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# Assessment of producers' attitude toward risk and information using panel data: The example of pesticide use in the French crop sector

A. Carpentier & R.D. Weaver

INRA  
Unité d'économie et sociologie  
rurales de Rennes  
Documentation  
65, rue de St-Brieuc  
35042 RENNES CEDEX

INRA-ESR, Rennes, France & Pennsylvania State University, State College, USA

## Summary

The objective of this paper is to analyze farmers' pesticide use in the French crop sector. Our study focuses on two issues which are successively addressed through the estimation of the production function and the use of an appropriate testing strategy: farmers' (lack of) information use and the coherency of their input choices with expected utility maximization. Within this context, we use a balanced panel data set drawn from the European Accountancy Data Network for 496 farmers and for the years 1987 to 1990, and analyze it using the Hansen's Generalized Method of Moments statistical framework.

## 1 Introduction

When farmers' pesticide use in the French crop sector is considered, two issues are of interest: farmers' (lack of) information use and the coherency of their input choices with expected utility maximization. They are successively addressed through the estimation of the production

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function and the use of an appropriate testing strategy. Within this context, the advantage of panel data over single cross-sections or time series is twofold. First, the combination of time-series and cross-sections allows the examination of producers' behaviour dynamics even if the observation period is small. Second, they allow inference and estimation robust to heterogeneity which is usually present in micro-economic data concerning agricultural production.

Farmers may use two different information sources to reduce the uncertainty they face and to decide their input uses on a more accurate basis. They may check the conditions prevailing in their fields and/or use their past experiences and the possible dynamic structure of the considered random events to gather information. In the second section, using a Translog (Christensen et al.) production function specification and instrumental variable techniques, we test these hypotheses and find that French crop growers don't use any of these two sources of information. Furthermore, the estimates of the considered production function parameters presented in the third section show that pesticides are generally used by farmers above their expected profit maximizing level. These results suggest that farmers' choices of pesticides would be coherent with expected risk-averse utility maximization if these inputs were actually risk-reducing. In the fourth section we specify a Cobb-Douglas function linking the conditional variance of the production to input uses along the lines of Just and Pope to assess the effects of pesticide uses on production risk. Our econometric results are consistent with a significant risk-reducing effect of pesticides on production variance suggesting that French crop growers use pesticides above their profit maximizing level to self-insure their profit. To conclude, we draw some implications of our results on farmers' pest management modelling and policy design.

Our empirical work makes use of a balanced panel data set drawn from the European Accountancy Data Network for 496 farmers and for the years 1987 to 1990, and is developed

within the Hansen's Generalized Method of Moments (GMM) statistical framework. The data set considers one aggregate output and three inputs: pesticides, fertilisers and an aggregate of all other variable inputs. All variables are measured as Paasche indices and are expressed in French Francs 1987 per hectare. We use a balanced panel data set drawn from the European Accountancy Data Network for 496 farmers and for the years 1987 to 1990. The revenue of the selected producers is dominated by oilseeds and cereals which are produced using intensive cropping technology. Most of the sample producers are located in the Large Paris Basin.

Table 1. Summary statistics of the data set (496 French farmers from 1987 to 1990).

	Mean (and standard deviation)				
	1987	1988	1989	1990	Total
Output (ff 87/ha)	7173.059 (2055.637)	8053.932 (2315.300)	7943.334 (2259.137)	8096.317 (2373.110)	7816.661 (2283.414)
Pesticides (ff 87/ha)	769.521 (257.500)	811.397 (260.577)	892.453 (285.218)	920.221 (287.954)	848.398 (279.607)
Fertilizers (ff 87/ha)	1045.896 (259.445)	1007.970 (248.808)	1012.651 (264.594)	1013.193 (247.462)	1019.927 (255.434)
Other variable inputs (ff 87/ha)	1093.632 (521.779)	1116.613 (519.960)	1100.827 (550.333)	1119.307 (569.988)	1107.595 (540.614)
Planted area (ha)	77.205 (44.165)	79.056 (44.849)	80.756 (46.785)	82.752 (48.656)	79.942 (46.158)

Table 1 presents a summary of the input and output data. The revenue for major crops in 1990 was as follows: wheat (41.8%), corn (14.1%), barley (9.2%), sunflower (7.8%), rapeseed (6.6%) and leguminous peas (4.4%).

## 2 Producers' information use assessment

### 2.1 Specification of the micro-econometric model

In empirical studies, a production function is specified as a functional form parametrized by a vector ( $p \times 1$ ) of parameters ( $\alpha_0$ ) linking yields ( $y$ ), input uses ( $x$ ) and the effects of random events ( $u$ ). When panel data are used the production function can be specified as follows:

$$(1) \quad y_{it} = \gamma_i \gamma_t f(x_{it}, \alpha_0) + u_{it} \quad \text{where} \quad E[u_{it}] = 0; \quad t=1, \dots, T; \quad i=1, \dots, N.$$

The subindices  $t$  and  $i$  respectively denote the  $t^{\text{th}}$  period and the  $i^{\text{th}}$  farmer. The  $\gamma_i$  term represents the  $i^{\text{th}}$  farm specific effect. It may embody the influence of the farmer management quality (Mundlak 1961) and/or the effects of omitted or unobservable quasi-fixed factors (Chamberlain 1984). The  $\gamma_t$  term represents time specific effects common to all farmers such as climatic effects. Those parameters are interpretable as disembodied Hicks neutral technological shifts. However, this equation describes only a technological relationship. The choice of an appropriate estimator for  $\alpha_0$  must rely on precise assumptions linking the  $y$ 's and the  $x$ 's on the one hand, and the  $u$ 's on the other hand. Basically, these assumptions are based on relationships induced by the dynamic structure of the technology and farmers' use of information.

In addition to (1), we suppose that the following assumptions are satisfied:

$$(2) \quad E[u_{it} / x_{it}, \dots, x_{it-1}] = E[u_{it}] = 0 \quad \text{where} \quad t=2, \dots, T; \quad i=1, \dots, N.$$

The production function model defined by (1) and (2) represent an essentially static technology. That is, we assume that the crop production dynamics are stable enough to be correctly described by the  $\gamma_i$  parameters. Finally, our last maintained assumption is that:

(3) The  $(y'_i, \gamma'_i, x'_i)$ ' vectors are independent and identically distributed<sup>1</sup>,  $i=1, \dots, N$ .

In fact, this assumption relies on two distinct assumptions. The first one is that the data set related to each farmer are independent, implying that all possible effects linking farmers' inputs choices and output are included in the  $\gamma_i$  parameters. The second one is that each farmer's data set is generated by the same underlying model. Given these three basic assumptions, the

estimation of  $\alpha_0$  can rely upon conditional moments of the form  $E[y_{it} - \gamma_i \gamma_i f_{it}(\alpha_0) / \gamma_i, \gamma_i, x_{it}^-] \equiv E[u_{it}(\alpha_0) / \gamma_i, \gamma_i, x_{it}^-] = 0$ , where  $t=2, \dots, T$  and  $x_{it}^- \equiv (x_{i1}, \dots, x_{i,t-1})'$ .

