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## Heterogeneity Bias, Panel Data, and the Productivity of Pesticides

Alain Carpentier\* and Robert D. Weaver\*\*

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### *Abstract*

Substantial over-estimation of the marginal productivity of pesticides is shown to result from exclusion of fixed firm and time effects when estimates are based on panel data. Estimates for French cereal farms are based on the Generalized Method of Moments and are robust to any form of heteroskedasticity.

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## Heterogeneity Bias, Panel Data, and the Productivity of Pesticides

### *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. Early positive econometric studies specified the functional role of pesticides in agricultural production as symmetric relative to that of other inputs (Headley (1968), Carlson (1977), Campbell (1976), McIntosh and Williams (1992)). The results of these studies indicated the marginal value productivity of pesticides exceeded their marginal costs. Lichtenberg and Zilberman (LZ) (1986) highlighted the role of pesticides by adapting the approach of normative studies where output is specified as the product of a damage abatement function and an anticipated, or normal, production function. 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 such an asymmetric role of pesticides would result in upward biased estimates of the productivity of pesticides. 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, these studies continue to find that estimates of marginal value productivity for pesticides that exceed marginal costs despite their use of their use of the LZ form.

In this paper, we consider the hypothesis that estimation of the marginal productivity of pesticides using panel data will result in substantial bias in estimates based on models which fail to incorporate fixed firm effects. While LZ focused on the asymmetric functional role of pesticides as a source of bias in estimates, our focus is on the possibility that over-estimation of the marginal productivity of pesticides may result from improper econometric specification and estimation when panel data is used.

### *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<sup>1</sup> damage functions which proportionately adjust potential production (Headley (1972), Hall and Norgaard (1973), Lichtenberg and Zilberman (1986)). In the single output case, this specification may be written:

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

where  $y$  is actual production,  $f(x^D)$  is potential production achievable from a vector of direct inputs  $x^D$ ,  $h(\cdot)$  is 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  $h(x^P)$  is interpretable as a cumulative probability distribution defined over the closed interval  $[0,1]$ . 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  $g(\cdot)$  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)). 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 grounds. For the case of multiple

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<sup>1</sup> See Lau (1972).

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  $x^P$  and  $x^D$  implies that optimal choices of  $x^P$  and  $x^D$  may be made independently. In other words, pest control inputs  $x^P$  will not affect the marginal rate of substitution among direct inputs  $x^D$ , and *vice versa*. 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) would be inadequate.

To avoid the restrictions that are implicit in the LZ asymmetric specification of the role of pesticides, we focus on a general function  $g(\cdot)$ , writing the single output production function:

$$(2) \quad y_{it} = g_{it}(x_{it}^a, x_{it}^p)$$

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  $g_{it}(\cdot)$ ) 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 (2) with an additive error as<sup>2</sup>:

$$(3) \quad y_{it} = \gamma_i \gamma_t f_{it}(x_{it}; \alpha) + u_{it} \quad t = 1, \dots, T \quad i = 1, \dots, N \quad \text{where } E[u_{it}] = 0.$$

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

$$(4) \quad E[u_{it}/\gamma_i, x_{it}, \gamma_t] = E[u_{it}] = 0 \quad \text{or equivalently} \quad E[y_{it}/\gamma_i, \gamma_t, x_{it}] = \gamma_i \gamma_t f(x_{it}).$$

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<sup>2</sup> Where the parameters' vector is defined as follows:  $\alpha' \equiv [\alpha_1, \dots, \alpha_K; \gamma_2, \gamma_3/\gamma_2, \dots, \gamma_T/\gamma_{T-1}]$  since we impose the first time effect to be unitary for identification purpose.  $K$  is the number of considered inputs.

