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Estimating the supply elasticity of cotton in Mali with the Nerlove Model: A bayesian method of moments approach

*Fousseini TRAORÉ**

* **Corresponding author**: International Food Policy Research Institute, Washington, DC 20006-1002, US
e-mail: *Fousseini.Traore@cgiar.org*

Summary *– Mali is among the first cotton growers in Africa. Since the early nineties, it has been reforming its cotton sector by means of different policy measures. In this paper, we estimate the supply elasticity of cotton in order to have a precise idea about how producers react to price changes and what are the potential bottlenecks. Contrary to all the previous studies which fail to consistently estimate the long run elasticity of supply, we apply the Bayesian method of moments, following Zellner's (1978) Minimum Expected Loss Estimators (MELO) approach. A key finding is that output supply elasticity is low in the short run due to structural constraints and high in the long run.*

Keywords: *Cotton, Mali, Nerlove model, Bayesian method of moments*

Estimation de l'élasticité de l'offre de coton au Mali à l'aide du modèle de Nerlove : une approche par la Méthode bayésienne des moments

Résumé – Le Mali compte parmi les premiers producteurs de coton en Afrique. Depuis le début des années quatre-vingt-dix, le pays a entamé une réforme du secteur à l'aide de différentes mesures. Dans cet article, nous estimons l'élasticité de l'offre de coton afin d'avoir une idée précise de la réaction des producteurs aux changements de prix ainsi que des freins potentiels. Contrairement aux études précédentes utilisant le modèle de Nerlove, nous estimons l'élasticité de long terme de l'offre par la Méthode bayésienne des moments, suivant la technique de l'Estimateur de la perte minimum espérée (MELO) développée par Zellner (1978). Le principal résultat est une élasticité de l'offre faible à court terme – du fait de contraintes structurelles- et élevée à long terme.

Mots-clés : Coton, Mali, modèle de Nerlove, méthode bayésienne des moments

JEL Classification: Q11, C11, C22

1. Introduction

Mali has been for a long time one of the largest cotton producers in Africa. During the eighties and the nineties it was the second producer in Africa after Egypt. Cotton production has a large impact on the country's economy. Mali had for many years half of its export earnings and millions of people depend on it. From a macroeconomic point of view, the cotton sector accounts for 20% of the agricultural production and 7% of the GDP.

Given the importance of cotton in the malian economy, it is important to know precisely the right elasticity of supply rather than using *ad hoc* methods when it comes to assessing the impact of policy *scenarii* related to the cotton sector. For example, when estimating the impact of the removal of global cotton subsidies on the malian cotton sector, many studies have highlighted the point that the supply elasticity of cotton is the key parameter (FAO, 2004; Araujo Bonjean *et al*., 2007) as it shows by how much producers would react to price changes. On the other hand, the knowledge of the supply elasticity is also crucial to determine the impact of domestic policies. For example, since the nineties, the malian government has been reforming the cotton sector in order to increase the transmission of the world cotton price to producers. Evaluating the impact of these reforms will require a precise knowledge of the supply elasticity of cotton. Finally, knowing the value of the supply elasticity can help think about the potential bottlenecks that producers face and how to alleviate them.

The question of estimating the supply elasticity of cotton in Mali using the Nerlove model has already been raised in the literature (Hugon and Mayeyenda, 2003; Vitale *et al.,* 2009, Gilson *et al.,* 2004; Shepherd, 2006). While these studies generally use good econometric techniques to estimate the elasticities (by dealing with unit root issues for example), they fail to consistently estimate the long run elasticity of supply. As shown earlier by Zellner (1978) and Zaman (1981), standard estimates of the long run parameter by this kind of models may not have finite moments and can be bi-modal. This result has recently been highlighted by means of Monte Carlo analysis (Diebold and Lamb, 1997; Shen and Perloff, 2001). To have a parameter with at least two finite moments, one should use the MELO (Zellner, 1978) extended by Diebold and Lamb (1997) and Shen and Perloff (2001). It is worth noting that the importance of the issue raised here goes beyond the Nerlove model. Actually this type of problem may occur for a large variety of models when a reduced form parameter is a non-linear function of some structural parameters. The method (MELO) is also suitable for problems estimating reciprocals and ratios of population means and regression coefficients.