That is, the components of  $x_{it}^-$  can be used to construct instruments for  $u_{it}(\alpha_0)$ .

Within this context, two reasons encourage us to check if wether or not  $x_{it}, \dots, x_{iT}$  can also be used to construct instruments for the  $u_{it}(\alpha_0)$ 's. From an econometric point of view the answer to this question is crucial. The potential efficiency gains in the estimation of  $\alpha_0$  associated with the inclusion of the  $x_{it}, \dots, x_{iT}$ 's in the construction of instruments for  $u_{it}(\alpha_0)$  are likely to be very important as shown by Chamberlain (1987, 1992a). From an economic point of view, the solution to this problem may provide some valuable insights concerning farmers' attitude toward information use. Along the lines of Chamberlain (1984), we briefly describe the four cases which may typically occur:

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<sup>1</sup> Where  $y_i$ ,  $x_i$  and  $x_{it}$  are respectively defined as  $(y_{i1}, \dots, y_{iT})'$ ,  $(x_{i1}, \dots, x_{iT})'$  and  $(x_{i1t}, \dots, x_{iKt})'$ .  $K$  is the number of considered inputs.

*Case 1:*  $E[u_{it}/x_{kit}] \neq 0$ . This conditional moment implies that the farmer  $i$  input  $k$  choices are endogenous with respect to  $u_{it}$ . The  $x_{kit}$  's can't be included in the construction of instruments for the  $u_{it}(\alpha_0)$ 's. This conditional moment suggest that the farmer  $i$  has got relevant information concerning  $u_{it}$  and that he is able to use it when he decides is input  $k$  choice. In this case, the farmer may have checked the conditions prevailing in his fields and/or may have used his past experiences and the possible dynamic structure of the  $u_{is}$  (e.g. an autoregressive process) to gather information.

*Case 2:*  $E[u_{it}/x_{kit}] = 0$ . This conditional moment implies that, either farmer  $i$  don't have got any information on  $u_{it}$  when chosing in input  $k$  quantity, or he does not use the information he has got. In this two cases, the  $x_{kit}$  's can be included in the construction of instruments for the  $u_{it}(\alpha_0)$ 's.

*Case 3:*  $E[u_{it}/x_{kis}] \neq 0$  for  $s > t$ . This moment condition indicates that farmers' input  $k$  choices are to some extent determined by past yields. As explained above, this causality relationship may be induced by the fact that farmer  $i$  uses his past experiences and the possible dynamic structure of the  $u_{is}$  to produce information on  $u_{it}$ . However, this relationship may be implied by inter-temporal constraints on farmer  $i$  input choices, such as financial constraints. In this case, the  $x_{kis}$  can't be used in the construction of instruments for the  $u_{it}(\alpha_0)$ 's.

*Case 4:*  $E[u_{it}/x_{kis}] = 0$  for  $s > t$ . In this case, farmer  $i$  behavior is essentially static, i.e. not influenced by past experiences. This conditional moment implies that the  $x_{kis}$  can be used in the construction of instruments for the  $u_{it}(\alpha_0)$ 's.

Finally, it should be noted that the specification (1)-(3) only implies:

$$(4) \quad E[u_{it}(\alpha_0)/\gamma_i, \gamma_t, x_{it}^-] = 0.$$

The inclusion of the  $\gamma_i$ 's and the  $\gamma_t$ 's in the conditioning variable set means implicitly that the fixed firm and period effects may be known by the farmers (see e.g. Chamberlain 1984; Carpentier & Weaver 1995a and b). As a consequence, these fixed effects may influence farmers' input choices. As shown below, this remark is very important for the choice of the estimation and inference methods.

## 2.2. Testing the French crop growers attitude toward information

Considering estimation of the parameters of the specified technology, two types of problem occur. Given that it is impossible to conduct tests without prior estimates of the considered model parameters, the first problem is estimating  $\alpha_0$  under the minimal assumptions (1)-(3). The second one is testing the hypothesis specified in the sub-section 2.3. In the next sub-sections, the estimation method for model the (1)-(3) and the inference method use to investigate the above hypothesis are successively (and logically) presented.

### *Estimation of the minimal specification parameters*

Consistent estimation of model (1)-(3) follows from Chamberlain's (1992a) and Wooldridge's (1991) application of Hansen's GMM. The approach allows convenient and robust estimation when panel data sets have large  $N$ , yet small  $T$ . While a small  $T$  allows direct parametrization of the fixed firm effects using dummy variables, an alternative approach must be taken for the individual effects.

As explained above, equations (1) and (2) can be combined to specify conditional moments of the following form:

$$(4) \quad E[y_{it} - \gamma_i \gamma_t f_u(\alpha_0) / \gamma_i, x_{it}^-] = E[u_{it}(\alpha_0, \gamma_t) / \gamma_i, x_{it}^-] = 0, \quad t=1, \dots, T.$$

By specifying the conditional moments by  $x_{it}^-$  and  $\gamma_i$  we implicitly assume that the  $\gamma_i$  term may be known by farmer  $i$  and, as a consequence, may affect farmer  $i$  input choices. As shown by Mundlak (1961), the omission of this possible dependence of the  $x_i$ 's on the  $\gamma_i$ 's may originate heterogeneity biases. To overcome this problem, we use the "fixed effects" approach defined by Chamberlain (1992a) and Wooldridge (1991). That is, the fixed firm effects are eliminated using a transformation of equations (4):

$$(5) \quad E[r_{it}(\alpha_0, \gamma_i, \gamma_{i-1})/\gamma_i, x_{it}^-] = E[r_{it}(\alpha_0, \gamma_i, \gamma_{i-1})/x_{it}^-] = 0$$

where  $t=2, \dots, T$  and  $r_{it}(\cdot)$  is defined in analogy to the first differencing transformation as:

$$(6) \quad r_{it}(\alpha_0, \gamma_i, \gamma_{i-1}) \equiv y_{it} - y_{it-1} \frac{\gamma_i}{\gamma_{i-1}} \frac{f_{it}(\alpha_0)}{f_{it-1}(\alpha_0)} = u_{it} - u_{it-1} \frac{\gamma_i}{\gamma_{i-1}} \frac{f_{it}(\alpha_0)}{f_{it-1}(\alpha_0)}$$

This transformation allows inference on  $\alpha_0$  and  $\gamma_i$  ( $t=2, \dots, T$ )<sup>2</sup> "conditional" on  $\gamma_i$  even if it is not observed by the econometrician.

