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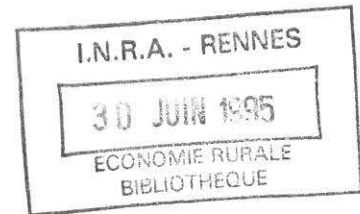
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*Heterogeneity in Production Technologies
and Estimation of the Pesticide Productivity*

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June 1995

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1. Introduction

In agricultural production processes pesticides represent a private input which only indirectly contributes to the productivity of other inputs. Further, the role of pesticides is conditional upon the presence of pests and the potential for or actual of damage. Within this context, pesticides are appropriately classified as damage control inputs which may be useful either in *precautionary* or *preventive* applications. The usefulness of pesticides does not extend to restoration of pest damage. While these characteristics of the private benefits of use of pesticides motivates their distinction from other private inputs which directly contribute to production, another aspect of their activity motivates further bases for their distinction. While the agricultural production process has traditionally been viewed as a closed process in which private inputs are coordinated to produce private outputs, in fact, the process is more accurately viewed as an open process jointly involving public good inputs and outputs, Weaver and Harper (1994), Weaver et al. (1995). From this perspective, pest infestations can be viewed as quasi-public inputs which are exogenous to the firm and pest treatments can be viewed as contributing to private output productivity as well as public good outputs which include environmental, human health, biodiversity, and pest resistance effects. To the extent that these public outputs are not adjusted to social optima, a role for public policy is motivated both in the short and long-run. In the short-run, a public interest exists in ensuring socially optimal utilization of all privately controllable inputs which result in private and public outputs. As is clear from the nonpoint pollution literature, determination of optimal policies necessary to induce such socially desirable input vectors depends upon knowledge of the marginal contributions of inputs such as pesticides to productivity. In the long-run, public research policy can play an important role in inducing technologies that alter public good productivity. Such options include either direct provision of public research or induction of private research through design of patent life and the scope of performance covered by patents, Weaver (1994).

The focus of this paper is the reconsideration of the marginal productivity of inputs which may contribute to the public good outputs associated with pesticide use. Here, past studies have reported estimates of pesticide expected marginal productivity that are of substantial magnitude (see Table 1). The credibility of these estimates is initially questionable under a simple theory of the firm of profit maximization. In particular, these estimates typically exceed zero suggesting that pesticides may be underused. Clearly, under alternative theories of the firm or production choices, reported results may be consistent with firm level equilibrium¹. Lichtenberg and Zilberman (1986) hypothesized that these estimates of marginal productivity of pesticides, based on usual econometric production functions, were biased. They argued for use of a specification where pesticides play an *asymmetric* role as a damage control agent following specifications used in normative and biological studies. While applications of

¹For example, if firms are risk averse, or if production and consumption decisions of farm households are integrated by preference valuation of personal health effects of pesticide use by the operator, past results may be consistent with firm level equilibrium.

their functional form to single crop and pest situations (e.g. Babcock *et al.*, 1992) produced results that are consistent with the Lichtenberg and Zilberman (1986) specifications, results based on geographical and crop aggregates or multipest exposure (Carrasco-Tauber and Moffitt, 1992; Ramos, 1993; Crissman *et al.*, 1994) have not supported these specifications. These results suggest that the asymmetric specification for the role of pesticides may not lie at the root of past estimates of marginal productivity that exceed marginal costs.

Table 1. Marginal return value of pesticide expenditure estimates (US or Can. \$) found in the literature^a

Reference	Sample Characteristics	Year of the data set	Indicator of Economic Efficiency in Use of Pesticides ^c
Headley (1968)	States of the US (Aggregated production)	1963	Between 2.90 and 4.66
Fischer (1970)	Canadian producers of apples	1966	Between 1.34 and 12.80
Campbell (1976)	Canadian producers of fruits	1970	Between 10.90 and 11.78
Carrasco-Tauber and Moffitt (1992)	States of the US (Aggregated production)	1987	4.94
Babcock <i>et al.</i> (1992)	North Carolina producers of apples	1976-1978	~ 3.40 ^b

a These estimates rely on Cobb-Douglas production function estimations.

b Computed from the information contained in Babcock *et al.* (1992).

c Under Cobb-Douglas technology, an expected maximizing firm would set its production elasticity equal to the expenditure share of revenue. Equivalently, the marginal revenue product with respect to pesticide expenditure would be unity. We define the indicator of economic efficiency as that marginal revenue product minus unity implying economic efficiency is indicated by zero.

Similarly, the presence of significant levels of risk aversion have not been established for agriculture. To the contrary, past studies have consistently found estimates that generally indicate small degrees of risk aversion (e.g. Pannell (1991) and, Saha *et al.* (1994)). Together these results leave in question the credibility of past estimates of the marginal productivity of pesticides.

The objective of this paper is to present evidence concerning the existence of a further basis for bias in past estimates of pesticide productivity: *heterogeneity bias*. To proceed, we will first review the extent and structure of heterogeneity found in agriculture by considering evidence for a panel of French crop farmers. Simple descriptive statistics suffice to illustrate that persistent heterogeneity exists across these firms. Next, we review the well known implication of such heterogeneity that econometric estimates will be biased when based on models which do not explicitly account for variation across firms. The implications of heterogeneity bias are explicitly considered and illustrated within the context

of a simple direct estimation of a production function. Here, the approach proposed by Chamberlain (1982,1984) is exploited to produce asymptotically unbiased estimates as well as to statistically test for the existence of fixed firm effects. Results confirm that substantial heterogeneity exists and, further, that the structure of such heterogeneity is correlated with pesticide and fertilizers choices. The implication of this result is that estimates would be biased if based on a specification which ignores the dependence between fixed effect measures of heterogeneity and the regressors. To close, we reconsider the role and nature of appropriate pesticide policy.

2. Heterogeneity in production technologies: Origins and evidence for the French crop sector

The neoclassical theory of the firm is often exploited under the maintained assumptions that firms face perfect and instantaneous information, as well as instantaneous and costless adjustment opportunities. Under such hypotheses, firms would immediately be forced by competitive market forces to adjust to exploit new technologies, leaving them each on the same production surface. If they all face the same price vector, then they could each be assumed to find an identical point on the production surface as optimal. Under such circumstances, the firms can safely be viewed as homogeneous. Where technology is also characterized by constant returns-to-scale, the firms are exactly replicable and a single firm may be used to represent an industry composed of more numerous identical firms. Suppose, instead, that firms jointly face a common technology though quasi-fixity of factors exists due to adjustment costs across an identical subvector of inputs. In this case, a distribution of *heterogeneous* firms would be induced by common underlying technology and prices. The firms would be heterogeneous and differentiable with respect to their positions on the common production surface, their positions being different due to differences in quasi-fixed factors. This point will be in a related paper. In this case, the firms may be viewed as heterogeneous in the sense that they are operating on technical surfaces which are differentiated by homothetic displacement of common surface as quasi-fixed factor levels vary.

