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Abstract. Spain occupies a first ranking position in worldwide production and exportation for olive oil and table olives. Such position is enforced by the positive evolution of investment demonstrated by an increase of approximately 5% of area dedicated to this cultivation during the last 6 years. This study analyzes Spanish olive sector investment decision taking into consideration the technical efficiency as a relevant element that could impact that decision by integrating the real option approach and a dynamic stochastic frontier model. This analysis has been applied to a 158 Spanish olive farms using FADN data set. The results show that the technical inefficiency persistence parameter is fairly low to unity, which means that small technical inefficiency is transmitted to the next time period. The olive groves investment is irreversible and characterized by uncertainty on price and discount rate. An increase of discount rate means that the farmers take the decision to postpone investment. An increase on price along with a decrease of discount rate leads to the decision to invest with no option value of waiting to invest. The results suggest that the decision of investment in Spanish olive depends also on technical inefficiency and its persistence. The increase of farms inefficiency means that the decision is to wait to invest. Consequently, the inefficient farmers take time and wait to invest, while a smaller persistence parameter leads to the decision to invest.

Keywords: Investment, olive sector, dynamic technical efficiency.

1. Introduction

The olive sector has an important social, economic and environmental role in Spain encompassing more than 2.5 million hectares¹ (Spanish Ministry of Environment and Rural and Marine Affairs, MARM, 2008a). With most of olive production concentrated in less-developed areas, this production activity represents an important source of employment and a solid column of social and economic development of such area. A further contribution of olive groves is the mitigation they provide for environmental problems such as desertification and loss of biodiversity associated to the production region.

World-wide, Spain occupies a first ranking position in worldwide production and exportation for olive oil and table olives. Such position is enforced by the positive evolution of investment demonstrated by an increase of approximately 5% of area dedicated to this cultivation during the last 6 years (Spanish Ministry of Environment and Rural and Marine Affairs, MARM, 2008_b).

As other types of investment, the olive sector investment is characterized by irreversibility and uncertainty (Dixit and Pindyck, 1994). The irreversibility is due to the presence of a sunk cost associated with various factors: a) the planting of new orchard, which includes pulling out the old ones when necessary, land preparation and new plantation material costs. b) the opportunity cost associated with the establishment expense and, c) the opportunity cost of the land while the orchard is being established.

The uncertainty is reflected through factors that affect future outcome and therefore, farmer's investment decision. Moreover, uncertainty can emerge from many sources as: market conditions, regulatory initiatives and constraints, farmer's knowledge and information access. Thus, farmers take time before

¹ Spain has a largest area of olive groves and the largest number of olive trees in the World (Spanish Ministry of Environment and Rural and Marine Affairs, 2008_a)

deciding to invest until they dispose of new information and diminish their uncertainty. Farmers who search information have more managerial experience which is associated to high technical efficiency level (Wilson et al., 2001).

This study analyzes Spanish olive sector investment decision under irreversibility and uncertainty taking into consideration the technical efficiency as a relevant element that could impact that decision by integrating the real option approach and a dynamic stochastic frontier model. The real option approach allows us to analyse the decision to invest under uncertainty and irreversibility. There is an extensive literature applying this approach to agricultural sector applications (e.g., Purvis et al., 1995; Engel and Hyde, 2003, Tauer, 2006, Stokes et al., 2009), with Price and Wetzstein (1999) addressing orchard management specifically. However, up to date no previous published papers have focused on the analysis of investment decision under uncertainty and irreversibility in Spanish olive sector. Moreover, the novelty of our approach is assessing the impact of managerial skills (the farmer's knowledge, information access...etc) on investment, such skills are associated to farms technical efficiency (Wilson et al., 2001 and Battese and Broca, 1997). The key question of our analysis is the evaluation of the relationship between the investment under uncertainty and irreversibility and the persistence of technical inefficiency.

A dynamic stochastic frontier model is developed to estimate the long run technical efficiency and its persistence. In a posterior step, the rate of technical efficiency and its persistence are used to evaluate their impact on investment decision. The measurement of long-run technical inefficiency levels and its persistence helps us to evaluate the subsistence of farms over the long run and adjustment factors and forces leading to technical inefficiency.

The next section presents a background and literature review for both approaches the dynamic efficiency and real option. Section 3 deals with the methodology approach. Section 4; discuss the econometric specification and empirical application. In section 5, we present the results and discussion, and in the last section, we draw our conclusions.

2. Background and literature review

2.1 The dynamic stochastic frontier model

The majority of traditional stochastic frontier models tend to estimate frontier function and firm-specific inefficiency levels assuming that inefficiency levels are time-invariant (e.g. Schmidt and Sickles, 1984; Kumbhakar, 1987; and Greene, 2008). These studies do not allow for the explanation of time-varying efficiency levels through a formulation of production inefficiency that is impacted by behavioral or structural linkages over time. The change in efficiency is autonomous with the passing of time. Therefore, their technical efficiency models remain static and they fail to associate measurable evolution in technical efficiency with an economic motivation, giving a limited analysis of production slack.