The approach to estimation firstly exploits (5) to build computable (unconditional) orthogonality conditions that are at the core of Hansen's GMM framework. Equations (5) imply that a  $l_t \times 1$  vector of instruments for  $r_{it}$  can be chosen as a known function of  $x_{it}^-$  and  $\tilde{\omega}_N$  where this last vector is a root  $N$  consistent estimator of some vector of parameters  $\omega$ . Usually we have:  $\omega = \theta$  where  $\theta \equiv (\gamma_2, \gamma_3/\gamma_2, \dots, \gamma_T/\gamma_{T-1}, \alpha')$ , and  $\tilde{\omega}_N = \tilde{\theta}_N$  is an initial (and easily computed) root  $N$  consistent estimator of  $\theta_0$ . If the instruments  $(w_{it}(x_{it}^-, \tilde{\omega}_N) \equiv w_{it}(\tilde{\omega}_N))$

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<sup>2</sup> For identification purpose we impose the restriction:  $\gamma_1 = 1$ .

are "rich" enough, they can be used to construct orthogonality conditions that identify  $\theta_0$  our parameters of interest:

$$(7) \quad E[w_{it}(\omega)'r_{it}(\theta)] = 0 \text{ if } \theta = \theta_0, \quad E[w_{it}(\omega)'r_{it}(\theta)] \neq 0 \text{ otherwise, } t=2, \dots, T.$$

Stacking these conditions over  $t$  we use the resulting orthogonality conditions as a basis of our estimation:

$$(8) \quad E[w_i(\omega)'r_i(\theta_0)] = 0 \quad \text{where } w_i \equiv \text{Diag}(w_{i2}, \dots, w_{iT}) \text{ and } r_i \equiv (r_{i2}, \dots, r_{iT})'.$$

The above unconditional moment restrictions and the law of iterated expectations allow the construction of method of moments estimators which minimize a quadratic form in the sample counterpart of these restrictions. In this context the efficient GMM estimator of  $\theta$  subject to (8) can be written:

$$(9) \quad \hat{\theta}_N \equiv \underset{\theta}{\text{Arg min}} \left[ \sum_{i=1}^N r_i(\theta)' w_i(\tilde{\omega}_N) \right] \tilde{\Omega}_N^{-1} \left[ \sum_{i=1}^N w_i(\tilde{\omega}_N)' r_i(\theta) \right]$$

where  $\tilde{\Omega}_N$  is a consistent estimator of the asymptotic variance-covariance matrix of the orthogonality conditions (8):  $\Omega_0 \equiv E[w_i(\omega)'r_i(\theta_0)r_i(\theta_0)'w_i(\omega)]$ . Given an initial root  $N$  consistent estimator of  $\theta_0$ :  $\tilde{\theta}_N$ ,  $\tilde{\Omega}_N$  can be defined as the sample counterpart of  $\Omega_0$  computed at  $\tilde{\theta}_N$  and  $\tilde{\omega}_N$ :

$$(10) \quad \tilde{\Omega}_N \equiv \frac{1}{N} \sum_{i=1}^N w_i(\tilde{\omega}_N)' r_i(\tilde{\theta}_N) r_i(\tilde{\theta}_N)' w_i(\tilde{\omega}_N).$$

The efficient GMM estimator of  $\theta_0$ :  $\hat{\theta}_N$  is root  $N$  consistent. Its asymptotic distribution is normal and is given by:

$$(11) \quad \sqrt{N}(\hat{\theta}_N - \theta_0) \xrightarrow{D} \mathcal{N}\left(0, (R_0' \Omega_0^{-1} R_0)^{-1}\right) \quad \text{where} \quad R_0 \equiv E\left[w_i(\omega)' \frac{\partial r_i(\theta_0)}{\partial \theta'}\right].$$

A consistent estimator of  $R_0$  is given by its sample counterpart computed at  $\hat{\theta}_N$  and  $\tilde{\omega}_N$ <sup>3</sup>:

$$(12) \quad \hat{R}_N \equiv \frac{1}{N} \sum_{i=1}^N w_i(\tilde{\omega}_N)' \frac{\partial r_i(\hat{\theta}_N)}{\partial \theta'}$$

which can be used to construct a consistent estimator of the asymptotic variance-covariance matrix of  $\hat{\theta}_N$ :

$$(13) \quad \hat{V}_N(\hat{\theta}_N) \equiv \frac{1}{N} (\hat{R}_N' \hat{\Omega}_N^{-1} \hat{R}_N)^{-1} \quad \text{where}^4 \quad \hat{\Omega}_N \equiv \frac{1}{N} \sum_{i=1}^N w_i(\tilde{\omega}_N)' r_i(\hat{\theta}_N) r_i(\hat{\theta}_N)' w_i(\tilde{\omega}_N).$$

When  $\tilde{\theta}_N$ , an initial estimator of  $\theta_0$ , is available, a convenient and asymptotically equivalent estimator of  $\hat{\theta}_N$  can easily be computed. Because it can (asymptotically) replace its corresponding GMM estimator, we also note this one step efficient estimator  $\hat{\theta}_N$ . It is given by (Newey 1985; Wooldridge 1991):

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<sup>3</sup> In the case where  $\omega = \theta_0$ ,  $\tilde{\omega}_N$  can be replaced by  $\hat{\theta}_N$ .

$$(14) \quad \hat{\theta}_N \equiv \tilde{\theta}_N - \tilde{c}_N \quad \text{where} \quad \tilde{c}_N \equiv \left[ \tilde{R}_N' \tilde{\Omega}_N^{-1} \tilde{R}_N \right]^{-1} \tilde{R}_N' \tilde{\Omega}_N^{-1} \frac{1}{N} \sum_{i=1}^N w_i (\tilde{\omega}_N)' r_i(\tilde{\theta}_N).$$

An important advantage of the estimation approach outlined above is that under any form of heteroskedasticity and temporal dependence of the  $u_{it}$ ,  $\tilde{\Omega}_N$  and  $\hat{\Omega}_N$  are consistent estimators of  $\Omega_0$  (Hansen; Newey & West 1987a). This allows us to conduct estimation and inference which are robust with respect to any form of heteroskedasticity and temporal dependence of the  $u_{it}$ .

*Test of the hypotheses related to information use*

Considering the discussion of farmers' information use provided in sub-section 2.1, three types of hypothesis may be checked. The first one is related to farmers' knowledge of  $\gamma_i$ . It is not considered here. In this paper we only assume that farmer  $i$  may know his own  $\gamma_i$ . That is we assume that farmers' input choices may be correlated to the fixed firm effects. In the context of the French crop sector production, this correlation was shown to be highly positive in the cases of pesticides and fertilizers. In particular, omission of this correlation was shown to originate heterogeneity biases which are some of the most likely causes of the usual (and substantial) "overestimation" of the pesticide expected marginal productivity, at least in the French crop sector case (Carpentier & Weaver 1995a and b). Here, we concentrate the discussion on inference related to the two other types of hypotheses: *i*-the minimal model specification (1)-(3) validity and, *ii*-farmers' information use related to the  $u_{it}$ 's as considered in the four described cases.