We consider evidence concerning the extent of such heterogeneity among crop farmers in France. First, the importance of pesticides in crop production is illustrated by their 75% share of the market for pesticides in France. More than 40% of the sales of pesticides, including 21% of the market share of fungicides, were used to grow cereals (Brouwer *et al.*, 1994). We first assess heterogeneity using simple descriptive statistics based on data drawn from the European Accountancy Data Network for 496 farmers in France for the years 1988 to 1990 (SCEES, 1989; Ivaldi *et al.*, 1994). The sample includes farms from three regions of France : Ile-de-France, Centre and Champagne. These represent a homogeneous area within the Paris basin. Agriculture in this region is dominated by cereals and oilseeds produced using intensive cropping technology. The revenue distribution 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%). In Table 2, summary data of the output and input data are presented² based on a disaggregation of the input vector used by past studies, e.g. Headley (1968) and Carrasco-Tauber and Moffitt (1992). Here, other inputs includes energy, seeds, crop services. Several conclusions can be drawn from Table 2. First, chemical input expenses individually account for large percentages of revenue suggesting substantial intensity in land use exists through the application of chemical. Second, the standard deviations indicate variation by year within the cross-sectional dimension. By comparison with the means, it is clear substantial variation exists within the cross-sectional dimension of this data. If input expenditure shares of revenue are interpreted as indicators of production characteristics³, this variation implies substantial variation in production across the cross-section dimension. The stability of this variation relative to the means suggests that in the temporal dimension the scale of cross-sectional variation is persistent.

Table 2. Summary statistics of the data set of 496 French farmers from 1988 to 1990

	Variable means (and standard deviations)			
	1988	1989	1990	Total
Output (French Francs 87/ha)	8053.9 (2315.3)	7943.3 (2259.1)	8096.3 (2373.1)	8031.2 (2315.7)
Pesticides (French Francs 87/ha)	811.4 (260.6)	892.5 (285.2)	920.2 (288.0)	874.7 (281.8)
Fertilizers (French Francs 87/ha)	1008.0 (248.8)	1012.7 (264.6)	1013.2 (247.5)	1011.3 (253.6)
Other variable inputs (French Francs 87/ha)	1116.6 (520.0)	1100.8 (550.3)	1119.3 (570.0)	1112.2 (546.8)
Planted area (ha)	79.1 (44.9)	80.8 (46.8)	82.8 (48.7)	80.9 (47.2)

To better understand the structure of the variation in the data, we decompose the total variation into variation across individuals (between variation) and across time (within variation). For a variable z_{it} ($i=1, \dots, N$; $t=1, \dots, T$), define total variation as $VAR_{tot}(z_{it})$, between individual (i) variation as $VAR_{bet}(z_{it})$, and within individual variation as $VAR_{wit}(z_{it})$. The three are related by decomposition :

$$(1) \quad VAR_{tot}(z_{it}) = VAR_{bet}(z_{it}) + VAR_{wit}(z_{it})$$

²Data were deflated to 1987 French francs and areas were normalized to hectares.

³ For example, if the production function were Cobb-Douglas in form, and if firms could be assumed to be profit maximizers, then the expenditure shares could be interpreted as production elasticities.

where :

$$(2a) \quad VAR_{tot}(z_{it}) \equiv (NT-1)\hat{V}_{tot}(z_{it}) \equiv \sum_{i=1}^N \sum_{t=1}^T (z_{it} - z_{..})^2$$

$$(2a) \quad VAR_{bet}(z_{it}) \equiv (N-1)T\hat{V}_{bet}(z_{it}) \equiv T \sum_{i=1}^N (z_{i.} - z_{..})^2$$

$$(2c) \quad VAR_{wit}(z_{it}) \equiv N(T-1)\hat{V}_{wit}(z_{it}) \equiv \sum_{i=1}^N \sum_{t=1}^T (z_{it} - z_{i.})^2$$

and $z_{i.}$ and $z_{..}$ represent respectively the individual means ($i=1, \dots, N$) and the total mean of z_{it} :

$$(3a) \quad z_{i.} \equiv \frac{1}{T} \sum_{t=1}^T z_{it}$$

$$(3b) \quad z_{..} \equiv \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T z_{it}$$

Results of such a decomposition of variation are reported in Table 3 for yield and the variable inputs. These results further substantiate that between variation dominates within variation and accounts for over 70% of the total variation. From Table 2, the extent of total variability was shown to be large and persistent over time. Here, we see that a large proportion of that total variation is interpretable as originating from between variation. Again, this result is robust across yield and different inputs. These statistics motivate the need for further modeling of the variation to understand the origins of persistence of substantial between variation while within variation is small.

Table 3. Variation decomposition of the data set variables.

	Variables			
	Yield	Pesticides	Fertilizers	Other variable inputs
VAR_{tot}	797.9×10^3	11.8×10^3	9.6×10^3	44.5×10^3
Share of VAR_{wit} in VAR_{tot} (%)	23.3%	19.6%	26.8%	14.4%
Share of VAR_{bet} in VAR_{tot} (%)	76.7%	80.4%	73.2%	85.6%

Before considering such a structural explanation of the data, is useful to consider the extent and structure of covariation in the data. The total covariation, $COV_{tot}(z_{1it}, z_{2it})$, is decomposable into within individual covariation $COV_{wit}(z_{1it}, z_{2it})$ and between individual covariation $COV_{bet}(z_{1it}, z_{2it})$ as follows for any two covariates (z_{1it}, z_{2it}) :

$$(4a) \quad COV_{tot}(z_{1it}, z_{2it}) \equiv (NT - 2)\hat{COV}_{tot}(z_{1it}, z_{2it}) \equiv \sum_{i=1}^N \sum_{t=1}^T (z_{1it} - z_{1i\cdot})(z_{2it} - z_{2i\cdot})$$

$$(4a) \quad COV_{bet}(z_{1it}, z_{2it}) \equiv T(N - 2)\hat{COV}_{bet}(z_{1it}, z_{2it}) \equiv T \sum_{i=1}^N (z_{1i\cdot} - z_{1\cdot\cdot})(z_{2i\cdot} - z_{2\cdot\cdot})$$

$$(4c) \quad COV_{wit}(z_{1it}, z_{2it}) \equiv N(T - 2)\hat{COV}_{wit}(z_{1it}, z_{2it}) \equiv \sum_{i=1}^N \sum_{t=1}^T (z_{1it} - z_{1i\cdot})(z_{2it} - z_{2i\cdot})$$

Table 4 presents results for this decomposition. Results confirm the importance of between covariation which is found to account for more than 85% of total covariation for each variable pair. Further, total covariation of inputs and yield is dominated by between variation. Within variation accounts for less than 12% of the total covariation. Differences in particular input use is indicated by covariation of input pairs. Here, total covariation is also predominantly accounted for by between rather than within variation. These conclusions are consistent with all input pairs. The general conclusion that producers operate at different positions in production space appears warranted by these results. Signs of covariations of inputs and yield are consistent with nonnegative marginal productivity of inputs.

