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Panel Data Estimation Methods on Supply and Demand Elasticities: The Case of Cotton in Greece

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This article examines the effects of the application of panel data estimation methods on a system of equations with unbalanced panel data. We apply pooled, random-effects, and fixed-effects estimation in three data sets: small, medium, and large farms to examine the relationship between farm size and the elasticity of cotton supply with respect to cotton price. Our results indicate that the adoption of various estimation methods entails different estimated parameters both in terms of their absolute value and in terms of their statistical significance. Additionally, the elasticity of cotton supply with respect to price varies according to farm size.

Key Words: farm size, panel data, supply elasticity, systems of equations

JEL Classifications: C33, D21, Q18

In recent years, many empirical studies that evaluate the effects of agricultural policies in Europe and United States have relied on data sets that are balanced or unbalanced panels. The use of farm-level data implies that we have to consider the application of proper panel data estimation methods so as to obtain estimates of parameters. The adoption of the appropriate estimation method is crucial because the estimated parameters are used for policy evaluation. Consequently, the increased reliability of the estimated parameters ensures that the policy evaluation will be more accurate.

Although there are a significant number of empirical papers that rely on the estimation of a system of equations with balanced or unbalanced panel data to evaluate agricultural policies, they do not use panel data estimation methods. Serra et al. (2005a, 2006) examined the effects of agricultural policies in the United States. They have estimated a system of equations using a balanced panel with farm-level data collected in Kansas. As for the unbalanced panel data sets, the most frequently used in agricultural economics in the European Union is the Farm Accountancy Data Network (FADN), which consists of farm-level data collected every year (Bakucs and Fertõ, 2009; Csajbok, Lansink, and Huirne, 2005; Karagiannis and Sarris, 2005; Melfou, Theocharopoulos, and Papanagiotou, 2009; Reidsma et al., 2009; Rezitis, Tsiboukas, and Tsoukalas, 2002). Many studies that evaluate the effects of Common Agricultural Policy estimate a system of equations and make use of the FADN data set. However, they do not take into account the panel structure of the data (Moro and Sckokai, 1999; Sckokai and Moro, 2006; Serra et al., 2005b).

In this study we focus on the estimation of a Seemingly Unrelated Regression System

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(SUR) with unbalanced panel data applying three estimation techniques: pooled, random-effects (RE), and fixed-effects (FE) estimation. We apply these methods to underline the different results obtained by adopting them. The effects of panel data estimation methods on estimated parameters have also been examined by Platoni, Sckokai, and Moro (2008). However, although they apply FE and RE estimation in a single equation, in a system of equations only, the RE method is applied. In this study, we apply all the different estimation techniques in a system of equations, i.e., in the same model. Thus, the difference in the estimated parameters is exclusively attributed to the estimation method.

In terms of economic analysis, the objective of this study is to examine the relationship between farm size and the elasticity of cotton supply with respect to its own price. The elasticities we estimate are short-run elasticities, which, generally, are smaller than the long-run supply elasticities as a result of the existence of fixed costs. Although producers in the short run can increase production by increasing variable inputs, in the long run, producers can adjust all input quantities. Small farmers use more variable inputs than medium and large farmers (European Commission, 2007, pp. A6–A13). This way, small farmers gain in terms of flexibility and therefore can better accommodate to output variation in the presence of price fluctuations (Mills and Schumann, 1985). Therefore, we expect the elasticity of the cotton supply to be decreasing with respect to farm size. This result was found by Adesoji (1991), who examined the relation of farm size and supply elasticity for U.S. dairy farms. He found that they move in the opposite direction in the short run but the reverse holds during the long-run period.

The European Union Cotton Market

The cotton sector is of limited importance to the European Union (EU) as a whole because cotton contributes only 0.5% to the final agricultural output. However, cotton production has strong regional importance to Greece and Spain, which are the main EU cotton producers. Greece is the major cotton-producing Member State of the EU given that 76% of the EU's total cotton output is grown in Greece. The share of cotton to total agricultural output in Greece is 9.1% and in Spain 1.3% (European Commission, 2007).

In terms of economic size classes, i.e., the classification that is used in the present study, the distribution of small-, medium-, and large-sized cotton farms in Greece and Spain is presented in Table 1.

In light of these results, it is quite clear that the number of cotton farmers in Greece is much

Table 1. Distribution of Cotton Farms per Size Category in Greece and Spain

Number of Cotton Farms per Size Category								
	2000		2003		2005		2007	
	Greece	Spain	Greece	Spain	Greece	Spain	Greece	Spain
Small farms	16.600	840	15.810	780	15.550	490	13.200	80
Medium farms	14.930	1.490	10.670	460	11.980	1.200	12.220	200
Large farms	10.520	1.930	5.720	1.390	5.980	1.290	7.510	1.420
Total	42.050	4.260	32.200	2.630	33.510	2.980	32.930	1.700
Share of Cotton Farms per Size Category to Total Number of Cotton Farms								
	2000		2003		2005		2007	
	Greece	Spain	Greece	Spain	Greece	Spain	Greece	Spain
Small farms	39.48%	19.72%	49.10%	29.66%	46.40%	16.44%	40.09%	4.71%
Medium farms	35.51%	34.98%	33.14%	17.49%	35.75%	40.27%	37.11%	11.76%
Large farms	25.02%	45.31%	17.76%	52.85%	17.85%	43.29%	22.81%	83.53%

Source: Farm Accountancy Data Network.

larger than in Spain. For example, the total number of cotton farms in Greece in 2000 is 42.050, in which 16.600 are small and 14.930 and 10.250 are medium and large, respectively. The total number of cotton farms in Spain in 2000 is 4.260, which corresponds to 840 small, 1.490 medium, and 1.930 large farms. In both countries, the number of cotton farms decreases from 2000 to 2003 but in Greece remains relatively stable after 2003. On the other hand, the number of cotton farms in Spain reduces greatly in 2007. This result can be attributed to the change in the cotton policy regime that took place in the EU from 2006. In Spain, during the cultivation year 2006–2007, there was a decrease in the area under cotton by 45%. On the contrary, in Greece, the cotton area increased by 4% (European Commission, 2007).

Taking into consideration the share of farms per size, it is clear that there is small change from year to year in Greece. However, the situation in Spain is completely different. The share of small and medium farms to total cotton producers gradually decreases and the corresponding share of large farms is almost doubled from 2000 to 2007. According to the FADN data, the total cost of production is higher in Spain, 3.037 €/ha, than in Greece, 2565 €/ha. Additionally, the total profit is larger in Spain, 745.5 €/ha, than in Greece, 596.8 €/ha (European Commission, 2007).

