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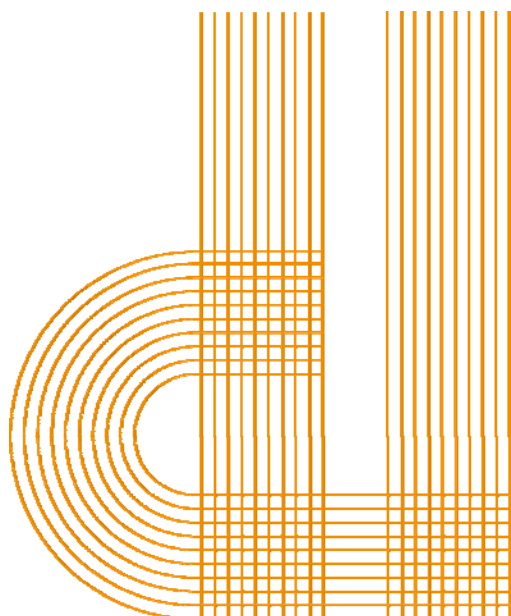
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Abstract

Using annual data, we have estimated the timber harvest of eucalyptus in the region of Galicia (Spain). The explanatory variables considered were price, pulp exports, and salvage timber. The latter variable was used as a proxy for forest fires. The problems related to spurious regression were addressed by applying the bounds testing approach to cointegration, and confidence intervals were constructed using the bootstrap technique. The results indicate that pulp exports have a positive effect on the harvested timber volume. Moreover, we find that salvage timber positively affects the timber supply. This result indicates that there is no substitution between salvage timber and non-damaged timber. It also suggests that the natural expansion of the eucalyptus in Galicia compensates for the destruction caused by forest fires, avoiding supply shortages. On the other hand, and according to the economic law of supply, the timber price shows a negative effect.

Keywords: eucalyptus, forest fires, cointegration, ARDL, bootstrap

1-. Introduction

Galicia is a Spanish region located on the northwest corner of the Iberian Peninsula, right at the north border of Portugal. This region is responsible for almost half of the Spanish timber production, and this level of production is achieved in spite of covering only 7.5% of the total Spanish forest area. Unfortunately, fire is a recurrent and serious threat to the forest and wooded area of this region, leading every year to important environmental, social, and economic damage. In fact, wildfires are no longer considered occasional events since the last decade the yearly fires has remained nearly constant at around 10,000 outbreaks, representing approximately 50% of the outbreaks of forest fires in all of Spain (MARM, 2009). Most of them are human induced and enhanced by gradual land abandonment and the favorable weather conditions (hot temperatures, dry conditions and strong winds). All these factors have allowed fires to spread quickly and favored the destruction of a large area of forest. The devastating numerous fires set in Galicia have motivated an urgent social consciousness of the problem and heated scientific debate (Chas-Amil, 2007a, 2007b; Díaz-Balteiro, 2007; Fernandes, 2008). However, despite the seriousness of the problem, there is an inexplicable lack of research that has empirically analyzed the impact of wildfires on the timber market in Galicia.

In general, there is not much literature examining the effects of wildfires on the main variables of the market. The scarce literature has primarily focused on investigating the effect on the market of timber damage by wildfires (Butry *et al.*, 2001; Prestemon *et al.*, 2006). This is the goal of our study. However, the current study differs from the previous in several points: First, we do not evaluate the effect of a unique wildfire but rather estimate the long-run impact of wildfires on the market along time. Second, we propose and develop a new methodological procedure to perform an

