{it} \end{aligned}$$

$$e^s = (\beta^w \beta_0^s)\, s_{it} + \beta^w \beta_1^s \left(1 - \exp\left[-\gamma(\hat{k}_{it} - \delta)^2\right]\right) s_{it}$$

The first part in each of the relationships above refer to irrigation water effectiveness output elasticities under the traditional irrigation technology while the second part (augmenting part) captures changes in those output elasticities due to farmers' transition to the innovative irrigation technology. The latter implies that given the soil and land characteristics and the atmospheric conditions of a plot, the percentage contribution of these characteristics and conditions to irrigation water effectiveness and output production may increase as farmers move to the upper technological regime (innovative irrigation technology).

Finally, the overall rate of technical change is calculated as the sum of output enhancing technical change:

$$TC = \beta^t + \sum_j \beta_j^{vt} \ln x_{jit}^v$$

and the rate of irrigation effectiveness technical change:

$$ITC = 2\beta^w \gamma \left(\hat{k}_{it} - \delta\right) \left(\beta_1^q q_{it} + \beta_1^d d_{it} + \beta_1^s s_{it}\right) \exp\left[-\gamma(\hat{k}_{it} - \delta)^2\right]$$

If $\gamma = \beta_j^{vt} = 0\ \forall j$ technical changes in crop technology are *Hicks* neutral. If only $\gamma = 0$ changes in irrigation technology have no effect in irrigation effectiveness. In the latter case it holds that $g_k(\bar{q}, \bar{d}, \bar{s}; k) = 0$ or $g_k(\bar{q}, \bar{d}, \bar{s}; k) = 1$. Finally, if $\gamma = \beta_j^{vt} = \beta^t = 0\ \forall j$ then changes in farm technology (including irrigation application) are absent.

4 Data and the Practical Problem

Sample Survey

Our case study involves a data set of Greek farmers cultivating vegetables in greenhouses. Specifically, our dataset includes 56 small-scale greenhouse farms randomly selected from the *Ierapetra Valley* in the Southeast part of the island of Crete, Greece.[7] In this specific area of Crete, vegetable cultivation under greenhouses has flourished over the last thirty years. The total acreage of greenhouses in the Ierapetra Valley in 2011 was 15,500 stremmas[8], accounting for the 25 per cent of the total acreage in Greece. The survey covers four cropping seasons from 2009-10 to 2012-13, resulting in a balanced panel dataset of 224 total observations. The survey was designed to examine empirically the effectiveness of irrigation water application and nitrate leaching from greenhouse farms financed by the *Agricultural Department of the Regional Directorate of Crete*. Water resources in this semi-arid area of the Mediterranean basin are limited and maintaining a sufficient level of good quality water reserves is an important public concern.

[7] The *Agricultural Census* published by the *Greek Statistical Service* was used to select a stratified random sample of greenhouse producers according to their size and specialization.

[8] One stremma equals 0.1 ha.

Surveyed farmers were asked to recall the exact time of adoption of modern irrigation technology together with some key variables related to their farming operation in the same year (*i.e.*, production patterns, input use, gross revenues, irrigation water use and cost, structural and demographic characteristics). In the final survey interviewers requested farmer recall data for the years 2010-2013 (with 2013 being the last cropping year before the survey was undertaken). All information was gathered using questionnaire-based field interviews undertaken by the extension personnel from the *Regional Agricultural Directorate*. The cropping period in greenhouse cultivation starts at the end of August/beginning of September until the end of May with significant fluctuations in crop yield during the season. Personal interviews took place at the beginning of June right after the end of the last cropping season in our sample.

A pilot survey executed at the beginning of the project finds that greenhouse farms mostly utilize a drip irrigation system where multiple tubes are attached to a water supply so that each line supplies one row of plants. The water supply comes from the local public irrigation network distributing throughout the Valley using the water stored in a small dam located in the center of the island. Approximately 80 per cent of greenhouse farms in the Valley are based on this public irrigation network for their water supply. The remaining farms have their own water wells and were excluded from our sample survey as they are using water of low quality at excessive rates. The drip irrigation system is controlled manually by the farmer according to his/her own perceptions about proper irrigation water application.

Since 2005, greenhouse farmers in the area had started adopting an overhead watering method using sprinkler heads connected to overhead water pipes emitting a mist across the entire greenhouse. The system is controlled automatically through timers and moisture sensors. This is considered more effective than the traditional drip irrigation practice as it also controls humidity rates within the greenhouse keeping evapotranspiration levels low. Hence, the overhead sprinkler irrigation system was considered the innovative irrigation technology in our empirical model and farmers were asked to recall the cropping year of adoption.

All monetary variables used in the econometric estimation were converted into 2010 constant prices. Finally, prior to econometric estimation, and to avoid problems associated with units of measurement, all variables were converted into indices, with the basis of normalization being the representative greenhouse farm. The representative farm was the one with the smallest deviation of all variables from the sample means.

Irrigation Technology Adoption

At the time of the survey, 33 farmers out of 56 had adopted the overhead sprinkler irrigation system in their greenhouses. The adoption rate more than doubled over the sample period, increasing from 23.21 per cent in 2010 to 58.93 per cent in 2013. The highest change in adoption rate is observed during the 2011-12 cropping period that followed a period with the most adverse climatic conditions for the farms in the area (see Table 5). The $\mathbf{z}$ vector of explanatory variables in the irrigation technology adoption model in (8) contains the following (see upper panel in Table 1): (a) the farmer's age measured in years; (b) the farmer's educational level measured in years of schooling; (c) the number of extension visits to the farm from the local public Extension Agency; (d) the size of the farm measured in stremmas (one stremma equals 0.1 ha), and (e) the total amount of subsidies received in euros.