### *Robust Estimation of the Marginal Productivity of Pesticides*

The form of equation (3) 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 (3). 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  $\gamma_i$  in equations (3) and (4). It follows that choices of inputs and outputs are functionally determined by the parameters of the production function implying the parameters are exogenous to and correlated with those choices. By implication, omission of  $\gamma_i$  from the model (3) 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  $\alpha$ . 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)<sup>3</sup>. To further illustrate this bias, suppose a regression based on (3) is restricted by  $E[\gamma_i/x_i] = E[\gamma_i] = \bar{\gamma}$  allowing (3) and (4) to be rewritten:

$$(5) \quad y_{it} = \bar{\gamma} \gamma_t f(x_{it}) + e_{it} \text{ where } e_{it} = u_{it} + \gamma_t (\gamma_i - \bar{\gamma}) f(x_{it}) \text{ and } E[e_{it}/x_{it}] = 0.$$

Taking the conditional expectation of  $y_{it}$  defined by (3) and written using (5) results in:

$$(6) \quad E[y_{it}/x_{it}, \gamma_t] = E[\gamma_i/x_{it}, \gamma_t] \gamma_t f(x_{it}) = \bar{\gamma} \gamma_t f(x_{it}) + E[(\gamma_i - \bar{\gamma})/x_{it}, \gamma_t] \gamma_t f(x_{it}, t).$$

Here the heterogeneity bias is indicated by the last term.

For direct estimation of the production function, we extend (4) to require strict exogeneity of inputs conditionally on time and farm effects (Chamberlain, 1982) by rewriting it as:

$$(7) \quad E[y_{it}/\gamma_i, x_i, \gamma_t] = \gamma_i \gamma_t f(x_{it}) \text{ where } x_i' \equiv [x_{i1}', \dots, x_{iT}'].$$

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<sup>3</sup> Campbell (1976) also notes this possibility.

While (4) only requires contemporaneous independence of input choices and  $u_{it}$  at time  $t$  for each farm, (7) rules out feed back between past levels of output and contemporaneous and future input choices<sup>4</sup>.

To achieve consistent estimation of model (3) and (7), 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  $\alpha$  using panel data sets where  $N$  tends to infinity, yet  $T$  is small. While a small  $T$  allows direct parameterization of fixed time effects using dummy variables, an alternative approach must be taken for individual effects. That is, given  $N$  firm effects, the parameters in equation (3) can not be estimated with only  $NT$  observations using one dummy variable for each firm. To proceed, we transform our model to eliminate the  $N$  firm effects. Estimation of  $\alpha$  is based on (3) augmented by conditional moment restrictions implied by the transformation of (7). Our approach assumes only 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  $i=1, \dots, N$ . Based on these estimates the underlying specification is tested.

In analogy to the first differencing used in the linear case, Chamberlain (1992b) proposed use of the following transformation of (7) to eliminate the individual effects:

$$(8) \quad E[r_{it}/\gamma_i, x_i, \gamma_t, \gamma_{t-1}] = E[r_{it}/x_i, \gamma_t, \gamma_{t-1}] = 0 \quad t = 2, \dots, T$$

where  $r_{it}(\alpha) \equiv y_{it} - y_{it-1} [\gamma_t/\gamma_{t-1}] f(x_{it}; \alpha) / f(x_{it-1}; \alpha)$ . Based on this transformation, the estimation problem involves estimation of (3) subject to (8). Our approach exploits (8) as an additional set of  $T-1$  equations that augment the model (2) of the mean of  $y_{it}$ . Estimation requires use of instruments for  $r_{it}$  which are unobservable. We define  $w_{it}$  as a  $1 \times 1$  matrix of instruments that are orthogonal to  $r_{it}$ . (8) indicates that these instruments can be chosen as known functions of  $x_i$  and  $\alpha$ . We use the sample counterpart of the following orthogonality conditions as a basis of our estimation:

$$(9) \quad E[w_{it}' r_{it}(\alpha^*)] = 0 \text{ if } \alpha^* = \alpha, \quad E[w_{it}' r_{it}(\alpha^*)] \neq 0 \text{ otherwise.}$$