The validity of the minimal model specification may be test along the lines of Hansen. Hansen's approach is to test the validity of the orthogonality conditions used for the construction of the GMM estimors. To do so, he recognizes that some of linear combinations of these orthogonality conditions may be imposed in estimation to identify the model

parameters. The excess conditions, which exist when the number of the initial (non redundant) orthogonality conditions exceeds the number of parameters to be estimated, can be viewed as over-identifying restrictions. Under the null that the model is correctly specified,  $H_0: E[w_i(\omega)'r_i(\theta_0)] = 0$ , these over-identifying restrictions would not be statistically different from zero. The following formula presents the Hansen's test (of over-identification) statistic for testing the null hypothesis that the over identifying restrictions used to estimate  $\theta_0$  under (1)-(3) are indeed zero<sup>4</sup>:

$$(15) \quad \hat{S}_N \equiv \frac{1}{N} \left[ \sum_{i=1}^N r_i(\hat{\theta}_N)' w_i(\tilde{\omega}_N) \right] \hat{\Omega}_N^{-1} \left[ \sum_{i=1}^N w_i(\tilde{\omega}_N)' r_i(\hat{\theta}_N) \right]$$

This test statistic, under the null hypothesis, converges in distribution to a centered  $\chi^2$  distribution with the number of degrees of freedom equal to the number of overidentifying restrictions (i.e. the numbers of orthogonality conditions used to build  $\hat{\theta}_N$  minus its number of elements). By design, this test procedure considers both the functional form specification and the validity of the instruments.

Investigating the farmers' information use question requires additional formalization. Consider first the case of input  $k$ . We are interested in checking if, wether or not, at period  $s$  farmers chose input  $k$  quantities using information they have got on current or past yields, that is, on the  $u_{it}$  's where  $t$  is equal or superior to  $s$ . Consider the hypothesis: farmers don't use information on  $u_{it}$  to decide  $x_{kis}$ . Given that our panel data set has small  $T$ , we can not estimate consistently the  $u_{it}$ 's individually because we can not estimate consistently the  $\gamma_i$ 's. As a result we can not check the validity of orthogonality conditions of the form:  $E[x_{kis}u_{it}(\theta_0)] = 0$ . Considering that the minimal model is correctly specified, this can only be statistically tested by testing the validity of the following null hypotheses:

$$(16a) \quad H_{0kts}: E[x_{kis}r_{it}(\theta_0)] = 0 \quad \text{where } 2 \leq t \leq T \text{ and } t-1 \leq s \leq T$$

$$(16b) \quad H_{0k(t+1)s}: E[x_{kis}r_{it+1}(\theta_0)] = 0 \quad \text{where } 2 \leq t \leq T \text{ and } t \leq s \leq T$$

That is, at time  $s$  farmers' input  $k$  choices are not correlated with  $u_{it}$  and,  $u_{it-1}$  or  $u_{it+1}$ . Note that writing  $H_{0kts}$  we restrict ourselves to the case where:  $\omega = \theta_0$ . Following Newey (1985) and Wooldridge (1990), we derive a statistic to test  $H_{0kts}$  from a first order Taylor expansion around  $\theta_0$  of the sample counterpart of the moment given in (16a) multiplied by root  $N$ :

$$(17) \quad \frac{1}{\sqrt{N}} \sum_{i=1}^N x_{kis}r_{it}(\hat{\theta}_N) = \frac{1}{\sqrt{N}} \sum_{i=1}^N x_{kis}r_{it}(\theta_0) + E \left[ x_{kis} \frac{\partial r_{it}(\theta_0)}{\partial \theta'} \right] \sqrt{N}(\hat{\theta}_N - \theta_0) + o_p(1)$$

where  $o_p(1)$  converges to 0 in probability. Given that under  $H_0$   $\hat{\theta}_N$  is root  $N$  consistent and rearranging the terms of equation (17), we have under  $H_0$  and  $H_{0kts}$ :

$$(18) \quad \begin{aligned} \frac{1}{\sqrt{N}} \sum_{i=1}^N x_{kis}r_{it}(\hat{\theta}_N) &= \frac{1}{\sqrt{N}} \sum_{i=1}^N x_{kis}r_{it}(\theta_0) \\ &+ E \left[ x_{kis} \frac{\partial r_{it}(\theta_0)}{\partial \theta'} \right] B_0 \frac{1}{\sqrt{N}} \sum_{i=1}^N w_i(\theta_0)' r_i(\theta_0) + o_p(1) \\ &= \sqrt{N} L_{0kts} + o_p(1) \end{aligned}$$

where:  $B_0 = (R_0' \Omega_0^{-1} R_0)^{-1} R_0' \Omega_0^{-1}$ . Under  $H_0$  and  $H_{0kts}$  the term  $\sqrt{N} L_{0kts}$  converges to a univariate centered normal distribution while it generally converges to a univariate non centered normal distribution when  $H_0$  holds but  $H_{0kts}$  doesn't. Moreover, this term and its asymptotic variance can easily be consistently estimated. This allows us to construct a test

statistic based on a the normalized quadratic form of  $\sqrt{N} L_{okts}$  to check the validity of  $H_{okts}$ .

Given that under  $H_0$   $\hat{\theta}_N$  is a consistent estimator of  $\theta_0$ , the term:

$$(19) \quad \hat{L}_{Nkts} \equiv \frac{1}{N} \sum_{i=1}^N x_{kis} r_{it}(\hat{\theta}_N) + \frac{1}{N} \sum_{i=1}^N x_{kis} \frac{\partial r_{it}(\hat{\theta}_N)}{\partial \theta'} \hat{B}_N \frac{1}{N} \sum_{i=1}^N w_i(\hat{\theta}_N)' r_i(\hat{\theta}_N)$$

where  $\hat{B}_N \equiv (\hat{R}'_N \hat{\Omega}_N^{-1} \hat{R}_N)^{-1} \hat{R}'_N \hat{\Omega}_N^{-1}$ , is a consistent estimator of  $L_{okts}$ . Gouriéroux et al. (1990)

showed that:

$$(20) \quad \begin{aligned} V[\sqrt{N} L_{okts}] &= E[x_{kis}^2 r_{it}(\theta_0)^2] \\ &+ E\left[x_{kis} \frac{\partial r_{it}(\theta_0)}{\partial \theta'}\right] B_0 \Omega_0 B_0' E\left[x_{kis} \frac{\partial r_{it}(\theta_0)'}{\partial \theta}\right] \\ &- 2 E\left[x_{kis} \frac{\partial r_{it}(\theta_0)}{\partial \theta'}\right] B_0 E[w_i(\theta_0)' r_i(\theta_0) x_{kis} r_{it}(\theta_0)] \end{aligned}$$

As argued above  $\hat{V}_N[\sqrt{N} L_{okts}]$ , a consistent estimator of  $V[\sqrt{N} L_{okts}]$ , can easily be constructed

by replacing  $\theta_0$  by  $\hat{\theta}_N$  and the asymptotic expectations by their sample counterpart:

$$(21) \quad \begin{aligned} \hat{V}_N[\sqrt{N} L_{okts}] &\equiv \frac{1}{N} \sum_{i=1}^N x_{kis}^2 r_{it}(\hat{\theta}_N)^2 \\ &+ \left[ \frac{1}{N} \sum_{i=1}^N x_{kis} \frac{\partial r_{it}(\hat{\theta}_N)}{\partial \theta'} \right] \hat{B}_N \hat{\Omega}_N \hat{B}_N' \left[ \frac{1}{N} \sum_{i=1}^N x_{kis} \frac{\partial r_{it}(\hat{\theta}_N)'}{\partial \theta} \right] \\ &- 2 \left[ \frac{1}{N} \sum_{i=1}^N x_{kis} \frac{\partial r_{it}(\hat{\theta}_N)}{\partial \theta'} \right] \hat{B}_N \frac{1}{N} \sum_{i=1}^N w_i(\hat{\theta}_N)' r_i(\hat{\theta}_N) x_{kis} r_{it}(\hat{\theta}_N) \end{aligned}$$

