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Lambarraa, Fatima, Kallas, Zein
Affiliation: Centre de Recerca en Economia i Desenvolupament Agroalimentaris. Parc Mediterrani de la
Tecnología Address: Edifici ESAB, Avinguda del Canal Olímpic s/n 15, City: Castelldefels Postal code: 08860
Country Spain. Telephone: 34-93-552-1208 Fax: 34-93-552-1001 E-mail: fatima.lambarraa@upc.edu

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Lambarraa, Fatima[1], Kallas, Zein[2]

[1,2]Affiliation: Centre de Recerca en Economia i Desenvolupament Agroalimentaris. Parc Mediterrani de la Tecnología Address: Edifici ESAB, Avinguda del Canal Olímpic s/n 15, City: Castelldefels Postal code: 08860 Country Spain. Telephone: 34-93-552-1208 Fax: 34-93-552-1001 E-mail: fatima.lambarraa@upc.edu

Abstract. The most of Spanish olive farms are concentrated in Less-Favoured Areas (LFA) with the majority of producer areas are under Objective 1 of the EU Regional Policy. The EU has long recognized such distinctive characteristics of those holdings with a specific support measures aiming to prevent the abandonment of olive groves as well as to support sustainable development of this sector. The main objective of this study is to evaluate the impact of LFA payment on the olive farms technical efficiency. Two sample farms located in LFA (63 farms receiving LFA payment support and 99 farms do not) have been observed from 2000 to 2004. A stochastic frontier production and Random-effect Tobit models have been used. Results indicate that LFA payment, age of manager, workforce composition and farm size affect efficiency levels. The LFA payment coefficient indicates a significant negative impact on the technical efficiency of Spanish olive farms. Farms that not receive LFA payment has a technical efficiency rate 0.15 percentage units upper compared to those that receive this payment.

Keywords: LFA payment, olive, technical efficiency, stochastic frontier, Random-effect Tobit.

1. Introduction

The Spanish olive sector has a distinguished presence in worldwide agriculture sector. Such situation is manifested by the importance of its production and exportation, being the leading country with 38.9% and 40% respectively (IOC, 2009). Moreover, this sector covers 2,483,697 hectares with 308 million trees, representing more than 25% of the world's growing area (MARM, 2009).

This sector is mainly made up by a large number of small farms size whose productions is characterized by vulnerability to annual variation, low profitably, and heterogeneity, both in space and time. Most of those holdings are concentrated in Less Favoured Areas (hereafter, LFA), and are considered under Community Regional Policy Objective 1 with a few exceptions. Beside its production function, in these areas the olive sector represents an important source of employment and a solid column of the social and economic development. It provides a full-time as well as seasonal employment -olive picking in particular- which supplement farm workers' income since demand for farm labour is concentrated in the rest of year. Moreover, olive farms play a role in the protection of the vulnerable area from desertification and loss of biodiversity. The olive cultivation is considered as an instrument tool in addressing environmental problems given it high undemanding, efficient water resource use and well-adaptability to Mediterranean region conditions. Its positive impact on the environment makes it's an important tool to combat desertification in these region.

The European Union (EU) has long recognized such special characteristics of the LFA. They has identified two main LFA types: a) mountain areas (in Spain, areas with a minimum altitude of 1000m or a slope greater than 20% or a minimum altitude of 600m plus a slope of at least 15%) and b) other LFA characterized by poor productivity, specific handicaps, low population, etc. It is worth to mention that 58% of the total Utilized Agriculture Area (UAA) in the EU is classified as LFA, while in Spain, 81.8% of UAA is located in LFA, in which 33.7% is LFA-Mountain and 48.1% in LFA-others.

The EU under the rural development program applied during 2000-2006[1] (Regulation No 1257/1999) has provided the LFA farms with a specific support measures as compensatory payment granted per hectare of agricultural area. These measures aim to avoid the abandonment of olive groves in marginal areas, to maintain a viable rural community, to promote sustainable farming systems which in particular take account of environmental protection requirements and to support a sustainable development through the promotion of healthy and quality products.