In this paper, instead of using the standard MELO estimator, we use the Bayesian Method of Moments (BMOM) approach developed by Zellner (1996) and Zellner and Tobias (2001). The BMOM analysis requires fewer assumptions than the traditional Bayesian approach as it relies only on

two moment conditions. It is thus a suitable approach if one has little knowledge of either the likelihood or the prior distribution of parameters. The Bayesian approach adopted here also avoids pretesting for unit root issues as the estimator is valid whether or not the time series are stationary (Sims *et al.,* 1990). Unlike the Classical theory, the Bayesian inferential theory when it comes to linear dynamic models is largely unaffected by the presence of unit roots. With Gaussian disturbances, the posterior density function will not be affected by the presence of unit roots. In particular the discontinuity one observes in the distribution of classical estimators when data are non-stationary is no more present with Bayesian approaches (Sims, 1988; Sims *et al.*, 1990; Bauwens *et al.*, 2003)[1].

The remaining of the paper is organized as follows. The next section presents the main characteristics and evolution of the malian cotton sector. The third section gives a brief description of the standard Nerlovian model. The estimation procedure is presented in section 4 and section 5 shows the data used. Finally, the results are presented in section six and the seventh section concludes.

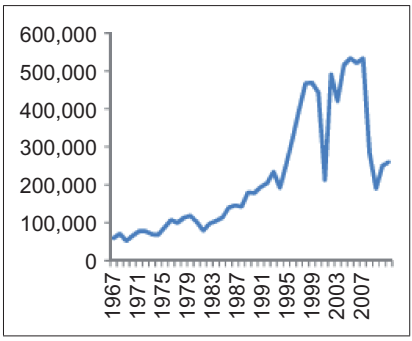
2. The Malian cotton sector

Mali is among the first cotton growers in Africa (after Egypt and Burkina Faso) with a record production of 600,000 metric tons in 2006. After a sharp decline in 2001 and 2008 due to a fall in world prices, the production has started to grow and reached 500,000 metric tons in 2011. Production has been growing since the sixties with a lot of fluctuations in the last ten years (figure 1). This production is made by 160,000 farms distributed in the south of the country and covering about 1,000,000 acres (figure 2). One can notice that the production and the acreages have moved together very closely, so yields have been stagnating since the beginning. Typical farms are small scale family farms (five acres on average), enrolled in producers' organizations. These organizations are directly involved in the management of the sector by participating in the price determination mechanism. They also have to make sure that cotton seed is commercialized. Lastly, since 2000-2001, producers' organizations are in charge of buying inputs from private agents and providing them to their members.[2]

[1] For instance, when estimating an autoregressive model, the asymptotic distribution of the least squares estimator changes depending on the value of the autoregressive coefficient. More precisely the estimator will follow a normal distribution if the coefficient is less than one, a ratio of Wiener processes if it is equal to one and a Cauchy distribution if it is greater than one.

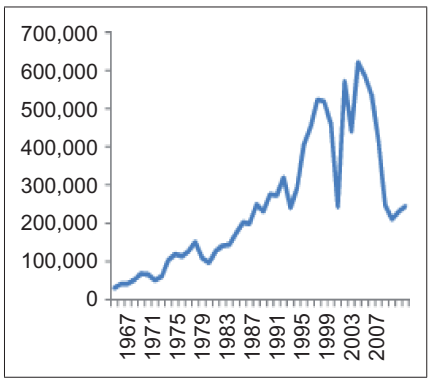
[2] CMDT was the sole provider of inputs until 2000. Since then this function has been transferred to producers' organizations.

