The analysis of irreversibility, uncertainty and dynamic technical inefficiency on the investment decision in Spanish olive sector

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Contributed Paper prepared for presentation at the International Association of Agricultural Economists Conference, Beijing, China, August 16-22, 2009

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1. Introduction

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 for Agriculture$_a$, 2008).

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. 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 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 (ROA) and a dynamic Stochastic Frontier Model (SFM) estimation. The ROA 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; 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 SFM is developed to estimate the long run technical efficiency and it persistence. In a posterior step, the rate of technical efficiency and it persistence are used to evaluate their impact on investment decision using ROA.

2. Literature review

This section contains a brief literature review for both approaches the dynamic SFM, ROA, and a brief discussion of different orchard replacement models used in the literature.

2.1 The dynamic stochastic frontier model

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; and Ahn and Schmidt, 1995). 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 limited number of studies focusing on this aspect about dynamic models efficiency (e.g. Ahn et al., 2002; Huang, 2004 and Tsionas, 2006) are characterized by a complex likelihood function specification as well as the difficulties of assuming the inference on unobserved firm-specific inefficiencies (Tsionas, 2006).

Tsionas (2006) proposes that the inefficiency factors need to be adjusted by time which depends on adjustment costs.

2.2 The real options approach

The dynamic version of discounted cash flow analysis and, in particular Net Present Value (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.

Myers (1977) 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". Dean (1951); Hayes and Garvin (1982) recognized that standard discounted cash flow undervalued investment opportunities as financial analysts ignored important strategic considerations.

In 1994, Dixit and Pindyck introduced the irreversibility model[1] 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.

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 (Hester and Cacho, 2003). Early examples include Graham et al., (1977) and Willis and Hanlon (1976), both of whom used the mathematical programming methodology. Childs et al., (1983) used the dynamic programming to maximise profit under the replacement policy applied to apple orchards. While, Cahn et al., (1997) used the simulation methodology to explore NPV 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).

[1] Dixit and Pindyck in their book "Investment under uncertainty"

The ROA 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.

3. Methodology

3.1 Dynamic stochastic frontier model

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

$$y_{it} = x_{it}\beta + v_{it} - u_{it} \qquad i = 1,\ldots,n, t = 1,\ldots,T \tag{1}$$

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 $IN(0,\sigma_v^2)$, $i = 1,...,n, t = 1,...,T$, 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:

$$\log u_{it} = z_{it}\gamma + \rho \log u_{i,t-1} + \xi_{it}, \text{ for } t = 2,\ldots,T \tag{2}$$

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

where $\xi_{it} \sim IN(0,\omega^2)$, for $t = 2,...,T$ is a random variable capturing the "unexpected log-efficiency sources" and $\xi_{i1} \sim IN(0,\omega^2/(1-\rho^2))$, for all $i = 1,...,n$. 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 estimation of the model in (2) and (3) applies the Bayesian inference approach to characterize the likelihood function. Even still involves a high dimensional which precludes a closed form solution to the likelihood function and thus, requires a numerical solution approach. Gibbs sampling[2] 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). The Markov Chain Monte Carlo (MCMC) scheme is used to provide conditional distribution to measure technical efficiency for each farm (Koop and Steel, 2001).

3.2 Real option methodology

Following Dixit and Pindyck (1994), we assume that the project value V follows a geometric Brownian motion with drift ℓ and diffusion Ω.

$$dV = \ell V dt + \Omega V ds \tag{4}$$

where ds is the increment of a Wiener process with $E\{ds\} = 0$ and $E\{(ds)^2\} = dt$.

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 (Dixit and Pindyck, 1994):

$$V = \left\{ \begin{matrix} AV^{\Gamma} & if \quad V \le H \\ V - K & if \quad V \ge H \end{matrix} \right\} \tag{5}$$

$H = \dfrac{\Gamma}{\Gamma - 1}\psi K$ 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

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

strategic value of the investment is given by NPV (V-K), there is no value in waiting to invest.

4. Empirical application

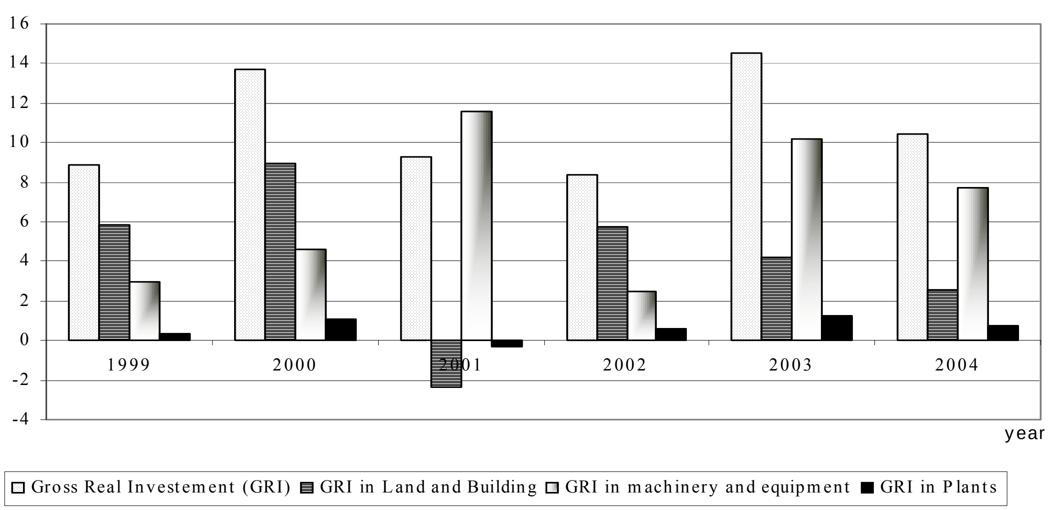
In this section, the investment of Spanish olive sector is analyzed followed by the empirical application of SFM and RO.