appropriate time series econometric analysis in Forest Economics. That is, we investigate first whether a long-run equilibrium relationship exists between the timber harvest and a set of explanatory variables. To avoid the possible existence of spurious relationships, we must take into account the presence of non-stationary processes. Therefore, we need to ensure that all the variables are cointegrated (Song *et al.*, 2011). Cointegration analysis is carried out using an autoregressive distributed lag (ARDL) model and the bounds testing approach proposed by Pesaran *et al.* (2001). The ARDL bounds testing approach has been successfully applied in different fields to find and contrast a long-run relationship among variables; however, it is practically unknown in Forest Economics. If a long-run relationship was verified, the following step would be to construct and estimate a model based on a general-to-specific approach. Finally, in a third step, we make use of estimated coefficients to calculate the point estimates of the long-run impact of the explanatory variables on the timber harvest. However, it is worth noting that we must be circumspect at this step, given that the point estimation is of only limited usefulness if we do not evaluate its statistical significance. For that reason, we also construct confidence intervals for the long-run effects using a specific nonparametric inferential method called "bootstrapping" (Efron & Tibshirani, 1998). This method allows us to estimate the variability of the point estimation and assess its statistical significance.

After this introduction, the remainder of this article is structured as follows: Section two provides a description of the empirical model and of variables considered in this study. Section three explains the three-step methodology. Section four contains the main results and discussion, and section five concludes.

2-. Empirical Model and Description of the Variables

We start our analysis assuming that the eucalyptus timber supply can be properly represented by the general model

$$\ln Y_t = \beta_0 + \beta_1 \cdot \ln P_t + \beta_2 \cdot \ln E_t + \beta_3 \cdot \ln D_t + \varepsilon_t, \ \forall t = 1,.....T \quad (1)$$

where ε_t is the disturbance term, which is assumed to be an independent and identically distributed random variable. Y_t is the dependent variable and, in our case, represents the volume in cubic meters of the eucalyptus timber supply. We center our analysis on the eucalyptus since it is the most important species in the region, accounting for about half the total volume of timber. The data were obtained from *Yearly Agricultural Statistics*, published by the regional government. On the other hand, the explanatory variables are contained in the vector *X = (P, E, D)*. The variable *P* is the price in Euros of the eucalyptus timber, with the data obtained from the same source. The variable *E* is the pulp exports valued in Euros. These data come from *International Trade Statistics*, published by the Spanish Ministry of Economy and Competitiveness. Finally, the variable *D* is the volume of salvage timber damaged by fire, measured in cubic meters. While there are different alternative approximations that measure forest fires (number of fires or burn hectares of forest), we consider salvage timber to be a better proxy to adequately reflect the forest fire effects on the market. Moreover, this approximation is commonly used in the literature (Butry *et al.*, 2001; Prestemon *et al.*, 2006). The data for this variable were obtained from the Coordinating Centre of the National Wildland Fire Information (CCINIF), a service under the General Directorate for Environment and Forestry Policy of the Spanish Ministry of Agriculture, Food and Environment. The sample period of our variables comprises the most recent information that spans from

1985 to 2008. Finally, we have taken a logarithm of our variables for two basic reasons: (1) to reduce the variability of the data; and (2) to interpret the estimated coefficients of the explanatory variables as elasticities.

3. Methodological Procedure

This section gives a brief presentation of the three-step procedure followed in this study to confirm the presence of a statistical relationship between the dependent and the explanatory variables, to model this relationship, and to quantify the long-run impacts of the explanatory variables on the eucalyptus timber harvest.

First Step: Looking for a Long-Run Relationship

The first step in our analysis is to validate the existence of a statistical relationship between the eucalyptus timber harvest (Y) and the set of the influencing factors (P, E, D). This problem can be solved using different traditional cointegration methods such as those developed by Engle and Ganger (1987) and Johansen and Juselius (1990). However, these methods have shown an important technical limitation: They can be used only when the variables are integrated of the same order. It is for that reason that in our study we make use of the autoregressive distributed lag (ARDL) bounds testing approach (Pesaran and Pesaran 1997, Pesaran *et al.*, 2001). This method has not yet been widely used in Forest Economics, although it has already been previously applied in different fields, given the multiple advantages it offers in comparison with traditional cointegration techniques.