Figure 1. **Production (tonnes)**



Source: CMDT (Compagnie malienne de développement des textiles).

Figure 2. **Acreages (hectares)**



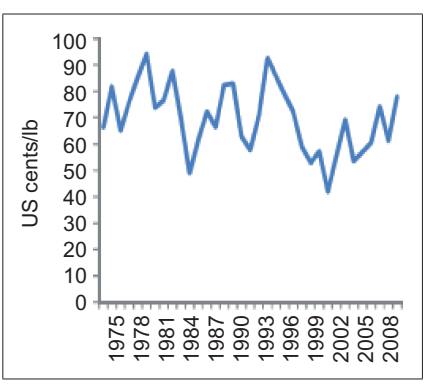
Although the number of producing farms seems to be limited, about 2 millions of people depend directly or indirectly on the cotton sector in Mali (Nubukpo and Keita, 2005). From a macroeconomic point of view, cotton accounts for 20% of the agricultural production, 7% of the GDP and represented until recent years half of the export earnings ($300 million). This significant position is now attenuated due to the recent gold boom. However cotton still represents 40% of malian exports.

Cotton was initially grown in Mali for domestic use. It became an industrial crop with the French colonization and particularly after WorldWar I when the French cotton national company CFDT (Compagnie française de développement des textiles). was created. When Mali became independent in 1960 and until 1974, the sector was managed by the CFDT, a public monopoly. In 1975, the CFDT was replaced by the CMDT, a semi-public company owned by the malian government (60%) and by CFDT (40%). This new company was first in charge of collecting and transforming cotton seed into fiber. Cotton exports were under the responsibility of another public company, SOMIEX (Société malienne d'importation et d'exportation). While

exports were made by SOMIEX, the OSRP (Office de stabilisation et de régulation des prix, another public company), was in charge of stabilizing and regulating prices and of receiving related payments. The OSRP office remunerated CMDT and SOMIEX on a fixed basis. Due to large cumulated deficits that occurred with the fall of world prices, the cotton sector was restructured in the early eighties.

In 1986, SOMIEX lost the monopoly and CMDT became an entirely autonomous entity. Nowadays, the sector is still organized through contracts between CMDT and the government. CMDT manages the cotton production by providing inputs to producers and exports the fiber on world markets. Besides organizing the production, CMDT is involved in some "development activities" (construction of rural roads, producers training etc.). To many observers, particularly advocates of privatization, these additional activities largely contribute to CMDT's deficits. Before the 2005 agreement between CMDT, producers and the government, the cotton price was established after a direct negotiation amongst CMDT and cotton growers. The system consisted of a minimum price with a subsidy if world prices were to increase. The exact mechanism behind this procedure was relatively opaque. Furthermore, the government had to make up for the successive deficits.

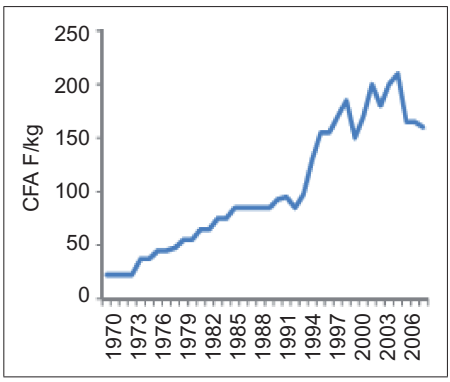
Figure 3. **World cotton price: Cotlook A index**



Source: National Cotton Council of America.

In 2001, world cotton prices fell down to an historic level (figure 3). The value of Cotlook A index was US$40 cents/lb., the lowest level since 1973. Many cotton sectors in Africa suffered from this price decline. In Mali, CMDT reacted by drastically reducing producers prices (figure 4). Producers organizations reacted by a boycott and the production fell by 50% (figure 1). To come up with the crisis, the government set up large consultations which led to a new price design mechanism involving CMDT, the Government and cotton producers unions in 2005. This new mechanism fixes a guaranteed minimum price for seed cotton at the beginning of the campaign. At the end of the campaign, a potential bonus may be paid to producers if world

Figure 4. **Producers price**



Source: CMDT.

prices have increased and if the gross benefit of the sector is positive. The gross revenue is calculated taking into account the evolution of the world price between March of campaign t and April of campaign t+1. In fact, the final price has always been much closer to the price announced and the bonus was less than 5% of the minimum price when it was effective.