Few stochastic frontier production studies account for dynamics in panel data models of technical inefficiency (e.g. Cornwell et al., 1990; Kumbhakar, 1990; Battese and Coelli, 1992; Lee and Schmidt, 1993 and Ahn and Schmidt, 1995). Such models aim to estimate the temporal pattern of time series variation in firm efficiencies levels. However, they are criticized by: a) the imposition of an arbitrary restriction on the short-run dynamic efficiency levels and, b) their incompatibility for the analysis of long-run dynamics on technical inefficiency.

Other studies, such as Ahn et al., (2000), allow firm specific technical inefficiency levels to follow an autoregressive process of order one (AR(1)). This approach does not require the imposition of the arbitrary restrictions on the short-run dynamic efficiency levels, but it is criticized by the absence of a theoretical justification. The authors claim that this is a useful approach to examine a dynamic link between technical innovations and production inefficiency levels by specifying an autoregressive processes implying the ability of firms to change systematically by a fixed percentage of their past-period inefficiency level. The limited number of studies focusing on this aspect about dynamic models efficiency (e.g. Ahn et al., 2002; Huang, 2004 and Tsionas, 2006) are justified by a complex likelihood function specification as well as the difficulties of assuming the inference on unobserved firm-specific inefficiencies (Tsionas, 2006).

The dynamic stochastic frontier models tend to estimate firms' long-run technical inefficiency level, given the pressure on a firm's ability to remain competitive in the long run unless they are technically

efficient. Tsionas (2006) proposes that the inefficiency factors need to be adjusted by time which depends on adjustment costs. The higher the cost of adjustment; the great is the probability of finding evidence of persistent technical inefficiency. In this study, we consider a dynamic stochastic frontier model with persistent technical inefficiency over time using a parameter inferences and inferences on technical inefficiency on a firm-specific basis.

2.2 The real options approach

The expanded NPV analysis reflects the traditional (static or passive) NPV of expected cash flow and the option value of operating and strategic adaptability. Thus, an options approach to capital budgeting quantifies the value of options, which is represented as a collection of real options. The most common options are to defer, contract, shut down, abandon, expand, default or switch between alternative. In this study, we are interested in the deferral option, or the option of waiting to invest. This option derives its value from reducing uncertainty by delaying an investment decision until more information has arrived, having this kind of managerial flexibility implies value to the firm from an opportunity cost perspective.

The dynamic version of discounted cash flow analysis and, in particular NPV offers significant advantages over static discounted cash flow analysis such as the incorporation of future uncertainty and offers the flexibility of the adjusting managers' decisions in the future. Such attributes allows managing risk and increasing the value of a project or strategy for situations that differ from those that were expected. This approach considers all important future uncertainties by solving a dynamic programming problem which provides the manager the possibility to take many future states into account and incorporates the best possible set of decisions at each time and state into the analysis. This approach uses the opportunity cost of capital as the discount rate to determine the project expected present value, and the estimation of the discounted rate is based on market data about projects with similar or identical risks.

There are three methodologies available to evaluate corporate risk and uncertainty. In addition to capital budgeting methods², there are portfolio analyses evaluating the risk in the context of the existing assets and projects, and the option pricing uses a direct analysis of risk via probability assignment (Brach, 2003).

Black and Scholes (1973) pioneered the concept allowing the pricing of call option on shares of stock. Myers (1977) built on this concept by considering how financial investments generate real options and he indicates that the use of traditional discounted cash flow approach ignores the value of options arising in uncertain and risky investment projects by viewing of discretionary investment opportunities as "growth options". Later, Kester (1984) discussed strategic and competitive aspects of growth opportunities. Other studies on real option approaches focused on methodological problems in analysing an investment decision. Dean (1951); Hayes and Abernathy (1980), and Hayes and Garvin (1982) recognized that standard discounted cash flow undervalued investment opportunities as financial analysts ignored important strategic considerations. Hodder and Riggs (1985), and Hodder (1986) indicated that the problem arises from abuse of discounted cash flow techniques, while Myers (1987) confirms that the problem results from various misapplications of the underlying theory.

In 1994, Dixit and Pindyck introduced the irreversibility model³ and were the first to point out the interactions between the irreversibility nature of investments in an uncertain future and the timing of those investments. With farms investing frequently in plants and machinery such investments embody three important characteristics: i) irreversibility, ii) uncertainty, and iii) the optimal timing of investment decisions. The uncertainty is associated with the future outcomes that can be greater or smaller profit. Irreversibility means that they are an initial cost of investment that must be at least partially sunk, thus the investment is partially or completely irreversible. The timing of investment means that prouge investment to get more information about the future.