We assume that farmers' educational level and age (as a proxy of his/her farming experience) together with the number of extension visits on-farm determine farmer's human capital. All three variables are assumed to be positively correlated with farmer's information level on the new equipment determining the information premium in (5). Human capital theory suggests that innovative ability is closely related to these variables, since these characteristics are associated with the resource allocation skills of farm operators (Nelson and Phelps, 1966; Huffman, 1977). Information gathering, regardless of whether or not it refers to the innovation itself, is expected to enhance resource allocation skills and to increase the efficiency of adoption decisions.

A farmer with a high level of resource allocation skills will make more accurate predictions of future yields and profitability and will thus make more efficient adoption decisions (Stigler, 1961). The expected impact of farm size on adoption time is also ambiguous. Larger farms may have a greater potential to adopt modern irrigation technologies because of the high costs involved in irrigation water. On the other hand, larger farms may have less financial pressure to search for alternative ways to improve water effectiveness and hence irrigation cost by switching to a modern irrigation technology (Putler and Zilberman 1984). The same applies for farms with higher subsidies received as they face financial constraints to support a capital intensive innovative irrigation technology.

Summary statistics of data used in the probit model are presented in the upper panel of Table 1. It is evident from these figures that older farmers, who are in general less educated than their younger counterparts, are not as eager to adopt the new overhead sprinkler irrigation technology. The average age and educational level of farmers adopting modern irrigation technologies is 33.3 years of age and 13.2 years in schooling, respectively, while farmers using traditional technologies are 53.9 years old with 9.8 years schooling on average. The number of extension visits on-farm was 5.85 times per cropping season for adopters and just 1.49 times for non-adopters in the sample. Finally, farms using the new irrigation technology were larger cultivating on average in an area of 6.37 stremmas which is considerably higher than the 4.11 stremmas for non-adopting farms. As expected adopters receive a larger amount of total subsidies necessary to finance their decision to switch irrigation practices.

Farm Production Data

For the empirical approximation of farm technology, we consider one output and four variable inputs together with irrigation water. Summary statistics of these variables appear in Table 1. Greenhouse farmers produce four different kinds of vegetables: tomatoes, peppers, cucumbers and aubergines.[9] Different crops (including quantities sold off the farm and quantities consumed by the farm household during the crop year) were aggregated into a single aggregate *Tornqvist* output index with the revenue shares of each crop defining the relevant weights. On average total revenues for sample participants were 78,528 Euros varying significantly between adopters and non-adopters. Farm labor was defined as the total working hours devoted to supervision and organizational activities as well as to field activities such as harvesting, planting, fertilization, spraying and irrigation water application. Farm labor includes farm owner, family members and hired workers with either permanent or seasonal occupation status.[10] On average farmers devote 592 hours in their greenhouses in all farming activities.

Land input includes the value of the total acreage (rented or owned) under greenhouses measured in stremmas. Given the nature of greenhouse cultivation which is an intensive farming activity, greenhouse farms are of small size 5.5 stremmas on average. Seed cost includes the cost of the new planting in every cropping year measured in Euros. At the beginning of each cropping season farmers buy the new plants from local private nurseries depending on their own perception about crop prices during the cropping season. On average the cost of new planting is 1,449 Euros per farmer.

Intermediate inputs consist of goods and materials used during the crop year, whether purchased off-farm or withdrawn from beginning inventories. These include pesticides, fuel and electric power, storage expenses, and chemical fertilizers also measured in Euros. The aggregation of this these categories into a single input index using *Tornqvist* procedures. Finally, irrigation water is measured in m^3 using the individual water meters installed in each farm. During the whole cropping period farmers in the sample are using 1,358 m^3 of irrigation water with adopters consuming larger amounts (due to their larger average size).

The aridity index in the irrigation effectiveness function, as a proxy of climatic changes, is defined as the ratio of the average temperature in the area where the farm is located over the total precipitation in the same area (Stallings, 1960). The meteorological data for the construction of the aridity index are obtained by the four local *Meteorological Stations* located throughout the Ierapetra Valley producing continuous spatial grids of weekly air temperature and precipitation for the whole area. It is not possible to define farm-specific indices of micro-climatic conditions for each farm in our sample.

Land surface slope is indicated during field personal interviews by extension personnel. Finally, to proxy soil water holding capacity we use previous field experiments undertaken by the Extension Personnel in several locations throughout the Ierapetra Valley on the saturated hydraulic conductivity of water in soil or the intrinsic permeability of the soil (van Bavel and Kirkham, 1949).[11]

[9] According to the local Agricultural Experimental Stations in the Ierapetra Valley 46.5 per cent of greenhouses cultivate tomatoes, 30.2 per cent peppers, 14.2 per cent cucumbers and the remaining 9.1 per cent aubergines. In sample stratification we took into account this specific crop distribution in the area.

[10] Given the competitive local labor market conditions we assume that family and hired labor are perfect substitutes, implying that returns to farm and off-farm work are equal.

[11] The hydraulic conductivity of a soil is a measure of the soil's ability to transmit water when submitted to a

Greenhouse farmers in the area are cultivating in different sandy soil textures such as pure sandy soil, sandy loam, sandy clay loam and sandy clay. Depending on the in situ specificities, the hydraulic conductivity of a soil varies significantly among farms.