Theoretical Framework

In this section, we present the theoretical framework that we used in this study. To compute the supply and the derived demand elasticities, we use duality theory and particularly a flexible functional form of profit function. Flexible functional forms of profit functions have been widely used in agricultural economics research (Abrar, Morrissey, and Rayner, 2004; Arnade and Kelch, 2007; Pope et al., 2007; Shumway, 1983; Sidhu and Baanante, 1981; Vilezca-Becerra and Shumway, 1994; Weaver, 1983). We choose the normalized quadratic profit function, which is one of the flexible functional forms that exist.

The normalized quadratic profit function has the following form:

$$
\begin{aligned}
\Pi / P_m = {} & a_o + \sum_{i=1}^{m-1} a_i \, (P_i / P_m) + \sum_{i=m+1}^{n} \beta_i Z_i \\
& + \frac{1}{2} \sum_{i=1}^{m-1} \sum_{j=1}^{m-1} a_{ij} \, (P_i / P_m)(P_j / P_m) \\
& + \frac{1}{2} \sum_{i=m+1}^{n} \sum_{j=m+1}^{n} \beta_{ij} Z_i Z_j \\
& + \sum_{i=1}^{m-1} \sum_{j=m+1}^{n} \gamma_{ij} \, (P_i / P_m) Z_j + \delta_1 t \\
& + \frac{1}{2} \delta_2 t^2 + \sum_{i=1}^{m-1} \varepsilon_i \, (P_i / P_m) t \\
& + \sum_{i=m+1}^{n} \zeta_i Z_i t
\end{aligned}
\tag{1}
$$

where Π is short-run profit (revenue minus variable costs) divided by the price of netput m (input or output); $P_1 \ldots P_{m-1}$ are the prices of the rest netputs (netputs are measured in negative units if they are inputs and in positive units in case that they refer to outputs) divided by the price of netput m; $Z_{m+1}, \ldots, Z_n$ are the quantities of quasifixed factors of production; t is a time trend; and α, β, γ, δ, ε, ζ are parameters to be estimated.

Applying Hotelling's lemma to equation (1) we obtain the supply of output y_i, and the derived demands for variable inputs of production x_i:

$$
\begin{aligned}
\frac{\partial \Pi}{\partial (P_i / P_m)} = y_i = a_i + \sum_{j=1}^{m-1} a_{ij} (P_j / P_m) \\
+ \sum_{j=m+1}^{n} \gamma_{ij} Z_j + \varepsilon_i t
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
\frac{\partial \Pi}{\partial (P_i / P_m)} = -x_i = (a_i + \sum_{j=1}^{m-1} a_{ij} (P_j / P_m) \\
+ \sum_{j=m+1}^{n} \gamma_{ij} Z_j + \varepsilon_i t)
\end{aligned}
\tag{3}
$$

for $i = 1 \ldots m-1$

To be consistent with competitive theory, the profit function must satisfy the following properties: linear homogeneity in prices, symmetry, i.e., $\alpha_{ij} = \alpha_{ji}$, monotonicity in prices and fixed inputs, convexity in prices, and concavity in quantities of fixed inputs. We impose linear homogeneity by dividing the profit function with the price of m netput (in our case input)[1] and symmetry before estimation. Convexity and monotonicity were checked after estimation.

Econometric Techniques

In this section, we present the econometric techniques that we applied to obtain estimators of the coefficients. As we noted in the introductory comments, we estimate a system of equations using three different econometric techniques. In the first case, we estimate the system without taking into consideration the panel specification of our data, i.e., pooled estimation. In the second case, we estimate the system using the one-way error components method for unbalanced panel data proposed by Biørn (2004) so as to obtain RE estimators. Finally, we use the least-squares dummy-variable approach to obtain the FE estimators.[2]

A. Pooled Data Estimation

It is well known that the appropriate way to estimate a system of M equations is the SUR proposed by Zellner (1962). In this case, the best linear unbiased estimator is the Generalized Least Squares (GLS). Up to now, this method has been used by various researchers in agricultural economics (Carlberg, 2002; Fousekis and Revell, 2000; Lee, Kennedy, and Fletcher, 2006).

B. Panel Data Estimation

The panel data estimation relies on the hypothesis that in the estimation procedure, we take into account the "heterogeneity" of each cross-sectional unit. Because it is well known by previous studies (Baltagi, 1985; Cai et al., 2008; El-Osta and Mishra, 2005; Kaltsas, Bosch, and McGuirk, 2008; Poudel, Paudel, and Bhattarai, 2009), the most frequently used models in panel data are the one-way RE and FE models. These models rely on the hypothesis that differences among cross-sectional units can be captured by means of an intercept term, which is specific for each cross-sectional unit. This specific intercept term is considered as a random disturbance in the RE model and as a fixed parameter in the FE model.

B1. One-way Random-effects Model. Avery (1977) was the first to suggest an appropriate method of estimating a SUR system with error components when the data set is a balanced panel. However, in most cases, we have to deal with unbalanced panels so we have to apply the method proposed by Biørn (2004). The main difficulty in applying both methods is that no econometric software supports the estimation of a SUR system with error components either for a balanced or for unbalanced data set. In the following analysis, we provide the approach suggested by Biørn (2004), which we use in the present study.

Consider a system that consists of M regression equations indexed by $m = 1,\ldots, M$. The data set is an unbalanced panel with N farms indexed by $i = 1,\ldots,N$, where each farm is observed in at least two and at most S periods. Let D_s denote the number of farms observed in s periods with $s = 2,\ldots S,$ and n corresponds to the total number of observations. Then the total number of farms observed up to S periods and the total number of observations are given by $D = \sum_{s=2}^{S} D_s$ and $n = \sum_{s=2}^{S} D_s s$, respectively. The farms are ordered in S groups so as the D_2 farms observed twice come first, the D_3 farms observed three times come second, etc. If the cumulative number of farms observed up to

[1] The derived demand equation for the numeraire input is given by the expression:

$$\begin{aligned} x_m = \Pi / P_m - \sum_{i=1}^{m-1} P_i \frac{\partial \Pi}{\partial (P_i / P_m)} &= a_0 \\ + \sum_{i=m+1}^{n} \beta_i Z_i - \frac{1}{2}\sum_{i=1}^{m-1}\sum_{j=1}^{m-1} a_{ij}(P_i / P_m)(P_j/P_m) \\ + \frac{1}{2}\sum_{i=m+1}^{n}\sum_{j=m+1}^{n} \beta_{ij} Z_i Z_j + \delta_1 t + \frac{1}{2}\delta_2 t^2 \\ + \sum_{i=m+1}^{n} \zeta_i Z_i t \end{aligned}$$

which is a quadratic function of normalized prices, quasi-fixed factors of production and time trend.

[2] To apply the FE estimation method, we had to eliminate all the farms that appeared only once in the samples.

s times is K_s, then the index sets of the farms observed s times can be written as:

$$\begin{aligned} &I_2 = 1,\dots\dots\dots,K_2\\ &I_3 = K_2+1,\dots\dots,K_3\\ &\vdots\\ &I_S = K_{S-1}+1,\dots\dots,K_S \end{aligned} \tag{4}$$

where $I_2,\ldots,I_S$ can be considered as balanced subpanels with $2,\ldots\ldots,S$ observations of each farm, respectively.

