The contribution of pesticides to agricultural production : a reconsideration

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The Contribution of Pesticides to Agricultural Production: A Reconsideration

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Abstract

Past studies have found estimates of the marginal productivity of pesticides that suggest they are under used. The specification and estimation of the marginal productivity of pesticides is reconsidered. First, we reconsider the hypothesis posed by Lichtenberg and Zilberman (1986) that over estimation of the marginal productivity follows from use of symmetric functional specifications for the role of pesticides. Based on a generalized specification of nonneutral factor augmentation, we show that the Lichtenberg and Zilberman specification amounts to restrictions of the more general symmetric specification. In the presence of multiple pests and pesticides, we argue such restrictions are unattractive. We present a production function where factor augmentation functions reflect damage control and show they are not constrained within the closed interval [0,1], obviating an interpretation analogous to Lichtenberg and Zilberman as cumulative density functions which might be empirically modeled as specialized subfunctions using Pareto, exponential, Weibull, or logistic functional forms. On this basis, we argue that a symmetric functional specification across all inputs is preferred. Given that input applications in agriculture are likely to alter the variance of output, we generalize our specification to be consistent with the Just and Pope (1978) functional form. This specification is consistent with the interpretation of pesticides as damage control inputs, yet it also allows for an impact of pesticides on the variance of output. Within the context of applications based on panel data, substantial temporal and cross-sectional heterogeneity can be expected to follow from persistent differential exposure to sequences of pest infestations and climate events, as well as differences such as management efficiency across firms and time. To accommodate these characteristics, we further generalize the specification to include fixed effects. The resulting model is estimated using Generalized Method of Moments (GMM) (Hansen, 1982) estimators which are robust to any form of heteroskedasticity. Further, this approach provides a valuable basis testing behavioral hypotheses implicit in the model specification and necessary for estimation. Model specification is validated and results are presented for a panel data set drawn from French agriculture. Estimated marginal productivity of pesticides is found to be substantially smaller than that presented in past studies. The results suggest that the heterogeneity bias may be large when estimation is based on production

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functions that ignore correlated fixed effects. Finally, we conclude with implications of our findings on pesticide regulation design.

Introduction

Empirical estimates of the productivity of pesticides are necessary elements of both microeconomic management decisions as well as economic evaluations and design of public policy. At a microeconomic level, such estimates provide a basis for assessment of allocative efficiency or of the cost and revenue implications of changes in availability of pesticides. Where management of external effects of pesticides is a policy goal, estimates may be used to characterize the marginal benefits of pesticides. Within this context, accurate estimation of the marginal productivity of pesticides is critical for sound environmental policy design. Past econometric results have generated particular concern with respect to the existence of a general and persistent allocative inefficiency in the use of pesticides. Early positive econometric studies found estimates indicating that the marginal value of productivity of pesticides substantially exceeded their marginal costs, suggesting that pesticides are under used (Headley, 1968; Carlson, 1977; Campbell, 1976; McIntosh and Williams, 1992). These estimates were based on specification of the role of pesticides in agricultural production as symmetric to that of other inputs. In contrast, normative studies of pest management have specified pesticides as damage control agents, distinguishing them from other directly productive inputs (Headley, 1972; Hall and Norgaard, 1973; Talpaz and Borosh, 1974). Lichtenberg and Zilberman (LZ) (1986) hypothesized that past econometric estimates of marginal productivity of pesticides based on symmetric treatment of pesticides 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 studies. With respect to past econometric estimates, they demonstrated that if their asymmetric specification were the true production function, use of other functional forms which do not recognize a special role of pesticides as damage control agents would result in upward biased estimates of the productivity of pesticides. They interpreted this result as suggesting that use of their functional specification would result in estimates which do not imply persistent under utilization of pesticides as predicted by past studies. LZ retained the focus of past econometric studies by considering only the functional role pesticides in affecting the conditional mean of output. While applications of their functional form to single crop and pest situations (e.g. Babcock et al., 1992) produced results that are consistent with the LZ specification, results based on geographical and crop aggregates or multipest exposure (Carrasco-Tauber and Moffitt, 1992; Ramos, 1993; Crissman et al., 1994) have not supported the specification. Further, in contrast to the prediction of LZ, these studies found that estimates of marginal value productivity for pesticides exceed marginal costs despite their use of the LZ form, suggesting that their asymmetric specification for the role of pesticides may not lie at the root of past estimates of marginal productivity that exceed marginal costs.

In this paper, we reconsider the question of *"what is the marginal productivity of pesticides?"* by focusing on two issues: 1) functional specification of the role of pesticides and 2) the econometric approach used in estimation. In our reconsideration of the specification of production functions involving damage control agents, we provide a clear theoretical motivation for the use of a general specification which treats pesticides and other inputs symmetrically. Further, we clarify that the LZ specification of an asymmetric role for pesticides results only when technology is restricted by a particular groupwise weak separability of inputs. Next, we reconsider the econometric estimation of the marginal productivity of damage control agents such as pesticides and expand the focus of past studies in two directions. First, while firms are presumed to face the same technology, persistent heterogeneity across firms is allowed in the form of fixed effects introduced in the specification of the conditional mean of the production function. We demonstrate that where such heterogeneity exists and is correlated with input choices, estimates the marginal productivity may be biased when based on specifications which ignore the dependence between fixed effect measures of heterogeneity and the regressors. We directly estimate the production function and argue this approach is both parsimonious and free of specification errors which are likely to accompany either a primal or dual approach. Such approaches necessarily incorporate both technical and behavioral specifications. The specification introduced requires robust estimation methods based on the Hansen's (1982) Generalized Method of Moments (GMM) framework as introduced by Chamberlain (1992a) and Wooldridge (1991). The GMM approach provides a convenient basis for specification tests not conducted in past studies. In particular, exogeneity of inputs with respect to output, a condition necessary to avoid simultaneity biases in direct estimation, is tested. Second, the potential for pesticides, as well as other inputs, to alter the variance of output is considered following Just and Pope (1978). While theoretical and normative empirical studies have cited pesticides as risk altering inputs (Feder, 1979; Horowitz and Lichtenberg, 1994), econometric studies have ignored this possibility. Empirically, while such a distinction among inputs has largely been explored only for fertilizer (Just and Pope, 1979; Love and Buccola, 1991; Wan, et al., 1992; Babcock, et al., 1987), and water, buildings and land (Griffiths and Anderson, 1982; Wan et al., 1992; Wan and Anderson, 1993). Antle (1988) provides empirical evidence for pesticides, however, this possibility has not, in general, been explored. The remainder of the paper follows this outline of our contribution.

Technology Involving Damage Processes: A Generalized Specification

Technologies are often affected by damage processes. In most cases, the manager of the technology may take preventive action to reduce the impacts of an exposure to a damage process. In some cases, such *ex ante* or *ex post* damage control actions may eliminate damage completely. Past specifications of the role of pesticides in agricultural production have distinguished damage agents and damage processes as external to the production process. In this sense, management is viewed as focusing on application of inputs that directly contribute to potential production. This potential is viewed as affected by external damage processes to result in actual production. Management may alter the damage level through the application of damage control agents. This type of damage process has been specified using separable[1] damage functions which proportionately adjust potential production (Headley, 1972; Hall and Norgaard, 1973; Lichtenberg and Zilberman, 1986), e.g.