5 Empirical Results

Adoption Behavior

In the first stage, the binary discrete choice model described in equation (8) is estimated as a simple probit regression model using conventional maximum likelihood (ML) method. The set of regressors addressing adoption behavior include farmer's age and educational level, the number of on-farm extension visits from local public extension agency, the size of the farm, and the level of subsidies received by the farmer. A quasi-linear specification is adopted that includes the linear terms of all explanatory variables together with a quadratic term of farmer's educational level yielding statistically significant parameter estimates.[12]

The ML parameter estimates of the probit model along with their corresponding *Huber-White* robust standard errors are reported in the upper panel of Table 2. All parameter estimates are found to be statistically significant at the 5 per cent significance level or lower. *McFadden's* R^2 indicates a good fit to the model. The estimation results indicate that farmer's educational level and extension visits together with farm size and subsidies received are positively related with farmer's probability to adopt the new overhead sprinkler technology. The educational effect as well as the positive sign associated with the variable describing exposition of farmers to extension services may indicate that there exists a positive value on waiting for better information. That is, greenhouse farmers who have better information assign a lower value on the option to wait and, for this reason, are more likely to adopt than other farmers (*i.e.*, they have a higher probability to adopt the overhead sprinkler technology at the time of the survey compared to less informed farmers).

In contrast, the parameter of farmer's age is found to be negative, implying a higher probability of adoption for younger farmers. Older farmers may tend to have shorter planning horizons and thus expect lower future returns from the implementation of the new irrigation technology. In addition, older farmers are often more risk averse and less willing to provide the labor required to install and implement the innovative irrigation technology. Additionally, larger farms that commonly face higher irrigation water cost are more likely to switch to the overhead sprinkler technology since the associated benefits from the reduced irrigation cost are significantly higher for them compared with smaller farms in the sample. Similarly, farms receiving more subsidies experience lower actual installation and implementation costs due to the higher financial aid received which in turn provide important economic incentives toward adopting the overhead sprinkler technology.

hydraulic gradient.

[12] A quadratic form was originally imposed to account for possible non-linear effects of these variables on individual adoption probabilities, but the econometric estimation of the model provided statistically insignificant estimates for the majority of the quadratic terms.

The marginal impact of each regressor along with their corresponding standards errors are reported in the lower panel of Table 2. The highest effect arises from farmer's educational level, followed by the number of extension visits on-farm, the size of the farm, farmer's age and the volume of subsidies received. Specifically, a one per cent increase in the value of these variables results *ceteris paribus* in a change in the probability of adoption of overhead sprinkler irrigation technology by 0.212, 0.169, 0.041, -0.012 and 0.0003 per cent, respectively.

The high positive effect of farmer's educational level is dampened by the negative coefficient of the corresponding quadratic term. This dampening effect may be the result of highly-educated farmers who are also well-informed about the innovative technology. Thus additional gains in educational levels (commonly in the form of training seminars) lead only to slight changes in the information premium. Our results imply that policies intending to advance adoption rates for overhead sprinkler technology among greenhouse farmers in the Ierapetra Valley should focus on increasing farmers' human capital levels rather providing economic incentives. In particular, training seminars targeting less-educated farmer groups combined with policies promoting more frequent on-farm visits by extension personnel would be more effective compared to policies subsidizing the new irrigation technologies.

Farm Production Model

Prior to the econometric estimation of the *translog*-transition production function, the non-linear specification of the irrigation water effectiveness function in (11) was statistically tested using a standard F-test.[13] A second-order *Taylor* series approximation around $\gamma = 0$ was developed for the transition function in (11) to address identification problems related with the parameters γ and δ, resulting in a non-linear equation for the irrigation water effectiveness function. Then, the *translog*-transition production function was estimated using the linearized specification of irrigation water effectiveness function and a standard F-test was performed to test the null hypothesis of linearity. The value of the F statistic was $F(6, 193) = 7.37$, well above the critical value at the 1 per cent level of significance which supports our non-linear specification for the irrigation water effectiveness function in (11).

Following the statistical testing, parameter estimates of the non-linear *translog*-transition production function along with their corresponding standard errors are presented in Table 3. All the first-order parameters of variable inputs and irrigation water are found to be statistically significant at least at the 5 per cent level with their magnitudes being bounded in the unit interval. The bordered *Hessian* matrix is found to be negative semi-definite at the point of approximation (*i.e.*, sample means). Hence, concavity of the production function is satisfied with respect to all variable inputs and irrigation water, implying positive and diminishing marginal products among greenhouse farmers in the sample.

Concerning the point estimates of the transition-related parameters, the grid search resulted in

[13] See Appendix A.1 for details.

a value of 3.5 for the γ and 0.60 for the δ parameter. The *wild bootstrap*[14] approach revealed that both parameters are statistically significant at the 5 per cent level. The high value of γ implies that the speed of transition between the drip and the overhead sprinkler irrigation technology regime among greenhouse farms is relatively quick, making it close to a threshold process. Accordingly, the value of the threshold parameter implies that when the conditional probability crosses the threshold of 60 per cent, farmers change irrigation technology moving to the overhead sprinkler system. Consequently, policy measures intending to enhance irrigation water effectiveness should target revising individual perceptions about the benefits of the new technology improving the information set within which individual decisions are made.

In the next step, we examine several hypotheses concerning the structure of greenhouse farm technology among sample participants using the generalized LR-test. First, the assumptions of no technical change ($\beta^t = \beta_j^{vt} = \gamma = 0 \; \forall j$), *Hicks*-neutral ($\beta_j^{vt} = \gamma = 0 \; \forall j$), and zero irrigation effectiveness ($\gamma = 0$) technical change are statistically tested. The LR-test statistic rejects all three hypotheses at the 5 per cent significance level, implying that technical change is a significant source of the observed TFP growth rate during the study period. The annual rate of technical change is estimated at 0.959 per cent driven mainly from neutral shifts of the production technology (0.726 per cent) while changes in irrigation technology also have a significant impact on irrigation effectiveness (0.11 per cent).