First, the ARDL approach can be used irrespective of whether the underlying explanatory variables are $I(0)$ or $I(1)$ or a mixture of both (De Vita & Abbott, 2002). However, in spite of this great advantage, it is necessary to check that the variables are

not $I(2)$ because if this were the case, the approach would produce spurious results (Oteng & Frimpong, 2006; Ouattara, 2006). Secondly, the ARDL model takes a sufficient number of lags to represent appropriately the data-generating process in a general-to-specific framework (Laurenceson & Chai, 2003). Another reason that justifies the use of this approach is that it is consistent and relatively more efficient in small or finite sample data sizes than the traditional cointegration techniques (Pesaran & Shin, 1999). Finally, an error correction model (ECM) can be derived from the ARDL model using a simple reparameterization (Banerjee et al., 1993). According to this, an ARDL representation of equation (1) can be characterized by the following ECM

$$\Delta \ln Y_t = \alpha_0 + \sum_{j=1}^{p-1} \alpha_j \cdot \Delta \ln Y_{t-j} + \sum_{i=1}^{K} \sum_{j=0}^{p-1} \delta_{ij} \cdot \Delta \ln X_{i,t-j} + \phi \cdot \ln Y_{t-1} + \sum_{i=1}^{K} \vartheta_i \cdot \ln X_{i,t-1} + \varepsilon_t \qquad (2)$$

where Δ is the first-difference operator, Y is the dependent variable, the vector $X = (P, E, D)$ contains the explanatory variables, and ε_t is assumed to be a white noise error term. ϕ and ϑ_i are the parameters that represent the long-run relationship, and α_j and δ_{ij} reflect the short-run dynamics of the model. Finally, K is the number of explanatory variables considered in the model, and p is the lag length.

The bounds testing approach allows us to study if there is a significant long-run relationship between the dependent variable Y and the vector of explanatory variables $X = (P, E, D)$. According to the specification of the model represented in equation (2), the testing procedure is based on alternative statistical tests to check the null hypothesis that the variables are not cointegrated (Pesaran et al., 2001). The first one is a F-statistic (F_{II}), which is associated to the hypothesis testing $H_0 : \alpha_0 = \phi = \vartheta_1 = ... = \vartheta_K = 0$. The second test is another F-statistic (F_{III}) that verifies the hypothesis

$H_0 : \phi = \vartheta_1 = ... = \vartheta_K = 0$. Finally, the third statistic is an individual t-statistic that checks the nullity of the parameter associated with the lagged dependent variable ($H_0 : \phi = 0$). Both the F-statistics and the t-statistic have a non-standard distribution under the null hypothesis of no relationship of cointegration. However, Pesaran *et al.* (2001) derived their asymptotic distributions under the assumptions of all variables being *I*(0) and all being *I*(1), respectively, and proposed critical value bounds for different scenarios. These critical values allow us to decide statistically about the acceptance or rejection of the null hypothesis. That is, under the null hypothesis, if the value of the different tests falls above the respective critical upper bound, then we reject the null hypothesis and have evidence of a long-run relationship. On the other hand, if the value is below the respective critical lower bound, then we cannot reject the null hypothesis of no cointegration and cannot confirm the existence of a long-run relationship between variables. Finally, if the value of the test lies between the upper and lower critical bounds, then the inference is inconclusive.

Second Step: Modeling the Eucalyptus Timber Supply

If the existence of a long-run relationship between variables was established by using the bounds testing approach, the second step is to construct an econometric model that represents properly the relationship between the dependent variable and its influencing factors. For this purpose, we propose a general-to-specific strategy, which is considered a leading methodology for empirical modeling (Hendry, 1993). The procedure starts with the estimation of the model represented by equation (2) using ordinary least squares, and where the optimal number of lags (*p*) is chosen according to some information criterion. The most insignificant variable is removed, and the model is estimated again. This process is repeated until all remaining coefficients of the model

are statistically significant at a concrete level (usually at 1, 5 or 10%). The model finally obtained using this reduction process must meet certain econometric requirements: (1) it must have a high Adjusted-R^2; (2) the estimated coefficients must be statistical significant and present a sign coherent with the economic theory; and, finally, (3c) it must not exhibit any problems of autocorrelation, heteroskedasticity, or misspecification. If the final model fulfills these requirements, then the estimated coefficients provide us with some important qualitative information. First, they reflect the most important variables to explain timber harvest; second, they tell us the sign of the effect of these explanatory variables. However, they do not allow us to quantify the long-run impact of each one of the explanatory variables on the dependent variable.