²In this methodology the risk is measured indirectly and the discount rate represents the opportunity cost of capital.

³ Dixit and Pindyck in their book "Investment under uncertainty" elaborated this notion

2.3 The Orchard investment analysis

The most of research in orchard investment developed by economists have used the mathematical programming approach to analyse the decision of investment. Such models have the maximization of the net present value (NPV) of the orchard as an objective, subject to optimal replacement of trees (Hester and Cacho, 2003). Early examples include Graham et al., (1977) and Willis and Hanlon (1976), both of whom used the mathematical programming methodology to address the profit maximization of apple cherry and pear orchard using the timing of replacement as a decision variable, while the second one built a temporal model for long-run orchard decision. Childs et al., (1983) and, later Thiele and Zhang, 1992 used the dynamic programming to maximise profit under the replacement policy applied to apple orchards. Applied to the same orchards, Cahn et al., (1997) used the simulation methodology to explore net present value under the planting density restriction. However, few models have used the econometric approach on orchard investment with emphasis on uncertainty, adjustment costs and informational imperfections (e.g. Bernstein and Nadiri, 1986). Dorfman and Heien (1989) presented a model of investment behaviour which incorporates uncertainty and adjustment costs through the maximization of the expected present value of almond orchard profits.

The real option approach to analysing orchard investment is undertaken by Price and Wetzstein (1999), which consider uncertainty on yield and price to analyse irreversible investment decisions in peach orchards. In the present study, we consider the real option approach as formulated by Dixit and Pindyck (1994) specification model to analyse the investment under uncertainty and irreversibility.

3. Methodology

3.1 Dynamic stochastic frontier model

Several methods are used to analyze technical efficiency in a production function. In this study, the Bayesian stochastic frontier production model is applied. Koop et al. (1995) and Osiewalski and Steel (1998) were the first that suggested the use of Bayesian methods for technical efficiency. They used a model with an informative prior for firm-specific intercepts. Such a model is similar to the classical fixed effects model assuming a distribution for inefficiency.

Many applications have used this approach. We point out among others Van den Broeck et al., (1994) that used a sampling technique to obtain the posterior distribution for the Erlang model. Koop et al., (1995) that developed a Gibbs sampling approach. Greene (1990 and 2000) evaluates a complicated integral using numerical and Monte Carlo integration. More recently, Tsionas (2000, 2002 and 2006) and Kozumi and Zhang (2005), used a Gibbs sampling method to analyze the case of non-integer shape parameter.

Following Tsionas (2006), the stochastic frontier production function with panel data can be expressed as follows:

$$y_{it} = x_{it}\beta + v_{it} - u_{it} \quad i = 1, \dots, n, t = 1, \dots, T \quad (1)$$

where x_{it} and β are a $k \times 1$ vector of regressors and parameters respectively.

v_{it} is a two-sided random errors that are assumed to be iid $IN(0, \sigma_v^2)$, $i = 1, \dots, n, t = 1, \dots, T$, and u_{it} is a vector of independently distributed and nonnegative random disturbances that represent technical inefficiency.

We assume that technical efficiency follows an autoregressive process:

$$\log u_{it} = z_{it}\gamma + \rho \log u_{i,t-1} + \xi_{it}, \text{ for } t = 2, \dots, T \quad (2)$$

$$\log u_{i1} = z_{i1}\gamma / (1 - \rho) + \xi_{i1}, \text{ for } t = 1 \text{ for all } i = 1, \dots, n. \quad (3)$$

where $\xi_{it} \sim IN(0, \omega^2)$, for $t = 2, \dots, T$ is a random variable capturing the “unexpected log-efficiency sources” and $\xi_{i1} \sim IN(0, \omega^2 / (1 - \rho^2))$, for all $i = 1, \dots, n$. The “systematic part” $z_{it}\gamma + \rho \log u_{i,t-1}$ reflects “expected” log-inefficiency sources. z_{it} and γ are an $m \times 1$ vector of covariates and parameters, respectively. We assume that v_{it} , u_{it} , x_{it} and z_{it} are independent.

The joint density of the model is given by:

$$\begin{aligned}
p(y, u | X, Z, \theta) &= \int_{R_+^{nT}} p(y, u | X, Z, \theta) du \\
&= (2\pi\sigma^2)^{-nT/2} \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^n \sum_{t=1}^T (y_{it} + u_{it} - x_{it}\beta)^2\right] \\
&\quad \times (2\pi\omega^2)^{-nT/2} \exp\left[-\frac{1}{2\omega^2} \sum_{i=1}^n \sum_{t=2}^T (\log u_{it} - z_{it}\gamma - \rho \log u_{i,t-1})^2 - \log u_{it}\right] \\
&\quad \times (1 - \rho^2)^{n/2} \exp\left[-\frac{1 - \rho^2}{2\omega^2} \sum_{i=1}^n (\log u_{i1} - z_{i1}\gamma / (1 - \rho))^2 - \log u_{i1}\right]
\end{aligned} \tag{4}$$

The first line of the joint density comes from the normality of $y_{it} | x_{it}, u_{it}, \theta$, while the second come from log-normality of $u_{it} | z_{it}, u_{i,t-1}, \theta$, and the last one is due to lognormal assumption on $u_{i1} | z_{i1}, \theta$.