Finally, the assumption of a linear homogeneous greenhouse technology (*i.e.*, constant returns to scale technology) is tested by imposing the following parameter restrictions in (9): $\sum_j \beta_j^v + \beta^w = 1$, and $\beta^t = \beta_j^{vt} = \beta_{jm}^{vv} = 0 \; \forall j, m$. Calculated LR-test statistic also rejected the null hypothesis indicating, that the scale effect is present constituting a significant bias in observed TFP growth rates. Specifically, returns to scale is found to be increasing (1.133 on the average), implying that farmers in the sample are operating below their optimal scale. With the average farm size of 5.44 stremmas, an intensive greenhouse farming system is smaller than the farm size maximising the ray average productivity. Moreover, as a result of the continued increase in average farm size, returns to scale follows a declining trend over time.

Based on the parameter estimates of the *translog*-transition production function, output elasticities of variable inputs and irrigation water are estimated and presented in the upper panel of Table 4. Land input together with seeds and intermediate inputs are found to have the greatest percentage impact on farm's crop production with their corresponding mean output elasticities being 0.374, 0.252, and 0.195, respectively. In contrast, crop production output is found to be less responsive to changes in labor input with a point estimate of 0.139. Finally, for irrigation water applied, the average point estimate of 0.175 is expected for water demanding crops like vegetables.

[14] See Appendix A.2 for details on the *wild bootstrap* approach.

Irrigation Water Effectiveness

Using equation (11), irrigation water effectiveness is found to be 74.3 per cent on average during the 2010-13 period. This point estimate includes all farms in the sample utilizing both the traditional drip irrigation system and the new overhead sprinkler technology. Discriminating between the two samples, point estimates are 69.7 per cent and 77.5 per cent for drip irrigation and overhead sprinklers users, respectively. These mean estimates are lower than those reported in the engineering literature on the effectiveness of drip and overhead sprinkler irrigation technologies. However, these values are not surprising given the specific soil and climatic conditions faced by greenhouse farmers in the area. Ierapetra Valley is a semi-arid area dominated by sandy soil textures with a poor water holding capacity preventing farmers from exploring the full potential of both irrigation technologies.

On the other hand, the 7.8 per cent difference in irrigation water effectiveness between the two groups of farmers does not reflect the actual difference among them. Farmers are maximizing their quasi-rents choosing an appropriate irrigation technology given the specific soil and microclimatic conditions in their plots. To assess this, we calculate the irrigation water effectiveness, assuming that all farms in the sample are using the traditional drip irrigation technology (*i.e.*, imposing $\gamma = 0$ in relation (11)) and compare the results with what we observe from the sample. Figure 1 presents the frequency distribution of irrigation water effectiveness under the traditional drip irrigation system (left panel) and the observed choices in the sample (right panel). Hypothetically, if all farms were utilizing the drip irrigation technology, their average irrigation water effectiveness would have been just 45.1 per cent. This figure is nearly 30 per cent lower than the observed irrigation water effectiveness among greenhouse farms in the area.

This implies that farmers are rational in their decisions choosing the irrigation technology that indeed brings significant improvements in their profits by reducing water waste on farm. Farmers are aware of the specific conditions they face on their fields and they choose the irrigation application practice maximizing their profits. Farmers cultivating in good quality soils or facing less adverse climatic conditions will postpone adoption until this new technology becomes a profitable decision for their farming operation.

However, this does not mean that the two alternative technologies do not exhibit differences in the effectiveness of irrigation water application. The lower panel of Table 4 presents the output elasticities of irrigation water effectiveness under both regimes. In the first column the calculated point estimates assume zero irrigation effectiveness, $\gamma = 0$, while the second presents the actual situation in the sample. Under both regimes, soil water holding capacity is found to have a positive percentage impact on greenhouse production, while on the other hand climatic conditions and land surface slope are found to have a negative percentage effect. Crop production is found to be more responsive to changes in soil water holding capacity under the innovative technology while changes in climatic conditions and land slope are found to have a greater impact on crop production under the traditional technology.

These results imply that overhead sprinkler technology significantly enhances soil characteristics and atmospheric conditions for adopters by lessening the adverse effects of climatic conditions on output and augmenting the positive impact of soil water holding capacity. Finally, the enhancing effect of irrigation technology switch (*i.e.*, the change in irrigation technology) is 0.11 on average, indicating important gains for individual producers by switching to a more advanced irrigation practice. However, this impact highly depends on the existing micro-climatic and soil conditions of the farms.

These results are also supported by the annual changes shown in Table 5. Irrigation water effectiveness increases as the percentage of adopters increases over time. Overall, irrigation water effectiveness is 13.31 per cent greater during the study period, starting from a minimum value of 71.03 per cent in 2009-10 and reaching a maximum value of 80.49 per cent in 2012-13 cropping season, that is, the season following the highest percentage change in the number of adopters. On the other hand, the smallest percentage increase in adopters is observed during the 2010-11 cropping season (10.69 per cent). However, this increase is not accompanied by an increase in irrigation effectiveness rates as one would expect. The adverse climatic conditions prevailing in the surveyed area during that period counterbalanced the associated gains in irrigation water effectiveness from the higher adoption rates. Nevertheless, these adverse climatic conditions provided at the same time important incentives for farmers to adopt the overhead sprinkler technology. This is illustrated by the significant increase in the percentage of adopters during the following cropping season (2011-12) which is actually the highest during the period analyzed.