Third Step: Estimating the Long-Run Effects

Once validated the adequacy of the model obtained using the general-to-specific strategy, the estimated long-run coefficients are used to evaluate the impact of the explanatory variable X_i on the variable Y. Following Bardsen (1989), the long-run impact can be estimated using the expression

$$\hat{\gamma}_i = -\frac{\hat{\vartheta}_i}{\hat{\phi}} \quad \forall i = 1,...K \tag{3}$$

where $\hat{\vartheta}_i$ and $\hat{\phi}$ are the estimated long-run coefficients in equation (2). The long-run impact estimate $\hat{\gamma}_i$ is of great importance because it shows how the dependent variable Y responds in the long run to any change in the explanatory variable X_i. However, the estimation of $\hat{\gamma}_i$ is not complete from an econometric point of view. We have only a single value that quantifies the long-run impact, but we do not know whether the long-run impact has a relevant effect. It is for this reason that we must statistically test the

null hypothesis $H_0 : \gamma_i = 0$ to accomplish an appropriate estimation of the long-run impact. The challenge is that it is not possible to use the classical inferential statistics here since the parameter γ_i does not follow a normal distribution (it is constructed from the quotient of two normal variables). A possible solution can be to construct a confidence interval for each γ_i using the bootstrap method (Efron & Tibshirani, 1998).

The main advantage of this non-parametric method is that it allows us to estimate confidence intervals empirically without assuming a specific distribution of γ_i. Another important characteristic of the bootstrap is that it allows us to get more accurate intervals (Brownstone & Valletta, 2001), and these intervals can be asymmetric (intervals that are longer on the left or right). Once the interval is constructed, we can determine the statistical significance of γ_i. That is, if the zero was contained in the interval, then the null hypothesis $H_0 : \gamma_i = 0$ would be accepted and, in consequence, the impact would not be statistically significant.

4. Empirical Results

First Step: Looking for a Long-Run Relationship

As mentioned above, the ARDL bounds testing approach allows us to study the existence of a long-run relationship between the eucalyptus timber harvest (*Y*) and the set of the influencing factors (*P, E, D*). If the variables are *I*(*d*) with $d \geq 2$, the bounds testing approach to cointegration cannot be applied since it is based on the assumption that the variables are *I*(1), *I*(0) or a mixture of both. This is the reason of why we must analyze first the order of integration of the variables considered in our study. This analysis has usually been done using the ADF (Dickey & Fuller, 1981) and P-P (Phillip & Perron, 1988) unit root tests. However, these tests have been strongly criticized

because of their low power in distinguishing between unit root and a near unit root process when the span of the data is not long enough. An alternative test that has shown more appropriate in small samples is the KPSS unit root test (Kwiatkowski *et al.*, 1992).

Table 1. ADF, P-P and KSPSS Unit Root Tests Results

	ADF TEST H_0 : Unit Root	P-P TEST H_0 : Unit Root	KPSS TEST H_0 : Stationary
UNIT ROOT TESTS AT LEVELS			
Y	-1.90(5)	-1.89(0)	0.64(3)***
P	-3.82(1)***	-4.18(14)***	0.24(2)
E	-1.56(0)	-1.55(3)	0.68(3)**
D	-3.71(0)***	-3.68(2)***	0.07(1)
UNIT ROOT TESTS AT 1st DIFFERENCE			
Y	-3.96(3)***	-5.24(2)***	0.17(2)
E	-5.25(0)***	-6.17(4)***	0.21(5)

The symbols *, ** and *** means rejection of the null hypothesis at the 10, 5 and 1 percent, respectively. For the KPSS and P-P tests, the number of bandwidth are shown in brackets according to the Newey-West Criterion using Bartlett Kernel. For the ADF test, the number of lags are shown in brackets according to the Schwarz information Criterion.