The system of M equations for individual i, observation t[3] is written as:

$$\begin{aligned} &y_{mit} = \boldsymbol{X}_{mit}\beta_m + \delta_{mi} + \lambda_{mit} = \boldsymbol{X}_{mit}\beta_m + \boldsymbol{u}_{mit}\\ &\quad m = 1,\dots.M, i \in I_s, t{=}1,\dots.S \end{aligned} \tag{5}$$

The dimensions of the matrices consisting of $\boldsymbol{y}_{mit}$, $\boldsymbol{X}_{mit}$, and β_m are $Mn \times 1$, Mnx k and $k \times 1$, respectively.

The usual assumptions made by ECM are:

$$\begin{aligned} E(\delta_{mi},\delta_{ji'}) &= \sigma^2_{\delta mj} & i &= i'\\ &= 0 & i &\neq i'\\ E(\lambda_{mit},\lambda_{ji't'}) &= \sigma^2_{\lambda mj} & i &= i', t = t'\\ &= 0 & i &\neq i', t \neq t' \end{aligned} \tag{6}$$

where i is the farm index and t is the sequence index, which counts the times that each farm is observed.

The variance–covariance matrix of the residuals in this case is equal to:

$$\boldsymbol{\Omega}_{u(s)} = \boldsymbol{C}_s \otimes \boldsymbol{\Sigma}_\lambda + \boldsymbol{F}_s \otimes (\boldsymbol{\Sigma}_\lambda + s\boldsymbol{\Sigma}_\delta) \tag{7}$$

where $\boldsymbol{F}_s = (1/s)\boldsymbol{H}_s$ and $\boldsymbol{C}_s = \boldsymbol{I}_s - (1/s)\boldsymbol{H}_s$, $\boldsymbol{I}_s$ is the identity matrix of dimension s, and $\boldsymbol{H}_s = \boldsymbol{h}_s\boldsymbol{h}_s{}'$ is the (sxs) matrix with all elements equal to one.

To compute the matrices $\boldsymbol{\Sigma}_\lambda$ and $\boldsymbol{\Sigma}_\delta$, we have to calculate the ($M \times M$) matrices of overall within farms and between farms (co)variation in the residuals u of the different equations, which can be expressed as:

$$\boldsymbol{W}_{uu} = \sum_{s=2}^{S}\sum_{i\in I_s}\sum_{t=1}^{s}(u_{it}-\bar{u}_i)(u_{it}-\bar{u}_i)' \tag{8}$$

[3] In this case, t is a sequence index, not a time index.

$$\boldsymbol{B}_{uu} = \sum_{s=2}^{S}\sum_{i\in I_s} s(\bar{u}_i-\bar{u})(\bar{u}_i-\bar{u})' \tag{9}$$

where $\bar{u}_i = (1/s)\sum_{t=1}^{s} u_{it}$ and $\bar{u} = (1/n)\sum_{s=2}^{S}\sum_{i\in I_s} su_i$.

Biørn (2004) proved that the matrices $\boldsymbol{\Sigma}_\lambda$ and $\boldsymbol{\Sigma}_\delta$ are given by the following expressions:

$$\hat{\Sigma}_\lambda = \frac{\hat{\boldsymbol{W}}_{uu}}{n-N} \tag{10}$$

$$\hat{\Sigma}_\delta = \frac{\hat{\boldsymbol{B}}_{uu} - ((N-1)/(n-N))\hat{\boldsymbol{W}}_{uu}}{n - \left(\sum_{s=2}^{S} D_s s^2\right)/n} \tag{11}$$

Using equations (8) and (9) to obtain estimates of the variance–covariance matrices $\hat{\Sigma}_\lambda$ and $\hat{\Sigma}_\delta$, these estimates are then substituted into equation (7). After the calculation of the variance–covariance matrix of the residuals, the coefficient's GLS estimators and their variance–covariance matrix can be computed by the following formulas:

$$\begin{aligned} \hat{\beta}_{GLS} &= \left(\sum_{s=2}^{S}\sum_{i\in I_s}\boldsymbol{X}'_{i(s)}\Omega^{-1}_{u(s)}\boldsymbol{X}_{i(s)}\right)^{-1}\\ &\quad\times\left(\sum_{s=2}^{S}\sum_{i\in I_s}\boldsymbol{X}'_{i(s)}\Omega^{-1}_{u(s)}\boldsymbol{y}_{i(s)}\right) \end{aligned} \tag{12}$$

$$V\left(\hat{\beta}_{GLS}\right) = \left(\sum_{s=2}^{S}\sum_{i\in I_s}\boldsymbol{X}'_{i(s)}\Omega^{-1}_{u(s)}\boldsymbol{X}_{i(s)}\right)^{-1} \tag{13}$$

Once again, because there does not exist any standard econometric software that provides automatic commands to estimate one-way SUR systems, we applied the following stepwise procedure for estimating the $\Omega^{-1}_{u(s)}$, the coefficient's GLS estimators, and their variance–covariance matrix:

Step 1: We run an OLS regression separately on all M equations for all observations $\boldsymbol{y}_{it}$ and $\boldsymbol{X}_{it}$. Using our estimation results, we form the corresponding vectors of residuals $\hat{\boldsymbol{u}}_{it} = \boldsymbol{y}_{it} - \boldsymbol{X}_{it}\hat{\beta}_{OLS}$ for all i and t.

Step 2: We compute the matrices of overall within and between farms (co)variation that is $\hat{\boldsymbol{W}}_{uu},\hat{\boldsymbol{B}}_{uu}$ by inserting the residuals $\hat{\boldsymbol{u}}_{it}$in equations (8) and (9).

Step 3: We calculate matrices $\hat{\Sigma}_\lambda,\hat{\Sigma}_\delta$ by inserting the matrices $\hat{\boldsymbol{W}}_{uu},\hat{\boldsymbol{B}}_{uu}$ in expressions (10) and (11).

Step 4: Using the results from the previous step and equation (7), we calculate the variance–covariance matrix $\Omega_{u(s)}$.

Step 5: We compute the matrix $\Omega_{u(s)}^{-1}$, which is inserted in equations (12) and (13) so as to calculate the GLS estimators as well as their variance–covariance matrix.