(1) $\quad y = f(x^D)\, g(x^P)$

where actual production y is proportional to potential production $f(x^D)$ achievable from a vector of direct inputs x^D. $g(\,)$ may be viewed as a damage abatement process that is manageable through the application of a vector of damage control agents, e.g. pesticides x^P. Given the definition of $f(x^D)$, the subfunction $g(x^P)$ is interpretable as a cumulative probability distribution defined over the closed interval $[0,1]$. For example, $g(x^P)$ is interpretable as $(1-d(x^P))$ where $d(x^P)$ is the percentage of destruction of potential production such that $g(0) = 0$ and $g(x^{P0}) = 1$ where x^{P0} indicates treatment sufficient to achieve elimination of the effects of the exposure on potential production. Lichtenberg and Zilberman (1986) and Carrasco-Tauber and Moffitt (1992) note that (1) is interpretable as a specific form of a more general form where x^P and x^D are only weakly separable :

(2) $\quad y = h(x^D, g(x^P))$.

However, in this case, the interpretation of $g()$ as a cumulative distribution function is not implied. The essence of the LZ specification is to treat pesticides asymmetrically in the production function. That is, while a Cobb-Douglas functional form would introduce separability among inputs, it would treat pesticides symmetrically with respect to other inputs. The LZ specification focuses on an asymmetric functional role of pesticides which is introduced explicitly through interpretation of the subfunction $g()$ as a cumulative density function.

The origin and rationale of this asymmetric functional specification for pesticides lies with the single pest/single pesticide case (e.g. Headley, 1972; Hall and Norgaard, 1973). These studies also noted that $g(x^P)$ would be conditional on the level of the pest population, z, allowing $g = g(x^P, z)$. Generalization of this type of specification to the case of multiple pests and multiple pesticides has been achieved by simply indexing z and x^P by type of pest, assumption of independence of pest damage and abatement processes $g_r(x_r^P, z_r)$, and definition of aggregate abatement $G = \prod_r g_r(x_r^P, z_r)$ (Babcock et al., 1992). While useful for field scale studies of singular damage processes, the usefulness of this specification for econometric study of more aggregate production processes can be criticized on several

[1] See Lau (1972).

grounds. For the case of multiple pests, the specification assumes damage and abatement processes are strongly separable across pests. This is not realistic. Even for a single damage process, (1) assumes the production process is strongly separable in the elements of x^P and x^D. In general, the specification of group-wise separability of the elements of x^P and those of x^D implies that optimal choices of the damage abatement inputs x^P and direct inputs x^D may be made independently. In other words, neither the presence of pests z, nor pest control inputs x^P will affect the marginal rate of substitution among direct inputs x^D. Similarly, the marginal rate of substitution between damage control agents is independent of the levels of direct inputs. This implies that damage abatement amounts to a homothetic shift of a potential production surface and use of direct inputs x^D homothetically shifts the damage abatement surface. Further, the specification of strong separability between the elements of x^D and x^P rules out any adjustment of direct inputs x^D as a result of the occurrence or treatment of damage processes. If damage abatement has nonhomothetic effects on production, then the specification in (1) or (2) would be inadequate.

Where production or damage processes are stochastic, an additive stochastic error has been added to the right hand side of (1) allowing its interpretation as the conditional mean of output (Headley, 1972; Hall and Norgaard, 1973; Lichtenberg and Zilberman, 1986). However, such a specification ignores the effects of direct inputs, damage agents, or damage control inputs on the variance of output (Just and Pope, 1978)[2]. To proceed, we pursue a fundamentally different approach which allows pest damage and pesticide use to more generally interact with the effects of direct inputs on both the mean and variance of outputs. This generalized specification also incorporates the a) the level of pest infestation, b) climatic events, and c) the economic characteristics of the firm (e.g. type of technology, quasi-fixed factors, management efficiency).

To proceed, define the production frontier as:

(3) $\quad f(y,x)=0$

where y is a $m \times 1$ vector of outputs, $x = (x_v, x_f)$, x_v is a $n \times 1$ vector of variable inputs, x_f is a $r \times 1$ vector of flows from quasi-fixed factors. The possibility of nonneutral factor effects resulting from vectors of exposures (z) and treatments (x^P) may be introduced using a vector of scaling functions:

(4) $\quad \phi_h = \phi_h(x^P, z)\, x_h^a$

where x_h^a is the level of the h^{th} input applied while x_h indicates the efficiency units affecting production[3], x^P is a vector of pesticide applications, and z is a vector of pest populations to which the production process is exposed. We further define $\phi_h(x^P, z)$ to satisfy the following properties: $\phi_h(0,0) = 1$, $\phi_h(x^P,0) \leq 1$, $0 < \phi_h(0,z) < 1$, $\phi_h(x^P,z) < 1$, $\phi_{hx^P}(x^P,0) \leq 0$, $\phi_{hz}(0,z) < 0$,

[2] Also see Horowitz and Lichtenberg (1994).

[3] This specification is analogous to that used in consideration of factor augmenting technical change. Alternatively, it is also the basis for input specific technical efficiency measures, see Schmidt and Lovell (1979).

$\phi_{hx^P}(x^P,z)<0$, and $\lim_{x^P \to x^{Pz}} \phi_h(x^P,z)=\phi_h^z$ where the superscript z indicates the efficient level given z and ϕ_h^z is the maximum value of the function $\phi_h(x^P,z)$. We may rewrite (3) using (4) as:

$$(5) \qquad f\left[y,\phi(x^P,z)x^a\right]$$

where $\phi()$ is a diagonal matrix composed of elements $\phi_h()$.

The functional properties of $f()$ are further described by:

$$(6) \qquad \frac{\partial f}{\partial x_h^a}=\frac{\partial f}{\partial x_h}\phi_h(x^P,z)$$

$$(7) \qquad \frac{\partial f}{\partial x^P}=\sum_h \frac{\partial f}{\partial x_h}\frac{\partial \phi_h}{\partial x^P}x_h^a$$

$$(8) \qquad \frac{\partial^2 f}{\partial x_h^a \partial z_s}=\phi_h\left(\sum_s \frac{\partial^2 f}{\partial x_k \partial x_h}\frac{\partial \phi_k}{\partial z_s}x_k^a\right)+\frac{\partial f}{\partial x_h}\frac{\partial \phi_h}{\partial z_s}$$

This generalized specification may be interpreted as taking a fundamentally different approach than the asymmetric specification used by Headley (1972), Hall and Norgaard (1973), and Lichtenberg and Zilberman (1986). By specification, (5) allows for a complete range of interactions among the elements of x^P, x^D, and z. From properties (6) - (8), it is clear that the factor effect processes described by $\phi(x^P,z)$, in general, would not generate effects constrained within the interval [0,1]. From this perspective, it is also apparent that where exposures or treatments generate nonneutral factor effects, and where those nonneutral processes are joint in the elements of the vectors x^P and z, then (5) may be usefully and equivalently rewritten in the general form to be used in this paper:

$$(9) \qquad g(y,x^a,x^P,z) \quad 0$$

Before proceeding, it is useful to establish the relationship between the proposed generalized approach in (5) and that employed by Headley (1972), Hall and Norgaard (1973), and Lichtenberg and Zilberman (1986). The following theorem establishes restrictions which are sufficient for (9) to take the form used by LZ.