In order to carry out the Bayesian inference, the likelihood function is completed with a prior distribution $p(\theta)$ for location parameters⁴ β , γ and ρ . The joint prior distribution is given by:

$$p(\beta, \gamma, \rho) = f_N^k(\beta | \bar{\beta}, \bar{V}_\beta) f_N^m(\gamma | \bar{\gamma}, \bar{V}_\gamma) p(\rho) \tag{5}$$

$f_N^k(x | m, V)$ refers to the density of the k-variate normal distribution with mean vector m and covariance V . ρ has a Jeffreys' prior distribution⁵ and is independent of γ , while scale parameter (σ and ω) are independent with inverted-gamma prior:

$$p(\zeta) \alpha \zeta^{-(n_\zeta + 1)} \exp(-q_\zeta / (2\zeta^2)), \quad n_\zeta \geq 0, q_\zeta > 0 \tag{6}$$

where ζ refers to any of σ , ω , and n_ζ, q_ζ are parameters of the prior distribution.

An application of Bayes' theorem by the multiplication of the u prior's given by (3) with the prior on structural parameters given in (5) and (6), gives a joint prior distribution involving θ and latent variables u (Tsonas, 2006):

$$p(\theta, u | y, X, Z) \propto p(y, u | X, Z, \theta) \times p(\theta) \tag{7}$$

where $p(y, u | X, Z, \theta)$ is the augmented likelihood function given in equation (4). The high dimensional integral precludes a closed form solution to the likelihood function and thus, requires a

⁴ There are assumed to be independent of the scale parameters σ and ω .

⁵ The Jeffreys's prior in the context of a simple AR(1) model has a following density:

$$p(\rho) \propto (1 + \rho)^{-1/2} (1 - \rho)^{-1/2}, \quad -1 < \rho < 1.$$

numerical solution approach. Gibbs sampling⁶ method with data augmentation has been used in order to make Monte Carlo draws from the joint posterior distribution of the model and to perform the computations (Gelfand and Smith, 1990, Tanner and Wong, 1987).

Using the conditional distribution of $u_{it} | \theta, y, X, Z$ provided by Markov Chain Monte Carlo (MCMC) scheme, the technical efficiency is measured for each farm (Van den Broeck et al., 1994, Koop and Steel, 2001).

3.2 Real option methodology

The first model in real option approach was developed by McDonald and Siegel (1986), with a starting point to find the optimal sunk cost (K) to pay in return for a given project.

Following Dixit and Pindyck (1994), we assume that the project value V follows a geometric Brownian motion with drift ℓ and diffusion Ω , which implies that the current value of the project is known, but the future values are always uncertain.

$$dV = \ell V dt + \Omega V ds \quad (8)$$

where ds is the increment of a Wiener process with $E\{ds\} = 0$ and $E\{(ds)^2\} = dt$. The assumption of V following a geometric Brownian motion is conditioned on the level of technical inefficiency. In principle, the technical efficiency function is not stochastic, but it can contain unknown parameters. In the SFM, technical inefficiency is combined with the two-sided error specification; thus, by its construction the technical inefficiency function can be scaled to behave as a probability density function which is combined with the two-sided error probability density function. This all leads to a common practice specifying a composed error with a non-zero expectation.

We define the value of the option to invest or the investment opportunities $F(V)$ and the objective is to find the rule that maximizes this value. Using a dynamic programming approach, we can derive the optimal investment.

The maximization of expected present value leads to:

$$F(V) = \max E \left[(V_T - K) e^{\psi T} \right] \quad (9)$$

where $V_t - K$ is the payoff from investing at time t , ε denotes the expectation, T is the (unknown) future time that the investment is made, ψ is a discount rate, and the maximization is subject to equation (8) for V .

We are interested with the way in which the investment decision is affected by uncertainty ($\Omega > 0$). Since V evolves stochastically, the problem is to determine the point or a critical value H at which it is optimal to invest; (i.e., invest when $V \geq H$). The Bellman equation over a time interval dt leads to the total expected return on the investment opportunities, $\psi F dt$, is equal to its expected rate of capital appreciation:

$$\psi F dt = \varepsilon (dF) \quad (10)$$

Using Ito's Lemma to expand dF , the Bellman equation becomes the following differential equation that must be satisfied by $F(V)$:

⁶ Gibbs sampling is an iterative approach that permit making draws from a joint distribution by doing an iterated sequential draws from the conditional distributions.

$$\frac{1}{2}\Omega^2V^2F''(V) + (\psi - o)V F'(V) - \psi F = 0 \quad (11)$$

where $F'(V) = \frac{dF}{dV}$, $F''(V) = \frac{d^2F}{dV^2}$ and o is the dividend rate.