B2. One-way fixed-effects Model. To obtain the FE estimators we follow the procedure that is described in the previous section but we modified the variance–covariance matrix of the residuals. It is well known that the GLS estimator is a weighted average of the between and within group estimators (Hsiao, 1986, p. 36). In the case that we exclude the between-group variation in the residuals from the variance–covariance matrix, we obtain the within-group or FE estimators. According to this property of GLS estimator, we modified the variance–covariance matrix described in equation (7) as follows:

$$\Omega_{FE} = C_s \otimes \Sigma_\lambda \tag{14}$$

The FE estimators and their variance–covariance matrix are given by the following formulas:

$$\hat{\beta}_{FE} = \left(\sum_{s=2}^{S}\sum_{i\in I_s} X'_{i(s)}\boldsymbol{\Omega}_{FE}^{-1}\boldsymbol{X}_{i(s)}\right)^{-1} \times \left(\sum_{s=2}^{S}\sum_{i\in I_s} \boldsymbol{X}'_{i(s)}\boldsymbol{\Omega}_{FE}^{-1}\boldsymbol{y}_{i(s)}\right) \tag{15}$$

$$V\left(\hat{\beta}_{FE}\right) = \left(\sum_{s=2}^{S}\sum_{i\in I_s} X'_{i(s)}\boldsymbol{\Omega}_{FE}^{-1}\boldsymbol{X}_{i(s)}\right)^{-1} \tag{16}$$

Statistical Tests

In our analysis we make the hypothesis that the estimated coefficients vary according with farm size as well as with the estimation method. As a result, it is necessary to examine if our hypotheses are valid by conducting some statistical tests. To examine the statistical significance of the differences in the estimated coefficients among the different types of farm size, we used the dummy variable approach proposed by Guajarati (1970). According to this approach, suppose that we have a set of $N = N_1 + N_2 + N_3$ observations of the same variables and there is a source of difference between the observations of subsamples N_1, N_2, and N_3. Then we run a regression by pooling the set of N observations and we use dummy variables in the coefficients that are affected by this source of difference. Consider, for example, the case that the source of difference affects the constant term and the slope coefficient, then we run a regression as follows:

$$y_{it} = a_1 + a_2D_1 + a_3D_2 + \beta_1X_{it} + \beta_2D_1X_{it} + \beta_3D_2X_{it} + \varepsilon_{it} \tag{17}$$

where $D_1 = 1$ if the observation lies in the N_2 set of observations

$D_1 = 0$, otherwise

$D_2 = 1$, if the observation lies in the N_3 set of observations

$D_2 = 0$, otherwise

To test the hypothesis of no parameter change, we have to test the joint hypothesis that $H_0 : a_2 = a_3 = \beta_2 = \beta_3 = 0$ against the alternative that at least one of the four hypotheses is not true. This test can be easily conducted by using the χ^2_J where J is the number of coefficients to be tested.

Additionally, we have to test which is the appropriate specification of our model, i.e., the pooled, the RE, or the FE. In the beginning, we test the pooled against the one-way FE model because the question of whether to pool the data or not naturally arises with panel data. In this case, we have to test the hypothesis that constant terms are homogeneous or not (Hsiao, 1986, p. 16). The null and the alternative hypotheses are:

$$H_0 : \alpha_1 = \alpha_2 = ... = \alpha_N$$

$$H_1 : \alpha_1 \neq \alpha_2 \neq .... \neq \alpha_N$$

Under the null hypothesis, the constant term is the same for all individuals and the pooled estimators are efficient. The null hypothesis represents a set of linear restrictions on coefficients so we can test the null by using the F-statistic written in terms of restricted and unrestricted model sum of squares. In our case, because we have a system of regression equations, we have to use the generalized F test statistic (Bun, 2004; Zellner, 1962). The F-statistic has the form:

$$F = \frac{(RRSS - URSS)/J}{URSS/(MNT - K)} \sim F_{(J,MNT-K)} \tag{18}$$

where $RRSS$ = residual sum of squares of the pooled model

$URSS$ = residual sum of squares of the FE model

J = number of linear restrictions equal with $M(N\text{-}1)$

M = number of equations

NT = number of observations

K = number of estimated coefficients

Finally, we examine if the appropriate panel model specification is the RE or the FE. The critical assumption in the RE model is that $\mathrm{E}(u_{it} / X_{it}) = 0$, i.e., there is no correlation between the included variables and the RE. If there is correlation between the included variables and the RE, that is $\mathrm{E}(u_{it} / X_{it}) \neq 0$, the RE estimators become biased and inconsistent (Baltagi, 2005). Hausman (1978) provides a test in which we compare these estimators. Under the null hypothesis H_0: $\mathrm{E}(u_{it} / X_{it}) = 0$ both estimators are consistent and the RE estimator is efficient, whereas under the alternative H_1: $\mathrm{E}(u_{it} / X_{it}) \neq 0$ the FE estimator is consistent but the RE estimator is not.

The test statistic is given by the expression:

$$h = g'\Psi^{-1}g \tag{19}$$

where $g = \hat{\beta}_{FE} - \hat{\beta}_{RE}$ with $\hat{\beta}_{FE}$,$\hat{\beta}_{RE}$ being the vectors of estimated coefficients without the constant terms and $\Psi = V(\hat{\beta}_{FE}) - V(\hat{\beta}_{RE})$. Under the H_0, the test statistic h is asymptotically distributed as χ^2_κ where κ is the dimension of vector $\hat{\beta}$.

Data

The data we use are from the EU FADN, National Statistical Service of Greece and Eurostat during the period 1991–2002. From the entire sample of farms that are characterized as cotton producers, we use the farms that produce only cotton as well as the farms that the proportion of cotton revenue to total revenue is equal or larger than 95%, so they are considered as pure cotton producers. According to standard FADN methodology, there are ten categories of farm size and our sample consists of farms that belong to first nine categories.[4] Details about the way that farms are grouping into nine categories are provided in Table 2 in the Appendix. However, as a result of limitations in the number of observations in each category, we grouped the farms into three size categories. First, the farms that belong to the first three categories are considered small-sized. Second, the farms that belong to the next three categories are considered as medium-sized and finally the farms of the three last categories as large-sized. After this grouping, we obtain three samples of unbalanced panel data. The sample of small-sized firms consists of 28 farms, the sample of medium-sized farms involves 206 farms, and finally the sample of large-sized includes 282 agricultural enterprises.[5] The number of observations of each sample is 108, 752, and 986 for small, medium, and large farms, respectively. The descriptive statistics of the variables are provided in Table 3.

Cotton farmers produce cotton using four variable inputs: labor, fertilizer, energy, and other intermediate inputs[6] and two quasi fixed inputs: land and capital. Cotton quantity and revenue are available from FADN data so we obtain cotton price by dividing revenue with quantity. As for the variable inputs, the FADN sample contains expenditures and quantity of labor, but only expenditures for fertilizer, energy, and the other intermediate inputs. Prices for energy and fertilizer are provided by Eurostat and the price index for the other intermediate inputs is provided by the National Statistical Service of Greece. To obtain quantities of energy and fertilizer, we divide the expenditures by the corresponding prices. The expenditures of the other intermediate inputs are divided by their price index so as to obtain their quantity measure. The quantity of land is available from FADN data and the value of

[4] Our sample does not contain farms that belong to the tenth category because there are no so large cotton producers in Greece.

[5] The initial number of farms in each sample was 75 small, 349 medium, and 456 large. However, we eliminated the farms that appeared only once in each sample to apply the FE estimation method.