Theorem 1

For the single output case, (5) may be written $y=f(\phi(x^P,z)x^a)$

The technology and damage control processes specified in (5)-(8) take the form

$$y=\phi(x^P,z)f(x^a)$$

only if i) $\phi_h(x^P,z)=\phi(x^P,z)$ *for all h, and ii)* $f(x)$ *is linearly homogenous in* x^a.

Together, conditions i) and ii) in Theorem 1 imply that $f()$ is groupwise separable in x^a and $\phi(x^P,z)$ is interpretable as in the LZ specification if $f(x^a)$ is interpretable as potential output. Importantly, this type of separability implies that the marginal rate of substitution between internal inputs x^D is independent of pest exposures z or treatments x^P. This implies that internal input choices may be made independently of pest exposures or treatments. Agronomic experience is inconsistent with this specification. The specification presented in (5) - (9) relaxes this groupwise separability. Further, it allows factor effect processes to be convex in x^P and conditional on z, relaxing LZ assumptions that $\lim_{x^P \to +\infty} \phi(x^P, z) = 1$ and $\phi(0, z) = 0$.

To avoid these restrictions on the factor effects, we focus on a general function $g()$ such as (9) as implied by the composition of $f()$ and $\phi(x^P, z)$. For the single output case, the production function may be written:

$$(10) \qquad y_{it} = g_{it}(x_{it}^a, x_{it}^P, z_{it})$$

where the subscripts i and t have been added to indicate an observation taken from the i^{th} firm and at the t^{th} time period. To accommodate heterogeneity implicit in panel data, we maintain that each farm's production surface (represented here by the function $g_{it}()$) represents a fixed homothetic displacement of the production surface associate with a common underlying technology. Similarly, the position of that production surface associated with the common technology at any time t is assumed to be a fixed homothetic displacement of a base technology. That is, we rewrite (10) as:

$$(11) \qquad y_{it} = \gamma_i \gamma_t g_{it}(x_{it}^a, x_{it}^P, z_{it})$$

Where y_{it} results from a stochastic production process where both mean and variance are conditioned by x_{it}, the Just and Pope specification for (11) can be adopted to provide an empirical framework. Within this specification, the impacts of stochastic error due to technical efficiency may affect both the conditional mean and variance of output [4]. Following Just and Pope (1978), the effects of inputs on the variance of output can be accommodated by specification of separable mean and variance effects. Applying this notion to (11), we have:

$$(12) \qquad y_{it} = \gamma_i \gamma_t f_{it}(x_{it}^a, x_{it}^P, z_{it}) + \varepsilon_{it} \gamma_i \gamma_t h_{it}(x_{it}^a, x_{it}^P, z_{it}).$$

Summarizing, the specification may be written[5]:

$$(13) \qquad y_{it} = \gamma_i \gamma_t f_{it}(x_{it}; \alpha) + u_{it} \qquad t = 1, \ldots, T \quad i = 1, \ldots, N$$

where

$$(14) \qquad u_{it} = \varepsilon_{it} \gamma_i \gamma_t h(x_{it}, \beta)$$

In addition to (13), we assume the following properties for ε_{it} and its relationship with x_{it}:

[4] Within the production frontier literature, stochastic error impacting Cobb-Douglas functions have been interpreted as stochastic deviations in technical efficiency, see e.g. Schmidt and Lovell (1979, 1980). Their specification of the error's impact on productivity of inputs parallels that of LZ by specifying factor neutral impacts as in Theorem 1.

[5] Where the parameter vectors are defined as follows: $\alpha' \equiv [\alpha_1, \ldots, \alpha_K; \gamma_2, \gamma_3/\gamma_2, \ldots, \gamma_T/\gamma_{T-1}]$ since we impose $\gamma_1 = 1$ for identification purpose and, $\beta' \equiv [\beta_1, \ldots, \beta_K; \sigma_\varepsilon]$. K is the number of considered inputs.

(15) $E[\varepsilon_{it}] = 0, \; V[\varepsilon_{it}] = \sigma_\varepsilon^2$

We add to these conditions on ε_{it}, the assumption that while x_{it}, γ_i, and γ_t are known to the firm, ε_{it} is not. While this assumption is traditionally implicit in econometric models, we state it explicitly and exploit its implications as restrictions in estimation:

(16) $E[\varepsilon_{it} / \gamma_i, x_{it}, \gamma_t] = E[\varepsilon_{it}] = 0$

These hypotheses have implications for both the conditional mean and variance of output :

(18) $E[y_{it} / \gamma_i, \gamma_t, x_{it}] = \gamma_i \gamma_t f(x_{it}),$

(19) $V[y_{it} / \gamma_i, \gamma_t, x_{it}] = \sigma_\varepsilon^2 \gamma_i^2 \gamma_t^2 h(x_{it})^2.$

Robust Estimation of the Marginal Productivity of Pesticides

The form of equation (13) requires estimation using panel data, the asymptotic bias (and inconsistency) of estimators based only on time series or only on a cross-section is simply stated following Chamberlain (1982, 1984). Consider estimation of (13). From the perspective of estimation, parameters of a production function are presumed to be known to the decision maker, yet unknown to the econometrician. Such is the case for γ_i in equations (13) and (18). Further, as is typically the case, we may presume that choices of inputs and outputs are functionally determined by the parameters of the production function implying they are exogenous to and correlated with those choices. By implication, omission of γ_i from the model (13) would result in errors that are correlated with the regressors. For a single cross-section, a regression of y_{it} on x_{it} would result in biased estimates of α. Further, no evidence of such a bias would be available from a single cross-section. This type of "heterogeneity bias" was recognized within the context of agricultural production by Hoch (1955), Mundlak (1961) and Chamberlain (1982, 1984)[6].

Applying this logic to the system (13)-(19), consider the graphical example presented in figure 1. Suppose that γ_t is unitary. Figure 1 indicates the response of the conditional expectation of y_{it} to x_{lit} when x_{lit} and γ_i are positively correlated [7]. The thick lines in bold represents the observed data distributions for a set of individuals over a time series. Estimated individual regressions based on (13) and (18) are indicated by the solid lines. In contrast, a regression based on (13) restricted by $E[\gamma_i / x_i] = E[\gamma_i] = \bar{\gamma}$ would allow (13) and (18) to be rewritten:

(20) $y_{it} = \bar{\gamma} \gamma_t f(x_{it}) + e_{it}$

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[6] Campbell (1976) also notes this possibility.

[7] Similar illustrations can be found in Mundlak (1961) and Hsiao (1986). Figure 1 would only be complicated by allowing $\gamma_t \neq 1$.

where $e_{it} = u_{it} + \gamma_t(\gamma_i - \bar{\gamma})f(x_{it})$ and $E[e_{it}/x_{it}] = 0$. Estimation of this model would result in the dotted lines. The dependence of the bias on the correlation between x_{lit} and γ_i can be illustrated more precisely. Taking the conditional expectation of y_{it} defined by (13) and written using (20) results in :

$$(21) \qquad E[y_{it}/x_{it},\gamma_t] = E[\gamma_i/x_{it},\gamma_t]\gamma_t f(x_{it}) = \bar{\gamma}\gamma_t f(x_{it}) + E[(\gamma_i - \bar{\gamma})/x_{it},\gamma_t]\gamma_t f(x_{it},t).$$

Here the heterogeneity bias is indicated by the last term.