Given the above notations, a consistent test of  $H_{0kts}$  against the alternative hypothesis:

$E[x_{kts}'r_{it}(\theta_0)] \neq 0$  at the confidence level  $\alpha$  can be defined as the test statistic:

$$(22) \quad \hat{S}_{Nkts} \equiv N \hat{L}'_{Nkts} \hat{V}_N [L_{0kts}]^{-1} \hat{L}_{Nkts}$$

associated with the critical region:  $\{N\hat{L}'_{Nkts} \hat{V}_N [L_{0kts}] \hat{L}_{Nkts} > \chi^2_{1-\alpha}(1)\}$  (Newey 1985)<sup>4</sup>.

### Results

Our empirical application uses a Translog form in the three considered inputs for  $f(\cdot)$ . This functional was chosen due to its flexibility. Thus (1) can be rewritten as:

$$(23) \quad y_{it} = \gamma_i \gamma_i \exp(\Delta x_{it} \alpha_0) + u_{it}$$

where the vectors  $\alpha_0$  and  $\Delta x_{it}$  are respectively given by  $\alpha_0 \equiv (\alpha_1, \dots, \alpha_K, \alpha_{11}, \dots, \alpha_{kk'(\geq k)}, \dots, \alpha_{KK})'$  and  $\Delta x_{it} \equiv (\ln x_{1it}, \dots, \ln x_{Kit}, \ln x_{1it} \ln x_{1it}, \dots, \ln x_{kit} \ln x_{k'(\geq k)it}, \dots, \ln x_{Kit} \ln x_{Kit})$ . Thus the vector of parameters of interest  $\theta_0$  has  $(T-1)+2K+K(K-1)/2=12$  elements. This vector is estimated under (1)-(3) by use of the one step efficient GMM estimator  $\hat{\theta}_N$  based on the orthogonality conditions (8):  $E[w_i' r_i(\theta_0)] = 0$ . The instruments  $w_i$  for the  $r_i(\cdot)$  are chosen as:

$$(24) \quad w_{it} = s_{it}^- \equiv (1, \Delta x_{i1}, \Delta x_{i2}, \dots, \Delta x_{i(K-2)}) \quad \text{and} \quad w_i = s_i^- \equiv \text{Diag}(s_{i2}^-, \dots, s_{iK}^-).$$

---

<sup>4</sup> In a similar context, Mairesse & Hall (1994) used an approach exclusively based on the Hansen's test of over-identification.

As a result, the construction of the estimator  $\hat{\theta}_N$  is based on 30 orthogonality conditions. The first step estimator of  $\theta_0$  is simply defined as a Non Linear Two-Stage Least Squares estimator based on the implicit equation defined by  $r_{it}(\cdot)$  and using the columns of  $W \equiv (w_1, \dots, w_N)'$  as instrumental variables:

$$(25) \quad \tilde{\theta}_N \equiv \underset{\theta}{\text{Arg min}} \left[ \sum_{i=1}^N r_i(\theta)' s_i^- \right] \left[ \sum_{i=1}^N s_i^-' s_i^- \right]^{-1} \left[ \sum_{i=1}^N s_i^-' r_i(\theta) \right]$$

This GMM estimator is root  $N$  consistent but not efficient (Hansen).

Considering the test of the assumptions underlying the minimal specification, the estimated value of  $\hat{S}_N$  is 13.76. As a consequence,  $H_0$  can not be rejected at a reasonable confidence level:  $P(\chi^2(18) > 13.76) \cong 0.74$  and we can conclude that (1)-(3) are acceptable.

Table 2. Test results of the hypotheses  $H_{0kts}$ .

	Pesticides		Fertilizers		Other variable inputs	
	Test statistic estimation	Prob <sup>a</sup>	Test statistic estimation	Prob <sup>a</sup>	Test statistic estimation	Prob <sup>a</sup>
<i>t=1988</i>						
<i>s=1987</i>	0.072	0.789	0.896	0.344	0.582	0.446
<i>s=1988</i>	0.502	0.479	0.588	0.443	0.807	0.369
<i>s=1989</i>	1.374	0.241	1.600	0.206	0.199	0.655
<i>s=1990</i>	3.411	0.065	2.169	0.141	0.249	0.618
<i>t=1989</i>						
<i>s=1988</i>	1.890	0.169	0.540	0.463	0.017	0.895
<i>s=1989</i>	0.636	0.425	0.013	0.910	0.419	0.517
<i>s=1990</i>	0.495	0.482	0.215	0.643	0.741	0.389
<i>t=1990</i>						
<i>s=1989</i>	1.692	0.193	0.024	0.877	0.349	0.555
<i>s=1990</i>	1.101	0.294	0.015	0.902	0.002	0.969

<sup>a</sup> Prob =  $P(\chi^2(1) > \text{Test statistic estimation})$ .

Given that  $H_0$  can be accepted, the test procedure developed above should lead us to reject  $H_{0kts}$  only if the corresponding orthogonality condition doesn't hold:  $E[x_{kts}r_{it}(\theta_0)] \neq 0$ . The results of the orthogonality conditions tests are presented in Table 2. They show that all the hypotheses  $H_{0kts}$  (where  $2 \leq t \leq T$  and  $t-1 \leq s \leq T$ ) can not be rejected for a confidence level inferior or equal to 5% (this confidence level was chosen by e.g. West). However, these hypotheses can generally be accepted with a confidence level much more larger.

Hence, this results suggest that the French crop growers' attitude toward variable input decisions is essentially static. The random variable  $u_{it}$  realization does not affect the current and subsequent choices of farmer  $i$ . In this case, we can reasonably assume that farmers' input  $x_{it}$  choices are strictly exogenous with respect to  $u_{it}$  conditionally on the fixed effects  $\gamma_i$  (Chamberlain 1984):

$$(26) \quad E[y_{it}/\gamma_i, \gamma_i, x_{it}] = E[y_{it}/\gamma_i, \gamma_i, x_{it}] = \gamma_i \gamma_i f_u(\alpha_0).$$

The term  $\gamma_i \gamma_i f_u(\alpha_0)$  can thus be considered as the expected yield of farmer  $i$  at time  $t$ . That is, at time  $t$ , there no other information (concerning his yield mean) available to farmer  $i$  than the deterministic relationship linking the input uses and the firm effect to the yield. The first conclusion of these tests is that farmers act as if they haven't got any information on  $u_{it}$ . The second conclusion considers the econometric estimation of  $\alpha_0$  and is developed in the next section.