[6] This category includes all other intermediate inputs of production like water, pesticides, etc.

Table 3. Descriptive Statistics of the Variables

Variable	Small Farms Mean	Small Farms Standard Deviation	Medium Farms Mean	Medium Farms Standard Deviation	Large Farms Mean	Large Farms Standard Deviation
Profits (€)	1920.1	1486.25	5,928.92	4007.19	19,812.46	11,709.32
Cotton production (kilos)	7063.89	2134.91	17,083.51	5810.44	45,321.81	20,874.37
Cotton price (€/kilo)	0.80	0.06	0.80	0.07	0.81	0.07
Labor (hours)	797.58	236.67	1,283.70	579.57	2,165.75	1,030.54
Labor price (€/hour)	1.99	0.56	1.91	0.46	1.83	0.47
Energy quantity	558.07	385.59	1,756.92	1205.87	5,061.44	4,385.02
Energy price (€)	0.46	0.15	0.46	0.15	0.46	0.15
Fertilizer quantity	1713.66	659.48	4,205.70	1811.71	10,591.38	5,831.47
Fertilizer price (€)	0.18	0.03	0.18	0.03	0.18	0.03
Other intermediate inputs (€)	1207.79	520.14	2,584.96	1140.34	12,990.48	6,299.23
Other intermediate inputs price (index)	185.51	30.51	185.51	30.51	185.51	30.51
Capital (€)	5870.54	5126.81	13,496.46	9521.70	27,764.78	18,646.8
Land (ha)	2.5	0.72	5.68	1.61	15.28	6.37

capital is deflated by the capital price index to obtain its quantity measure. Finally, we include a time trend to take into account the effect of technology change in the cotton production.

For each sample of farms we estimate a system of four equations: cotton supply and the derived demands of fertilizer, energy, and the other intermediate inputs. Labor is our numeraire input. STATA 10 (College Station, TX) econometrics software is used for the estimations.

Estimation Results

In this section we present the estimated supply and derived demand functions, which are obtained by applying all estimation techniques, the results of which are obtained by the statistical tests as well as the elasticities for small-, medium-, and large-sized farms. Initially, we pooled the data for all farms to test if the parameter estimates differ by size. Using the dummy variables approach, under the hypothesis that farm size affects both constant terms and slopes, we found that the differences in parameters are statistically significant. The χ^2_{52} statistic is equal to 965.73 at the 5% level of significance with the corresponding critical value 69.83. Estimation results for small-, medium-, and large-sized farms are reported in Tables 4, 5, and 6, respectively.

The absolute value of the estimated coefficients is fairly different when either comparing the coefficients of pooled with the corresponding RE and FE or the coefficients of RE with the FE. For example, the coefficient of cotton supply with respect to cotton price for large-sized farms is equal to 0.145, 0.244, and 0.330 when we apply the pooled, RE, and FE methods, respectively. The statistical significance of the estimated parameters is improved when we apply the panel data estimation methods. The standard errors of the RE coefficients are smaller than the standard errors of the pooled coefficients in 59 of 78 cases. The result is similar when we compare the standard errors of the FE estimators with the corresponding of pooled estimators because they are smaller in 43 of 66 cases. The obtained results make clear that when we take into account the panel specification of our data, the statistical significance of the estimated parameters is increased.

Additionally, we checked if the properties of the profit function are satisfied. According to the obtained results, the profit function is increasing in the price of output and decreasing in input prices. We also checked the eigenvalues and the determinants of the principal minors of Hessian matrix and we found that the only case that the convexity property is not satisfied as

Table 4. Estimated Parameters of Supply and Demand, Small-Sized Farms

	Cotton Supply			Fertilizer Demand			Energy Demand			Other Intermediate Inputs Demand		
Variables	Pooled	RE	FE	Pooled	RE	FE	Pooled	RE	FE	Pooled	RE	FE
Constant	0.298	0.174	—	0.512	0.574	—	1.424	1.064	—	1.257	2.655	—
	(0.137)	(0.147)		(0.185)	(0.114)		(0.379)	(0.116)		(0.511)	(0.147)	
Price of cotton	0.823	2.105	0.874									
	(0.262)	(0.299)	(0.306)									
Price of fertilizer	–0.184	–0.263	–0.416	–1.696	–1.869	–1.919						
	(0.080)	(0.070)	(0.080)	(0.134)	(0.068)	(0.071)						
Price of energy	–0.053	–0.154	–0.168	0.208	0.266	0.243	–1.597	–1.591	–1.644			
	(0.040)	(0.043)	(0.051)	(0.061)	(0.035)	(0.037)	(0.126)	(0.042)	(0.046)			
Price of other	–0.643	–2.147	–0.496	1.170	0.808	0.924	0.424	0.126	0.195	–2.773	–2.541	–1.264
intermediate inputs	(0.319)	(0.337)	(0.328)	(0.209)	(0.076)	(0.081)	(0.164)	(0.040)	(0.042)	(0.640)	(0.405)	(0.404)
Quantity of capital	0.196	0.381	0.135	–0.198	–0.092	–0.132	0.101	0.344	0.325	1.653	1.285	1.167
	(0.085)	(0.088)	(0.107)	(0.123)	(0.072)	(0.076)	(0.215)	(0.066)	(0.072)	(0.342)	(0.089)	(0.093)
Quantity of land	0.314	0.357	0.278	–0.161	–0.040	0.077	0.006	–0.013	0.065	–0.699	–0.565	–0.912
	(0.065)	(0.074)	(0.099)	(0.101)	(0.061)	(0.059)	(0.203)	(0.062)	(0.061)	(0.259)	(0.065)	(0.060)
Time trend	0.307	0.575	0.322	–0.227	–0.031	0.119	1.075	0.852	1.044	–1.378	–0.461	–1.020
	(0.104)	(0.115)	(0.125)	(0.134)	(0.088)	(0.091)	(0.282)	(0.092)	(0.096)	(0.370)	(0.118)	(0.105)

Source: Own computations.

Note: Numbers in parentheses are standard errors, significant at the 0.05 level.