Table 4. Covariation decomposition of each pair of the data set variables.

		Pesticides	Fertilizers	Other variable inputs
	COV_{tot}	48.5 x10 ³	30.4x10 ³	64.3x10 ³
Yield	Share of COV_{wit} in COV_{tot} (%)	8.6%	9.6%	11.2%
	Share of COV_{bet} in COV_{tot} (%)	91.4%	90.4%	88.8%
	COV_{tot}		2.5x10 ³	5.1x10 ³
Pesticides	Share of COV_{wit} in COV_{tot} (%)		12.8%	8.0%
	Share of COV_{bet} in COV_{tot} (%)		87.2%	92.0%
	COV_{tot}			5.4x10 ³
Fertilizers	Share of COV_{wit} in COV_{tot} (%)			5.8%
	Share of COV_{bet} in COV_{tot} (%)			94.2%

3. Heterogeneity and econometric productivity measures

The existence and structure of variation of input and output combinations across individual farmers and across time was established in the previous section. In this section, we review the econometric implications of the between variation observed in the French panel data. Mundlak (1961) provided an early consideration of the implications of cross-sectional variation in product vectors for estimation of production functions. In particular, where such variation can be interpretable as originating from homothetic displacements of individual production surfaces, Mundlak noted that estimation of marginal productivities of inputs using a specification which ignores such individual displacement would result in inconsistent estimates and what he labeled as *heterogeneity bias*. Begin by considering a generally specified homothetic production function such as the Cobb-Douglas function:

$$(5a) \quad y_{it} = \gamma_{it} + \sum_{k=p,e,d} \alpha_{kit} x_{kit} + u_{it}; \quad t = 1, \dots, T; \quad i = 1, \dots, N$$

where y_{it} is the natural logarithm of yield, x_{pit} is the natural logarithm of pesticide use, x_{eit} is the natural logarithm of fertilizer use, x_{dit} is the natural logarithm of other variable input use, and u_{it} is a random disturbance. In general, this specification admits nonhomothetic displacements of individual production functions over individuals and over time. Where displacement is homothetic, the α_{kit} would be constant over i and t , though variation in γ_{it} over each dimension would be consistent with homotheticity. Suppose homothetic displacements over time are purely random while those over the cross-sectional dimension are constant over individuals. Our motivation of such displacements by reference to differences in quasi-fixed factor endowments is consistent with those of Mundlak (1961, 1990), and Chamberlain (1982, 1984)⁴. In this case, we may simplify (5a) as :

$$(5b) \quad y_{it} = \gamma_i + \sum_{k=p,e,d} \alpha_k x_{kit} + u_{it}; \quad t = 1, \dots, T; \quad i = 1, \dots, N$$

$$(5c) \quad E(u_{it}) = 0$$

We elaborate this traditional specification by noting that the disturbance is typically unknown to the farmer implying (5c) can be augmented by:

$$(6) \quad E(u_{it}/x_{it}) = 0$$

where $x_{it} \equiv (x_{pit}, x_{eit}, x_{dit})'$. From the perspective of observed data which reflects economic choices, if the disturbance is interpreted as reflecting random homothetic shifts in the production surface, then

⁴ It is often the case that many quasi-fixed inputs are unobservable even in the richest data sets, e.g. soil quality, management quality, climatic characteristics that are site specific to the farm. In all cases, γ_i may be interpreted as determined by the quasi-fixed factors. This type of interpretation is feasible for Cobb-Douglas functional forms. In this spirit, we are free to interpret

$\gamma_i = \sum_k \gamma_k \theta_{ki}$ where θ_{ki} is a time invariant quasi-fixed factor, see e.g. Hausman and Taylor (1981).

(6) is interpretable as implying that the origins of all such shifts are independent of economic choices of x_{it} . An important implication of this condition is that if condition (6) could be imposed as a constraint on the estimation of (5b), then the inconsistency in estimation induced by the simultaneity of choices of x_{it} and y_{it} could be circumvented. Further, while the parameters of a production function may be presumed to be known to the decision maker, they are unknown to the econometrician. This observation motivates a further restriction on the expectation of u_{it} , i.e. :

$$(7) \quad E(y_{it}/x_{it}, \gamma_i; \alpha) = \gamma_i + \sum_{k=p,e,d} \alpha_k x_{kit} \Leftrightarrow (5a) \text{ and } E(u_{it}/x_{it}, \gamma_i; \alpha) = 0$$

Estimation of (5) clearly calls for cross-sectional and temporal variation to allow estimation of the firm specific effects indicated by γ_i . Use of only cross-sectional data would result in inconsistent estimators, Chamberlain (1982, 1984). The logic of this argument follows directly from consideration of estimation of (5) subject to $\gamma_i = \bar{\gamma}$, allowing (5a) to be written :

$$(8) \quad y_{it} = \bar{\gamma} + \sum_{k=p,e,d} \alpha_k x_{kit} + e_{it}$$

where $e_{it} = u_{it} + (\gamma_i - \bar{\gamma})$ and $E(e_{it}/x_{it}) = 0$. If, instead, (7) were true, the associated disturbances and resulting residuals would be correlated with the regressors and result in asymptotically biased estimated of $\alpha \equiv (\alpha_p, \alpha_e, \alpha_d)'$. Most important, estimation of the misspecification using a single cross-section would preclude detection of such bias, Hoch (1955), Mundlak (1961) and Chamberlain (1982, 1984)⁵.

Within the context of a linear function such the production function, the intuition of this argument is illustrated in Figure 1. Consistent with results of tables discussed above, a positive response of the conditional expectation of y_{it} to x_{it} is presented, however, it is also presumed the x_{it} and γ_i are positively correlated.⁶ The thick lines represent the observed data distributions for a set of individuals over a time series. Estimated individual regressions based on (7) are indicated by the solid lines. In contrast, a regression based on (7) restricted by $E(\gamma_i/x_{it}) = E(\gamma_i) = \bar{\gamma}$. Estimation of this model would result in the dotted lines.