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<sup>4</sup> See Chamberlain (1982, 1984), Wooldridge (1991), Mairesse and Hall (1993), and Hall and Mairesse (1994) for discussions regarding to this point.

$$(10) \quad E[w_i(\alpha)' r_i(\alpha)] = 0$$

where  $w_i(\alpha) \equiv \text{Diag}[w_{i2}(\alpha), \dots, w_{iT}(\alpha)]$  and  $r_i(\alpha)' \equiv [r_{i2}(\alpha), \dots, r_{iT}(\alpha)]$ . Defining  $\tilde{w}_{it}$  as equal to  $w_{it}(x_i, \tilde{\alpha}_N)$  where  $\tilde{\alpha}_N$  is an initial  $\sqrt{N}$ -consistent estimator of  $\alpha$ , the efficient GMM estimator of  $\alpha$  subject to (10) can be written:

$$(11) \quad \hat{\alpha}_N^{GMM} \equiv \underset{a}{\text{Arg min}} \sum_{i=1}^N r_i(a)' \tilde{w}_i [\tilde{\Omega}_N]^{-1} \sum_{i=1}^N \tilde{w}_i' r_i(a)$$

where  $\tilde{\Omega}_N \equiv \frac{1}{N} \sum_{i=1}^N \tilde{w}_i' r_i(a) r_i(a)' \tilde{w}_i$  is a consistent estimator of the asymptotic covariance matrix of

orthogonality conditions (10). For the choice of instruments, we adopt the recommendation of

Wooldridge (1991)<sup>5</sup>:

$$(12) \quad \tilde{w}_{it} \equiv [\partial f(x_{it}; \tilde{\alpha}_N) / \partial \alpha_1, \dots, \partial f(x_{it}; \tilde{\alpha}_N) / \partial \alpha_K, f(x_{it}; \tilde{\alpha}_N)]$$

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

$$(13) \quad \tilde{\alpha}_N \equiv \underset{a}{\text{Arg min}} \sum_{i=1}^N r_i(a)' s_i \left[ \frac{1}{N} \sum_{i=1}^N s_i s_i' \right]^{-1} \sum_{i=1}^N s_i' r_i(a)$$

where  $s_i$  is designed as  $w_i$  is, with  $s_{it} \equiv [\ln x_i', 1]$ . 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  $\alpha$  asymptotically equivalent to  $\hat{\alpha}_N^{GMM}$  as follows:

$$(14) \quad \hat{\alpha}_N = \tilde{\alpha}_N - [\tilde{R}_N' \tilde{\Omega}_N^{-1} \tilde{R}_N]^{-1} \tilde{R}_N' \tilde{\Omega}_N^{-1} \frac{1}{N} \sum_{i=1}^N \tilde{w}_i' r_i(\tilde{\alpha}_N)$$

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<sup>5</sup>Chamberlain (1992a) derived optimal instruments for this type of problem. However, their application requires use of *ad hoc* parameterization of the conditional mean of  $\gamma_i$  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.



where  $\tilde{R}_N \equiv \frac{1}{N} \sum_{i=1}^N \tilde{w}_i \partial r_i(\tilde{\alpha}_N) / \partial \alpha$ . The asymptotic variance of  $\hat{\alpha}_N$  can be estimated by

$$\frac{1}{N} \left[ \hat{R}_N' \hat{\Omega}_N^{-1} \hat{R}_N \right]^{-1}. \text{ An important property of this approach is that the resulting estimators are robust to}$$

any kind of heteroskedasticity for  $r_{it}$  (Hansen (1982), Newey and West, (1987a)) allowing us to ignore possible effects of inputs on the variance of output as suggested by Just and Pope (1979).

### *Empirical Application*

To illustrate the importance of incorporation of fixed effects when models such as equations (3) and (7) 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%). Data were deflated to 1987 French francs and areas were measured in hectares.