Previous literature has demonstrated that policy support could have impact on different farms' aspects. In this line, some papers have analyzed their impact on production decision (Moro and Sckokai, 1999; Oude Lansink and Peerlings, 1996), investment decision (Oude Lansink *et al*., 2001; Carey and Zilberman, 2002 and Wabi *et al*., 2006) and technical efficiency (Bezlepkina *et al*., 2005, Kleinhanß *et al*., 2007, and Lambarraa *et al*., 2009). However, up to date, there are no published studies that have analyzed the impact of LFA payment on farm's technical efficiency, especially in Spain.

The main objective of this study is to analyze the determinants factor of farms technical efficiency as well as the impact of LFA payment on such efficiency. To achieve this objective, we assess a technical efficiency of two different samples farms located in LFA and differentiate by receiving or not a support payment using a stochastic frontier (SF) model. In the follow-up a Random-effect Tobit regression is carried out for all sample data using estimated technical efficiency ratio. This analysis allows the exploration of the relationship between technical efficiency and other specific variables for all samples as a whole with a special attention for payment factors. This step allows also to check results consistency SF model and to compare both results. The analysis focuses on farm-level data observed from 2000 to 2004, based on the Farm Accountancy Data Network (FADN).

The remainder of this paper is organized as follows. The second section gives a review of the SF methodology and Tobit estimation. This is followed by an empirical application. In Section 4 the results are discussed. Finally, some conclusions are outlined.

2. Methodology

To analyze the impact of LFA payment on technical efficiency, first a stochastic frontier methodology has been used. This technique implies a specification of two error components. The technical inefficiency error term that measures the extent to which actual production falls short of maximum attainable output, and is augmented by a two-sided error component (v) representing other factors that might generate irrelevant noise in the data (such as measurement error and unobserved inputs). v_{it} is assumed to be iid $N(0,\sigma_v^2)$, and u_{it} is a vector of independently distributed and nonnegative random disturbances.

We use maximum likelihood techniques to estimate the stochastic production frontier model. This model can be expressed as follows:

$$y_{it} = f(x_{it}, t; \beta)e^{v_{it} - u_{it}} \quad [1]$$

where y_{it} is the output of the *i-th* firm ($i = 1,...,N$) in period $t = 1,...,T$, $f(x_{it}, t; \beta)$ represents the production technology, x_{it} is a $(1 \times K)$ vector of inputs and other factors influencing production associated with the i-*th* firm in period t, β is a $(K \times 1)$ vector of unknown parameters to be estimated.

The technical efficiency of a producer at a certain point in time can be expressed as the ratio of actual output to the maximum potential output:

[1] The regulation 1698/2005 is the actual rural development program applied from 2007 to 2013

$$ET_{it} = \frac{y_{it}}{f(x_{it}, t; \beta)e^{v_{it}}} = e^{-u_{it}}$$ [2]

Following Battese and Coelli (1995), technical inefficiency is assumed to respond to the following pattern of behaviour: $u_{it} = g(\delta z_{it}) + \eta_{it}$, where z_{it} is a $(M \times 1)$ vector of that includes the determinants of a farm's technical inefficiency, δ is a $(1 \times M)$ vector of unknown coefficients, and $\eta_{it} \sim N(0, \sigma_{\eta}^2)$ is a random variable defined by the truncation of the normal distribution such that the truncation point is -δz_{it}.

The Tobit model is used to explore the relation between technical efficiency scores and farms specific factors. The SF approach provides efficiency measure with a distribution bounded between 1 and 0. Since the efficiency scores are double censored, the ordinary least squares methods cannot be applied because it will give a biased estimation. Thus, a Tobit model as a limited dependent variable approach is applied.

The Tobit model can be specified as (Kmenta, 1990; and Wooldridge, 2002):

$$ET_{it} = \alpha^T F + \lambda^T P + \varepsilon_{it}$$ [3]

Where ET_{it} is a latent variable that refers to the technical efficiency of LFA olive farm *i* en period *t*, and F is a vector of farm specific variable, P is a vector of external factor representing payment and time in this case, and is likely to affect the technical efficiency. However, due to nature of the technical efficiency measure, we have:

$$\begin{aligned} ET_{it} &= 0 && if \quad ET_{it} \leq 0 \\ ET_{it} &= ET_{it}^* && if \quad 0 \prec ET_{it} \prec 1 \\ ET_{it} &= 1 && if \quad 1 \leq ET_{it}. \end{aligned}$$ [4]

To explore the effect of farm characteristics and external factor on the technical efficiency score, ta random-effect Tobit models is used. The objective of the use of the random-effect Tobit model is to exploit the nature of panel data, capturing individual specific-effects and assuming no correlation between the individual specific effects and explanatory variables.