Table 1 shows the results of the ADF, P-P, and KPSS unit root tests. As we can observe, the tests provide clear evidence that the variables *Y* and *E* have a unit root in their levels (they are *I*(1)), and the variables *P* and *D* are stationary (they are *I*(0)). That is, none of them is *I*(*d*) with $d \geq 2$ and, consequently, we can make use of the bounds testing approach to study the existence of a cointegration relationship between variables. However, we must first determine an appropriate lag length *p* for the ARDL model represented in equation (2). In our study, the optimal number of lags is selected according to the Schwarz Bayesian Information Criterion (SBIC), which is found to be

$p = 1$. The main reason for using the SBIC is that Pesaran and Shin (1999) have demonstrated empirically that this criterion has a better performance with small sample size. Moreover, these authors also recommend choosing a maximum of two lags when the periodicity of the data is annual.

Table 2 shows the values of the F_{II}, F_{III} and t_{III} statistics, and the corresponding critical bounds represented in Pesaran *et al.* (2001). As we can see, the F-statistics and t-statistic are $F_{II} = 8.18$, $F_{III} = 8.12$ and $|t_{III}| = 4.02$, which in all these cases above, their respective critical bounds are at the 5% significance level. Therefore, the null hypotheses of no cointegration are rejected in each case. Moreover, we can affirm from a statistical point of view that we have conclusive evidence of a long-run relationship between the eucalyptus timber harvest (*Y*) and the explanatory variables (*P, E* and *D*).

Table 2. Critical Values and Bound Test for Cointegration.

Test Value	Lower Bound Critical Value	Upper Bound Critical Value	Long-run Relationship
$F_{II} = 8.18$	2.79	3.67	YES
$F_{III} = 8.12$	3.23	4.36	YES
$|t_{III}| = 4.02$	2.85	3.78	YES

The Critical Values are for a level of significance of $\alpha=0.05$. F_{II} is the value of the F statistic associated with a model with restricted intercept and no trend. F_{III} represents the F statistic of the model with unrestricted intercept and no trend and t_{III} is the t statistic of the models without trend.

Second Step: Modeling the Eucalyptus Timber Supply

Once we have found a statistical long-run relationship, the next step is to build a model that accurately captures this relationship. For this purpose, and as mentioned

above, we use a general-to-specific modeling strategy. That is, our empirical analysis starts with the parameter estimation of the general model represented by equation (2) using ordinary least squares. Then, this general model is shortened by successively deleting the less statistically significant differenced variables. The elimination of the lagged level variables is not allowed in this case since they represent the cointegration relationship. The procedure finishes when all differenced variables are statistically significant at a concrete level; in our case, that is determined to be $\alpha = 10\%$.

Table 3 shows the estimated long-run parameters ($\hat{\vartheta}_P, \hat{\vartheta}_E, \ \hat{\vartheta}_D$ and $\hat{\phi}$) of the model finally obtained using the general-to-specific process. As we can see, all estimates are highly significant (p-value < 0.01) and, therefore, are statistically relevant to explain the eucalyptus timber harvest. The positive sign of the coefficient $\hat{\vartheta}_P$ is consistent with the economic law of supply: if the price of the eucalyptus timber increases, then the timber harvest will be greater. The positive value of the estimated coefficient $\hat{\vartheta}_E$ is also coherent with our a priori expectations: If the pulp exports rise, then the eucalyptus timber increases. This result confirms our expectations since the pulp industry is the main buyer of eucalyptus timber in Galicia. The majority of the pulp production is exported to European countries such as United Kingdom, Germany, Switzerland and Austria. Indeed, the pulp industry is considered the most internationally competitive wood industry in Galicia (Díaz-Balteiro, 2007). More novel and interesting is the positive sign observed for the coefficient $\hat{\vartheta}_D$. This estimate implies that we have found a positive relationship between salvage timber and timber harvest: The higher the quantity of salvage timber, the higher will be the volume of cuts. Therefore, it indicates that forest fires produce an increase in the eucalyptus timber supply. This positive relationship can be explained according to the rational behavior of the agents. Once the timber is damaged by fire, the forest owners are aware that a delay in the cuts of the

salvage timber could lead to important economic losses motivated by the wood decay. It is for this reason that they act rationally and anticipate the decision to cut, thereby contributing to the increase in the eucalyptus timber supply.