The dependence of the bias on the correlation between x_{it} and γ_i is apparent by decomposing the homothetic shift represented by γ_i into a deviation representing the heterogeneity bias and the mean, e.g. (7) can be written:

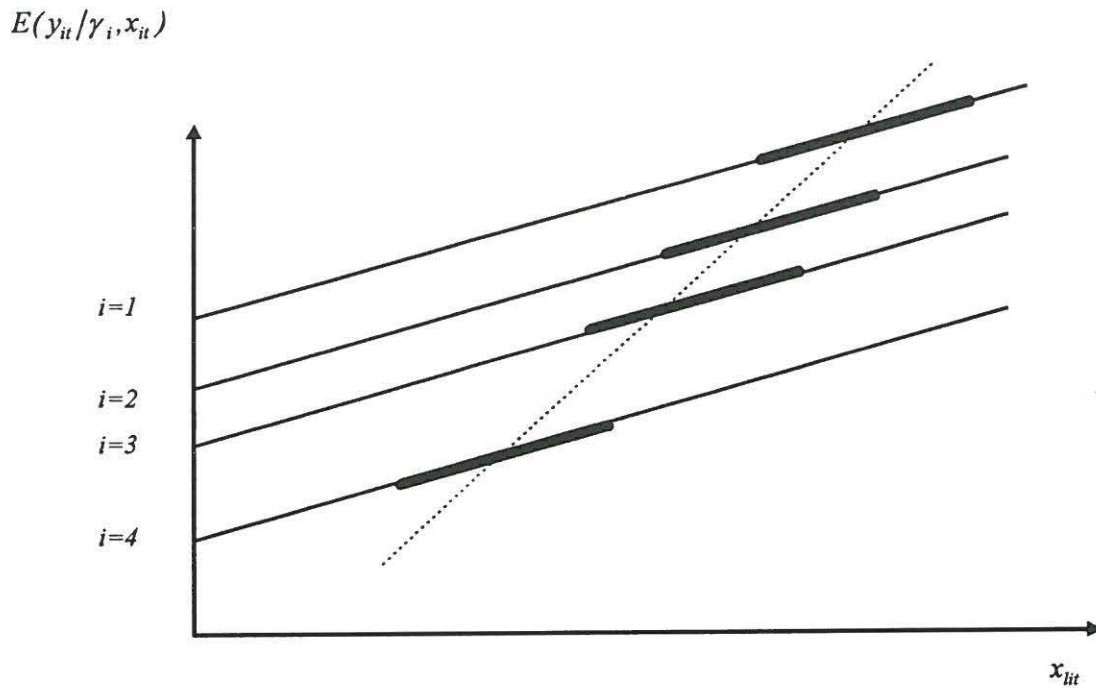
$$(9) \quad E(y_{it}/x_{it}) = E(\gamma_i/x_{it}) + \sum_{k=p,e,d} \alpha_k x_{kit} = \bar{\gamma} + \sum_{k=p,e,d} \alpha_k x_{kit} + E[(\gamma_i - \bar{\gamma})/x_{it}].$$

⁵ Campbell (1976) also notes this possibility.

⁶ Similar figures can be found in Mundlak (1961), Hsiao (1986) or Hsiao *et al.* (1994).

Where the bias and the regressors are positively correlated, the conditional expectation of the heterogeneity bias will also be positive.

Figure 1. Response of the conditional expectation of y_{it} to x_{lit} .
 (γ_i and x_{lit} are positively correlated, $\gamma_1 > \gamma_2 > \gamma_3 > \gamma_4$)



4. Inference on the French crop production technology using panel data

To allow assessment of the importance of the panel estimation approach presented here, we adopt the Cobb-Douglas form used by past studies. To begin, consider a less restrictive specification of (5b) in which temporal fixed effects are allowed as well as time varying regressor parameters :

$$(10a) \quad y_{it} = \gamma_t + \gamma_i + \sum_{k=p,e,d} \alpha_{kt} x_{kit} + u_{it}$$

As noted by Carpentier and Weaver (1995a and b), this specification allows for jointness in pest treatment processes and private input processes. In contrast, Lichtenberg and Zilberman (1986) argued for a separable form between these processes resulting in a functionally asymmetric specification of role of pesticides in agricultural production. Carpentier and Weaver argue that such a specification is both unnecessary and inappropriate where multiple pests occur and where the processes may be joint. Within the context of homothetic shifts, the parameter γ_t is interpretable reflecting disembodied, Hicks neutral technological progress or other temporally correlated effects. The parameters α_{kt} may be

interpreted as resulting from nonhomotheticity. Restating (7) for the generalization in (10a), we have the condition of exogeneity of input choices x_{it} conditionally on $\alpha_t \equiv (\alpha_{pt}, \alpha_{et}, \alpha_{dt})'$, γ_t and γ_i :

$$(10b) \quad E(y_{it}/\gamma_t, \gamma_i, \alpha_t, x_{it}) = \gamma_t + \gamma_i + \sum_{k=p,e,d} \alpha_{kt} x_{kit}$$

This assumption excludes the possible endogeneity of farmers' input choices with respect to u_{it} . It relies on the fact that farmers are assumed not to use the information generated during the production process, except possibly time effects common to all farmers such as some climate elements and/or new inputs which are easily observable and known by farmers when they chose their input quantities. Assumption (10b) is consistent with opinions of French agricultural scientists and previous studies on the same data set (Carpentier, 1995; Carpentier and Weaver, 1995a; 1995b).

In this paper, consistent estimation of equations (10) results from application of Chamberlain's (1982, 1984) Π matrix framework. The approach also allows specification tests of the model and provides a basis for robust inference on α_t and γ_t ($t=1, \dots, T$) using panel data sets where N tends to infinity, yet T is small. Estimation of this type of specification is complicated by an apparent lack of degrees of freedom. While cross-sectional variation would typically accommodate a small number of fixed time effects and time varying slopes as implied by small T , the presence of N individual effects challenges the data substantially. The pedestrian approach of introducing dummy variables for $N-1$ firm effects is infeasible since only NT observations are available. To proceed, we assume that the vectors (x_i, y_i) defined where x_i is $T \times K$ and y_i is $T \times 1$ are independent and identically distributed across individuals ($i=1, \dots, N$) with finite fourth moments and $E(x_i x_i')$ nonsingular. Details on estimation are available from the authors. In brief, the approach taken is to break the estimation into several steps.