The specification of the production function represented in equations (3) and (7) involves two structural hypotheses: 1) the existence of fixed firm and time effects and 2) a functional form in which the role of pesticides is symmetric with that of other inputs. We maintain the hypothesis of input-output separability of the production frontier and specify the empirical functional forms of  $f()$  in (3) 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). We first test the overall specification of the mean function (3) augmented by the orthogonality condition (10) and then present evidence to validate of two structural hypotheses.

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  $y_{it}$  in (3) and (7). 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 in e.g. (3). Such a condition fails to test whether the associated residuals are orthogonal to the regressors, as required by (7). 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 will 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. Hansen's test statistic for testing the null hypothesis that the over-identifying restrictions are indeed zero is the following :

$$(15) \quad \sum_{i=1}^N r_i(\hat{\alpha}_N)' \hat{w}_i \left[ \sum_{i=1}^N \hat{w}_i' r_i(\hat{\alpha}_N) r_i(\hat{\alpha}_N)' \hat{w}_i \right]^{-1} \sum_{i=1}^N \hat{w}_i' r_i(\hat{\alpha}_N).$$

Given that  $\hat{\alpha}_N$  is asymptotically normal, based on (3) and (7), and standard regularity conditions, the Hansen statistic converges in distribution to a  $\chi^2$  distribution with the number of degrees of freedom equal to the number of the over-identification restrictions, in this case to  $(T-2)K$ . By design, the Hansen statistic tests both the conditional mean specification and the sufficiency of instruments (orthogonality with respect to the disturbance).

This same approach is used to assess the importance of inclusion of fixed firm effects in the specification of the conditional mean function. 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 (3)-(7) that is most crucial to our specification and its estimation. As shown above, when estimation ignores this possible dependence, estimators will suffer from heterogeneity bias. To establish evidence concerning this hypothesis, we estimate (3) subject to (7) as well as the further restriction:

$$(16) \quad E(\gamma_i / x_i) = E(\gamma_i) = \bar{\gamma}$$

If this restriction holds, then (3) and (7) can be rewritten as the conventional production function which includes no fixed firm effects, e.g. (5). It follows that we may use the over-identification statistic to test the validity of the "no fixed firm effects" model specified by (3), (7) and (16). The logic of this specification test is that if we can not reject (3) and (7) using a Hansen test, yet we can reject an explicit alternative hypothesis defined by (3), (7) and (16), then we can not reject the presence of heterogeneity bias. The "no fixed firm effects" system 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 analogous to that described by equation (14). In this case, the overidentification statistic (equation (15)) has a limiting  $\chi^2$  distribution with  $(T-1)K$  degrees of freedom.

To explore the validity of the specification of symmetric functional role of pesticides with respect to other inputs, we indirectly test as an alternative hypothesis that (5) may be written incorporating a cumulative distribution function as a damage function following LZ. Two alternative specifications of the cumulative distribution function of damage are considered. The first one uses an exponential cumulative distribution function as damage abatement function for pesticides:

$$(17) \quad y_{it} = \bar{\gamma}\gamma_t \prod_{k=2}^K x_{kit}^{\alpha_k} [1 - \exp(\eta_{0i} - \eta_{1i}x_{lit})] + e_{it} \quad \text{where} \quad E[e_{it}/x_i, \gamma_t] = 0.$$

The second one uses a logistic cumulative distribution function:

$$(18) \quad y_{it} = \bar{\gamma}\gamma_t \prod_{k=2}^K x_{kit}^{\alpha_k} (1 + \exp(\eta_{0i} - \eta_{1i}x_{lit}))^{-1} + e_{it} \quad \text{where} \quad E[e_{it}/x_i, \gamma_t] = 0.$$

Each of these alternative specifications were estimated with nonlinear ordinary least squares. Under the null hypothesis that specification (3) and (7) is true, each of the estimators used to test the structural hypotheses is subject to heterogeneity biases.