In addition to the estimated coefficients, Table 3 also provides a battery of diagnostic tests on the final ARDL model. These tests prove the econometric strength of our estimations. Specifically, the estimated model has a goodness of fit relatively high (Adjusted-$R^2 = 0.63$), and passes all the diagnostic tests commonly used in the literature to detect problems of serial correlation, heteroskedasticity, and non-normality of the residuals. As a result, we can affirm that the regression residuals behave statistically as a white noise process. We also checked the existence of misspecification problems using the Ramsey's RESET Test. The results of this test allowed us to assert that there is no a general specification error of the model. That is, there is neither omission of relevant explanatory variables, nor incorrect choice of the functional form of the model. Finally, following Pesaran and Pesaran (1997), we examine the stability of the long-run coefficients using the cumulative sum of the recursive residuals (CUSUM) and the cumulative sum of squares (CUSUMQ) tests. The plots of the CUSUM and CUSUMSQ indicate the stability of the long-run coefficients of the model since the residuals lie within the upper and lower bounds of the critical values. The stability is also corroborated by using the recursive least squares procedure.[2]

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[2] For sake of brevity, the plots of CUSUM, CUSUMSQ, and recursive least squares for each estimated parameter are not reported here, but they can be sent upon request.

Table 3. Long-run coefficients and diagnosis tests

Long-run Coefficients			Estimated Value	P-value
$\hat{\alpha}_0$			5.30	0.00
$\hat{\phi}$			-0.70	0.00
$\hat{\vartheta}_P$			0.49	0.00
$\hat{\vartheta}_D$			0.11	0.00
$\hat{\vartheta}_E$			0.17	0.00
DIAGNOSTIC CHECKING				
			Value	**P-value**
Adjusted-R^2			0.69	-
Autocorrelation	Lagrange Multiplier (LM) Test	LM(1)	2.54	0.14
		LM(2)	1.19	0.34
	Ljung-Box Q-Statistic	Q(1)	2.20	0.14
		Q(2)	2.21	0.33
Heteroskedasticity	White´s Test		0.82	0.60
	Breusch-Pagan-Godfrey Test		1.70	0.19
Normality	Jarque-Bera Test		1.21	0.54
Misspecification	Ramsey Test		0.15	0.71

Note: These results are based on the ECM restricted.

Third Step: Estimating the Long-Run Effects

The long-run coefficients estimated in the previous step give us only qualitative information: the sign and the statistical significance of the explanatory variables. However, they do not allow us to directly quantify the long-run impact of these

variables on the eucalyptus timber supply. It is for this reason our study estimates these long-run impacts using the long-run coefficients ($\hat{\vartheta}_P, \hat{\vartheta}_E,\ \hat{\vartheta}_D$ and $\hat{\phi}$), and the expression represented in equation (3).

Table 4. Point and Bootstrap Interval Estimation of the Long-run Effects

Coefficient	Estimated Effect (percentage)	Bootstrap Confidence Interval
$\hat{\gamma}_P$	0.7044	[0.1570, 1.4081]
$\hat{\gamma}_E$	0.2482	[0.1081, 0.4066]
$\hat{\gamma}_D$	0.1526	[0.0395, 0.2791]

The bootstrap confidence interval is constructed using the accelerated bias-corrected method considering 10,000 replications and a confidence interval of 90%.