To proceed, a set to T reduced forms in parameters is defined that describe the relationship between y and the elements of x . That is, suppose γ_i is a latent variable unknown by the econometrician which does not condition the expectation of y , i.e. :

$$(11) \quad E(y_{it}/\gamma_t, \alpha_t, x_i) = \gamma_t + E(\gamma_i/\gamma_t, \alpha_t, x_i) + \sum_{k=p,e,d} \alpha_{kt} x_{kit} + E(u_{it}/\gamma_t, \alpha_t, x_i)$$

where : $x_i' \equiv (x'_{i1}, \dots, x'_{iT})'$. Identification and consistent estimation requires further specification of $E(u_{it}/\gamma_t, \alpha_t, x_i)$. To start, suppose that :

$$(12) \quad E(u_{it}/\gamma_t, \alpha_t, x_i) = 0$$

where $x_i' \equiv (x'_{i1}, \dots, x'_{iT})'$. Condition (12) requires that input choices are strictly exogenous to output conditionally on time and farm effects (Chamberlain, 1982; 1984). In the absence of specific priors, a linear approximation is assumed allowing use of a general linear predictor of γ_i given x_i :

$$(13) \quad EL(\gamma_i / \gamma_t, \alpha_t, x_i) = \sum_{s=1}^T \sum_{k=p,e,d} \lambda_{ks} x_{kis}$$

This approach is motivated by interpretation of γ_i as a latent variable, the conditional expectation of which can be written as a linear function of all past, current, and future period elements of x_i . Under assumptions (11), (12) and (13), the correlation between γ_i and farmers' choices of input k , that is the potential source of heterogeneity bias on α_{kt} , can be detected by a test of $\lambda_{ks} = 0, \forall s = 1, \dots, T$.

The problem is now the estimation of the parameters of (11) and (13). These reduced forms can be estimated using a two step procedure.

To proceed, we first estimate the simple linear forms interpretable as reduced forms in parameters based on (11), (12) and (13):

$$(14) \quad EL(y_i / x_i) = \pi_{ot} + \sum_{s=1}^T \sum_{k=p,e,d} \pi_{kts} x_{kit}, \quad t = 1, \dots, T$$

where $x_i \equiv (1, x_i')$. The resulting parameter vector: $\pi_t \equiv (\pi_{ot}, \pi_{pt1}, \pi_{et1}, \pi_{dt1}, \dots, \pi_{ptT}, \pi_{etT}, \pi_{dtT})'$ provide a basis for determining the structural parameters of interest: α_t , γ_t and $\lambda \equiv (\lambda_{p1}, \lambda_{e1}, \lambda_{d1}, \dots, \lambda_{pT}, \lambda_{eT}, \lambda_{dT})'$.

Then, we estimate the parameters of (11) and (13) using Classical Minimum Distance (Chamberlain, 1982 and 1984; Newey and McFadden, 1995) or Asymptotic Least Squares estimators (Gouriéroux, Monfort and Trognon, 1985; Trognon, 1994). These estimators make use of the existing relationships between the vector of auxiliary parameters: $\pi \equiv (\pi_1', \dots, \pi_T')'$ and the vector of parameters of interest: $\beta \equiv (\gamma_1, \dots, \gamma_T, \alpha_1', \dots, \alpha_T', \lambda')'$:

$$(15) \quad \begin{aligned} \pi_{ot} &= \gamma_t \\ \pi_{kts} &= \lambda_{ks} \quad (t \neq s) \\ \pi_{ktt} &= \alpha_{kt} + \lambda_{kt} \end{aligned} \quad \forall t, s = 1, \dots, T; \quad \forall k = p, e, d$$

Our estimators of π and β are consistent and asymptotically normal. Furthermore, our inference framework uses estimators of the asymptotic variance-covariance matrix of our parameter estimators that are robust to any form of autocorrelation (given i) or heteroskedasticity on ε_{it} . This is an attractive property given our use of a linear predictor of γ_i to approximate its conditional expectation (Chamberlain, 1982; 1984), and the possibility that inputs such as pesticides or fertilizers affect yield variance (Just and Pope, 1978).

5. The results and their implications on pesticide policy design

Before presenting results, specification tests based on nested restrictions of π are reported to resolve specification. To proceed, we first present unrestricted estimates of β . Next, we restrict $\beta = \beta_\alpha$ to eliminate time varying marginal effects by imposing what has been labeled the Chamberlain restriction :

$$(16) \quad \alpha_{kt} = \alpha_k \quad \forall t = 1, \dots, T; \quad \forall k = p, e, d$$

Of further interest is the conditionality of firm effects which may be tested as the restriction that $\beta = \beta_\lambda$ a sufficient condition for which is simply:

$$(17) \quad \lambda_{kt} = 0 \quad \forall t = 1, \dots, T; \quad \forall k = p, e, d$$

Testing of this restriction is important to final estimation. Rejection implies that firm effects are correlated and implies that estimation must circumvent heterogeneity bias. Estimation subject to the restriction results in estimates corresponding to those resulting from use of only a single cross-section data. Finally, we jointly restrict β to $\beta_{\lambda\alpha}$ where (16) and (17) are imposed. This restricted estimator can be compared to the conventional error component estimator (Hsiao, 1986).

Results are summarized in Table 5. Restrictions (16) and (17) are each rejected for our sample, while restriction (15) can not be rejected. These results imply three main conclusions. First, the results are consistent (fail to reject) with the specification presented in equations (10a) and (12). Second, the results of these hypothesis tests fail to reject the hypothesis that the mean productivity elasticities of inputs are time-varying. Third, results indicate the existence in the sample analyzed of statistically significant correlations between the firm specific effects and farmers' input choices.

This last conclusion implies that heterogeneity bias would result if estimation were based on only one cross-section would be substantial. We estimate this bias to be in the range of 0.20 for pesticides, 0.10 for fertilizers, 0.07 for the other variable inputs for our sample. We conclude that omission of correlated firm effects would result, for this sample, in substantial overestimation of the marginal expected productivity estimates of these inputs. The marginal expected productivity losses associated with a reduction of the use of these inputs would be overestimated by factors of 3 for pesticides, 2 for fertilizers, and 1.5 for the other variable inputs.

If producers were profit maximizers, omission of the correlated firm specific effects would also imply substantial underestimation (in absolute value) of the own price elasticities of the demand of these inputs (in the short run). These results, however, are not supportable given results reported in Carpentier and Weaver (1995a). The positive and rather strong correlation between the firm effects and, fertilizer and pesticides use suggests that the firm effect latent variable can be interpreted as an intensification level measure. If this hypothesis were true it would mean that the own price elasticities of the variable input demands would be substantial in magnitude in the long run. For example, if an *ad valorem* tax were imposed on pesticide price, farmers would certainly be incited to adopt less

intensive technologies and, as a consequence, reduce drastically their pesticide uses. Similar remarks hold in the case of the output price decrease implemented by the 1992 CAP.