4.1 Characteristic of investment in Spanish olive sector

The analysis of the investment focuses on three indicators: the Gross Real Investment (GRI), the Investment Rate (IR) and the Investment Spikes (IS). We used a balanced panel data of 158 olive farms from the Farm Accountancy Data Network (FADN), available over the periods 1999-2004.

Figure 1 shows the evolution of this different type of GRI by year. As we can see there is a clear increasing tendency of total investment (more than 60%), until having a peak in 2003. Such positive evolution is explained mainly by the increase in "machinery and equipment" investment associated to the increase in "plant" investment.

Figure.1. Evolution of GRI by year and type



The distribution of IR shows that zero investments account for about 71% of the total observation, positive investment account for 7% and negative for 22%. The majority of positive IR observations (77.2%) has an IR superior to 90%. The IR interval [0-5%], and [80-90%] each comprise 5.1% of total observations. While, the IR intervals [10-20%], [50-60%], and [70-80%] each account for 2.5% of total observations. The IR interval [40-50%] accounts for 4% of the total of observations. At the last ranking, we find IR interval [30-40%] which represents 1% of total observations. The IS fluctuate from 16.2 % in 1994 to 1% in 2004, with a peak in 2001 (39.1%). The 93% of farms with positive IR have an IS superior to 20%.

4.2 Estimation of dynamic stochastic model

The dynamic SFM is specified as Cobb-Douglas (C-D)[3] :

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \beta_T t + v_{it} - u_{it} \tag{6}$$

where k, j = 1,…,K indicate the inputs used in the production process.

Production y_{it} is defined as total olive sales in currency units divided by the olive price indice. Vector x_{kit} is composed of five inputs and a time trend (*t*). Input variables are labor hours (x_L), expenditure on fertilizers (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.

[3] 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).

4.3. The construction of olive grove investment project (ROA)

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:

$$V_n = \frac{\left[\dfrac{\rho}{1 - \left[\dfrac{1}{(1+\rho)^T} \right]} PV_n \right]}{\rho} \tag{7}$$

where *n:* 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*. [4] The numerator of equation (7) provides the annuity equivalent to the present value of investment.

Besides FADN data set, additional data have been used from the Spanish Ministry of Agriculture, Statistical National Institute (SNI, 2008), and published studies (Barranco et al., 2006; Spanish Ministry for Agriculture$_b$, 2008).

After the simulation of V_n using a Monte Carlo simulation, the optimal investment trigger value H is calculated. The technical inefficiency have been included in the production variable using equation (2) and (3) of the dynamic SFM.

5. Results and discussion

The results derived from the estimation of the C-D dynamic SFM are presented in Table 1. First-order parameters β_k of labor, fertilizer, and other inputs are all positive and

[4] Because of the alternant of olive grove production, and in order to decrease it volatility,the time period is defined by two years long (the good plus the bad production year)

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 Tsionas (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 2 shows farm specific efficiency frequency and posterior statistics for technical efficiency for two models; the first one represents the static C-D production, while the second one is the C-D 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).

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 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 3 presents the NPV, 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.

Uncertainty in price combined with discounted rate play an important role on the decision to invest in Spanish olive sector. Table 4 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 5 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 vise-versa. 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.

Table 6 shows the results 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

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

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 its persistence impact. The increase of farms inefficiency means that the decision is to wait to invest. Consequently, at higher inefficiency persistence the decision to invest.

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.

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Table 1. Results for dynamic SFM using Cobb-Douglas functional form

Production frontier model		
Beta	Mean	S.D,
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		
Gama		
constant	-0.80347	(0.33760)***
size	0.00297	(0.00326)
size^2	-0.000004	(0.00001)
age	-0.00309	(0.00544)
Gama_1		
Constant_1	-1.11615	(0.59947)**
Size_1	-0.06831	(0.00956)***
Size^2_1	0.00027	(0.00005)***
Age_1	-0.00213	(0.01568)
sigma	0.40012	(0.01299)***
omega	0.48895	(0.07169)***
Omega_1	0.10751	(0.14599)
Rho	0.29373	(0.08210)***

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

Table 2. Frequency Distribution of Technical Efficiency and posterior statistics

	Static model		Dynamic model	
Efficiency level	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 3. NPV, option value, and Trigger value For Olive Investment under Alternative Discount rate percentages

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

NPV: Net Present Value, H: *Trigger value and F(V): Option value*

Table 4. NPV, option value, and Trigger value For Olive Investment under Alternative price increase percentage and Discount rate percentages

Discount rate			Price increase				
			5%	10%	15%	20%	25%
	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 5. NPV, option value, and Trigger value For Olive Investment under Alternative 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 6. NPV, option value, and Trigger value For Olive Investment under Alternative Rho 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 €