The random-effect Tobit model for technical efficiency measure can be expressed as:

$$ET_{it} = \alpha^T F + \lambda^T P + \upsilon_i + \varepsilon_{it}$$ [5]

assuming that ET_{it} is censored at 0 and 1, the random-effects υ_i are iid $N(0, \sigma_{\upsilon}^2)$ and ε_{it} are iid $N(0, \sigma_{\varepsilon}^2)$ independently of υ_i.

3. Empirical application

As mentioned for empirical application we have used the FADN data for the period 2000-2004. The FADN Data set was launched in 1965 with the objective to monitor the income and business activities of agricultural holdings and to evaluate the impacts of the Common Agricultural Policy measures. It is a European system of sample surveys that take place each year and collect information from each farm includes physical, structural, economic and financial data. This data set provides representative data of EU agricultural holdings along three dimensions: region, economic size and type of farming. This dataset classifies farms into different typologies that allow identifying the main types of farming. In this study, we used the olive farms located in LFA other than mountains, given that the majority of the data available is located in this area. Moreover, This LFA type is more representatives in the Spanish case representing 60% of Spanish LFA area. Aggregates data on annual input and output price indices are taken from

Eurostat. A two unbalanced panel data sample of Spanish olive farms are used. A total of 162 olive farms are observed from 2000 to 2004, which 99 farms of the sample receive the LFA payment support.

Following previous studies (e.g Karagiannis and Tzouvelekas, 2001), the production frontier function in [1] is specified as a Translog function that takes the form:

$$Lny_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k Lnx_{kit} + \sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{jk} Lnx_{kit} Lnx_{jit} + e_{it} \qquad [3]$$

Where $i = 1,\ldots,N$ indexes the farms in the sample, $t = 1,\ldots,T$ indicates the time period, $k, j = 1,\ldots,K$ indicate the conventional inputs used in the production process, β is the vector of parameters to be estimated, and, as noted, $e_{it}=v_{it}-u_{it}$ is a stochastic composite error term.

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_{it} is defined as a (1×15) vector that contains five inputs. The first input, x_1, includes labour input and is measured in labour hours per year, x_2 comprises pesticides, x_3 represents fertilizers, x_4 symbolizes the hectares occupied by olive groves, and x_5 comprises variable crop-specific inputs other than fertilizers and pesticides. Input use variables x_2, x_3 and x_5 are expressed as implicit quantity indices by dividing the consumption of these inputs in currency units by their respective price indices.

Given that the Battese and Coelli (1995) model does not really exploit the nature of panel data, an alternative method are used to overcome such a limitation. A restricted version of the fixed effects technique is used by incorporating regional dummies into the production technology function (Álvarez and Orea, 2004 and Lambarraa et *al.,* 2007). The use of regional dummies assumes that farms are heterogeneous across regions, while homogeneity is assumed within regions only for unobserved variables. Specifically, we used 5 dummy variables to identify the different Spanish regions.

The technical inefficiency effects function is specified as a linear function $u_{it} = \sum_{m=1}^{M} \delta z_{mit} + \eta_{it}$, with $M = 7$. The components of z_{it} include a constant (z_1), a workforce composition (z_2) which is computed as the ratio of family labour hours to total labour hours, a dummy variable equal to 1 if the holding is renting agricultural land and zero otherwise (z_3), the age of the holding's primary decision maker (z_4), time (z_5), farm size (z_6) expressed in European Size Unit (ESU), and payment ratio (z_7) which is computed as the ratio of LFA subsidies about total subsides. Maximum- likelihood methods are applied in model estimation.