### 3 Estimation of the expected yield model parameters

#### 3.1 Estimation method under the strict exogeneity assumption

The results of the tests described above show that we are allowed to construct an estimator of  $\theta_0$  on the basis of the conditional moments (26). The estimation of models similar to ours has already been studied by several authors, empirically (Hausman et al. 1984, Carpentier & Weaver 1995a and b) or theoretically (Wooldridge 1990 and 1991, Chamberlain 1992a and b). Chamberlain (1992a and b) showed that using a fixed effect approach allows the construction of efficient estimators of  $\theta_0$ . That is, because of our lack of knowledge concerning the firm fixed effects, the use of the conditional moments:

$$(27) \quad E[r_i(\theta_0)/x_i] = E[r_i(\theta_0)/x_{i-1}, x_{ii}] = 0$$

is warranted. Chamberlain (1987, 1992a) also showed how an efficient estimator (i.e. efficient among the class of the root  $N$  estimators) of  $\theta_0$  can be constructed on the basis of (27) within the GMM framework. Such an estimator may be constructed as the efficient GMM estimator (i.e. efficient among the class of GMM estimators based on the considered set of orthogonality conditions) of  $\theta_0$  based on the following orthogonality conditions:

$$(28) \quad E[A_i(\theta_0)' \Omega_i(\theta_0)^{-1} r_i(\theta_0)] = 0$$

where  $\Omega_i(\theta_0) \equiv E[r_i(\theta_0)r_i(\theta_0)'/x_i]$  and  $A_i(\theta_0) \equiv E[(\partial r_i(\theta_0)/\partial \theta')/x_i]$ . The term  $A_i(\theta_0)' \Omega_i(\theta_0)^{-1}$  is the so-called optimal instrument derived from the conditional restriction (28) (Newey 1993). Unfortunately, the construction of this estimator is not easily tract in practice. This is

due to the nature of the optimal instruments for which it is difficult to construct consistent estimators. Consider the case of  $A_i(\theta_0)$ :

$$(29) \quad A_i(\theta_0) = -\frac{\partial[f_u(\alpha_0)/f_{u-1}(\alpha_0)]}{\partial\alpha'} f_{u-1}(\alpha_0) E[\gamma_i/x_i]$$

As mentioned above it is difficult to construct a root  $N$  consistent estimator of  $E[\gamma_i/x_i]$ .

The construction of such estimators requires use of an *ad hoc* parametrization of  $E[\gamma_i/x_i]$  or nonparametric methods (Chamberlain 1992b).

The approach chosen in this paper is much more simpler. It was suggested by Wooldridge (1991) and Davidson and McKinnon. We simply chose the instruments which are the closest to the optimal instruments and for which we can easily construct a root  $N$  consistent estimator.

Following the recommendations of Wooldridge (1991), and adopt the instruments:

$wr_i(\theta_0) \equiv \text{Diag}(wr_{i_2}(\theta_0), \dots, wr_{i_\pi}(\theta_0))$  where:

$$(30) \quad wr_{i_\pi}(\theta_0) \equiv \left[ \frac{\partial[f_u(\alpha_0)/f_{u-1}(\alpha_0)]}{\partial\alpha'} f_{u-1}(\alpha_0), f_u(\alpha_0) \right]$$

to construct a one step efficient GMM estimator based on the orthogonality conditions (8). It should be noted that our choice of instruments was also motivated by the construction of the over-identification test statistic. While the optimal choice of instruments gives as many orthogonality conditions as there are parameters to be estimated, our choice of instruments provides more orthogonality conditions than needed to identify the model parameters and, as a result, over-identifying restrictions to be tested. The construction of the one step efficient GMM estimator  $\hat{\theta}_N$  is based on 30 orthogonality conditions. In this case,  $\hat{\theta}_N$  the first step

estimator of  $\theta_0$  is simply defined as the following Non Linear Two-Stage Least Squares estimator:

$$(31) \quad \hat{\theta}_N \equiv \underset{\theta}{\text{Arg min}} \left[ \sum_{i=1}^N r_i(\theta)' s_i \right] \left[ \sum_{i=1}^N s_i' s_i \right]^{-1} \left[ \sum_{i=1}^N s_i' r_i(\theta) \right]$$

where  $s_{it} \equiv [1, \Delta x_{i1}, \dots, \Delta x_{iT}]$  and  $s_i \equiv \text{Diag}(s_{i2}, \dots, s_{iT})$ .

### 3.1. Results and implications

Results are reported in Table 3. The Hansen's over-identification test statistic estimation is equal to 19.20. Given that the number of over-identifying restriction is equal to 18, we can not reject the validity of the orthogonality conditions underlying the construction of  $\hat{\theta}_N$ .  $P(\chi^2(18) > 19.20) \cong 0.40$ . That is, our both assumptions, i.e. the strict conditional exogeneity of the farmers' input choices and the Translog functional form for the yield conditional mean model, are not rejected by our data set. It should be noted that the pesticides and fertilizers first order coefficients may be affected by substantial heterogeneity biases. A simple estimation by Non Linear Least Squares of the parameters of model (1) gives a first order coefficient estimate equal to 0.333 for pesticides and equal to 0.198 for fertilizers. Moreover, the dependence of farmers' input choices with respect to farm effects also affects the estimation of the Translog model second order parameters (see Carpentier).

The results indicates that all inputs are applied above their expected profit maximizing level at the sample mean point. The estimated expected productivity elasticity of each input is inferior two the share of their corresponding expenses in the total product value (0.11% for pesticides, 0.12 for fertilizers and 0.14 for the other variable inputs). The results show that

fertilizers and pesticides are (slightly) cooperant in the Rader sense. This was expected since the farmers of the data set use intensive cropping technologies (Carpentier). These results seem in accordance with the French agricultural scientists.

Table 3. Conditional mean yield parameter estimates (and asymptotic standard deviation).  
Conditional mean yield parameter estimates (and asymptotic standard deviation).

				Input coefficients		
				Pesticides	Fertilizers	Other variable inputs
<b>Translog first order parameters</b>				0.092 (0.031)	0.033 (0.018)	0.107 (0.014)
<b>Translog second order parameters</b>						
	Pesticides		-0.044 (0.038)	0.002 (0.070)	-0.063 (0.043)	
	Fertilizers			-0.006 (0.058)	-0.052 (0.053)	
	Other variable inputs				0.102 (0.023)	
				Time effects		
				1988/1987	1989/1988	1990/1989
				1.116 (0.010)	0.975 (0.009)	1.013 (0.009)

However, two points must be discussed. First, the estimates show the expected marginal productivity of the other variable inputs aggregate is increasing. This surprising result may highlight the heterogeneity of this aggregate which includes very different inputs such as seeds, energy, ... Second, the estimated fertilizer expected marginal productivity is rather small. An

abundant has been devoted to this usual "under-estimation" of the marginal productivity of fertilizers. In our case, this result may be originated by three factors. First, as it is well known, fertilizers, which are plant nutrients, are subject to the Von Liebig effect. The marginal effect of fertilizers is null as soon as the plant needs are satisfied (Berck & Helfand). Second, farmers uninformed about the initial stock nutrients in their soil may overused fertilizers (Babcock). Finally, massive fertilizer uses result in an increase in the likelihood of severe fungi damage (Meynard). A farmer who ignores or under-estimates this effect may apply fertilizers in excess (Harper & Zilberman).