The specification presented in (13) - (19) must be distinguished from that which would result from an error components specification of temporal and cross-sectional effects. For example, Griffiths and Anderson (1982) specify $\gamma_t = 1$ and $\gamma_i = \bar{\gamma}$ in (13) and use an additive, error components decomposition of ε_{it}. They estimate the resulting model using panel data. Their specification has been frequently applied to panel data (Babcock et al, 1987; Wan, Griffiths and Anderson, 1992; Wan and Anderson, 1993). However, where fixed temporal and individual effects exist which are correlated with input choices, specification (20) augmented with error components would remain a misspecification of equation (13)-(19) and the resulting estimators will remain biased despite the inclusion of error components.

Before proceeding, we extend (18) and (19) to require strict exogeneity inputs by rewriting them based on $x_i' \equiv [x_{i1}', \ldots, x_{iT}']$:

$$(22) \qquad E[y_{it}/\gamma_i, x_i, \gamma_t] = \gamma_i\gamma_t f(x_{it})$$

$$(23) \qquad V[y_{it}/\gamma_i, x_i, \gamma_t] = \sigma_\varepsilon^2\gamma_i^2\gamma_t^2 h(x_{it})^2.$$

Equations (22) and (23) augment the restrictions underlying (18) and (19). While (18) and (19) only require contemporaneous independence of input choices and u_{it} at time t for each firm, the conditions (22) and (23) require that input choices are strictly exogenous to output conditionally on time and farm effects (Chamberlain, 1982). That is, at time t, $x_{it},\ldots,x_{i1}$ and $y_{it-1},\ldots,y_{i1}$ may be assumed known to the firm and (22) and (23) rule out feed back between past levels of output and contemporaneous and future input choices. This specification is equivalent to the hypothesis that choices at time t are not constrained by intertemporal inertial output adjustment processes. This follows since Conditions (22) and (23) imply that $x_{i,s+1}$ incorporates no information on y_{it}, (Chamberlain, 1982, 1984; Wooldridge, 1991; Mairesse and Hall, 1994; Hall and Mairesse, 1995). Importantly, (22) also implies that mean of u_{it} conditional on x_{it} is zero, that is stochastic shocks occurring as a result of pest infestations at time t do not affect input choices at time t. While some uncertainty concerning the validity of this restriction must be acknowledged *a priori*, our approach provides a basis for testing it explicitly.

To achieve consistent estimation of model (13)-(15) and (22)-(23), we adopt Chamberlain's (1992a) and Wooldridge's (1991) application of Hansen's (1982) GMM. This approach provides a convenient basis for specification tests of our model. Further, Wooldridge (1991) and Chamberlain (1992a) showed that the approach provides a basis for robust inference on α and β using panel data sets where N tends to infinity, yet T is small. While a small T allows direct parameterization of the fixed time effects using dummy variables, an alternative approach must be taken for the individual effects. That is, given N firm effects, the parameters in equation (13) can not be estimated with only NT observations using one dummy variable for each firm. Also, we transform our model to eliminate the N firm effects. The vectors (x_i, y_i) defined where x_i is $T \times K$ and y_i is $T \times 1$ are assumed independent and identically distributed across individuals $i=1,\ldots,N$. Estimation involves two steps. In the first step, α is estimated subject to (13) and the moment restrictions implied by (22). In the second step, the same approach is applied to estimate the mean and variance parameters α and β subject to (13)-(15) and the moment restrictions implied by (22) and (23). In both steps the underlying specifications are tested. To facilitate incorporation of (22) in estimation, and in analogy to the first differencing used in the linear case, Chamberlain (1992b) proposed use of the following transformation of (22) to eliminate the individual effects. The result is a set of $T-1$ restrictions on conditional means of the transform :

$$(24) \qquad E\left[r_{it}/\gamma_i, x_i, \gamma_t, \gamma_{t-1}\right] = E\left[r_{it}/x_i, \gamma_t, \gamma_{t-1}\right] = 0 \qquad t = 2,\ldots,T$$

where $r_{it}(\alpha) \equiv y_{it} - y_{it-1}\left[\gamma_t/\gamma_{t-1}\right] f(x_{it};\alpha)/f(x_{it-1};\alpha)$. The estimation problem involves estimation of (13) subject to (24).

Our approach exploits (24) as additional set of $T-1$ testable restrictions that augment the model (13) of the mean of y_{it}. Restrictions (24) provide the motivation for orthogonality conditions which are the core of the GMM approach. As conditional moment restrictions, (24) imply that the residuals r_{it} and functions of x_i have a correlation equal to zero. Thus, a $1 \times l$ matrix of instruments (w_{it}) for r_{it} can be chosen as known functions of x_i (and α) to construct unconditional moment restrictions that identify our parameters of interest:

$$(25) \qquad E\left[w_{it}' r_{it}(\alpha^*)\right] = 0 \text{ if } \alpha^* = \alpha, \quad E\left[w_{it}' r_{it}(\alpha^*)\right] \neq 0 \text{ otherwise}, \quad t=2,\ldots,T.$$

We stack these conditions over t and use the resulting orthogonality conditions as a basis of our estimation:

$$(26) \qquad E\left[w_i(\alpha)' r_i(\alpha)\right] = 0$$

where $w_i(\alpha) \equiv \begin{bmatrix} w_{i2}(\alpha) & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & w_{iT}(\alpha) \end{bmatrix}$ and $r_i(\alpha) \equiv \begin{bmatrix} r_{i2}(\alpha) \\ \vdots \\ r_{iT}(\alpha) \end{bmatrix}$.

These 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 unconditional moment restrictions. Defining $\widetilde{w}_{it} = w_{it}(x_i, \widetilde{\alpha}_N)$ where $\widetilde{\alpha}_N$ is an initial $\sqrt{N}$-consistent estimator of α, the efficient GMM estimator of α subject to (26) can be written :

$$(27) \qquad \hat{\alpha}_N^{GMM} \equiv \underset{a}{Arg\,min} \sum_{i=1}^{N} r_i(a)' \widetilde{w}_i \left[\widetilde{\Omega}_N\right]^{-1} \sum_{i=1}^{N} \widetilde{w}_i' r_i(a)$$

where $\widetilde{\Omega}_N \equiv \frac{1}{N}\sum_{i=1}^{N} \widetilde{w}_i{}' r_i(a) r_i(a)' \widetilde{w}_i$ is a consistent estimator of the asymptotic covariance matrix of orthogonality conditions (26). For the choice of instruments, we adopt the recommendation of Wooldridge (1991)[8]:

$$(28) \qquad \widetilde{w}_{it} \equiv \left[\partial f(x_{it};\widetilde{\alpha}_N)/\partial\alpha_1, \ldots, \partial f(x_{it};\widetilde{\alpha}_N)/\partial\alpha_K, f(x_{it};\widetilde{\alpha}_N)\right]$$