Rental land is expected to increase farm's efficiency (Lambarraa *et al.,* 2007). Direct costs of land rentals may create stronger incentives to work the land in a more efficient manner, relative to the opportunity costs borne by owned land. A farmer's age is also likely to influence technical efficiency. Younger farmers should be expected to be more prone to introduce changes in farm management techniques that increase efficiency, relative to elderly ones (Battese and Coelli, 1995). The variable time is also expected to influence technical efficiency. Since farm managers are likely to learn from their errors, the passage of time should be expected to improve technical efficiency (Battese and Coelli, 1995). To the extent that family labour is more relevant in small, less competitive farms, it may be associated to a higher level of inefficiency (Lambarraa *et al.,* 2007 and 2009). Family size is expected to increase farms technical efficiency (e.g. Gianakas *et al.,* 2003; Alvarez and Arias, 2004 and Tsionas, 2006). While, subsidies are expected to have negative impact about technical efficiency (e.g. Bezlepkina *et al.,* 2005, Kleinhanß *et al.,* 2007, and Lambarraa *et al.,* 2009). Results derived from the estimation of the model are presented in the following section.

For Random-effect Tobit model, we used the same variables above mentioned as well as the altitude level variable assumed to be zero for altitude less than 300m and 1 otherwise. It is expected that the altitude level affect negatively the technical efficiency. To mention that in this specification model, the payment variables is introduced as a dummy variable equal to 1 value for farms receiving LFA payment and o otherwise. The technical efficiency scores are assumed censored at 0 and 0.9 (the maximum value).

4. Results

Summary statistics for the variables used in the analysis are given in Table 1. This table shows that sample farms' average annual output totals around 26,379.38 €. Table 1 also indicates that sample farms employ 3,022 labour hours per year, 79% of which are family labour. They spent by year 1,424 € for fertilizers, 1,448 for pesticides and 3,829 as other crop specific cost by. Sample farms have, on average, 25.13 ha of land, of which 8% is rented. The farms size expressed in European Size Unit (ESU) is about 34.8. The average farmer's age in the sample is 57 years.

Results derived from simultaneously estimating the Translog production frontier and the technical inefficiency equation are presented in Table 2. The variance parameter, γ, is statistically significant which suggests the relevance of technical inefficiency in explaining output variability among Spanish LFA area olive farms. Estimated δ coefficients provide an explanation of the determinants of sample farms' technical inefficiency. As expected, the coefficient representing a farmer's age is positive and statistically significant for both models which suggests that young farmers are more efficient in comparison to older ones. Thus, younger farmers may be more likely to introduce efficiency-improving changes in their holdings relative to aged ones. Farms renting land are shown to be more efficient relative to farms owning cultivated land. This provides evidence that land rental costs motivate more efficient operations relative to the opportunity costs of owned land.

The workforce composition shows that farms with a higher proportion of family labour and not receiving payment are more efficient relative to the farms with a higher proportion of remunerated work. The negative coefficient for the variable time in the case of the model representing farms not receiving payment suggests that the technical efficiency of those farms tended to increase throughout the period studied. This result suggests that farm managers not receiving subsidies learn from their errors and experience, and has an optimal allocation of managerial effort. For the farms located in LFA but receiving payment, the results shows that technical inefficiency of those farms has been decreasing over time. This provides evidence that farmers receiving payment does not improve their efficiency levels with the passage of time.

The impact of subsidies on technical efficiency is analyzed through the payment ratio coefficient. The results show a significant negative impact of subsidies on the technical efficiency of LFA Spanish olive farms. Specifically, LFA payment seems to have had a relevant negative effect on the technical efficiency level of Spanish olive farms. This result is compatible with reduced motivation to produce efficiently as a response of farmer's decision to trade off market income for subsidy income. Other studies that analyze the impact of subsidies on technical efficiency of farms located in conventional area find similar results (e.g. Lambarraa et al., 2009; Bezlepkina et al., 2005; Guyomard et al., 2006; Kleinhanß et al., 2007 and Emvalomatis et al., 2008).

The negative impact of LFA payment on farms technical efficiency is explained by the fact that subsidies guaranteed a large part of farmer's income in LFA which decrease TE. This decrease is caused by a non-optimal allocation of managerial effort which is manifested by sign difference of time coefficient for both models. Thus, farmers not receiving LFA payment improve their TE through time, while farms receiving LFA payment doesn't.

Results on technical efficiency distribution by year and interval in both cases are presented in Table 3. As we can see, the evolution of TE by year shows an upper TE average level for farms not receiving payment along years. The difference of TE average level between both farms (receiving and not) fluctuate from a minimum of 8 points to a maximum of 22 points registered in 2003, in all case a higher level of technical efficiency is registered at level of farms that doesn't receive payment. Moreover, such distribution shows that 68% of farms that do not receive payments are concentrated in high TE interval level (>60 %), while just 40% of farms that receive payment are present in these interval. Estimated average efficiency levels for sample farms receiving payment are about 52.6% while for those not receiving payment are 66.2%.