Following Feder, the fact that pesticides are used above their profit maximizing level (at the sample mean point) suggests that farmers' choices of pesticides would be coherent with expected utility maximization if these inputs were actually risk-reducing. We investigate this last hypothesis in the next section.

## 4 Estimation of the yield variance model parameters

### 4.1 The Just & Pope (1978) specification

Along the lines of Just & Pope (1978) we specify a function linking the conditionnal variance of the production to input uses to assess the effects of pesticides on production risk:

$$(32) \quad u_{it} \equiv \varepsilon_{it} \gamma_i \sigma_0 h(x_{it}, \beta_0) \quad \text{where} \quad E[\varepsilon_{it}/x_{it}, \gamma_i] = E[\varepsilon_{it}] = 0, \quad E[\varepsilon_{it}^2/x_{it}, \gamma_i] = E[\varepsilon_{it}^2] = 1$$

This specification assumes that the firm fixed effect affecting the yield mean also affects the yield variance. This assumption implicitly implies that the fixed effect represents farmer  $i$  target yield. However this assumption is necessary to estimate  $\beta$  since we do not impose on the serial correlation of the  $\varepsilon_{it}$  (Wooldridge 1990, Ahn & Schmidt 1995). It should be noted that this specification includes as a special case the Griffiths and Anderson's (1982) specification which is usually used in this context (Babcock et al. 1987, Wan et al. 1992, Wan & Anderson 1993). This last specification assumes a Balestra and Nerlove's (1966) composite error structure for  $\varepsilon_{it}$  and assumes that  $\gamma_i = \gamma, \forall i = 1, \dots, N$ . Thus, its estimation by weighted least squares may result in estimates subject to heterogeneity biases (see Carpentier 1995).

### 4.2 Estimation of the yield variance model parameters

Using (32) and (26), we use the following conditional moments to estimate  $\delta_0 \equiv (\sigma_0^2, \beta_0)'$ :

$$(33) \quad E[y_{it}^2/\gamma_i, x_{it}] = \gamma_i^2 [\gamma_i f_u(\alpha_0)^2 + \sigma_0^2 h_u(\beta_0)^2], \quad t = 1, \dots, T$$

Applying the "fixed effects" approach described above (see section 2.2), we use the following transformation to eliminate the  $\gamma_i^2$  terms:

$$(34) \quad E[v_{it}(\theta_0, \delta_0)/\gamma_i, x_i] = E[v_{it}(\theta_0, \delta_0)/x_i] = 0, \quad t = 2, \dots, T$$

where, in analogy with  $r_{it}(\cdot)$  function, the  $v_{it}(\cdot)$  function is defined as:

$$(35) \quad v_{it}(\theta, \delta) \equiv y_{it}^2 - y_{it-1}^2 \left[ \gamma_i^2 f_{it}(\alpha)^2 + \sigma^2 h_{it-1}(\beta)^2 \right] / \left[ \gamma_{i-1}^2 f_{it-1}(\alpha)^2 + \sigma^2 h_{it-1}(\beta)^2 \right], \quad t = 2, \dots, T$$

Stacking these conditions over  $t$  and explicitly using the estimator of  $\theta_0$  constructed in the preceding section, the conditional moment used to build an estimator of  $\delta_0$  are given by:

$$(36) \quad E[v_i(\theta_0, \delta_0)/x_i] = 0$$

In analogy with our choice of instruments for the conditional mean model estimation we chose instruments of the form  $wv_i(\ddot{\theta}_N, \dot{\delta}_N) \equiv \text{Diag}(wv_{i2}(\ddot{\theta}_N, \dot{\delta}_N), \dots, wv_{it}(\ddot{\theta}_N, \dot{\delta}_N))$  where  $\dot{\delta}_N$  is an initial estimator of  $\delta_0$  and:

$$(37) \quad wv_{it}(\ddot{\theta}_N, \dot{\delta}_N) = - \frac{\partial \left[ \left[ \ddot{\gamma}_{i,N}^2 f_{it}(\ddot{\alpha}_N)^2 + \dot{\sigma}_N^2 h_{it}(\dot{\beta}_N)^2 \right] / \left[ \ddot{\gamma}_{i-1,N}^2 f_{it-1}(\ddot{\alpha}_N)^2 + \dot{\sigma}_N^2 h_{it-1}(\dot{\beta}_N)^2 \right] \right]}{\partial \delta^t} \\ \times \left[ \ddot{\gamma}_{i-1,N}^2 f_{it-1}(\ddot{\alpha}_N)^2 + \dot{\sigma}_N^2 h_{it-1}(\dot{\beta}_N)^2 \right]$$

Given that the parameter vector  $\theta_0$  is not solely included in the instruments, the construction of the efficient GMM estimator of  $\delta_0$  (or of its corresponding one step estimator) based on the orthogonality condition:

$$(38) \quad E[wv_i(\theta_0, \delta_0)'v_i(\theta_0, \delta_0)] = 0$$

is a little bit more complicated than the ones presented in the preceding sections. Using the estimators  $\hat{\delta}_N$  and  $\hat{\theta}_N$ , the efficient GMM estimator of  $\delta_0$  based on (38) can be defined as:

$$(39) \quad \hat{\delta}_N \equiv \underset{\delta}{\text{Argmin}} \left[ \sum_{i=1}^N wv_i(\hat{\theta}_N, \hat{\delta}_N)'v_i(\hat{\theta}_N, \delta) \right]' \hat{\Psi}_N^{-1} \left[ \sum_{i=1}^N wv_i(\hat{\theta}_N, \hat{\delta}_N)'v_i(\hat{\theta}_N, \delta) \right]$$

where  $\hat{\Psi}_N$  is an estimator of  $\Psi_0 = V[wv_i(\hat{\theta}_N, \hat{\delta}_N)'v_i(\hat{\theta}_N, \delta_0)] = V[wv_i(\theta_0, \delta_0)'v_i(\hat{\theta}_N, \delta_0)]$ . As shown by, e.g., Newey (1993),  $\hat{\Psi}_N$  can not be constructed simply as the sample counterpart of  $\Psi_0$  computed at  $\hat{\delta}_N$  and  $\hat{\theta}_N$ . This can be shown by deriving the first order Taylor expansion of  $\Psi_0$  around  $\theta_0$  and  $\delta_0$ :

$$(40) \quad \Psi_0 = V \left[ \sum_{i=1}^N wv_i(\theta_0, \delta_0)'v_i(\theta_0, \delta_0) / \sqrt{N} + E \left[ wv_i(\theta_0, \delta_0)' \partial v_i(\theta_0, \delta_0) / \partial \theta' \right] \sqrt{N} (\hat{\theta}_N - \theta_0) \right]$$