A convenient and asymptotically equivalent estimator of $\hat{\alpha}_N^{GMM}$ was proposed by Wooldridge (1991). It is based on the initial estimator $\widetilde{\alpha}_N$:

$$(29) \qquad \widetilde{\alpha}_N \equiv \underset{a}{Arg\,min} \sum_{i=1}^{N} r_i(a)' s_i \left[\frac{1}{N}\sum_{i=1}^{N} s_i s_i{}'\right]^{-1} \sum_{i=1}^{N} s_i{}' r_i(a)$$

where s_i is designed as w_i is, with $s_{it} \equiv \left[ln\, x_i{}', 1\right]$. This estimator is interpretable as a nonlinear two stage least squares estimator that is $\sqrt{N}$-consistent (Hansen 1982) and provides the basis for an estimator of α asymptotically equivalent to $\hat{\alpha}_N^{GMM}$ as follows:

$$(30) \qquad \hat{\alpha}_N = \widetilde{\alpha}_N - \left[\widetilde{R}_N{}' \widetilde{\Omega}_N^{-1} \widetilde{R}_N\right]^{-1} \widetilde{R}_N{}' \widetilde{\Omega}_N^{-1} \frac{1}{N}\sum_{i=1}^{N} \widetilde{w}_i r_i(\widetilde{\alpha}_N)$$

where $\widetilde{R}_N \equiv \frac{1}{N}\sum_{i=1}^{N} \widetilde{w}_i\, \partial r_i(\widetilde{\alpha}_N)/\partial\alpha$. The asymptotic variance of $\hat{\alpha}_N$ can be estimated by $\frac{1}{N}\left[\hat{R}_N{}' \hat{\Omega}_N^{-1} \hat{R}_N\right]^{-1}$.

We next jointly estimate the conditional mean and variance of y_{it} providing estimates of α and β. Combining conditional moments (22)-(23) and equations (13)-(15) gives :

$$(31) \qquad E\left[y_{it}^2 / \gamma_i, x_i, \gamma_t\right] = \gamma_i^2 \gamma_t^2 \left[f(x_{it})^2 + \sigma_\varepsilon^2 h(x_{it})^2\right] \qquad t = 1, \ldots, T.$$

By a transformation[9] similar to $r(.)$ we eliminate γ_i^2 from (31). That is, define

$$(32) \qquad m_{it}(\alpha, \beta) \equiv y_{it}^2 - y_{it-1}^2\left[\gamma_t^2/\gamma_{t-1}^2\right]\left[f(x_{it})^2 + \sigma_\varepsilon^2 h(x_{it})^2\right] / \left[f(x_{it-1})^2 + \sigma_\varepsilon^2 h(x_{it-1})^2\right]$$

$$\equiv y_{it}^2 - y_{it-1}^2\left[\gamma_t^2/\gamma_{t-1}^2\right]\left[g(x_{it})\right] / \left[g(x_{it-1})\right]$$

noting that:

$$(33) \qquad E\left[m_{it} / x_i, \gamma_t, \gamma_{t-1}\right] = 0 \qquad t = 2, \ldots, T$$

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[8] Chamberlain (1992a) derived optimal instruments for this type of problem. However, their application requires use of ad hoc parameterization of the conditional mean of γ_i and the variance of $r_i(\alpha)$, or nonparametric methods (see also Newey (1993)). 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 provides more orthogonality conditions than needed to identify the model parameters and, as a result, over-identifying restrictions to be tested along the lines of Hansen.

[9] The transformation defined by (33) is more tractable than the transformation proposed by Wooldridge (1990) in the same context.

Based on this transformation, we use an estimator of the form of $\tilde{\alpha}_N$ as an initial $\sqrt{N}$-consistent estimator of β :

(34) $$\hat{\beta}_N \equiv \underset{b}{Arg\,min} \sum_{i=1}^{N} m_i(\hat{\alpha}_N, b)' s_i \left[\frac{1}{N} \sum_{i=1}^{N} s_i s_i' \right]^{-1} \sum_{i=1}^{N} s_i' m_i(\hat{\alpha}_N, b)$$

where $m_i' \equiv [m_{i2}, \dots, m_{iT}]$. We define the matrix of instruments associated with the stacked vectors $rm_i(\hat{\alpha}_N, \hat{\beta}_N)' \equiv [m_i(\hat{\alpha}_N)', u_i(\hat{\alpha}_N, \hat{\beta}_N)'] \equiv r\hat{m}_{it}$ as follows:

(35) $$w\hat{v}_i \equiv \begin{bmatrix} \hat{w}_i & 0 \\ 0 & \hat{v}_i \end{bmatrix}.$$

In (35), $\hat{w}_i$ is defined by (26) and (28), and $\hat{v}_i$ is designed as $\hat{w}_i$ is, with:

(36) $$\hat{v}_{it} \equiv \left[\frac{\partial g(x_{it}; \hat{\alpha}_N, \hat{\beta}_N)}{\partial \alpha_1}, \dots, \frac{\partial g(x_{it}; \hat{\alpha}_N, \hat{\beta}_N)}{\partial \alpha_K}, g(x_{it}; \hat{\alpha}_N, \hat{\beta}_N), \frac{\partial g(x_{it}; \hat{\alpha}_N, \hat{\beta}_N)}{\partial \beta'} \right]$$

A simple one-step efficient estimator asymptotically equivalent to the GMM efficient estimator based on the orthogonality conditions:

(37) $$E[wv_i(\alpha, \beta)' rm_i(\alpha, \beta)] = 0,$$

is given by :

(38) $$\begin{bmatrix} \overline{\alpha}_N \\ \overline{\beta}_N \end{bmatrix} = \begin{bmatrix} \hat{\alpha}_N \\ \hat{\beta}_N \end{bmatrix} - \left[\hat{A}_N' \hat{\Psi}_N^{-1} \hat{A}_N \right]^{-1} \hat{A}_N' \hat{\Psi}_N^{-1} \frac{1}{N} \sum_{i=1}^{N} w\hat{v}_i' rm_i(\hat{\alpha}_N, \hat{\beta}_N)$$

where $$\hat{A}_N \equiv \frac{1}{N} \sum_{i=1}^{N} w\hat{v}_i' \left[\frac{\partial rm_i(\hat{\alpha}_N, \hat{\beta}_N)}{\partial \alpha'}, \frac{\partial rm_i(\hat{\alpha}_N, \hat{\beta}_N)}{\partial \beta'} \right]$$

$$\hat{\Psi}_N \equiv \frac{1}{N} \sum_{i=1}^{N} w\hat{v}_i' rm_i(\hat{\alpha}_N, \hat{\beta}_N) rm_i(\hat{\alpha}_N, \hat{\beta}_N)' w\hat{v}_i.$$

This estimator is consistent and asymptotically normal. An estimator of its variance is provided by $\frac{1}{N}\left[\overline{A}_N' \overline{\Psi}_N^{-1} \overline{A}_N \right]^{-1}$.

[10] Some of these fixed inputs, such as capital, can be known to the econometrician. Other are unknown : soil quality, management quality,.... However, even in the case where they are measured, fixed inputs are embodied in γ_i due to identification features. This specific problem of panel data econometrics was, for example, discussed by Hausman and Taylor (1981) and Wooldridge (1991). This problem is not too serious in our application since our primary interest is attached to the coefficients of the variable inputs.

Empirical Application

To illustrate the importance of incorporation of fixed effects when models such as equations (13)-(15) and (22)-(23) are estimated with panel data, we present estimates for data drawn from the European Accountancy Data Network for 496 farmers in France for the years 1987 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 part of 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 1, summary data of the output and input data are given. Data were deflated to 1987 French francs and areas were normalized to hectares. The data contains a reasonable disaggregation of variable inputs (fertilizers, pesticides, seeds, crop services, energy). Quasi-fixed factors includes land, available family labor, accountancy measures of building and machinery capital.