Table 4 reports the estimation of Random-effect Tobit model. All the coefficients are statistically significant except land rental variable. Comparing the results with SF model, we find that the sign of age variable is similar showing results consistency. The work force composition is found to have a negative relationship with technical efficiency score which is consistent with the SF results for farms not receiving payments. Farms size variable is found to have a positive relationship with TE scores. Furthermore, the negative sign of altitude coefficient shows that technical efficiency decreases with altitude level. Thus, technical efficiency increases with farm size, while farms managed by aged farmers and having lower proportion of remunerated work, and having high altitude tend to be inefficient. The LFA payment and technical efficiency score has a negative relationship confirming SF results, and showing that the LFA payment has a negative impact on technical efficiency of olive farms.

5. Conclusion

Spanish LFA presents more than 80% of total utilized agriculture area. The olive sector is one of the main farming activities mostly located in these areas. Given the relevance of this sector in the Spanish agriculture and the prominent position of Spanish production and exportation worldwide, the relative technical efficiency has been analyzed of Spanish olive farms located in LFA. Specifically, this paper assesses the impacts of LFA compensatory payment on technical efficiency of Spanish olive farms. A stochastic frontier model was estimated using a two unbalanced panel data of 162 olive farms observed from 2000 to 2004, which 99 farms receive the LFA payment support. Follow up by a Tobit model that analyzes the relationship between technical efficiency scores and other variables for sample as whole.

Estimated average efficiency levels for sample farms are about 52.6% for farms receiving payment and 66.2% for farms do not. Parameters of technical inefficiency equation suggest that several variables affect efficiency levels, but do not have the same impact in both cases. Technical efficiency scores seem to be positively correlated with farms' size, age of manager, while, the farm rents cultivated land decrease it. On the other hand, workforce composition shows that farms with a higher proportion of family labour and not receiving payment are more efficient relative to the farms with a higher proportion of remunerated work.

Result also suggests that farm managers which not receive compensatory allowance learn from their errors and experience, and has an optimal allocation of managerial effort. Such results are supported by the negative sign of payment ratio coefficient, which provides a negative direct impact of LFA aid scheme on technical efficiency of LFA olive farms. Results also shows for all sample as whole that technical efficiency increase with farm size, and decrease in the case of farms managed by aged farmers, having lower proportion of remunerated work, and having high altitude. The LFA payment and technical efficiency score has a negative relationship which confirm the results of the first analysis, and shows that the LFA payment has a negative impact about technical efficiency of olive farms.

Finally, the LFA aid scheme applied during the 2000-2004 has had a negative impact on technical efficiency of olive farms located in these areas. Future regulation in LFA support scheme need to take into consideration this fact by designing an adequate compensation scheme that help farms to improve their technical efficiency and to survive in these marginal areas.

Table 1. Description of the sample data

Variable	Unit of measure	Mean	Std Dev	Minimum	Maximum
Fertilizers	€	1,424.40	2,961.82	0.00	55,093
Pesticides	€	1,448.53	3,555.72	0.00	62,123.31
Other crop costs	€	3,828.92	4,715.28	91.19	70,315.61
Labour	hour	3,022.97	1,600.28	850	19,117
Land	ha	25.13	42.50	0.00	377
Output	€	26,379.38	38,044.62	2	494,547.14
Workforce composition		0.79	0.19	0.00	1.00
Age	Year	57	14.88	30	100
Size	(ESU)	34.86	67.08	2.52	452
Rented area ratio		0.08	0.23	0.0	1.0

Table 2. Maximum likelihood estimates of the stochastic frontier model for olive farms in Spain, 2000-2005