Finally, since 2001, due to the huge amount of CMDT's deficits, the malian authorities, supported by the World Bank have decided to privatize it. Four subsidiary companies have been created and the process is still ongoing. Each new company will have a monopoly power in its operating area. However, to date, the Government has not yet succeeded in this attempt.

3. The Nerlove supply model

The standard Nerlove model (Nerlove, 1956; Nerlove and Addison, 1958) with adaptive expectations and partial adjustments is given by its structural form as follows:

$$A_t^* = \beta_0 + \beta_1 P_t^e + \beta_2 Z_t + u_t \tag{1}$$

$$P_t^e - P_{t-1}^e = \gamma(P_{t-1} - P_{t-1}^e) \tag{2}$$

$$A_t - A_{t-1} = \theta(A_t^* - A_{t-1}) \tag{3}$$

$$u_t \sim (0, \sigma_u^2) \tag{4}$$

Where $A_t{}^*$ is the (long run) desired acreage, $P_t{}^e$ is the expected price, Z_t is a vector of exogenous variables (a trend for a proxy for technical

progress or prices of competing crops), γ and θ are respectively the adaptive and the partial adjustment parameters. In the standard approach, γ and θ should lie between 0 and 1. The adaptive expectation hypothesis emphasizes that the expected price at time t is revised in proportion to the difference observed between last period price and the previous expectation while the partial adjustment indicates that farmers are only able to cultivate a fraction of the area desired due to constraints (credit constraints, input or land constraints . . .).

Combining (1)-(4) eliminates the unobserved variables $A_t{}^*$ and $P_t{}^e$ and gives the reduced form:

$$A_t = b_0 + b_1 P_{t-1} + b_2 A_{t-1} + b_3 A_{t-2} + b_4 Z_t + \nu_t \tag{5}$$

where

$b_0 = \beta_0 \gamma \theta$

$b_1 = \beta_1 \gamma \theta$

$b_2 = (1-\gamma) + (1-\theta)$

$b_3 = (1-\gamma)(1-\theta)$

$b_4 = \beta_2 \gamma \theta$

$\nu_t = \theta u_t - [\theta(1-\gamma)] u_{t-1}$

The long run parameter is given by:

$$\alpha = \frac{b_1}{1 - b_2 - b_3} = \frac{b_1}{\delta} \tag{6}$$

and the long run elasticity

$$\alpha^* = \alpha \frac{\bar{P}}{\bar{A}} = \frac{b_1}{1 - b_2 - b_3} \cdot \frac{\bar{P}}{\bar{A}} \tag{7}$$

where $\bar{P}$ denotes the mean of price and $\bar{A}$ the mean of acreages.

Given that in Mali, the price setting mechanism is such that the cotton company announces the purchase price of seed cotton to producers at the beginning of the marketing year (before planting), one cannot work farther with the adaptive expectation hypothesis. Indeed, in this situation, the price that will prevail at the harvesting time is known with certainty. As a consequence, the expected price is replaced by the current one. Equation (2) then becomes (2'):

$$P_t^e = P_{\mathrm{t}} \tag{2'}$$

And we have:

$$A_t = b_0 + b_1 P_{t-1} + b_2 A_{t-1} + b_3 Z_t + \nu_t \tag{5'}$$

where

$b_0 = \beta_0 \theta$
$b_1 = \beta_1 \theta$
$b_2 = (1 - \theta)$
$b_3 = \beta_2 \theta$
$\nu_t = \theta u_t$

and which gives

$$\alpha = \frac{b_1}{1 - b_2} = \frac{b_1}{\delta} \tag{6'}$$

$$\alpha^* = \alpha \frac{\bar{P}}{\bar{A}} = \frac{b_1}{1 - b_2} \cdot \frac{\bar{P}}{\bar{A}} \tag{7'}$$