Table 6 presents estimates of irrigation water effectiveness and adoption rates calculated at soil and climate conditions quartiles means. The soil and climatic conditions variable are proxied as the potential irrigation water effectiveness that would result assuming that drip irrigation technology is used (*i.e.*, $\gamma = 0$). The results indicate a robust positive relation between soil and climate conditions and irrigation water effectiveness, revealing at the same time significant interactions between those conditions and overhead sprinkler technology adoption rates. Farmers facing poor soil and climate conditions exhibit a higher probability to adopt the new irrigation technology. Specifically, farms in the first quartile present the highest mean adoption probability (49.34 per cent) which in turn follows a descending path across quartiles. This result is further confirmed by the observed percentage of adopters in each quartile presenting a similar decreasing trend. Adverse soil and climatic conditions lead to significant water losses which, in turn, encourage farmers to adopt more effective technologies to reduce water waste and the associated high irrigation cost.

In addition, potential differences from drip irrigation technology are estimated for each quartile as the difference between the estimated irrigation water effectiveness minus the potential irrigation water effectiveness that would result assuming that drip irrigation technology is used (*i.e.*, $\gamma = 0$). The results attribute significant irrigation water effectiveness increases to the adoption of overhead sprinkler technology. Farmers in the first quartiles who would potentially face the greatest water losses due to adverse soil and climatic conditions are those who benefit most from the adoption of the new irrigation technology. Farmers in the fourth quartile are also found to benefit from the adoption of overhead sprinkler irrigation technology but to a less extent given the associated potential losses from the use of the drip irrigation technology are substantially lower.

The latter implies that policies intending to advance diffusion rates would not significantly improve effectiveness for farms facing favorable soil and climatic conditions. These results validate our analysis implying, that the impact of overhead sprinkler technology on irrigation water effectiveness is subject to soil and climatic characteristics of the plot. In particular, overhead sprinkler technology is preferred in terms of irrigation water effectiveness for specific plots in the sample with poor soil and atmospheric conditions. A direct implication of this finding is that policies intending to effectively reduce irrigation water waste through enhancing overhead sprinkler technology adoption rates should target specific farm groups facing the most adverse soil and climatic conditions.

Finally, Figure 2 presents an estimated normal kernel density for irrigation water effectiveness on an annual basis. We also, employ the DIP test, (see Appendix A.2 for details) which is appropriate to test the null of uni-modality in the distribution of irrigation water effectiveness. The test results are depicted as bootstrapped probability values (see Table 7). This modality test allows us to examine if farmers share distinctive technology steady-states or they share a common steady state technology regime. The irrigation water effectiveness distribution appears uni-modality in all years apart from the period 2011. This indicates that initially (2010) farmers share a basic common technology while in the next year (2011) a substantial portion of farmers move to the upper technology regime following the adverse climatic conditions of the previous year. For the two consecutive years (2012 and 2013), all the farmers tend to move to the new technology regime.

Productivity Measurement

The empirical results concerning the decomposition of TFP changes based on equation (7) are reported in Table 8. The average annual TFP growth rate was 1.14 per cent during the 2010-13 cropping seasons. The greatest part of that growth was due to technical change (84.22 per cent) driven primarily from shifts of the productive component of farm technology. Those shifts accounted for the 74.40 per cent of the observed productivity changes. The presence of scale economies combined with the actual increases in aggregate variable input growth during the period was found to contribute 8.96 per cent to observed productivity rates being thus the second most important source of TFP growth. Finally, changes in climatic conditions also contributed positively to productivity rates accounting for the remaining 6.78 per cent. The positive effect of climatic conditions on TFP growth is the outcome of the negative effect of climatic conditions on irrigation water effectiveness combined with the gradual improvements in atmospheric conditions (decreases in aridity index) during the period analyzed.

The average contribution of non-water variable inputs is 0.07 per cent, accounting for the 6.44 per cent of observed productivity growth rates. Intermediate inputs (3.84 per cent) present the highest effect due to the gradual intensification of crop production over years. Despite the high output elasticity of land, its relative contribution to observed TFP growth is zero as changes in the total acreage were minimal during the period analyzed. Crop sharing contracts are rarely used by farmers in the sample, resulting in time-invariant cultivated acreages. Increases in seeds input account for the 2.03 per cent of TFP growth, whereas the corresponding figure for labor input is considerably lower (*i.e.*, 0.35 per cent). On the other hand, increases in irrigation water input constituted a significant contributor of TFP growth accounting for 2.75 per cent of observed productivity changes. Operation at a sub-optimal scale for greenhouse farms induced intensification of farm production increasing variable input use which was translated into significant productivity improvements during the cropping periods analyzed.

Overall technical change accounting for the both output enhancing and irrigation water effectiveness components was estimated at 0.96 per cent, constituting the most important source of TFP growth. This figure includes both the output enhancing component of technical change capturing neutral and variable input intensive or saving technical changes and the irrigation effectiveness technical change component measuring the indirect impact of changes in irrigation technology on TFP growth through their impact on irrigation water effectiveness. Specifically, output enhancing technical change was driven mainly from neutral shifts of the production frontier (63.56 per cent) and to a lesser extent from the biased component (10.84 per cent).

Irrigation water effectiveness technical change contributed also significantly to TFP growth accounting for 9.64 per cent increases in productivity rates. As farmers move gradually to overhead sprinkler technology, the new technology augments soil and climatic conditions enhancing irrigation water effectiveness and consequently productivity growth. Traditional measures of irrigation water technical change fail to account for both the transition process involved and the indirect impact of irrigation technology on productivity through enhancements in irrigation water effectiveness leading to biased measures of technical change. In this case study, the estimated contribution of technical change associated with irrigation water effectiveness implies that measured TFP growth would significantly misstate the true effect of technical change if the distinct characteristics that underline irrigation water technology were not taken into account.