		Farms not receiving payment		**Farms receiving payment**	
Variables	Parameter	Estimate	Standard Error	Estimate	Standard Error
Frontier production function					
Constant	β_0	-1.819169	(1.150838)**	4.366926	(0.288369)***
Labor	β_{LB}	1.329936	(0.715413)**	-0.006458	(0.005961)*
Pesticides	β_P	-0.008546	(0.000878)***	-0.006552	(0.001994)
Fertilizers	β_F	-0.285566	(0.685340)	0.009719	(0.020920)
Land	β_L	0.012262	(0.007185)**	-0.000126	(0.002011)
Other Inputs cost	B_I	-0.003682	(0.006810)	-0.000301	(0.002323)
Fertilizers× Pesticides	$\beta_{F.P}$	0.230452	(0.043881)***	0.005919	(0.009247)
Pesticides × Labour	$\beta_{P.LB}$	0.001539	(0.000960)*	-0.001328	(0.002005)
Land × Pesticides	$\beta_{L.P}$	0.620959	(0.154610)***	0.008218	(0.009243)
Fertilizers × Labour	$\beta_{F..LB}$	0.006574	(0.001820)***	0.001521	(0.001816)
Fertilizers × Land	$\beta_{F.L}$	0.425518	(0.158870)***	-0.013078	(0.007831)**
Land × Labour	$\beta_{L.LB}$	0.004138	(0.001925)***	-0.000175	(0.002313)
Other Inputs × Pesticides	$B_{I.P}$	-0.043305	(0.038298)*	-0.001684	(0.012417)
Fertilizers × Other Inputs	$\beta_{F.I}$	0.001028	(0.000966)*	0.002321	(0.002223)*
Other Inputs × Labour	$B_{I.LB}$	0.062396	(0.087600)	0.050065	(0.009201)***
Other Inputs × Land	$B_{I.L}$	-0.000947	(0.001346)	0.001888	(0.002056)
Inefficiency effects model					
Constant	δ_0	-0.409155	(0.915886)	-16.81055	(3.944711)***
Workforce composition	δ_{WC}	-0.160004	(0.077375)***	0.002787	(0.014996)
Land rental	δ_{RP}	-0.004693	(0.003472)*	-0.187509	(0.033665)***
Age	δ_A	0.075494	(0.052626)*	0.197012	(0.036342)***
Time	δ_T	-0.001201	(0.003336)	0.044359	(0.009054)***
Farm size	δ_{FS}	-0.143274	(0.051590)***	-0.063397	(0.009828)***
Payment ratio	δ_{PR}			0.147402	(0.024559)***
sigma-squared	σ^2	1.0610633	(0.16641533)***	18.848632	(3.579496)***
gamma	γ	0.8832044	(0.03129757)***	0.992639	(0.002424)***
Log likelihood function		-348.6593		-233.2492	
LR test of the one-sided error		84.785261		82.080646	

Note: ***, ** and * indicate that the parameter is significant at the 1% and 5% and 30% respectively.

Table 3. **Mean technical efficiency by year and farms**

Efficiency interval	**2000**		**2001**		**2002**		**2003**		**2004**	
	P	NP	P	NP	P	NP	P	NP	P	NP
<20	3	0	3	0	5	2	17	7	0	0
20-30	3	2	3	5	0	2	4	3	0	0
30-40	3	3	8	7	2	9	7	5	0	5
40-50	1	7	6	6	6	7	0	5	0	6
50-60	3	17	6	7	4	5	6	18	4	9
60-70	15	17	10	7	7	12	2	32	0	18
70-80	10	29	12	22	11	23	4	15	0	30
80-90	3	11	1	36	8	32	4	5	0	14
90>	0	1	0	2	1	0	0	0	0	0
Mean	59	67	53	70	60	68	36	58	55	68

P and NP refer to farms receiving LFA payment and do not respectively.

Table 4. Two-limit Random-effect Tobit model results

		Random-effects Tobit Model	
Variables	Parameter	Estimate	Standard Error
Constant	α_0	22.86209	(10.18155)***
Land rental	α_{RL}	0.021929	(0.043443)
Age	α_A	-0.003183	(0.000576)***
Time	λ_T	-0.010931	(0.00509)***
Farm size	α_{FS}	0.000377	(0.000182)***
Payment	λ_P	-0.087332	(0.024373)***
Workforce composition	α_{WC}	-0.183440	(0.049314)***
Altitude	α_{AL}	-0.031076	(0.029264)*
Sigma_u		0.107318	(0.010964)***
Sigma_e		0.157443	(0.005351)***
Log likelihood function		179.79436	

Note: *** and * indicate that the parameter is significant at the 1% and 30% respectively

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