The specification of the production function represented in equations (13)-(15) and (22)-(23) involves three principle structural hypotheses: 1) the existence of fixed firm and time effects, 2) a functional form in which the role of pesticides is symmetric with that of other inputs, and 3) a functional form following Just and Pope in which inputs affect the variance of output. We maintain the hypothesis of input-output separability of the production frontier and specify the empirical functional forms of *f( )* and *h( )* in (13) to be Cobb-Douglas. While this is a restrictive functional form, we employ it here to allow direct comparison of our results with those of past studies which have employed the Cobb-Douglas form. We specify the input vector in the form of pesticides, fertilizer, and other inputs (including energy, seeds, crop services). Such aggregates are used by past studies e.g. Headley (1968) and Carrasco-Tauber and Moffitt (1992)

To proceed in estimation and inference, we first test the overall specification of mean function (13) augmented by the orthogonality condition (26) and then present evidence to validate of the first two structural hypotheses. An important advantage of the estimation approach outlined in equations (24)-(30) is that $\tilde{\Omega}_N$, $\hat{\Omega}_N$, $\hat{\Psi}_N$ and $\overline{\Psi}_N$ are robust estimators of the orthogonality conditions asymptotic variance-covariance matrix under any form of heteroskedasticity (Hansen, 1982; Newey and West, 1987a). It follows that $\hat{\alpha}_N$ is robust under any form of heteroskedasticity. This result allows us to conduct specification tests of the conditional mean function based on estimation of $\hat{\alpha}_N$ which has not incorporated explicit specifications of heteroskedasticity, e.g. equations (14) and (15).

Our approach focuses on testing the validity of the restrictions on the conditional mean which are implied by our specification of the conditional mean of y_{it} (13) and (22). This approach may be compared to the traditional approach of testing specifications of conditional mean functions by testing the joint hypothesis that all parameters are zero. Such a condition fails to test whether the associated residuals are orthogonal to the regressors. As example, where a specification omits relevant variables, such a joint test could reject the null hypothesis based on the significance of the variables included in the model. In contrast, a test of the orthogonality of the estimated residuals with respect to the regressors would provide a stronger test of the validity of the specification. Hansen's approach is to test the validity of the such orthogonality conditions. To do so, Hansen recognizes some of the orthogonality conditions may be imposed in estimation. However, when the number of orthogonality conditions exceeds the number of parameters to be estimated, the excess conditions can be viewed as over-identification restrictions. Under the null hypothesis that the conditional mean specification is valid these restrictions would not be statistically different from zero. The following formula presents the test statistic for testing the null hypothesis that the over-identifying restrictions are indeed zero:

$$(39) \qquad \sum_{i=1}^{N} r_i(\hat{\alpha}_N)'\hat{w}_i \left[\sum_{i=1}^{N} \hat{w}_i' r_i(\hat{\alpha}_N) r_i(\hat{\alpha}_N)'\hat{w}_i \right]^{-1} \sum_{i=1}^{N} \hat{w}_i' r_i(\hat{\alpha}_N).$$

Given that $\hat{\alpha}_N$ is asymptotically normal, based on the specifications (13) and (22), and standard regularity conditions, the Hansen statistic converges in distribution to a χ^2 distribution with the number of degrees of freedom equal to the number of the over-identification restrictions (the number of independent orthogonality conditions minus the number of independent parameters estimated), that is, to *(T-2)K* in our case. By design, this statistic tests both the conditional mean specification and the validity of instruments (orthogonality with respect to the disturbance).

This same approach is used to access the importance of inclusion of fixed firm effects in the specification of the conditional mean function. The specification of (13) includes the hypothesis that firm effects exist and (22) supposes that input choices may not be independent of such effects. This latter hypothesis is consistent with the logic that input choices are derived from a consideration of the parameters of the underlying production function which are known to the producer. While the existence of firm effects is of interest, it is the dependence of input choices on such effects that is the element of the specification in (13)-(22) that is most crucial to estimation. As shown above, when estimation ignores this possible dependence, estimators will suffer from heterogeneity bias. We establish evidence concerning this hypothesis by estimating (13) subject to both (22) and :

$$(40) \qquad E(\gamma_i / x_i) = E(\gamma_i) = \bar{\gamma}$$

Note that if this restriction holds, then (13) and (22) can be rewritten as the conventional production function which includes no fixed firm effects, e.g. (20). It follows that we may use the over-identification statistic to test the validity of the model specified by (13), (22) and (40) . The logic of the specification test is that if we can not reject (13) and (22) using a Hansen test, and if we can reject an explicit alternative hypothesis defined by (13), (22) and (40), then we can not reject the presence of heterogeneity bias.

The system under "no fixed firm effects" was estimated with an initial estimator using standard nonlinear ordinary least squares as described above in equation. This initial estimate was exploited using an asymptotically equivalent to a GMM estimator as described by equation (30). Following the approach outlined above in equations (26)-(28) , the estimators were based on :

$$(41) \qquad E\left[q_i(\alpha)' e_i(\alpha)\right] = 0$$

where $q_i(\alpha) \equiv \begin{bmatrix} q_{i1}(\alpha) & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & q_{iT}(\alpha) \end{bmatrix}$, $e_i(\alpha) \equiv \begin{bmatrix} e_{i1}(\alpha) \\ \vdots \\ e_{iT}(\alpha) \end{bmatrix}$ and

$q_{it} \equiv \left[\partial f(x_{it};\alpha)/\partial \alpha_1, \ldots, \partial f(x_{it};\alpha)/\partial \alpha_K, f(x_{it};\tilde{\alpha}_N)\right]$. In this case, the overidentification statistic (equation (39)) has a limiting χ^2 distribution with $(T-1)K$ degrees of freedom.

To construct our specification based on an asymmetric functional role of pesticides with respect to other inputs, we present results based on (20) incorporating a cumulative distribution function as a damage function following LZ. We evaluate the implications of the Lichtenberg and Zilberman specification for parameter estimates, using two alternative specifications of the cumulative distribution function. The first one incorporates in (20) an exponential cumulative distribution function as damage abatement function for pesticides :

$$(42) \qquad y_{it} = \bar{\gamma}\gamma_t \prod_{k=2}^{K} x_{kit}^{\alpha_k}\left[1 - exp(\eta_{01} - \eta_{11}x_{1it})\right] + e_{it}$$

where $E\left[e_{it}/x_i, \gamma_t\right] = 0$. The second uses a logistic cumulative distribution function :

$$(43) \qquad y_{it} = \bar{\gamma}\gamma_t \prod_{k=2}^{K} x_{kit}^{\alpha_k}\left(1 + exp(\eta_{01} - \eta_{11}x_{1it})\right)^{-1} + e_{it}$$

where $E\left[e_{it}/x_i, \gamma_t\right] = 0$. Each of these alternative specifications were estimated with nonlinear ordinary least squares. Under the null hypothesis that specification (13)-(15) and (22)-(23) is true, estimators used for (42) and (43) subject to heterogeneity biases.