Table 5. Estimated Parameters of Supply and Demand, Medium-sized Farms

	Cotton Supply			Fertilizer Demand			Energy Demand			Other Intermediate Inputs Demand		
Variables	Pooled	RE	FE	Pooled	RE	FE	Pooled	RE	FE	Pooled	RE	FE
Constant	0.220	0.207	—	0.142	0.192	—	0.549	0.490	—	0.181	0.233	—
	(0.043)	(0.050)		(0.068)	(0.049)		(0.068)	(0.048)		0.098)	(0.050)	
Price of cotton	0.275	0.242	0.258									
	(0.067)	(0.067)	(0.076)									
Price of fertilizer	–0.212	–0.408	–0.440	–1.098	–1.248	–1.275						
	(0.027)	(0.029)	(0.032)	(0.045)	(0.032)	(0.033)						
Price of energy	–0.007	–0.142	–0.194	0.270	0.240	0.216	–1.485	–1.663	–1.668			
	(0.022)	(0.024)	(0.027)	(0.030)	(0.021)	(0.021)	(0.041)	(0.027)	(0.029)			
Price of other	–0.074	0.168	0.226	0.446	0.276	0.290	0.628	0.522	0.495	–1.298	–0.665	–0.572
intermediate inputs	(0.078)	(0.073)	(0.080)	(0.051)	(0.032)	(0.033)	(0.043)	(0.024)	(0.026)	(0.117)	(0.092)	(0.100)
Quantity of capital	0.084	0.042	0.042	–0.043	–0.019	–0.029	–0.025	–0.043	–0.066	0.423	0.340	0.349
	(0.015)	(0.017)	(0.020)	(0.025)	(0.015)	(0.016)	(0.024)	(0.015)	(0.016)	(0.036)	(0.016)	(0.017)
Quantity of land	0.635	0.734	0.788	–0.410	–0.373	–0.385	–0.086	–0.125	–0.145	–0.893	–0.839	–0.789
	(0.034)	(0.038)	(0.046)	(0.059)	(0.034)	(0.035)	(0.058)	(0.035)	(0.038)	(0.082)	(0.035)	(0.035)
Time trend	0.248	0.299	0.375	–0.315	–0.238	–0.199	0.181	0.237	0.175	–0.585	–0.558	–0.488
	(0.030)	(0.036)	(0.048)	(0.044)	(0.032)	(0.036)	(0.045)	(0.033)	(0.040)	(0.037)	(0.036)	(0.039)

Source: Own computations.

Note: Numbers in parentheses are standard errors, significant at the 0.05 level.

Table 6. Estimated Parameters of Supply and Demand, Large-sized Farms

	Cotton Supply			Fertilizer Demand			Energy Demand			Other Intermediate Inputs Demand		
Variables	Pooled	RE	FE	Pooled	RE	FE	Pooled	RE	FE	Pooled	RE	FE
Constant	0.025	0.016	—	–0.264	–0.117	—	–0.215	0.056	—	–0.175	–0.091	—
	(0.040)	(0.038)		(0.064)	(0.038)		(0.150)	(0.036)		(0.061)	(0.038)	
Price of cotton	0.145	0.244	0.330									
	(0.032)	(0.035)	(0.040)									
Price of fertilizer	–0.071	–0.091	–0.128	–0.528	–0.584	–0.596						
	(0.014)	(0.016)	(0.018)	(0.022)	(0.016)	(0.016)						
Price of energy	–0.071	–0.195	–0.217	0.171	0.256	0.227	–1.107	–1.357	–1.339			
	(0.010)	(0.009)	(0.010)	(0.016)	(0.008)	(0.008)	(0.041)	(0.010)	(0.011)			
Price of other	–0.042	–0.121	–0.182	0.163	0.172	0.187	0.188	0.292	0.259	–0.502	–0.588	–0.632
intermediate inputs	(0.038)	(0.039)	(0.043)	(0.022)	(0.018)	(0.019)	(0.016)	(0.009)	(0.009)	(0.052)	(0.050)	(0.055)
Quantity of capital	0.124	0.132	0.107	–0.105	–0.102	–0.104	–0.125	–0.087	–0.022	0.080	0.076	0.088
	(0.009)	(0.008)	(0.010)	(0.015)	(0.008)	(0.008)	(0.036)	(0.008)	(0.009)	(0.014)	(0.008)	(0.009)
Quantity of land	0.780	0.843	0.859	–0.815	–0.805	–0.798	–0.783	–0.605	–0.463	–0.880	–0.891	–0.874
	(0.026)	(0.023)	(0.027)	(0.044)	(0.021)	(0.021)	(0.109)	(0.022)	(0.024)	(0.040)	(0.023)	(0.024)
Time trend	0.167	0.267	0.257	–0.252	–0.205	–0.105	0.149	0.132	0.090	–0.315	–0.347	–0.327
	(0.021)	(0.022)	(0.038)	(0.033)	(0.021)	(0.026)	(0.078)	(0.020)	(0.029)	(0.032)	(0.022)	(0.028)

Source: Own computations.
Note: Numbers in parentheses are standard errors, significant at the 0.05 level.

for small farms in the RE model.[7] These results are reported in the Table 7 in the Appendix.

Taking into consideration the previously mentioned analysis about the estimated coefficients in all cases, it is clear that their values are affected by the estimation method. Therefore, our conclusions about cotton supply and input demands depend on the estimation method. To examine the appropriate specification of our model and as a result the appropriate estimation method, we applied two statistical tests. First, we test the pooled model against the FE model; thus, we computed the F-statistic for all samples. The values of F-statistic are reported in the Table 8 that follows.

In view of these results, it is clear that the null hypothesis about the common constant term for all farms is rejected in all cases. This means that the FE model is more preferable than the pooled model so in the estimation procedure, we have to take into account the "heterogeneity" of each cross-sectional unit.

Afterward, the question that arises is which of two panel models is the most appropriate. In this case we have to test the FE model against the RE model using the Hausman test. We computed the h-statistic for all samples and we found that the appropriate specification of our model is the FE because the H_0 hypothesis is strongly rejected. The values of h-statistic are presented in the Table 9.

Because h is distributed asymptotically as χ^2_{22}, which has a critical value of 33.9 at 5% level of significance, it is evident that the RE model is not appropriate.

In view of this analysis, we conclude that the right specification of our model and our data are the FE and as a result, the FE estimators are consistent. In terms of policy analysis, this means that we have to use the elasticities based on FE estimators in case we want to make policy simulations.

We now turn the analysis to our estimated elasticities. The elasticities of supply and derived demands for each sample and all estimation methods are reported in Tables 10, 11, and 12, respectively.

[7] This result may provide some indication that small farmers are not profit maximizers.

Table 8. F Test Statistic for All Samples

Sample	F-Statistic	F-Critical Value
Small-sized farms	2.52	1.27
Medium-sized farms	5.72	1.09
Large-sized farms	3.79	1.08

Source: Own calculations.

All own price elasticities have the correct sign, i.e., cotton supply elasticity is positive and input demand elasticities are negative. However, there is strong variability in the value of the estimated elasticities, which depends on the farm size and the estimation method.

Our results indicate that the elasticity of cotton supply with respect to cotton price is larger in value for small farms than for medium- and large-sized farms. In the case of pooled estimation, the elasticity of cotton supply with respect to cotton price decreases as farm size increases. The calculated cotton supply elasticities for small-, medium-, and large-sized farms are 0.861, 0.272, and 0.149, respectively. In the RE and FE models, this elasticity is also larger in value for small farms than for medium and large farms; however, it is not smaller for large farms relative to the medium farms. For example, in the RE model, the elasticity of the cotton supply with respect to cotton price is equal to 2.202, 0.239, and 0.251 for small, medium, and large farms, respectively. In the FE model, the corresponding values are 0.914, 0.255, and 0.339. Previous studies for Greece (Katranidis and Velentzas, 2000; Lianos and Rizopoulos, 1988; Zanias, 1981) estimated that the elasticity of cotton supply with respect to cotton price varies from 0.41 to 0.70.