4. Estimation methodology

As highlighted in the introduction, Zellner (1978) has shown that the OLS estimate of given by (6) and (6') has no finite moments and can be bi-modal. To deal with this issue, he proposed in a Bayesian framework, the MELO estimator based on a generalized quadratic loss function given by[3]:

$$GQL = (b_1 - \delta\,\acute{\alpha})^2 = \delta^2(\alpha - \acute{\alpha})^2 \tag{8}$$

and which has at least finite first and second moments. The MELO of α ($\acute{\alpha}_{MELO}$) is the one that minimizes the expected loss function. Following Zellner (1978), extended by Diebold and Lamb (1997), the MELO estimate of α is given by:

$$\hat{\alpha}_{MELO} = \frac{E(b_1)}{E(\delta)} \cdot \frac{1 + \frac{cov(b_1 \cdot \delta)}{[E(b_1)E(\delta)]}}{1 + \frac{var(\delta)}{[E(\delta)]^2}} = \frac{E(b_1)}{E(\delta)}.F \tag{9}$$

where $E(b_1)$ and $E(\delta)$ denote respectively the posterior means of b_1 and δ, $cov(b_1, \delta)$ the posterior covariance between b_1 and δ, $var(\delta)$ the posterior variance of δ and F is the shrinkage (or correction) factor.

[3] Another way of thinking would consist of formulating and executing a formal mixture model that is capable of addressing the bi-modality. We are grateful to an anonymous referee for pointing out this alternative strategy.

Let X = [1P A_{-1} Z], $y = A$, $D = (y, X)$ and $B = [b_0\, b_1\, b_2\, b_3]^1 . \hat{b}_0$

Under the assumption of a normal likelihood function and a diffuse prior for the coefficients (as in Diebold and Lamb, 1997), the posterior density will be a multivariate Student distribution with mean vector $B = [\hat{b}_0\, \hat{b}_1\, \hat{b}_2\, \hat{b}_3]^1$ equal to the OLS estimates. In this paper, however, instead of using the standard Bayesian approach, we use the Bayesian Method of Moments (BMOM) developed by Zellner (1996), Zellner and Tobias (2001) and Shen and Perloff (2001).[4] This approach involves fewer assumptions and is more suitable when little information is available for either the likelihood function or the prior distribution of the parameters. Furthermore, the Bayesian approach with a slight modification is appropriate when residuals are serially correlated (Zellner and Geisel, 1970; Tiffin, 2004)[5]. Finally, with BMOM one does not need to pretest for unit roots, since the Bayesian estimator is valid whether the underlying time series are stationary or not (Sims *et al.,* 1990).

Two assumptions are made with regards to the reduced form equation:

Assumption 1: $X'E\,(v/D) = 0$

The error term is uncorrelated with the regressors given the data D.

Under Assumption 1, the posterior mean of B given the data is:[6]

$$E(B|D) = (X'X)^{-1}X'y = \hat{B} \tag{10}$$

where $\hat{B}$ is the least square estimate of B.

Assumption 2: $Var\,(v|\sigma^2, D) = \sigma^2\,(X'\,X)^{-1}\,X'$

where σ^2 is the variance parameter given by:

$$E(\sigma^2|D) = s^2 = \frac{\hat{\nu}'\hat{\nu}}{T-k} \tag{11}$$

T is the number of observations and k the number of explanatory variables (here 4).

This assumption implies $Var\,(B|D) = \sigma^2\,(X'\,X)^{-1}$

The variance of the coefficients can then be estimated by:

$$Var\,(B|D) = \sigma^2(X'X)^{-1} \tag{12}$$

[4] The two approaches (MELO and BMOM) use the same objective function here but differ in estimation procedures. We do not use an informative prior. Another way of thinking would consist of using a balanced loss function (Shen and Perloff, 2001).