6 Concluding Remarks

Current debates on water management issues in agriculture have resulted in many policy recommendations aiming to enhance effective water management mainly through the promotion of modern irrigation technologies. Nevertheless, the effectiveness of these policies depends on the proper measurement of irrigation water effectiveness and agricultural productivity. Properly measuring the impact of irrigation water technology on productivity growth requires defining the technology that can address three important issues related with irrigation water use: a) irrigation water applied deviates from the amount of water that is actually consumed by the crop; b) the transition between the alternative irrigation technologies does not take place in a single time period; and c) changes in irrigation technology influences output growth indirectly by augmenting farms' soil characteristics and atmospheric conditions which, in turn, affect irrigation water effectiveness.

In light of the above, this paper presents an integrated framework for measuring irrigation water effectiveness within a transition-production function estimation that allows for a smooth transition between traditional and innovative irrigation technologies. The analysis was carried out within a decomposition framework which enables the proper measurement of technical change effects on TFP growth. The econometric model was based on a two-stage estimation procedure that allows us to incorporate the smooth transition process into our decomposition framework. Our empirical model was applied to a panel data set of 56 small-scale greenhouse farms in Greece observed during the period 2010-2013.

Our results indicated that during the period analyzed the speed of transition between traditional (drip) and innovative (overhead sprinkler) irrigation technologies is relatively quick, approximating a threshold process. Farmers with a conditional probability to adopt higher than 0.60 switched to the overhead sprinkler irrigation technology, while this probability is mostly impacted by the farmer's educational level and the number of on-farm extension visits. We also find that in the beginning of the period farmers shared a basic common technology. Later a substantial portion of farmers gradually moved to the upper technology regime while the remaining farmers remained in the basic technology regime.

Moreover, our results indicate that farmers facing poor soil and climate conditions exhibit a higher probability to adopt the new irrigation technology while the transition to the overhead sprinkler irrigation technology is highly beneficial. In particular, farmers who potentially face the greatest water losses due to adverse conditions benefit most from the adoption of new technology. These results validate our analysis, implying that the impact of overhead sprinkler technology on irrigation water effectiveness is subject to the soil characteristics and the atmospheric conditions of the plot. In particular, we find that the overhead sprinkler technology is more beneficial in terms of water irrigation effectiveness for the plots in the sample that face poor soil and atmospheric conditions.

Regarding productivity growth, we find that the average annual TFP growth rate is 1.14 per cent during the period analyzed. The greatest part of that growth is attributed to technical change (84.22 per cent), followed by scale effect (8.96 per cent) and changes in climatic conditions (6.78 per cent). Irrigation water effectiveness technical change contributes significantly to TFP growth, accounting for 9.64 per cent increases in productivity rates. We find that as farmers move gradually to overhead sprinkler technology, the new technology augments soil and climatic conditions enhancing irrigation water effectiveness and consequently productivity growth. This high figure for irrigation water effectiveness technical change implies that measured TFP growth can significantly misstate the true effect of technical change if the distinct characteristics underlining irrigation water technology are not taken into account.

Our results suggest that policies aiming to enhance adoption rates for overhead sprinkler technology should be directed toward increasing farmer's human capital levels rather providing economic or other incentives. In particular, training seminars targeting target groups of less-educated farmers and more frequent on-farm extension visits can be more effective than other policies such as subsidizing new irrigation technology. Moreover, policy schemes aiming to enhance irrigation water effectiveness through advancing diffusion rates can be more effective if they target specific groups of farmers who face the most adverse soil and climatic conditions.

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A Appendix

A.1 Testing the Specification of Irrigation Water Effectiveness Function

The specified non-linear *translog*-transition production function has an identification problem concerning the parameters γ and δ. This implies that the null hypothesis $H : \gamma = 0 \wedge \delta = 0$ cannot be tested. To overcome this problem we develop a second-order *Taylor* series approximation of $F(\hat{k}_{it}; \gamma, \delta)$ around $\gamma = 0$, which results in the following non-linear equation for the irrigation water effectiveness function:

$$\ln g_{it} = -\left[\vartheta_0 q_{it} + \vartheta_1 d_{it} + \vartheta_2 s_{it} + \left(\vartheta_3 q_{it} + \vartheta_4 d_{it} + \vartheta_5 s_{it} + \vartheta_6 q_{it}\hat{k}_{it} + \vartheta_7 d_{it}\hat{k}_{it} + \vartheta_8 s_{it}\hat{k}_{it}\right)\hat{k}_{it}\right]$$

By the estimating the *translog*-transition production function using the above linearized specification of irrigation water effectiveness function, we can test the null hypothesis of linearity $H : \vartheta_3 = \vartheta_4 = \vartheta_5 = \vartheta_6 = \vartheta_7 = \vartheta_8 = 0$ using a standard F-test (the F-version of the linearity test performs better in small samples; see for example Luukkonen *et al.*, (1998) and Christopoulos and Leon-Ledesma (2008). If the null hypothesis of linearity is rejected against the alternative, then we proceed to the econometric estimation of the *translog*-transition production function using the specification in (11) for the irrigation water effectiveness function.