Table 5. Estimates of the four restricted π vectors (and asymptotic standard deviation estimates).

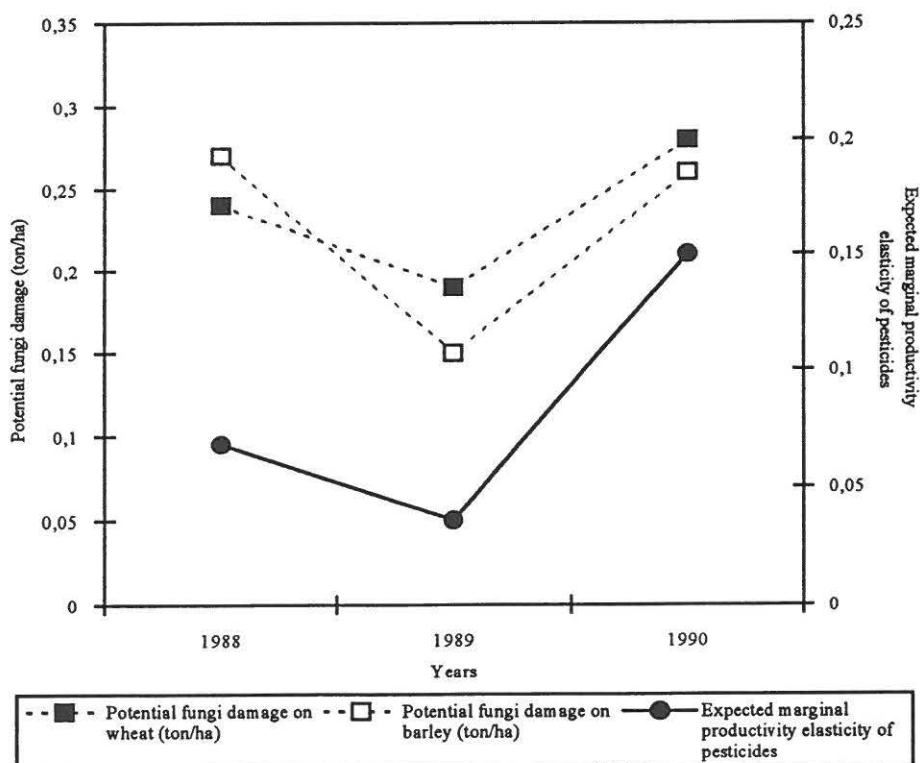
Year (t)	Fixed time effects (γ_t)	Expected productivity elasticities of inputs (α_{kt})			Correlation coefficients of input choices with the firm effects (λ_{kt})		
		Pesticides	Fertilizers	Other inputs	Pesticides	Fertilizers	Other inputs
Estimates of β (Test value : 10.99 ; Prob(Test value < $\chi^2(9)$)= 0.723)							
1988	2.314 (0.131)	0.063 (0.039)	0.107 (0.041)	0.159 (0.032)	0.275 (0.063)	0.031 (0.057)	0.079 (0.049)
1989	2.496 (0.124)	0.036 (0.038)	0.065 (0.037)	0.139 (0.030)	-0.009 (0.065)	0.113 (0.065)	0.020 (0.050)
1990	2.478 (0.118)	0.157 (0.040)	0.035 (0.041)	0.068 (0.031)	0.101 (0.054)	0.084 (0.063)	-0.093 (0.048)
Estimates of β_α (Test value : 47.28 ; Prob(Test value < $\chi^2(15)$)= 0.999)							
1988	2.393 (0.108)	0.096 (0.345)	0.081 (0.032)	0.116 (0.028)	0.247 (0.061)	0.072 (0.056)	0.114 (0.048)
1989	2.371 (0.109)	0.096 (0.345)	0.081 (0.032)	0.116 (0.028)	-0.014 (0.064)	0.092 (0.065)	-0.025 (0.049)
1990	2.386 (0.108)	0.096 (0.345)	0.081 (0.032)	0.116 (0.028)	0.104 (0.053)	0.088 (0.061)	-0.076 (0.047)
Estimates of β_λ (Test value : 123.67 ; Prob(Test value < $\chi^2(18)$)= 0.999)							
1988	2.952 (0.098)	0.267 (0.030)	0.187 (0.034)	0.190 (0.022)	0	0	0
1989	3.070 (0.089)	0.223 (0.027)	0.157 (0.032)	0.196 (0.020)	0	0	0
1990	2.956 (0.092)	0.369 (0.029)	0.127 (0.035)	0.134 (0.020)	0	0	0
Estimates of $\beta_{\alpha\lambda}$ (Test value : 158.75 ; Prob(Test value < $\chi^2(24)$)= 0.999)							
1988	0.299 (0.073)	0.282 (0.023)	0.171 (0.025)	0.171 (0.017)	0	0	0
1989	0.297 (0.074)	0.282 (0.023)	0.171 (0.025)	0.171 (0.017)	0	0	0
1990	2.962 (0.075)	0.282 (0.023)	0.171 (0.025)	0.171 (0.017)	0	0	0

Before considering estimated production elasticities it remains of interest to verify the statistical significance of their variation over time periods. To proceed, we test the hypotheses :

$$(18) \quad H_{0k} : \alpha_{kt} = \alpha_k, \quad \forall t = 1, \dots, T; \quad k = p, e, d$$

Results indicated that H_{0e} could not be rejected at the 5% level, that is that the expected productivity elasticities of pesticides and of the other variable inputs may be accepted as varying over time. These results are also consistent with evidence presented in the opening of the paper that supported the hypothesis that individual producer choices are relatively static over time⁷. The temporal variation in production elasticities for pesticides verifies that our empirical framework based on Cobb-Douglas production functions with time varying parameters is able to describe the role of these protective inputs in pest damage control.

Figure 2. Estimates of the expected productivity elasticities of pesticides and estimates of potential fungi damages on wheat and barley in Bretagne (Moquet, 1994), in 1988, 1989 and 1990



This point is further illustrated by the consistency of the estimated elasticities with observed temporal variation of pest damage. The production of our sample farmers is dominated by cereals, especially wheat and barley (on average, they represent respectively 41.8% and 9.2% of the farmers'

⁷ Carpentier and Weaver (1995a, 1995b) and Carpentier (1995) provide other proofs of (12).

revenue in 1990). In the context of intensive cropping technology, fungi infestation is one of the major source of damage on these crops. Fungicides accounted for 48% of the market of cereal pesticides in France in 1986 (Brouwer *et al*, 1994).