The solution to the Bellman equation leads to the optimal investment trigger value (Dixit and Pindyck, 1994):

$$V = \begin{cases} AV^\Gamma & \text{if } V \leq H \\ V - K & \text{if } V \geq H \end{cases} \quad (12)$$

$H = \frac{\Gamma}{\Gamma-1}\psi K$ is the optimal investment trigger or threshold value of the project that would cause immediate investment, which accounts for both irreversibility and uncertainty. V represents the value of the decision; either the decision is to invest now or to wait to invest. If the value of the investment opportunity is less than the trigger value, the value AV^Γ consists in both NPV and option value. In the other case (if $V > H$), the strategic value of the investment is given by NPV ($V-K$), there is no value in waiting to invest.

The point of indifference between investing or not investing is the Marshallian trigger value:

$$M = \psi K \quad (13)$$

4. Empirical application

In this section, first the empirical application of SFM is presented, reporting the data sources, functional form specification and variables used in the analysis. The second point reports the construction of olive grove investment project, as well as the used data and variables in the analysis of investment decision.

4.1 Estimation of dynamic stochastic model

The dynamic stochastic frontier model have been estimated using a balanced panel data of 158 Spanish olive farms observed during 6 years from 1999 to 2004.

Even though our analysis is based on farm-level data, aggregate measures are used to define some variables that are unavailable from the FADN dataset. Input and output price indices are necessary to deflate all monetary variables which are derived from Eurostat (2008) using 1999 as the base year.

The dynamic stochastic functional form is specified as Cobb-Douglas⁷ that takes the form:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^K \beta_k \ln x_{kit} + \beta_T t + v_{it} - u_{it} \quad (14)$$

where $k, j = 1, \dots, K$ indicate the conventional inputs used in the production process.

Production y_{it} is defined as an implicit quantity index by dividing total olive sales in currency units by the olive price index. Vector x_{kit} is defined as a $(I \times 6)$ vector composed of five inputs and a time trend (t). Input variables are labor (x_L), defined as total hours spent on farm work, expenditure on fertilizers

⁷ The Translog functional form results were not robust, with many coefficients being much less than twice their respective standard errors (the distributional assumptions make it difficult to have conclusive claims about the distribution of the Lagrange multiplier statistic).

(x_F), pesticides (x_P), and other inputs such as plants costs and farming overhead (x_I). The total area occupied by olive groves defines the land variable x_{LND} .

Vector z_i , in the technical inefficiency effects function, is a (1x3) vector that specifies the variables age and farm size. The older farmers are expected to be less efficient in comparison to younger ones (Battese and Coelli, 1995). The farm size is represented by the log of total area and its square (e.g. Gianakas et al., 2003; Alvarez and Arias, 2004 and Tsionas, 2006), since scale effects might be important in explaining technical efficiency. A statistical package GAUSS 7 has been employed to estimate the dynamic stochastic frontier model.

4.2. The construction of olive grove investment project (real option approach)

After the estimation of the dynamic stochastic frontier model, the investment decision has been analyzed using the real option approach.

For the empirical application, a capital budgeting model is developed for an olive investment project along a 50 year planning horizon. A cash flow and a present value of the project have been calculated.

Following Purvis et al., (1995), the variability of investment return can be approximated using the variance of $\Delta \ln V_n = \ln(V_n) - \ln(V_{n-1})$, where V_n is the value of the equivalent opportunity to invest in perpetuity, and is given by:

$$V_n = \frac{\left[\frac{\psi}{1 - \left[\frac{1}{(1+\psi)^T} \right]} PV_n \right]}{\psi} \quad (15)$$

where n denotes the time period, and PV_n the present value of the project.

The value V_n supposes that the investment can be reinitiated at the end of its usual life at the same sunk cost K .⁸ The numerator of equation (15) provides the annuity equivalent to the present value of investment.

Table 1 provides the mean and the distribution of uncertain variables used on the simulation model. The olive production variable is simulated using the logistic growth function⁹. We used a FADN data set for production variable as well as plantation and collection costs. Additional data have been used from the Spanish Ministry of Environment and Rural and Marine Affairs, Statistical National Institute, and published studies (Barranco et al., 2006; Spanish Ministry of Environment and Rural and Marine Affairs (MARM), 2008c; SNI, 2008; Abós et al., 2007; Muñoz-Cobo et al., 2008 and Carbonell, 2008). The sunk cost magnitude reflects the cost of preparation of plantation for new trees, which includes: a) removing out the old ones when necessary plus other land preparation costs, b) the cost of new planting materials (that is, the trees and other related costs), and, c) the opportunity cost of the establishment expense and the opportunity cost of the land while the orchard is being established (since it takes about 5 years to realize the initial marketable harvest).