Results from estimation of  $\alpha$  based on equation (3) estimated using  $\hat{\alpha}_N$  are presented in Table 1. As indicated by the Hansen statistic, the specifications (3) and (7) can not be rejected. Estimated asymptotic standard errors confirm that each parameter is statistically significant, except for fertilizers. In this case, the estimated parameter is small in magnitude as well. Before discussing these results, it is

of interest to present results for tests of the two structural hypotheses. The statistical significance of the fixed time effects reported in Table 1 leads us to accept the hypothesis that  $\gamma_t \neq 1$  without further investigation. With regard to the hypothesis concerning the existence of fixed firm effects, Table 1 presents estimates of equations (3) and (7) subject to (16) described above. As indicated by the Hansen test statistic, the orthogonality hypothesis stated in equation (16) can be rejected with more than 99% confidence, allowing us to strongly reject the "no fixed effects" model. This result implies that if equations (3), (7) and (16) were used to estimate the conditional mean of output, heterogeneity bias would result due to the fact that (16) does not hold. The last column in Table 1 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. Given that the share of pesticides cost in product value is 0.111 at the sample mean point, 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 firm effects" model imply pesticides are underused substantially. This 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 directly, instead we consider estimates of the LZ specification using two alternative damage function specifications. Results reported in Table 2 indicate parameter estimates are comparable across alternative specifications of the functional form of the damage function. In each case, a substantial positive heterogeneity bias is found relative to the estimates based on a model including fixed firm effects.

## ***Conclusions***

The objective of this paper was to investigate the hypothesis that over-estimation of the marginal productivity of pesticides may result from "heterogeneity bias" due to use of estimators based on panel data and specifications of conditional mean functions that exclude fixed effects. The nature of

this heterogeneity bias was presented and an estimation approach was introduced. Both direct and indirect specification tests indicated neither fixed firm, nor fixed time effects could be rejected. Final parameter estimates imply a substantially smaller marginal productivity of pesticides than has been found in past studies. Our results indicate this difference may be due to heterogeneity bias of past estimates based on panel data and specifications which exclude fixed effects. To further confirm the implications of fixed effects on the resulting estimate marginal productivity of pesticides and to explore evidence concerning asymmetry of the role of the functional role of pesticides, we present estimates based on the LZ specification. First, results 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.

Appendix

Table 1. Parameters estimate of the Cobb-Douglas (mean) production function with additive error

	Parameters estimates (asymptotic standard error)		Estimated heterogeneity bias <sup>3</sup>
	Fixed firm effect model <sup>1</sup>	Without correlated fixed firm effect model <sup>2</sup>	
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
$\gamma_{88}/\gamma_{87}$	1.119 (0.010)	1.124 (0.008)	0.005
$\gamma_{89}/\gamma_{88}$	0.978 (0.009)	0.955 (0.008)	-0.023
$\gamma_{90}/\gamma_{89}$	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)	

<sup>1</sup> These estimates and associated statistics correspond to the GMM estimation of (13) and (22).

<sup>2</sup> These estimates and associated statistics correspond to the GMM estimation of (13), (22) and (41).

<sup>3</sup> Defined parameters estimate of the model without correlated fixed firm effects minus parameters estimate of the model allowing correlated fixed firm effects.

Table 2. 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 <sup>1</sup>		
		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
$y_{it} = \bar{\gamma} \gamma_t \prod_{k=2}^K x_{kit}^{\alpha_k} [1 - \exp(\eta_{0l} - \eta_{1l} x_{lit})]$	NLOLS	0.404	0.199	0.117
$y_{it} = \bar{\gamma} \gamma_t \prod_{k=2}^K x_{kit}^{\alpha_k} [1 + \exp(\lambda_{0l} - \lambda_{1l} x_{lit})]^{-1}$	NLOLS	0.321	0.198	0.118

<sup>1</sup> Evaluated at the sample mean point when they are not constant.

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