Table 4 presents the point estimates of the long-run effects of the explanatory variables on eucalyptus timber supply (γ_i). As previously mentioned, the parameter γ_i does not follow a normal distribution and, therefore, the traditional statistical inference methods do not work in this case. This problem can be unravelled by means of the bootstrap method (Efron & Tibshirani, 1998). In the literature, we can find different procedures to construct a bootstrap confidence interval such as the normal approximation method, the percentile method, the percentile t-method, the bias-corrected percentile, and the accelerated bias-corrected method. The optimal choice of one or another method depends on the specific problem object of analysis. However, we have applied here the accelerated bias-corrected method. There are two basic reasons that explain this technical choice: First, it is a method that provides more efficient

interval than the other methods (Briggs et al., 1997). Second, Efron and Tibshirani (1998) recommend it for general use. Table 4 also shows the bootstrap confidence intervals with a confidence level of 90%. A detailed analysis of Table 4 allows us to underline some important results:

- Price elasticity $\hat{\gamma}_P$ is estimated to be 0.70; therefore, a 1% increase in the price of eucalyptus timber will lead to a 0.70% increase of the eucalyptus supply. The bootstrap technique gives us a confidence interval of (0.16, 1.41). According to this interval, the impact of price on eucalyptus timber is statistically significance since it does not include the value zero. This result confirms the microeconomic theory in the sense that the price is a relevant variable to determine the supply of a good.

- Pulp exports have also a significant impact on timber supply. Specifically, the estimated elasticity $\hat{\gamma}_E$ tells us that an increase of 1% in the pulp exports will imply an increase of 0.25% in the wood production of eucalyptus. The corresponding bootstrap confidence interval is estimated to be (0.11, 0.41). Therefore, we can reject the null hypothesis that this variable has no significant impact on the timber supply since the interval does not contain the zero value.

- Finally, the estimated elasticity $\hat{\gamma}_D$ allows us to approximate the impact of forest fires on the eucalyptus timber harvest. Moreover, this estimated elasticity also allows us to see whether there is a substitution effect between salvage timber and no-damaged timber in Galicia. To be more precise, a substitution effect would imply that the presence of more salvage timber would not modify the eucalyptus timber supply since it would be expected a reduction in the cuts of no-damaged timber. If this were the case, the estimated elasticity would be

close to zero and not statistically significant. As we can see in Table 4, $\hat{\gamma}_D$ is equal to 0.15, which implies that an increase of 1% in the volume of salvage timber will raise 0.15% in eucalyptus cuts. The bootstrap confidence interval is (0.04, 0.27). This interval does not include the value zero, so we have statistical arguments that allow us to affirm: (1) that forest fires have a limited but significant impact on eucalyptus timber supply; and (2) that there is no a substitution effect between salvage timber and no-damaged timber. Moreover, another important implication of our results is that the continuous destruction of the stock caused by the forest fires and by increasing cuts have not led to a shortage of the eucalyptus timber supply in the market. This result seems initially paradoxical since one could expect a priori that a reduction of the resource would imply problems of non-availability of eucalyptus timber in Galicia. However, we observe that there are no supply problems because the eucalyptus stock is increasing. In fact, if we compare the *Second* and *Third National Forest Inventory*, we observe that the volume of eucalyptus growing stock in Galicia has increased by 122%.[3] González-Gómez *et al*. (2011) provide two possible explanations for the eucalyptus growing stock increase: First, there are better investment and institutional conditions for the plantation of eucalyptus than for other species (growing rate, low maintenance and regeneration costs, and subsidies). Therefore, the owners expand eucalyptus plantations, transforming bare land, substituting other forest species for eucalyptus, or reforesting land previously devoted to agricultural use. The second explanation is that the eucalyptus is a species that expands rapidly without active

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[3] *The National Forest Inventories*, published by the Spanish Ministry of Agriculture, Food and Environment, provide data at the regional and national levels of the growing stock (volume and number of trees) and the extent of the forest area. The *Second National Forest Inventory* finished in 1995, and the *Third National Forest Inventory* concluded in 2007.

intervention of the forest owners (Montoya, 1995). Indeed, we observe that the continuous abandonment of land devoted to agricultural in rural areas of Galicia is usually occupied by plantations of eucalyptus. Additionally, we must also keep in mind that the eucalyptus is a species that has easy vegetative reproduction from stumps, which favors fast regeneration after a clearcut or a forest fire.