[5] This will be the case with adaptative expectations. However in our model, the price is known at the period of planting.

[6] See Zellner and Tobias (2001) for the full derivation of the equations.

Following Zellner (1996) and Zellner and Tobias (2001), the maximum entropy (maxent) approach can be used to compute the BMOM posterior density function given these two moment conditions. The density for $B = [b_0\ b_1\ b_2\ b_3]$[1] that maximizes entropy given the data and the two moment constraints is the multivariate normal distribution given by:

$$f(B|D) \sim MVN((X'X)^{-1}X'y, s^2(X'X)^{-1}) = MVN(\hat{B}, s^2(X'X)^{-1}) \qquad (13)$$

One can then use this density to compute the estimates (moments) in equation (8) by means of Monte Carlo integration (Zellner and Tobias, 2001) and then compute the BMOM estimate of $\acute{\alpha}_{MELO}$ in equation (9).

5. Data

Data comes from various sources. Cotton seed output and producers' prices come from the Malian Cotton Company (CMDT). To have real prices, and due to lack of information on consumer price index, nominal prices have been deflated by the GDP deflator provided by the International Finance Statistics of the International Monetary Fund. The sample range goes from 1967 to 2009.

There is a debate in the literature on whether the output or the area planted should be used to estimate supply elasticities in agriculture (Askari and Cummings, 1977). On the one hand, using acreage means that farmers can produce more only by extending areas. On the other hand, using production *per* unit area means that producers will respond to price changes by producing more intensively, *i.e.*, by increasing yields. Thus, the best way to capture producers' response is to use total production. By doing so, producers may respond to price incentives by using either more land or more intensive techniques.

We use a trend as a proxy for technological innovation. We also include prices of other crops grown with cotton (mainly maize and millet) to take into account the effect of rotational constraints on cotton production. We are aware of the fact that other factors such as institutional ones can have an effect on cotton supply. However the supply elasticity of cotton will remain unbiased as long as the remaining factors are not correlated with both cotton prices and the error term. Taking into account factors that are not correlated with both prices and the error term will only improve standard errors and other regression statistics (such as the adjusted R-squared) but will not affect the coefficients[7]. Furthermore, we use afterwards a dummy variable to take account the crisis the sector has been facing since 2001.

[7] This is a standard omitted variable issue. The coefficient of interest (here the supply elasticity) will be unbiased as long as the omitted variable is not correlated with both the main variable and the error term. One can however improve other regression statistics by adding more relevant explanatory variables.

Table 1. Descriptive statistics

	Mean	Standard deviation	Minimum	Maximum
Acreage (1,000 ha)	221.226	157.057	51.783	533.223
Production (1,000 tonnes)	245.448	170.685	29.888	620.665
Producers price (US$/tonne)[8]	315.068	72.689	175.600	443.500
Producers price (CFA F/kg)[9]	101.681	62.345	17	210

Source: FAOSTAT and CMDT (Mali).

6. Results

Tables 2 and 3 below show the results. One can notice a high value for both short run and long run elasticities (1.16 and 2.68). It is also worth noting that the coefficients of maize and millet prices are not significant due to the fact that those crops are mainly grown for home consumption and to increase cotton yields. Our results for the supply elasticity are on average higher than previous estimates which range from 0.12 to 0.80. To have an idea of what these high values mean, one needs to take account all the issues that the malian cotton sector has faced in recent years (see section 2).