A.2 Obtaining p-values for the Transition Parameters

To obtain the associated p-values of the transition parameters we follow a *wild bootstrap* approach. First, we estimate the model assuming that $F(\hat{k}_{it}; \gamma, \delta) = 0$ and we obtain the estimated residuals v^0_{it}. From these residuals we extract a sample of M observations $h = v^0_{it} w_{it}$ where w_{it} is a random sequence with $E(w_{it}) = 0$ and $E(w^2_{it}) = 0$. The pseudo-disturbances w_{it} are generated following a *Rademacher* distribution as:

$$w_{it} = \begin{cases} 1 & \text{with} \quad p = 0.5 \\ -1 & \text{with} \quad p = 0.5 \end{cases}$$

Then we generate an artificial series for y_{it} using the parameter estimates of the model under the assumption $F(\hat{k}_{it}; \gamma, \delta) = 0$ and the above bootstrapped residuals. We estimate again the model with these artificial data and calculate the simple t-test. We repeat the above procedure 5,000 times to form a bootstrapping distribution. The p-value of the test can be obtained as the proportion of times the t-test is smaller than the bootstrapped t-test. Davidson and Flachaire (2008) showed that distortion obtained from the above *wild bootstrap* process is not larger than that of other standard bootstrap methods. They also show that this approach perform very well even in the case of non symmetrically distributed errors.

A.3 The DIP Test of Modality

The DIP statistic has been proposed by Hartigan and Hartigan (1985) and measures unimodatility of a sample as the maximum difference between the empirical distribution function and the unimodal distribution function that minimizes that maximum difference. In particular the DIP test considers that a distribution function F is unimodal with mode q if F is convex to the left $(-\infty, q)$ and concave to the right $(q, -\infty)$. The test is based on the idea of a *minorant*. Within this context we define the greatest convex minorant of F in $(-\infty, \alpha)$ as the *supremum* of all convex functions $G(z)$, $\{\sup G(z) \text{ for } z \geq \alpha\}$, that are not greater than F. Accordingly, the least concave *majorant* of F in $(\alpha, -\infty)$ as the *infimum* of all concave functions $R(z)$, $\{\inf R(z) \text{ for } z \geq \alpha\}$, that are not less than F.

The DIP test of a distribution function F is given by:

$$D(F) = \inf_{R \in U} \sup_{-\infty < z < \infty} [F(z) - R(z)]$$

where U is the class of all unimodal distribution functions.

The null hypothesis the distribution function F has a unimodal density f is tested against the alternative that it has more than one. Hartigan and Hartigan (1985) replaced the theoretical distribution F with the empirical one $\tilde{F}$ of a random n-sample. The null hypothesis that the function F is unimodal is rejected against the alternative when $D(\tilde{F})$ exceeds the α critical level. In other words, the reference distribution for estimating the DIP statistic is the uniform unimodal distribution. Following Cheng and Hall (1998) p-values are calculated by comparing the DIP statistic obtained with those for repeated samples of the same size from a uniform distribution.

Tables and Figures

Table 1: Summary Stattisitcs of the Variables

Variable	Non Adopters	Adopters	All Farms
Number of farms	23	33	56
Irrigation Technology Adoption Model			
Farmer's Age (in years)	53.98	33.32	41.80
Farmer's Education (in years)	9.77	13.17	11.77
No of Extension Visits	1.49	5.85	4.06
Farm Size (in stremmas)	4.11	6.37	5.44
Subsidies (in Euros)	569.6	796.1	703.1
Translog-Transition Production Function			
Output (in Euros)	57,952	87,424	78,528
Labor (in hours)	333.0	772.4	591.9
Seeds (in Euros)	1,271	1,574	1,449
Intermediate Inputs (in Euros)	7,893	9,579	8,886
Irrigation Water (in m^3)	1,202	1,467	1,358
Irrigation Water Effectiveness Function			
Soil Water Holding Capacity (in cm/s)	1.31×10^{-3}	2.60×10^{-3}	1.96×10^{-3}
Climatic Conditions	1.11	1.25	1.19
Land Surface Slope (in degrees)	0.09	0.11	0.10

Table 2: Maximum Likelihood Parameter Estimates of the Probit Model

Parameter	Estimate	St.Error	Parameter	Estimate	St.Error
Constant	-6.0926	1.8643**	Extension Visits	0.4842	0.0835**
Farmer's Age	-0.0337	0.0115**	Farm Size	0.1198	0.0523*
Farmer's Education	0.6086	0.2891*	Subsidies	0.0010	0.0003**
Farmer's Education-Squared	-0.0233	0.0115*		—	
Pseudo R-squared			0.7078		
Marginal Effects:					
Farmer's Age	-0.0117	0.0040**	Farm Size	0.0414	0.0180*
Farmer's Education	0.2121	0.0978*	Subsidies	0.0003	0.0001**
Extension Visits	0.1688	0.0301**		—	

The marginal effects were evaluated at the mean values while their corresponding standards errors were obtained using the *Delta* method.
* and ** indicate statistical significance at the 5 and 1 per cent level, respectively.

Table 3: Parameter Estimates of the *Translog*-Transition Production Function

Parameter	Estimate	St.Error	Parameter	Estimate	StError
β_0	-0.0747	0.0356**	β_{AL}^{vv}	0.3194	0.1315**
β_A^v	0.3580	0.1000**	β_{AC}^{vv}	-0.0807	0.1885
β_L^v	0.1534	0.0568**	β_{AI}^{vv}	-0.1100	0.2044
β_C^v	0.2597	0.0669**	β_{LC}^{vv}	-0.3222	0.0818**
β_I^v	0.1968	0.0590**	β_{LI}^{vv}	0.0986	0.0998
β^w	0.1728	0.0256**	β_{CI}^{vv}	-0.3966	0.1213**
β^t	0.0073	0.0042*	β_0^q	1.6686	0.6863**
β_A^{vt}	0.0254	0.0318	β_0^d	0.2879	0.5333
β_L^{vt}	-0.0036	0.0169	β_0^s	-1.0467	0.4937**
β_C^{vt}	-0.0231	0.0227	β_1^q	-1.7247	1.0711*
β_I^{vt}	-0.0103	0.0191	β_1^d	-0.8507	0.6899
β_{AA}^{vv}	0.1947	0.1450	β_1^s	1.2814	0.6899*
β_{LL}^{vv}	0.0490	0.0735	γ	3.5000	1.6924**
β_{CC}^{vv}	0.3027	0.0902**	δ	0.6000	0.3409**
β_{II}^{vv}	0.2614	0.0611**			
R^2			0.9435		

Where A refers to land under greenhouse cultivation, L to labor used, C to seeds, I to other intermediate inputs, t to time, q to soil water holding capacity, d to aridity index, and s to land surface slope.
Standard errors for the γ and δ parameters were obtained using a *wild boostrap* approach.
* and ** indicate statistical significance at the 10 and 5 per cent level, respectively.