These results are in accordance with the past literature, which found an inverse relation between the farm size and the elasticity of supply

Table 9. Hausman Test Statistic for All Samples

Sample	h-Statistic
Small-sized farms	337.1
Medium-sized farms	376.4
Large-sized farms	784.9

Source: Own calculations.

Table 10. Elasticities of Supply and Demand, Pooled Estimation

Small-Sized Farms					
	Cotton	Fertilizer	Energy	Other Intermediate Inputs	Labor
Cotton	0.861	–0.243	–0.082	–0.611	0.076
	(0.274)	(0.106)	(0.062)	(0.304)	(0.104)
Fertilizer	0.149	–1.742	0.247	0.864	0.481
	(0.065)	(0.137)	(0.072)	(0.154)	(0.122)
Energy	0.033	0.161	–1.429	0.236	0.999
	(0.025)	(0.047)	(0.113)	(0.091)	(0.147)
Other intermediate inputs	0.304	0.700	0.293	–1.192	–0.105
	(0.151)	(0.125)	(0.113)	(0.275)	(0.147)
Labor	0.028	0.081	0.642	0.235	–0.985
	(0.053)	(0.092)	(0.147)	(0.201)	(0.479)
Medium-Sized Farms					
	Cotton	Fertilizer	Energy	Other Intermediate Inputs	Labor
Cotton	0.272	–0.204	–0.006	–0.070	0.008
	(0.066)	(0.026)	(0.017)	(0.074)	(0.024)
Fertilizer	0.229	–1.157	0.227	0.464	0.237
	(0.030)	(0.047)	(0.025)	(0.053)	(0.045)
Energy	0.012	0.424	–1.861	0.972	0.454
	(0.036)	(0.047)	(0.051)	(0.067)	(0.065)
Other intermediate inputs	0.060	0.354	0.397	–1.015	0.204
	(0.063)	(0.040)	(0.027)	(0.092)	(0.049)
Labor	0.007	0.065	0.178	0.057	–0.307
	(0.010)	(0.017)	(0.014)	(0.024)	(0.080)
Large-Sized Farms					
	Cotton	Fertilizer	Energy	Other Intermediate Inputs	Labor
Cotton	0.149	–0.071	–0.084	–0.044	0.050
	(0.033)	(0.015)	(0.012)	(0.039)	(0.015)
Fertilizer	0.074	–0.540	0.207	0.171	0.088
	(0.015)	(0.023)	(0.020)	(0.023)	(0.025)
Energy	0.053	0.125	–0.956	0.141	0.638
	(0.007)	(0.012)	(0.035)	(0.012)	(0.039)
Other intermediate inputs	0.046	0.174	0.237	–0.550	0.094
	(0.041)	(0.024)	(0.020)	(0.056)	(0.024)
Labor	0.036	0.113	0.737	0.103	–0.989
	(0.013)	(0.021)	(0.052)	(0.020)	(0.074)

Source: Own computations.

Notes: Elasticities are computed at the sample mean values; numbers in parentheses are standard errors computed with the delta method provided by Papke and Wooldridge (2005).

with respect to price. Mills and Schumann (1985) find that there is an inverse relation between the degree of output variation and capital intensity of a firm, so small firms have the ability to vary production more intensely than large firms. Following this result, short-run supply elasticities are lower for larger farms.

Own price elasticities for inputs are different in three samples and different estimation methods. Specifically, the elasticity of fertilizer

Table 11. Elasticities of Supply and Demand, Random-Effects Estimation

	Cotton	Fertilizer	Energy	Other Intermediate Inputs	Labor
Small-Sized Farms					
Cotton	2.202	–0.348	–0.235	–2.043	0.424
	(0.313)	(0.093)	(0.066)	(0.320)	(0.109)
Fertilizer	0.213	–1.920	0.316	0.597	0.794
	(0.057)	(0.070)	(0.042)	(0.056)	(0.073)
Energy	0.094	0.206	–1.423	0.070	1.052
	(0.026)	(0.027)	(0.037)	(0.022)	(0.048)
Other intermediate inputs	1.015	0.483	0.087	–1.092	–0.493
	(0.159)	(0.045)	(0.028)	(0.174)	(0.046)
Labor	0.221	0.324	0.736	–0.237	–1.043
	(0.054)	(0.049)	(0.047)	(0.047)	(0.148)
Medium-Sized Farms					
Cotton	0.239	–0.393	–0.109	0.160	0.104
	(0.066)	(0.028)	(0.018)	(0.069)	(0.028)
Fertilizer	0.441	–1.314	0.202	0.287	0.385
	(0.032)	(0.034)	(0.017)	(0.033)	(0.028)
Energy	0.229	0.377	–2.084	0.809	0.670
	(0.038)	(0.032)	(0.034)	(0.038)	(0.040)
Other intermediate inputs	–0.137	0.219	0.330	–0.520	0.107
	(0.059)	(0.025)	(0.015)	(0.072)	(0.022)
Labor	0.055	0.124	0.233	0.013	–0.426
	(0.012)	(0.011)	(0.008)	(0.011)	(0.039)
Large-Sized Farms					
Cotton	0.251	–0.091	–0.232	–0.125	0.198
	(0.036)	(0.016)	(0.011)	(0.040)	(0.014)
Fertilizer	0.095	–0.598	0.310	0.181	0.012
	(0.017)	(0.016)	(0.009)	(0.019)	(0.013)
Energy	0.145	0.187	–1.172	0.219	0.621
	(0.007)	(0.006)	(0.008)	(0.006)	(0.009)
Other intermediate inputs	0.132	0.183	0.368	–0.644	–0.039
	(0.042)	(0.019)	(0.011)	(0.055)	(0.014)
Labor	0.152	0.060	0.668	0.003	–0.884
	(0.012)	(0.011)	(0.013)	(0.012)	(0.025)

Source: Own computations.