Figure 2 compares our estimates of the expected productivity elasticities of pesticides in 1988, 1989 and 1990 and the estimated potential fungi damages for wheat and barley in Bretagne (Moquet, 1994). It shows that potential fungi damages and estimates of the expected marginal productivity elasticity of pesticides are positively linked in this case. Although further investigation of this linkage must be pursued, this graphic indicates that our framework is consistent with the protective characteristics of pesticides.

To further consider the point, in Table 6 we compare our estimated elasticities with observed expenditure shares of revenue to assess the extent of *ex post* economic inefficiency implied.

Table 6. Sample mean point estimates of the expected productivity elasticities of the considered inputs and the shares of their cost in gross value of output (by year)^a.

	Year		
	1988	1989	1990
Pesticides			
Expected productivity elasticity estimate (Asymptotic standard deviation estimate)	0.068 (0.039)	0.036 ^b (0.038)	0.150 (0.040)
Cost share in gross value of output	0.107	0.111	0.123
Fertilizers			
Expected productivity elasticity estimate (Asymptotic standard deviation estimate)	0.070 ^b (0.032)	0.070 ^b (0.032)	0.070 ^b (0.032)
Cost share in gross value of output	0.137	0.134	0.140
Other variable inputs			
Expected productivity elasticity estimate (Asymptotic standard deviation estimate)	0.167 (0.032)	0.140 (0.030)	0.067 ^b (0.031)
Cost share in gross value of output	0.151	0.148	0.156

a The reported estimates correspond to estimates of β where the restriction $\alpha_{e1} = \alpha_{e2} = \alpha_{e3}$ is imposed.

b Significantly (at the 5% level) different from its associated cost share in gross value of output at the mean point of the considered year.

Table 6 presents sample means of estimated production elasticities and compares them to input expenditure shares in gross value of output. Under profit maximization and under the hypothesis that the production function is Cobb-Douglas, the production elasticity would equal the expenditure share for each input and each year. Where the former exceeds (is less than) the latter the input use is sub or super optimal relative to its expected profit maximizing level. Here, we find that fertilizers are overused by substantial degrees at the sample mean points. Pesticides are significantly overused in 1989, that is when the estimated potential fungi damages are relatively low. This result stands in striking contrast to results of previous studies which have consistently found estimated marginal productivities of pesticides to imply under-utilization (see Table 1.). Furthermore, this result suggests that farmers systematically use pesticides based on expectations of relatively high potential damages. This attitude would be consistent with farmers' risk aversion or prudence if pesticides were actually risk-reducing inputs. However, in every case, our results indicate that farmers' do not use the information generated during the production process to update their beliefs concerning pest infestations and, as a consequence, to adapt their pesticide use to the actual conditions prevailing in their fields.

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Appendix : Estimation Details

Suppose γ_i is a latent variable unknown by the econometrician which does not condition the expectation of y , i.e.

$$(A1) \quad E(y_{it}/\gamma_t, \alpha_t, x_i) = \gamma_t + E(\gamma_i/\gamma_t, \alpha_t, x_i) + \sum_{k=p,e,d} \alpha_{kt} x_{kit} + E(u_{it}/\gamma_t, \alpha_t, x_i)$$

where : $x'_i \equiv (x'_{i1}, \dots, x'_{iT})'$. Identification and consistent estimation requires further specification of $E(u_{it}/\gamma_t, \alpha_t, x_i)$. To start, suppose that :

$$(A2) \quad E(u_{it}/\gamma_t, \alpha_t, x_i) = 0$$

As noted in discussion of (7), equation (A2) represents an restriction implied by our interpretation of the model. Further, while (10b) required contemporaneous independence of input choices and u_{it} at time t for each firm, condition (A2) requires that input choices are strictly exogenous to output conditionally on time and farm effects (Chamberlain, 1982; 1984). That is, at time t , (x_{it}, \dots, x_{it}) and $(y_{it-1}, \dots, y_{it})$ are known to the firm, and (A2) rules out feed back between past levels of output and contemporaneous and future input choices. Intuitively, this condition rules out the presence of intertemporal constraints as a constraint on choices at time t . Equivalently, condition (A2) implies that $x_{i,s>t}$ incorporates no information on y_{it} , or u_{it} (Chamberlain, 1982, 1984; Hall and Mairesse, 1995) allowing (A1) to be written :

$$(A3) \quad E(y_{it}/\gamma_t, \alpha_t, x_i) = \gamma_t + E(\gamma_i/\gamma_t, \alpha_t, x_i) + \sum_{k=p,e,d} \alpha_{kt} x_{kit}$$

Specification of the conditional mean function for γ_i given x_i is difficult to motivate. In the absence of specific priors, a linear approximation is assumed allowing use of a general linear predictor of γ_i given x_i :

$$(A4) \quad EL(\gamma_i/\gamma_t, \alpha_t, x_i) = \sum_{s=1}^T \sum_{k=p,e,d} \lambda_{ks} x_{kis}$$

allowing (A3) to be written:

$$(A5) \quad EL(y_{it}/\gamma_t, \alpha_t, x_i) = \gamma_t + \sum_{s=1}^T \sum_{k=p,e,d} \lambda_{ks} x_{kis} + \sum_{k=p,e,d} \alpha_{kt} x_{kit}, \quad t = 1, \dots, T$$

For identification, we restrict the unconditional mean of $\gamma_i : E(\gamma_i) = 0$. The parameters λ_{ks} are simply the coefficients associated with x_{iks} in the linear regression of γ_i on x_i . Under (10a) and (A2), these parameters provide a basis for consistent estimation of α_t and γ_t as well as for testing for the correlation firm effects.