Table 2. Short run estimates: Output

	BMOM		
	Mean coef.	S.D	95% HPDI
Intercept	–3.41	1.04	[–5.46, –1.36]
Price_{t-1}	3.24	1.02	[1.26, 5.23]
Output_{t-1}	0.62	0.13	[0.36, 0.87]
Maize	–0.89	1.59	[–4.01, 2.23]
Millet	1.98	1.70	[–1.36, 5.33]
Trend	0.04	0.02	[0.00, 0.08]
Observations		43	

Note: Coef: coefficient; SD: posterior standard deviation; HPDI: Highest posterior density interval. Here this is the shortest credible interval [a, b] for each b_i such that p (a $p(a \leq b_i \leq (b|D) = \int_a^b p(b_i|D)db_i = 0.95$.

Table 3. Elasticities of supply

Short run elasticities	Long run elasticities[10]
1.18	2.80
(0.37)	(1.08)

Note: Standard errors in parenthesis.

[8] Data from 1991 to 2009.
[9] 1 CFA F = US 0.0021. The CFA Franc is the currency used in Mali as well as in the West African Economic and Monetary Union.
[10] All the variances have been computed with the delta method.

The malian cotton sector has been experiencing a huge crisis since 2000 which has not yet been resolved (see section 2), exhibiting large variations in supply (see figure 2). In both 2000 and 2007, cotton production fell by 50% over the previous years. To take into account this evolution which corresponds to outliers in the data, we introduce a dummy variable. The new equation is:

$$A_t = b_0 + D_t + b_1 P_1 + \pi D_t \cdot P_t + b_2 A_{t-1} + b_3 Z_t + \nu_t \qquad (14)$$

where D_t is a dummy variable equals to 1 if $t \in \Omega = \{2000, 2007, 2008, 2009\}$ and 0 otherwise. The coefficients for the price variable are then given by $b_1 + \pi$ if $t \in \Omega$ and by b_1 otherwise.

As shown in Table 4, the elasticities are not so different for the two periods under consideration. However, taking into account outliers gives estimates more consistent with the theoretical literature. The supply has been inelastic—less than one—since 1967 even though producers have had access to credit. That is, some institutional constraint prevented producers from increasing their acreages and to receiving input provisions for more than three hectares before 1995.[11] Furthermore, the low supply elasticity found in the short run could be due to resource constraints on family labor, the availability of equipment or to food subsistence requirements (Vitale *et al.*, 2009). As a consequence, we observe a low partial adjustment coefficient (less than 0.75) and high long run elasticity (higher than one). However, the elasticities can be asymmetric (higher with price decreases and lower with price increases) in particular over the last decade.

Table 4. Elasticities of supply before and after 2000[12]

Short run elasticities		**Long run elasticities**	
1967–1999; 2001–2006	{2000,2007,2008,2009}	1967–1999; 2001–2006	{2000,2007,2008,2009}
0.79	0.65	1.10	0.99
(0.30)	(0.95)	(0.48)	(1.27)

Note: Standard errors in parentheses.

7. Conclusion

The aim of this paper was to consistently estimate the supply elasticity of cotton in Mali. The short run elasticities appear to be in the range found in the literature but the long run ones are higher. The low short run elasticities are mainly due to the level of price rigidity during the seventies and the eighties, as well as to resource and institutional constraints on acreages. As a

[11] We are grateful to a referee for raising this point.
[12] Regression outputs are available upon request.

consequence we observe a low partial adjustment coefficient and high long run elasticity. However these long run elasticities might be asymmetric (higher with price decreases and lower with price increases).

The study provides policy makers and researches with new and unbiased estimates of the supply elasticity of cotton in Mali that could be useful for policy analysis. For example, the low value of the elasticity found in the short run may be due to insufficient access to credit, poor quality of soil, lack of equipment, non-incentive price setting mechanisms and food subsistence needs (Vitale *et al.*, 2009) but also to institutional constraints on acreages. The sharp increase that occurred after 2001 might also be asymmetric, *i.e.*, much lower in case of price increases.

This study should be extended to other crops in order to obtain unbiased estimates of the supply elasticities with the Nerlove model. Given that the Nerlove model has been extensively used in the literature, previous studies should also be reassessed with regards to the new estimation procedure.

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