Table 1 presents summary statistics for the variables used in the estimation of the production system in equations (13)-(15) and (22)-(23). All variables were measured on a per hectare basis. Quasi-fixed factors were found statistically insignificant and were dropped from the model to facilitate estimation. Their joint insignificance suggests that their near proportionality with land and the independence of output per hectare from the scale of land cultivated. Results from estimation of α estimated using $\hat{\alpha}_N$ are presented in Table 2. As indicated by the Hansen statistic, the hypotheses stated in (13) and (22) can not be rejected. This result validates the hypothesis implicit in (22) that input choices are unaffected by contemporaneous stochastic disturbances, including for example pest infestations. This suggests that for the present sample, important opportunities may exist for improved pest management systems such as Integrated Pest Management which facilitate input adjustment to contemporaneous pest exposures. Estimated asymptotic standard errors confirm that each parameter is statistically significant, except for fertilizers. Here the estimated parameter is quite small. Before discussing these results, it is of interest to present results for tests of the three structural hypotheses. The statistical significance of the fixed time effects reported in Table 2 lead us to accept the hypothesis that $\gamma_t \neq 1$ without further investigation. This result is also consistent with the presence of time related shifts in technology. Our results suggest that while these time effects vary across years, such variation is not large. With regard to the hypothesis concerning the existence of fixed firm effects, we note that their existence implies both that $\gamma_i \neq \bar{\gamma}$ and that input choices are dependent on γ_i. We focus on the latter implication of the existence of fixed firm effects and explore its validity by testing the alternative hypothesis that fixed firm effects are not independent of the regressors. Table 2 presents estimates of equations (13) and (22) subject to (40) described above. As indicated by the Hansen test statistic, the orthogonality hypothesis stated in equation (41) can be rejected with more than 99% confidence. This result implies that if equations (13), (22) and (41) were used to estimate the conditional mean of output, heterogeneity bias would result due to the fact that (40) does not hold. The last column in Table 2 presents point estimates of this heterogeneity bias. The results provide a striking illustration of the magnitude of this bias. For the sample studied, results indicate that use of a model that excludes fixed firm effects will result in substantial over-estimation of the marginal productivity of pesticides. During the sample years, the share of pesticide expense relative to the value of output was as follows: .107 (1987 and 1988), .111 (1989), and .121 (1990). Given that the share of pesticides in product value is *0.111* at the sample mean, our "fixed firm effects" estimates imply that pesticides are applied only slightly in excess of their expected profit maximizing level. In sharp contrast, estimates associated with the rejected "no fixed effects" model imply pesticides are under-used substantially. This "no fixed effects" result is consistent with the preponderance of past estimates based on models that exclude fixed firm effects.

The second structural hypothesis specified a symmetric functional role of pesticides relative to other inputs. We do not test this hypothesis explicitly, instead we consider the implications of the alternative hypothesis of an asymmetric role for pesticides presented by LZ using exponential and a logistic damage functions. Results reported in Table 3 indicate that parameter estimates for these alternative specifications are comparable across alternatives. In each case, a substantial positive heterogeneity bias is found relative to the estimates based on a model including fixed firm effects.

We proceed by accepting the specification of the mean function including both "firm fixed effects" and a symmetric functional role for pesticides as presented in equations (13) and (22). We next move to present results from joint estimation of the conditional mean and conditional variance of output as specified in equations (13)-(15) and (22)-(23). Results of this estimation are presented in Table 4. First, the overall specification is tested using the Hansen test following the same logic as pursued for validation of the specification of the conditional mean. The corresponding GMM overidentification statistic is given by:

$$(44) \qquad \sum_{i=1}^{N} rm_i(\bar{\alpha}_N, \bar{\beta}_N)' w\bar{v}_i \left[\sum_{i=1}^{N} w\bar{v}_i' rm_i(\bar{\alpha}_N, \bar{\beta}_N) rm_i(\bar{\alpha}_N, \bar{\beta}_N)' w\bar{v}_i \right]^{-1} \sum_{i=1}^{N} w\bar{v}_i' rm_i(\bar{\alpha}_N, \bar{\beta}_N).$$

Under (13)-(15) and (22)-(23) and standard regularity conditions, this statistics has a limiting χ^2 distribution with $3(T-1)(K+1)-(2K+T)$ degrees of freedom. Results reported in Table 4, suggest that while the overall model incorporating both the conditional mean and variance can not be rejected at the 15% level of significance, a joint Wald test that the β_k's are zero can not be rejected. Together these results suggest that the hypothesis that inputs affect the variance of output as posited by the Just and Pope specification can be rejected. However, it should be noted that the parameters estimates have expected signs. As in Antle's (1988) study, pesticides reduce yield risk. A positive effect on yield variance is found for fertilizers as in Just and Pope (1979), Babcock et al. (1987) or Love and Buccola (1991).

Table 5 presents estimates of the own short-run elasticities of demand for pesticides based on a behavioral hypothesis of expected profit maximization and the mean of Paasche price indexes for the sample years as published by SCEES (1990, 1991). Both comparative static and *mutatis mutandis* elasticities. Our estimates based on the "firm fixed effects" model indicate substantial own price elasticity of demand for pesticides in both cases. However, based on the "no fixed effects" model, substantially less elasticity is indicated. This difference confirms that the differences in estimated production elasticities are sufficiently substantive to play a dominate role in the calculation of the elasticities. For comparison with other econometric studies, only, McIntosh and Williams (1992), Chambers and Lichtenberg (1994) and Oskam (1992) present estimates of elasticities. Both these studies use aggregate data as well as dual approaches, rendering comparison difficult. Chambers and Lichtenberg (1994) find estimates comparable to our "fixed effects" model, while McIntosh and Williams (1992) and Oskam (1992) finds near inelasticity.

Conclusions

The objective of this paper was to investigate two hypotheses concerning the over-estimation of marginal productivity of pesticides. The first hypothesis is that of Lichtenberg and Zilberman that over estimation my result from use of a symmetric functional specification for the role of pesticides relative to other inputs. Based on neoclassical production theory we show that, in general, the asymmetric form can be viewed as a restricted case of more general symmetric functional forms. The second hypothesis considered is that over estimation may result from "heterogeneity bias" that results estimators are based on panel data and drawn from specification of conditional mean functions that exclude fixed effects. The nature of this heterogeneity bias was presented and an estimation approach was introduced. In addition to these concerns, we noted that pesticides might be expected to influence the variance of output as well as its conditional mean. Following Just and Pope, we extended our specification to allow for this possibility. The resulting estimation approach was applied to agricultural data drawn from a panel of French cereal farms. Specification tests indicated neither fixed firm, nor fixed time effects could be rejected. Elaboration of the specification to allow the variance of output to respond to changes in inputs was not strongly supported by the data. Final parameter estimates imply a substantially smaller marginal productivity of pesticides that has been found in past studies. Our results indicate this difference is due to heterogeneity bias associated with past estimates which have excluded fixed effects from their specifications. To further confirm the implications of fixed effects on the resulting estimate marginal productivity of pesticides, we present estimates based on the LZ specification. First results of strongly support the conclusion that use of their specification instead of one in which pesticides play a symmetric role has little impact on the magnitude of the estimated marginal productivity of pesticides. This result is consistent with past applications of the LZ specification which have continued to find estimates that suggest that the marginal productivity of pesticides exceeds their real marginal cost. Further, this result confirms our conclusion that while functional specification is allows worthy of concern, appropriate specification of fixed effects is crucial when panel data is used. Our results show that substantial heterogeneity bias may result from omission of fixed effects and their stochastic implications. Avoiding this bias, our results find estimates of marginal productivity of pesticides that are consistent with 1) slight over use, rather than substantial under use as indicated by past results; and 2) substantial own price elasticity of demand compared to past estimates. Extending these results to the design of policy to manage externalities associated with pesticides, our results imply a substantially flatter marginal social cost function for reductions in pesticide use relative to that implied by past results. Given an elastic marginal social benefit function, our results imply that substantially smaller taxes might be optimal than suggested by past results.