⁸ Because of the alternant of olive grove production, and in order to decrease its volatility (makes the changes in the current cash flow substantial), the time period is defined by two years long (the good production year plus the bad production year).

⁹ The production is not considered having an effect on the investment decision, following the results of the dynamic stochastic frontier model; the technical change effect is zero.

Price uncertainty is taken under consideration to analyze the investment under alternative discount rates (e.g. Purvis et al., 1995 and Engel and Hyde, 2003). Later, inefficiency and its persistence have been incorporated into the investment project to evaluate their impact about investment decision.

Before starting the simulation, a distribution is fitted for each variable using three statistical tests: Anderson-Darling, Chi-square, and, Kolmogorov-Smirnov. Price, discount rate, and technical efficiency have been considered to have a lognormal distribution, while technical inefficiency persistence has been considered to have a beta distribution (Tsonas, 2006).

After assigning the distribution for each uncertain variable, V_n is simulated for each specific case using a Monte Carlo simulation. Given the result of such simulation, the optimal investment trigger value H is calculated, and compared to the expected investment return under real option criterion to evaluate the investment decision.

We start by simulating the impact of discount rate on the decision of investment followed by evaluating the impact of the combination discount rate changes and price uncertainty. Subsequently, we evaluate the impact of the technical inefficiency and its persistence. For this reason, the technical inefficiency have been included in the production variable using equation (2) and (3) of the dynamic stochastic frontier model. Then, using the parameters resulted from the estimation of dynamic stochastic frontier model, we can evaluate the impact of both technical efficiency, and its persistence about the investment decision.

5. Results and discussion

The results derived from the estimation of the Cobb Douglas dynamic stochastic frontier model are presented in Table 2. First-order parameters β_k of labor, fertilizer, and other inputs are all positive and statistically significant, indicating that the production is increasing in such inputs. Pesticide is negative but statistically weak and not significant.

Land is negative and statistically significant, which is not an unusual result in such cases, given that is a fixed input and cannot be adjusted in orchard crops. The time trend is negative but statistically not significant, which suggests that the technology embodied in the trees is unchanged. Therefore, any growth taking place over time is from the installed trees and is not able to be added over time, which essentially means that there is no additional technical change effect.

The estimation results of the gamma component reveals that only the constant and size variable included in Gamma 1 component are significant implying that technical inefficiency increases at a decreasing rate for larger farms. The posterior mean for the autoregressive component is 0.294 which is fairly small and far from unity which suggests means that a small quantity of technical inefficiency is transmitted to the next time period and, thus, there is not as much friction of inefficiency over time.

The comparison of our results with previous studies shows a similarity with Ahn et al., (2002) study, that had a persistence component equal to 0.18. While the comparison with Tsonas (2006), that had a persistence component close to 1, indicate that the technical inefficiency of Spanish olive farms are minimally persistent, which suggests a lower cost of adjustment as well as less competition in this sector.

Table 3 shows farm specific efficiency frequency and posterior statistics for technical efficiency for two models; the first one represents the static Cobb-Douglas production, while the second one is the Cobb-Douglas dynamic frontier used in this study.

The distribution of estimated technical efficiency scores by farm for the short run shows a fluctuation between a minimum of 65.6% and a maximum of 83.7%. This short term efficiency takes an average value of 78.1% throughout the period studied, implying that output could have increased substantially if technical inefficiency were eliminated. The majority of farmers have efficiency scores in the range 70-80% (82% of the sample), followed by the range 80-90% (16% of the sample). While, the range 60-70% is placed last representing 2% of total sample. Technical efficiency fluctuates over time from a peak of 91.1% in 1999 to a minimum of 72.6% in 2003.

Referring to long- run predicted technical efficiency, the measure ranges from 39.4% to 76.5%, and with an average value of 72.7% through the period studied. The vast majority of olive farms in the sample have a dynamic efficiency scores in the range 70-80%, which represents 81.7% of the total sample. The

range 60-70% is second and presents 15.8% of the total sample. Finally, the range 50-60% presents only 1.3% of the total sample, followed by the ranges 40-50% and < 40% with 0.6%, respectively. The difference between static and dynamic technical inefficiency are not very important, as we can see that the static inefficiency is 0.06 percentage units upper compared to the dynamic frontier model. This result is consistent with the low persistence inefficiency, which shows that the most of farms are reasonably keeping efficiency at the same level from short to long term.