In addition to (A5) we may specify for each time period what can be interpreted as a reduced form relation between y and x . That is, define unrestricted linear predictors of y_{it} using on $^c x_i \equiv (1, x'_i)'$ as :

$$(A6) \quad EL(y_i / {}^c x_i) = \pi_{ot} + \sum_{s=1}^T \sum_{k=p,e,d} \pi_{kts} x_{kit}, \quad t = 1, \dots, T$$

These reduced forms provide T equations which reflect the structure of covariance among y and x . In the spirit of structural covariance analysis, estimated parameters from each these T equations : $\pi_t \equiv (\pi_{ot}, \pi_{pt1}, \pi_{et1}, \pi_{dt1}, \dots, \pi_{ptT}, \pi_{etT}, \pi_{dtT})'$ provide a sufficient basis for identification of the parameters of interest : α_t, γ_t and $\lambda \equiv (\lambda_{p1}, \lambda_{e1}, \lambda_{d1}, \dots, \lambda_{pT}, \lambda_{eT}, \lambda_{dT})'$.

$$(A7) \quad \begin{aligned} \pi_{ot} &= \gamma_t \\ \pi_{kts} &= \lambda_{ks} \quad (t \neq s) \\ \pi_{kt} &= \alpha_{kt} + \lambda_{kt} \end{aligned} \quad \forall t, s = 1, \dots, T; \quad \forall k = p, e, d$$

or more compactly in conventional notation:

$$(A8) \quad \pi = R\beta$$

where $\pi \equiv (\pi_1', \dots, \pi_T')'$, $\beta \equiv (\gamma_1, \dots, \gamma_T, \alpha_1', \dots, \alpha_T', \lambda')'$ and R is a restriction matrix.

Next consider estimation of β and explicit testing of the restrictions (A8) to allow inference concerning validity of (10a) and (A2) (Chamberlain, 1982, 1984). In addition, we will test three other restrictions of particular interest. We follow the inference method proposed by Chamberlain (1982, 1984). In the first step, OLS is used to compute a \sqrt{N} -consistent estimator of π : $\hat{\pi}$. Next, Asymptotic Least Squares (ALS) (Gouriéroux, Monfort and Trognon, 1985; Trognon, 1994)⁸ is used along with the first step estimator to compute a \sqrt{N} -consistent estimator of β : $\hat{\beta}$ and test its associated restriction. Noting $X \equiv ({}^c x_1, \dots, {}^c x_N)'$ and $Y_t \equiv (y_{1t}, \dots, y_{Nt})'$, OLS is applied to (A6) resulting in the \sqrt{N} -consistent estimator of π :

$$(A9) \quad \hat{\pi} \equiv \begin{bmatrix} \hat{\pi}_1 \\ \vdots \\ \hat{\pi}_T \end{bmatrix} \equiv \begin{bmatrix} (XX)^{-1} X Y_1 \\ \vdots \\ (XX)^{-1} X Y_T \end{bmatrix}$$

This estimator is strongly consistent and asymptotically normal :

$$(A10) \quad \sqrt{N}(\hat{\pi} - \pi) \xrightarrow{N \rightarrow +\infty} N(0, \Omega)$$

where :

$$(A11) \quad \Omega = E[(\varepsilon_i \varepsilon_i') \otimes \Phi_x^{-1} ({}^c x_i {}^c x_i') \Phi_x^{-1}]$$

$$(A12) \quad \Phi_x \equiv E({}^c x_i {}^c x_i')$$

⁸ This second step can receive various interpretations. Chamberlain (1982, 1984) uses the one developed within the Minimum Distance Estimation framework (see e.g. Newey and McFadden, 1995). Here we have chosen to consider this second step as the second step of an ALS estimation for ease of presentation.

$$(A13) \quad \varepsilon_i \equiv (\varepsilon_{i1}, \dots, \varepsilon_{iT})' \text{ and } \varepsilon_{it} \equiv y_{it} - \pi_i' \varepsilon_i x_i.$$

A consistent estimator of the asymptotic variance of $\hat{\pi}$ is given by (White, 1980) :

$$(A14) \quad \hat{\Omega} \equiv \frac{1}{N} \sum_{i=1}^N (\hat{\varepsilon}_i \hat{\varepsilon}_i') \otimes \hat{\Phi}_x^{-1} (\varepsilon_i \varepsilon_i') \hat{\Phi}_x^{-1}$$

$$(A15) \quad \hat{\Phi}_x \equiv \frac{1}{N} \sum_{i=1}^N (\varepsilon_i \varepsilon_i')$$

$$(A16) \quad \hat{\varepsilon}_i \equiv (\hat{\varepsilon}_{i1}, \dots, \hat{\varepsilon}_{iT})' \text{ and } \hat{\varepsilon}_{it} \equiv y_{it} - \hat{\pi}_i' \varepsilon_i x_i.$$

It is important to note that the consistency property of this estimator is robust to any form of autocorrelation (given i) or heteroskedasticity on ε_{it} . This is an attractive property given our use of a linear predictor of y_i to approximate its conditional expectation (Chamberlain, 1982; 1984), and the possibility that inputs such as pesticides or fertilizers affect yield variance (Just and Pope, 1978).

The second step can easily be developed is the ALS framework (Trognon, 1994). In this step we use the auxiliary parameter estimates $\hat{\pi}$ and the estimating constraint (A8) to build an ALS estimator of our parameter of interest β . Given (A8) and (A10) we can write :

$$(A17) \quad \hat{\pi} = R\beta + \mu \text{ where } \sqrt{N}\mu \xrightarrow{N \rightarrow +\infty} N(0, \Omega)$$

This equation can be interpreted of a linear model where the error vector μ is approximately distributed as $N(0, \Omega/N)$. An optimal ALS estimator of the parameter of interest β can be constructed as the vector b that minimizes (Gouriéroux, Monfort et Trognon, 1994):

$$(A18) \quad (\hat{\pi} - Rb)' \hat{\Omega}^{-1} (\hat{\pi} - Rb)$$

that is, the GLS estimator based on (27) (Trognon, 1994) :

$$(A19) \quad \hat{\beta} \equiv (R' \hat{\Omega}^{-1} R)^{-1} R' \hat{\Omega}^{-1} \hat{\pi}$$

This estimator is \sqrt{N} -consistent :

$$(A20) \quad \sqrt{N}(\hat{\beta} - \beta) \xrightarrow{N \rightarrow +\infty} N(0, (R' \Omega^{-1} R)^{-1}) \equiv N(0, \Psi)$$

A consistent estimator of its asymptotic variance is easily constructed as follow :

$$(A21) \quad \hat{\Psi} \equiv (R' \hat{\Omega}^{-1} R)^{-1}$$

where $\hat{\Omega}$ is given by (A14).

Given $\hat{\pi}$, $\hat{\beta}$ and $\hat{\Omega}$ a test of (A8) can be constructed by noting that (Chamberlain, 1982; 1984; Trognon, 1994) :

$$(A22) \quad \hat{T}(R) \equiv N(\hat{\pi} - R\hat{\beta})' \hat{\Omega}^{-1} (\hat{\pi} - R\hat{\beta}) \xrightarrow{N \rightarrow +\infty} \chi^2(q)$$

where q is the number of constraints imposed on π to get β , that is the number of lines of π minus the number of lines of β : $T(1+3T) - (T+3T+3T)$ in our case.