This expression explicitly takes into account the fact that  $\hat{\theta}_N$  is an estimator of  $\theta_0$ . Gouriéroux et al. have shown that a consistent estimator of  $\Psi_0$  ( $\hat{\Psi}_N$ ) can be constructed as the sample counterpart of:

$$(41) \quad \Psi_0 = E \left[ wv_i(\theta_0, \delta_0)' v_i(\theta_0, \delta_0) v_i(\theta_0, \delta_0)' wv_i(\theta_0, \delta_0) \right] \\ + N F_0 (J_0' \Sigma_0^{-1} J_0)^{-1} F_0' - D_0 F_0 C_0 - C_0' F_0' D_0'$$

where  $F_0$ ,  $C_0$ ,  $D_0$ ,  $J_0$  and  $\Sigma_0$  are respectively defined as:

$$(42a) \quad B_0 \equiv E \left[ wv_i(\theta_0, \delta_0)' \partial v_i(\theta_0, \delta_0) / \partial \theta' \right],$$

$$(42b) \quad C_0 \equiv E \left[ wr_i(\theta_0)' r_i(\theta_0) v_i(\theta_0, \delta_0)' wv_i(\theta_0, \delta_0) \right]$$

$$(42c) \quad D_0 \equiv N B_0 (J_0' \Sigma_0^{-1} J_0)^{-1} J_0' \Sigma_0^{-1} \quad \text{where} \quad (J_0' \Sigma_0^{-1} J_0)^{-1} = V \left[ \sqrt{N} (\ddot{\theta}_N - \theta_0) \right]$$

$$(42d) \quad J_0 \equiv E \left[ wr_i(\theta_0)' \partial r_i(\theta_0) / \partial \theta' \right]$$

$$(42e) \quad \Sigma_0 \equiv E \left[ wr_i(\theta_0)' r_i(\theta_0) r_i(\theta_0)' wr_i(\theta_0) \right].$$

computed at  $\dot{\delta}_N$  and  $\ddot{\theta}_N$ .

### 4.3 Results and implications

Our application uses a Cobb-Douglas form in the three considered inputs for  $h(\cdot)$ . Thus  $u_{it}$  may be rewritten as:

$$(43) \quad u_{it} \equiv \varepsilon_{it} \gamma_i \sigma_0 h(x_{it}, \beta_0) = \varepsilon_{it} \gamma_i \sigma_0 \exp(\ln x_{it}' \beta_0)$$

where  $\beta_0 \equiv (\beta_1, \dots, \beta_K)'$  is a vector of 3 elements.

The one step efficient estimator  $\ddot{\delta}_N$  based on the 12 orthogonality conditions (38) is constructed as described above (see section 2) with the following initial Non Linear Two Stage Least Squares estimator:

$$(44) \quad \dot{\delta}_N \equiv \underset{\delta}{\text{Arg min}} \left[ \sum_{i=1}^N q_i' v_i(\ddot{\theta}_N, \delta) \right]' \left[ \sum_{i=1}^N q_i' q_i \right]^{-1} \left[ \sum_{i=1}^N q_i' v_i(\ddot{\theta}_N, \delta) \right]$$

where  $q_i$  is defined as  $q_i \equiv \text{Diag}(q_{i2}, \dots, q_{iT-1})$  with  $q_{it} \equiv (1, \Lambda x_{it}, \dots, \Lambda x_{iT})$  and  $\Lambda x_{it} \equiv (\ln x_{1it}, \dots, \ln x_{Kit}; x_{1it} \ln x_{1it}, \dots, x_{Kit} \ln x_{Kit}; \ln x_{1it}/x_{1it}, \dots, \ln x_{Kit}/x_{Kit})$ .

Table 4. Parameter estimates of the yield conditional standard deviation model (and asymptotic standard deviation estimates).

Conditional standard deviation parameter estimates (and asymptotic standard deviation estimates)			
Input coefficients			
Pesticides	Fertilizers	Other variable inputs	$\ddot{\sigma}_N$
Cobb-Douglas parameters			
-1.857 (0.539)	-0.291 (0.566)	0.596 (0.356)	0.044 (0.034)

The results are reported in Table 4. The Hansen's (1982) test statistic estimate is equal to 15.06. As a consequence, the model of the yield conditional variance (43) can be accepted with only a low confidence level:  $P(\chi^2(8) > 15.06) \cong 0.07$ . However, as expected, the results show that pesticides are risk (measured as yield variance) decreasing inputs. An 1% increase in pesticide use is estimated to lead to a decrease in yield variance equal to 3.714%. This effect is statistically significant. Only Antle (1988) found similar results, at least to our knowledge. The fertilizers and the other inputs are shown not to significantly affect yield variance. This result is rather surprising when compared those of the studies using US data. A positive effect on yield variance has been found for fertilizers by Just & Pope (1979), Babcock et al. (1987) or Love & Buccola (1991).

## 5. Concluding comments

In the context of agricultural production analysis, the advantage of panel data over single cross-sections or time series is twofold.

First, the combination of cross-sections and time series allows the examination of producers' behaviour dynamics even if the observation period is limited. In particular, although our panel data set covers only four years it allows to test some important aspects of farmers' behaviour dynamics. From an econometric point of view, the serial dimension of a panel data set allows the use of instrumental variable techniques to circumvent some problems related to the endogeneity of some variables. The implementation of these techniques does not require the use of "external" variables able to identify the parameters of interest. This is due to the availability of predetermined lagged variables as long as the dynamics of the considered technology satisfies certain conditions (see, e.g., Mairesse & Hall 1994, Hall & Mairesse 1995). However it should be noted that the construction of orthogonality conditions integrated over  $i$  on the basis of conditional expectations integrated over  $t$  without further precautions may originate estimation problems in certain circumstances (see, e.g., Chamberlain 1984 or Hayashi 1992). This point is crucial in our study since the use of panel data sets with small  $T$  to investigate dynamic patterns of considered phenomena relies heavily on the validity of this construction.

Second, panel data allow inference and estimation robust to heterogeneity which is usually present in micro-economic data. This advantage, firstly pointed out by Mundlak (1961) in an agricultural production context, is not considered so far in this paper. However some studies conducted with this data set show that the omission of this eventual heterogeneity and of its implications on the choice among inference methods is of considerable importance. In particular, this omission would result in the rejection of the strict exogeneity hypothesis and in

the conclusion that the sample farmers use pesticides below their expected profit maximizing level (Carpentier & Weaver 1995a and b, Carpentier 1995).

The results presented in this paper provide some evidences to support the hypothesis that the French crop growers' pesticide choices are consistent with the expected risk averse utility maximization. Obviously, further investigation are needed to confirm this point. In particular, the troublesome estimated effects of the fertilizers and of the other variable inputs on the expected yield lead us to be prudent in the interpretation of our results. However, the inference method which is used in this paper seems to provide enough promising results to constitute a strong empirical background for future studies about farmers' behaviour toward input use.

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