Table 4 presents the net present value, option value and trigger value found by varying the percentage of discounted rate. The results indicate that a decrease of discount rate leads to an increase on option value and a decision to invest. Thus, at higher discount rate (8%) the decision is wait to invest, while a decrease of discount rate value shows a decrease of the trigger value and farmers take the decision to *invest*.

Uncertainty in price combined with discounted rate play an important role on the decision to invest in Spanish olive sector. Table 5 shows the simulation results by varying olive price and discounted rate. At a lower discount rate level ($\leq 7\%$), an increase in price leads to the decision is to invest with no option value of waiting to invest.

Moreover, the lower price increase combined with higher discount rate delays the investment decision in the olive sector. So, at higher discount rate (e.g., 8%) and lower price increase (5 % and 10%), the decision is to wait to invest with an important option value of waiting. Such a situation changes when the discount rate decreases, which means that the increase of price market level encourage farmers to take the decision to invest at farm level.

A table 6 presents the effect of dynamic technical inefficiency and its persistence in investment decision. A higher technical inefficiency rate leads to the decision is wait to invest with important option value for waiting, and vice-versa. As the farmers' technical efficiency increases, the decision changes to invest, and they is no option value to wait to invest. This indicates that the technical inefficiency increases the option value of waiting to invest and therefore delays the investment decision, while being technically efficient leads to farmers being more decisive about the investment decision.

On other hand, Table 7 shows the net present value, option value, trigger value for olive investment under an alternative technical inefficiency persistence increase. As the persistence of technical inefficiency increases the decision is wait to invest, and under small percentage of persistence of technical inefficiency the decision is to invest.

An increase in the persistence parameter of technical inefficiency leads to higher costs of adjustment combined with strong competition. Thus, the farmers take the decision to wait to invest. However, at small persistence parameter of technical inefficiency, the decision is to invest.

6. Conclusion and recommendation

The purpose of this paper is the evaluation of the investment decision under uncertainty and irreversibility allowing for long run inefficiency and its persistent impact on investment decisions. This analysis has been applied to a 158 Spanish olive farms using FADN data set.

The dynamic stochastic frontier model has been used to explain the variation in long-run farm efficiency. Such a model assumes the autoregressive term of technical inefficiency over time which reflects an element of the adjustment cost. Then, the real option approach has been used to analyze investment under uncertainty and irreversibility.

The empirical results show that the technical inefficiency persistence parameter is fairly low to unity, which means that small technical inefficiency is transmitted to the next time period. The technical efficiency average is 72.7% and the static inefficiency is 0.06 percentage points greater compared to the dynamic technical efficiency.

The olive groves investment is irreversible and characterized by uncertainty on price and discount rate that play an important role on the decision to invest in Spanish olive sector. An increase of discount rate means that the farmers take the decision to postpone investment. An increase on price along with a decrease of discount rate leads to the decision to invest with no option value of waiting to invest.

The results also suggest that the decision of investment in Spanish olive sector does not depend alone on discount rate and olive price, but also on technical inefficiency and it persistence. The increase of farms

inefficiency means that the decision is to wait to invest and, conversely, the more technically efficient the farmer more likely the decision is to invest. Consequently, the inefficient farmers take time and wait to invest, while a smaller persistence parameter leads to the decision to invest.

The investment in Spanish olive sector is characterized by uncertainty related to olive price as well as discounted rate. Moreover, the timing of optimal investment decision is affected positively by the high score of olive Spanish farms technical efficiency, as well as its low persistence through time.

The recent CAP reform policy implemented after 2006, and modified in 2007 can have a possible positive impact about olive investment. Such policy is decoupled by 93% and combined with the price support which can stabilize farm income and diminish the uncertainty related to price. This policy can allow the farm operator to have a more secure environment to future investment, which is guaranteed by the high technical efficiency scores of Spanish olive farms associated to low persistent inefficiency through time.

Finally, for further research, the analysis of the impact of allocative inefficiency about the decision of investment in Spanish olive sector can be an effective tool to evaluate the relationship between the economic survival of farms conditioned by policy reforms and its decision to invest.

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Table 1. Uncertainty assumptions and Variables mean

Uncertainty	Unit	Distribution	Notes
Olive price	1.67 €/kg	lognormal	Mean= 1.67, Std.Dev.=1%
Discount rate	0.05 %	lognormal	Mean= 0.05, Std.Dev.=3%
Technical efficiency	0.72 %	normal	Mean= 0.72, Std.Dev.=4%
Production	3617 kg/ha	logistic	Mean= 3617, Std.Dev.=2185
Persistence	0.29	Beta	Min. =0.1, Max.= 0.9
Sunk cost	7555 €/ha		

Table 2. Results for dynamic stochastic frontier model using Cobb-Douglas functional form