Notes: Elasticities are computed at the sample mean values; numbers in parentheses are standard errors computed with the delta method provided by Papke and Wooldridge (2005).

with respect to its price range from –0.540 to –1.971, the corresponding elasticity for energy range from –0.956 to –2.091, and the elasticity of other intermediate inputs with respect to its price varies from –0.447 to –1.192. Additionally, in some cases, the demand changes from elastic to inelastic and vice versa. This change is attributed to the different estimation method. For example, the demand for other intermediate inputs in medium-sized farms is elastic when we

Table 12. Elasticities of Supply and Demand, Fixed-Effects Estimation

Small-Sized Farms					
	Cotton	Fertilizer	Energy	Other Intermediate Inputs	Labor
Cotton	0.914	–0.550	–0.257	–0.472	0.365
	(0.320)	(0.106)	(0.077)	(0.312)	(0.143)
Fertilizer	0.337	–1.971	0.288	0.682	0.663
	(0.065)	(0.073)	(0.044)	(0.060)	(0.076)
Energy	0.103	0.188	–1.470	0.109	1.071
	(0.031)	(0.029)	(0.041)	(0.023)	(0.056)
Other intermediate inputs	0.234	0.553	0.135	–0.543	–0.379
	(0.155)	(0.048)	(0.029)	(0.174)	(0.049)
Labor	0.099	0.205	0.730	–0.154	–0.880
	(0.071)	(0.051)	(0.054)	(0.049)	(0.170)

Medium-Sized Farms					
	Cotton	Fertilizer	Energy	Other Intermediate Inputs	Labor
Cotton	0.255	–0.424	–0.143	0.215	0.103
	(0.075)	(0.031)	(0.021)	(0.076)	(0.033)
Fertilizer	0.475	–1.343	0.182	0.301	0.385
	(0.034)	(0.035)	(0.018)	(0.034)	(0.028)
Energy	0.312	0.339	–2.091	0.766	0.674
	(0.043)	(0.033)	(0.036)	(0.040)	(0.042)
Other intermediate inputs	–0.184	0.229	0.313	–0.447	0.089
	(0.065)	(0.026)	(0.016)	(0.078)	(0.023)
Labor	0.059	0.127	0.235	0.005	–0.426
	(0.014)	(0.011)	(0.009)	(0.012)	(0.041)

Large-Sized Farms					
	Cotton	Fertilizer	Energy	Other Intermediate Inputs	Labor
Cotton	0.339	–0.129	–0.259	–0.189	0.237
	(0.041)	(0.018)	(0.012)	(0.045)	(0.018)
Fertilizer	0.133	–0.609	0.275	0.196	0.005
	(0.018)	(0.017)	(0.010)	(0.020)	(0.013)
Energy	0.162	0.166	–1.156	0.195	0.634
	(0.008)	(0.006)	(0.009)	(0.007)	(0.011)
Other intermediate inputs	0.198	0.199	0.327	–0.693	–0.031
	(0.047)	(0.020)	(0.011)	(0.061)	(0.015)
Labor	0.185	0.050	0.690	0.004	–0.929
	(0.016)	(0.011)	(0.014)	(0.013)	(0.029)

Source: Own computations.
Notes: Elasticities are computed at the sample mean values; numbers in parentheses are standard errors computed with the delta method provided by Papke and Wooldridge (2005).

apply the pooled estimation method and inelastic in case of RE and FE estimation. This practically means that the adoption of the right estimation method is crucial to arrive at a right conclusion about the magnitude of the elasticities.

All in all, considering the aforementioned discussion as well as the results of specifications tests, we conclude that the right specification of our model and our data are the FE and as a result, the FE estimators are consistent.

Consequently, the elasticities based on FE estimators are the accurate policy variables in case we want to make policy simulations.

Concluding Remarks

In this study, we have attempted to evaluate the results of three different estimation methods when they are applied in a system of equations and the dataset is an unbalanced panel. These methods are applied in three data sets named small-, medium-, and large-sized farms because we also wanted to examine the relation between the own price elasticity of supply and the farm size.

According to our results, the adoption of different estimation techniques leads to quite different results in terms of the absolute value of the estimated parameters as well as in terms of their statistical significance. The absolute value of the estimated parameters is fairly different when either comparing the coefficients of pooled with the corresponding FE and RE or the coefficients of FE with the RE. In view of the fact that the estimated parameters are affected by the estimation method, it was necessary to examine the appropriate specification of our model and as a result the appropriate estimation method. We test the pooled against FE model and we found that the FE model is preferable, i.e., in the estimation procedure, we have to applied panel data estimation methods. Afterward, we test the FE against the RE model and we found that the FE estimators are consistent. Therefore, we conclude that the classical regression model with a single constant term is inappropriate for our model and our data because among all estimators, the FE estimators are consistent.

As for the elasticity of cotton with respect to its own price, we found that it varies according to farm size. The elasticity of cotton supply with respect to cotton price is larger in value for small farms in all cases. In the case that we apply the pooled estimation method, it becomes apparent that as the farm size increases, the elasticity of cotton supply decreases. In the FE and RE models, the elasticity of cotton supply is larger for small farms than for medium and large farms; however, it is not smaller for large farms relative to the medium farms. As we mentioned earlier, the consistent estimators are the FE, so we come to the conclusion that the elasticity of cotton supply with respect to cotton price is not smaller for large farms relative to the medium farms. According to this result, it is evident that it is important to apply the appropriate estimation method to come to the right conclusions about the key policy parameters.

All in all, the estimation method matters to come to the right conclusions about the estimated coefficients and the estimated elasticities based on them. Moreover, the elasticity of cotton supply with respect to cotton price is larger for small farms relative to their larger "counterparts." In terms of policy, this practically means that small farmers will be expected to produce more when, for example, the applied policy tends to increase product price.

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Appendix

Each farm in the FADN sample has its own size which is determined by the Standard Gross Margin (SGM) of the output that produces. The SGM is defined as: SGM = value of output from one hectare or animal – cost of variable inputs required producing that output. The SGM is expressed in terms of European Size Units (ESU), which value is expressed as fixed number of Euro. One ESU corresponds to 1200 Euros. The economic size classes in terms of ESU are presented in Table 2.

Table 2. Size Class per Category

Category	Size Classes
1	<2 ESU
2	2–<4 ESU
3	4–<6 ESU
4	6–<8 ESU
5	8–<12 ESU
6	12–<16 ESU
7	16–<40 ESU
8	40–<100 ESU
9	100–<250 ESU
10	≥250 ESU

Source: European Commission.

Table 7. Principal Minors and Eigenvalues of the Hessian Determinants

	H_1	H_2	H_3	H_4	Eigenvalues			
Small-Sized Farms								
Pooled	0.823	1.312	2.130	2.055	3.626	1.780	1.222	0.261
RE	2.105	3.325	5.934	-2.452	4.552	2.137	4.576	-0.160
FE	0.874	1.409	2.334	0.080	2.582	1.717	1.390	0.013
Medium-Sized Farms								
Pooled	0.275	0.409	0.362	0.208	2.037	1.478	0.506	0.137
RE	0.242	0.382	0.157	0.063	1.917	1.510	0.322	0.067
FE	0.258	0.393	0.129	0.039	1.902	1.559	0.263	0.050
Large-Sized Farms								
Pooled	0.145	0.155	0.071	0.024	1.186	0.679	0.325	0.091
RE	0.244	0.293	0.135	0.024	1.510	0.759	0.459	0.045
FE	0.330	0.395	0.184	0.026	1.472	0.807	0.581	0.037

Source: Own computations.