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Appendix

Figure 1. Response of the conditional expectation of y_{it} to x_{lit} in natural logarithm.
(γ_i and x_{lit} are positively correlated, $\gamma_1 > \gamma_2 > \gamma_3 > \gamma_4$ and γ_t is constant over time)

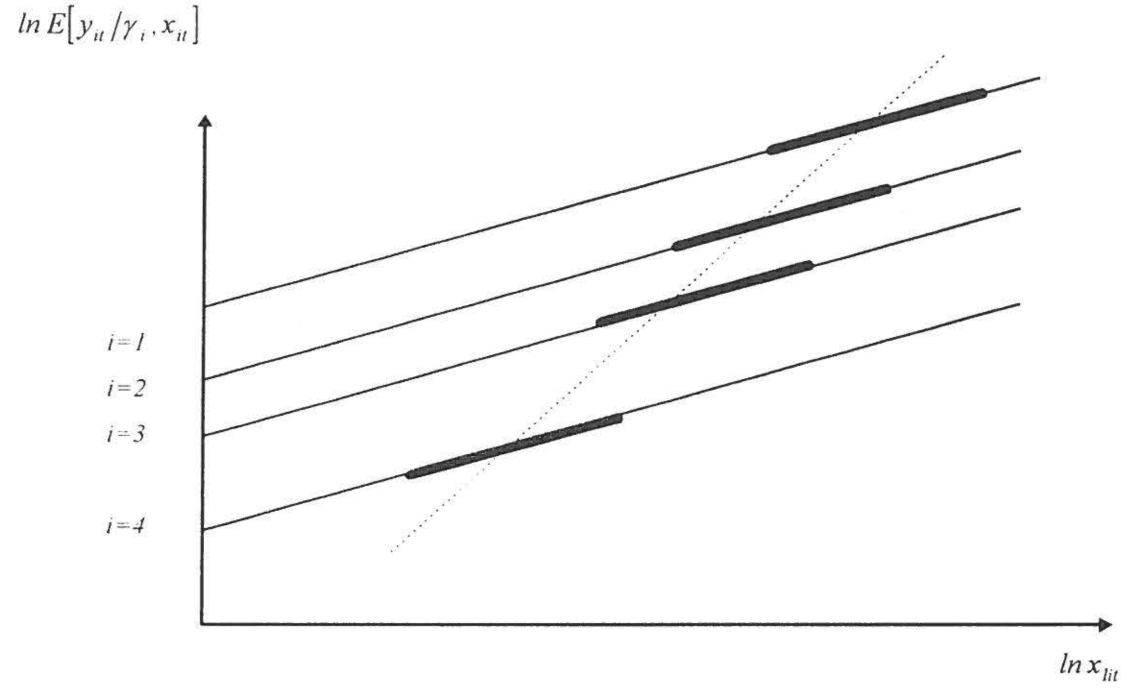

Table 1. Summary statistics of the data set of 496 French farmers from 1987 to 1990

	Variable 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 2. Parameter estimates of the Cobb-Douglas (mean) production function with additive error

	Parameter estimates (asymptotic standard error)		Estimated heterogeneity bias[3]
	Fixed firm effect model[1]	Without correlated fixed firm effect model[2]	
Pesticides	0.102 (0.033)	0.332 (0.024)	0.230
Fertilizers	0.018 (0.0033)	0.214 (0.030)	0.196
Other variable inputs	0.120 (0.025)	0.111 (0.019)	-0.009
γ_{88}/γ_{87}	1.119 (0.010)	1.124 (0.008)	0.005
γ_{89}/γ_{88}	0.978 (0.009)	0.955 (0.008)	-0.023
γ_{90}/γ_{89}	1.016 (0.009)	1.007 (0.007)	-0.009
Hansen's test statistic	8.562	37.423	
Test ddf (Prob($\chi^2(ddl)$<test stat.))	6 (0.80)	9 (0.99)	

[1] These estimates and associated statistics correspond to the GMM estimation of (13) and (22).
[2] These estimates and associated statistics correspond to the GMM estimation of (13), (22) and (41).
3 Defined as parameter estimates of the model without correlated fixed firm effects minus parameter estimates of the model allowing correlated fixed firm effects.

Table 3. Estimates of the marginal productivity elasticity of pesticides, fertilizers and other variable inputs with different yield specifications and estimation methods

Specification	Estimation method	Marginal productivity elasticity estimates[1]		
		Pesticides	Fertilizers	Other variable inputs
$y_{it} = \gamma_i \gamma_t \prod_{k=1}^{K} x_{kit}^{\alpha_k}$	GMM	0.102	0.018	0.120
$y_{it} = \bar{\gamma}\gamma_t \prod_{k=1}^{K} x_{kit}^{\alpha_k}$	GMM	0.332	0.214	0.111
$y_{it} = \bar{\gamma}\gamma_t \prod_{k=2}^{K} x_{kit}^{\alpha_k}\left[1 - exp(\eta_{01} - \eta_{11} x_{1it})\right]$	NLOLS	0.404	0.199	0.117
$y_{it} = \bar{\gamma}\gamma_t \prod_{k=2}^{K} x_{kit}^{\alpha_k}\left[1 + exp(\eta_{01} - \eta_{11} x_{1it})\right]^{-1}$	NLOLS	0.321	0.198	0.118

[1] Evaluated at the sample mean point when they are not constant.

Table 4. Parameters estimate of the Just and Pope specification with individual and time fixed effects[1]

	Parameters estimates (and asymptotic standard deviation estimates)	
	Mean (α_k)	Standard deviation (β_k)
Pesticides	0.108 (0.029)	-1.148 (1.017)
Fertilizers	0.014 (0.031)	0.188 (0.897)
Other variable inputs	0.120 (0.024)	2.485 (1.669)

Hansen's test statistic :	35.105	Wald statistic (H_0 : $\beta_k = 0\ \forall k$)	3.19
Test ddf (Prob($\chi^2(ddl)$<test stat.)) : (0.89)	26	Test ddf (Prob($\chi^2(ddl)$<test stat.)) : (0.64)	3

[1] These estimates and associate statistics correspond to the GMM estimation of the conditional mean and variance models described above.

Table 5. Short-run own price elasticities of pesticide demand at the sample mean point[1]

Short-run price elasticity of pesticide demand	With fertilizers and other variable inputs held constant[2]	With variable input adjustments[3]
"Firm fixed effects" model	-1.15	-1.17
"No firms fixed effects" model	-0.51	-0.67

[1] Producers are assumed to maximize their expected profit.

[2] Corresponds to $\left.\dfrac{\partial x_{1it}}{\partial p_{1it}}\right|_{x_{2it}=cst,\, x_{3it}=cst}$

[3] Corresponds to $\dfrac{\partial x_{1it}}{\partial p_{1it}}$.

Table 6. Expected marginal product value and net return of pesticides at the sample mean point (ff. 87/ha)

	Expected marginal product value of pesticides	Expected marginal net return of pesticides
"Firm fixed effects" model	0.94	-0.02
"No firm fixed effects" model	2.81	1.85