Production frontier model		
Parameter (equation 1)	Mean	Standard error
constant	-0.53062	(0.56709)
labor	0.61843	(0.05656)***
fertilizers	0.04728	(0.02062)***
pesticides	-0.00700	(0.02070)
land	-0.47923	(0.16141)***
Other inputs	0.06400	(0.02847)***
trend	-0.00682	(0.01843)
Dynamic Technical efficiency model		
Parameter (equation 2)		
constant	-0.80347	(0.33760)***
size	0.00297	(0.00326)
(size) ²	-0.000004	(0.00001)
age	-0.00309	(0.00544)
Parameter (equation 3)		
Constant ₁	-1.11615	(0.59947)**
Size ₁	-0.06831	(0.00956)***
(size) ₁ ²	0.00027	(0.00005)***
Age ₁	-0.00213	(0.01568)
sigma	0.40012	(0.01299)***
Omega (ω)	0.48895	(0.07169)***
Omega ₁	0.10751	(0.14599)
Rho (ρ)	0.29373	(0.08210)***

Note: *** and ** indicate that the parameter is significant at the 1% and 5% respectively.

Table 3. Frequency Distribution of Technical Efficiency and posterior statistics

Efficiency level	Static model		Dynamic model	
	Frequency	Percentage of farms	Frequency	Percentage of farms
<40	0	0	1	0.6
40-50	0	0	1	0.6
50-60	0	0	2	1.3
60-70	3	2	25	15.8
70-80	130	82.2	129	81.7
>80	25	15.8	0	0
Mean		0.78102		0.72752
S.d.		0.02363		0.05296
Median		0.78227		0.73199
Minimum		0.65611		0.39411
Maximum		0.83696		0.76495

Table 4. Net present value, option value, and Trigger value For Olive Investment under Alternative Discount rate percentagesNPV: Net Present Value, H: *Trigger value* and *F(V)*: *Option value*

	Discount rate percentage decrease					
	0.08%	0.07%	0.06%	0.05%	0.04%	0.03%
<i>NPV</i>	15.745 €	22.116 €	30.956 €	43.377 €	61.052 €	86.521 €
<i>H</i>	16.562 €	16.189 €	15.702 €	15.819 €	15.671 €	15.371 €
<i>F(V)</i>	8.546 €	11.920 €	16.388 €	23.226 €	32.475 €	45.148 €

Table 5. Net present value, option value, and Trigger value For Olive Investment under Alternative price increase percentage and Discount rate percentages

		Price percentage increase					
		5%	10%	15%	20%	25%	
Discount rate percentage increase	0,03%	NPV	90.723 €	91.991 €	97.462 €	103.616 €	109.087 €
		H	14.616€	4.484€	2.549€	2.091€	1.746€
		F(V)	45.105 €	-	-	-	-
	0,04%	NPV	61.051 €	65.108 €	69.671 €	73.728 €	77.784 €
		H	16.729€	4.665€	3.030€	2.148€	1.839€
		F(V)	34.287 €	-	-	-	-
	0,05%	NPV	43.377 €	46.437 €	49.880 €	52.940 €	56.000 €
		H	17.180€	9.203€	3.167€	2.319€	1.929€
		F(V)	24.812 €	8.906 €	-	-	-
	0,06%	NPV	30.956 €	33.304 €	35.946 €	38.294 €	40.643 €
		H	18.499€	14.265€	3.531€	2.369€	1.974€
		F(V)	18.552 €	16.107 €	-	-	-
	0,07%	NPV	22.116 €	23.948 €	26.010 €	27.842 €	29.674 €
		H	19.743€	12.256€	3.587€	2.376€	2.015€
		F(V)	13.695 €	9.465 €	-	-	-
0,08%	NPV	15.744 €	17.197 €	18.831 €	20.284 €	21.737 €	
	H	23.103€	19.514€	3.524€	2.459€	2.093€	
	F(V)	10.487 €	10.496 €	-	-	-	

Table 6. Net present value, option value, and Trigger value For Olive Investment under Alternative technical efficiency percentages decrease.

	Technical efficiency percentages decrease						
	0%	-5%	-10%	-15%	-20%	-25%	-30%
NPV	86.521 €	80.468 €	75.100 €	68.591 €	63.681 €	56.771 €	52.261€
H	1.086 €	1.399 €	2.244 €	5.468 €	6.1801 €	1.025.769 €	9.514.868 €
F(V)	-	-	-	-	55.902 €	51.842 €	40.803 €

Table 7. Net present value, option value, and Trigger value For Olive Investment under Alternative Rho percentages increase.

	Persistence percentages increase				
	0% (0,29)	+ 25%	+ 50%	+75%:0,50	+100%
NPV	84.704 €	91.155 €	94.714 €	105.724 €	113.684 €
H	10.761 €	11.215 €	39.664 €	166.592 €	903.300 €
F(V)	26.382 €	31.060 €	77.057 €	100.867 €	112.675 €