5. Summary and Conclusions

The region of Galicia, Spain, has numerous damaging forest fires every year, which has led to a profound social consciousness of the problem and a controversial political and scientific debate. However, in spite of the relevance of the problem, no empirical analyses have been carried out for understanding the impact of the forest fires on the main variables of the timber market. Our study attempts to fulfil this gap by estimating the long-run impact of forest fires on the eucalyptus timber harvest along time. This is an important contribution of our research since the great majority of the studies on this topic analyse only the market impact of a unique wildfire. Moreover, we proposed and developed a three-step procedure as a guide to conduct a robust econometric analysis. In the first step, we made use of the ARDL bounds testing approach to check the existence of a long-run relationship between the eucalyptus timber harvest and a set of explanatory variables, such as the eucalyptus timber price (P), pulp exports (E), and the eucalyptus salvage timber (D). The latter variable is considered a good proxy of forest fire damage. Once the existence of a long-run relationship among the variables was confirmed, the following step was to estimate the eucalyptus timber supply using the ARDL model and assuming a general-to-specific approach. Finally, in the third step, we calculated the long-run impact of the explanatory

variables on the timber supply and also estimated the confidence intervals associated with each impact.

From our point of view, our methodological research sheds some light on how to carry out an appropriate, exhaustive econometric time series analysis in the field of forest economics and, specifically, in studying the impact of forest fires on the timber market. Moreover, we also consider that our empirical findings to be an important contribution to the scarce literature existing on this topic. The main results and contributions can be summarized in the following points:

1. The bounds testing approach allow us to reject the null hypothesis of no cointegration. Therefore, we have statistical evidences that the explanatory variables represented by the vector $X = (P, E, D)$ are important to explain the long-run dynamic of the eucalyptus timber supply.

2. Our estimated ARDL model meets some important econometric requirements, necessary to make a correct interpretation of the results. First, it has a relative high Adjusted-R^2. Second, all the estimated coefficients are statistically significant at 10%, and all of them had a coherent sign. Third, the model does not present any problem of autocorrelation, heteroskedasticity, or misspecification. Therefore, from an econometric point of view, we can say that these characteristics make our model particularly valid to capture the relationship between eucalyptus timber supply and the explanatory variables considered in our study.

3. From the estimated coefficients of the model, we obtain a point estimate of the long-run impact for each explanatory variable on the eucalyptus timber harvest. However, it is worth noting that point estimation is not enough if we wanted to carry out a detailed econometric study. We needed to provide

information about the statistical significance and the variability of the point estimates. It is for this reason, and given the limitations of the classical statistics, that we make use of the bootstrap method to construct confidence intervals for each point estimate of the long-run impact. In our opinion, the inclusion of bootstrap intervals provided more relevant information and gave more consistency to our results.

4. The positive long-run impact estimated for the explanatory variable Price (P) confirms the economic theory. The impact of this variable is estimated to be 0.70. Therefore, it informs us that a 1% in the price of eucalyptus will produce a 0.70% increase in the eucalyptus supply. The bootstrap confidence interval allows us to affirm that the impact of this variable is statistically significant.

5. Our study also confirms the existence of a positive and significant impact of the variable pulp exports (E). Specifically, we estimate that an increase of 1% in the pulp exports lead to an increase of 0.25% in the eucalyptus timber supply.

6. We approximated the damage from forest fires through the volume of salvage timber. Our estimates revealed that if the eucalyptus salvage timber rises by 1%, then the eucalyptus timber supply increases by 0.15%. The analysis of the corresponding bootstrap interval reveals that this long-run effect is statistically significant.

7. The result of the latter point allows us to conclude that forest fires have a limited but significant impact on eucalyptus timber supply and that there is no substitution effect between salvage timber and no-damaged timber. Moreover, the positive effect also suggests that the forest fires have not

caused supply shortages. The eucalyptus is an abundant natural resource in Galicia, thanks to its fast vegetative reproduction.

8. Finally, this study represents only a first attempt of estimating the long-run impact of wildfires on the timber supply of one of the most important forest species in Galicia: the eucalyptus. We are aware that further research is needed to analyze the effects on the timber supply of other important species for the Galician forest sector, such as the maritime pine.

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