Table 4: Output Elasticities, Returns to Scale and Irrigation Technology Effect

	All farms	
Variable Input Elasticities		
Land	0.3742	
Labor	0.1393	
Seeds	0.2522	
Intermediate Inputs	0.1946	
Irrigation Water	0.1728	
Returns to Scale	1.1332	
	Drip Irrigation	Overhead Sprinklers
Irrigation Water Effectiveness Elasticities		
Soil Water Holding Capacity	0.0224	0.0756
Climatic Conditions	-0.1734	-0.0657
Surface Slope	-0.2017	-0.0480
Effect of Irrigation Technology	0.1099	

Table 5: Adoption Rates, Climatic Conditions and Irrigation Water Effectiveness over the 2010-13 Period

Year	2010	2011	2012	2013
% of Adopters	23.21	33.90	47.43	58.93
Change in Adopters	—	10.69	13.53	11.50
Probability to Adopt	0.3493	0.3677	0.4498	0.4680
Climatic Conditions	1.1316	1.4305	1.1025	1.0932
Irrigation Water Effectiveness	0.7103	0.7161	0.7392	0.8049

Table 6: Irrigation Water Effectiveness and Adoption Rates per Soil and Climate Conditions Quartiles

	Soil and Climate Conditions Quartiles			
	First	Second	Third	Fourth
Irrigation Water Effectiveness	0.6760	0.6981	0.7783	0.8181
Potential Difference from Drip Technology	0.4627	0.3424	0.2572	0.1051
% of Adopters	21.14	16.07	12.07	9.36
Probability to Adopt (%)	49.34	46.80	35.25	32.09

Table 7: Values of Calibrated DIP Modality Test for Irrigation Water Effectiveness

	G-Function Values			
Year	2010	2011	2012	2013
DIP test	0.371	0.006*	0.570	0.101**

* and ** indicate statistical significance at the 10 and 1 per cent level, respectively.

Table 8: Decomposition of TFP Growth (Average Annual Values for the 2010-13 Period)

Components	TFP Growth	(%)
TFP Growth	1.1396	
Scale Effect:	0.1024	(8.96)
Land	0.0000	(0.00)
Labor	0.0039	(0.35)
Seeds	0.0231	(2.03)
Intermediate Inputs	0.0438	(3.84)
Irrigation Water	0.0314	(2.75)
Climatic Effect	0.0775	(6.78)
Overall Technical Change:	0.9598	(84.22)
Output Enhancing TC	0.8499	(74.40)
Neutral TC	0.7261	(63.56)
Biased TC	0.1238	(10.84)
Irrigation Water Effectiveness TC	0.1099	(9.62)

Figure 1: Frequency Distribution of Potential Irrigation Water Effectiveness under Both Technological Regimes

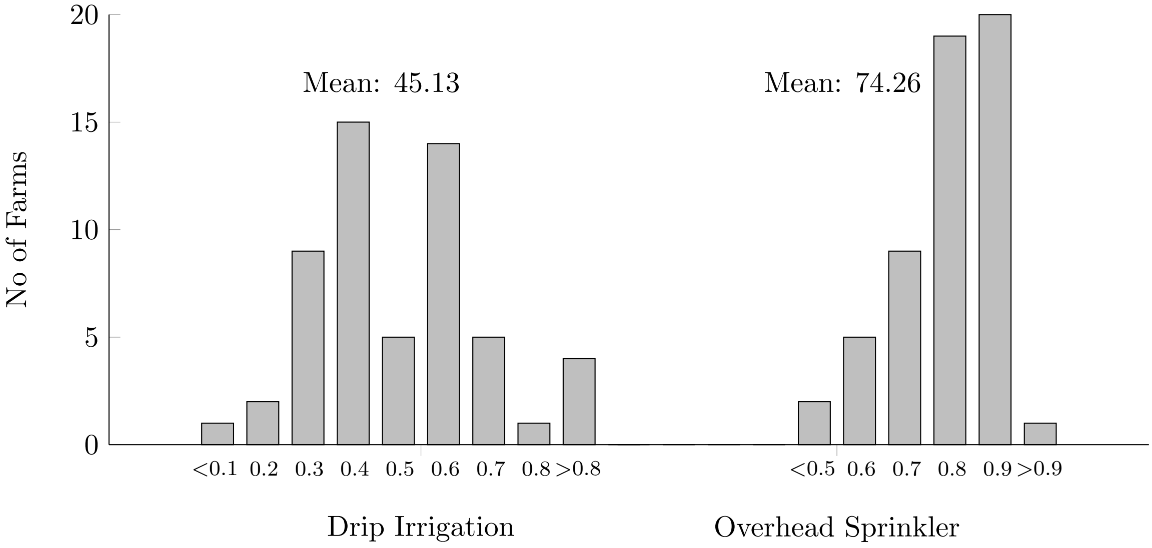

Figure 2: Annual Irrigation Water Effectiveness Densities