Technical change and agricultural supply-demand analysis problems of measurement and problems of interpretation

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TECHNICAL CHANGE AND AGRICULTURAL SUPPLY-DEMAND ANALYSIS
PROBLEMS OF MEASUREMENT AND PROBLEMS OF INTERPRETATION

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INTRODUCTION

The purpose of the present paper is to explore various issues related to the measurement of technical change and incidentally to the measurement of total factor productivity growth rate.

Principles of duality enable the economist to model the technology of a multiinput-multioutput technology by means of a transformation function or its dual : cost, profit or revenue functions. The use of a flexible functional form which can be either the true function or a second order local approximation to this underlying function around a point of expansion does not impose a priori restrictions on technology characteristics : separability, jointness, substitution, returns to scale, nature of technical change. Furthermore, like some degree of temporariness is likely to characterize the equilibrium of almost industries and especially agricultural activity, many empirical studies are based on a restricted or short-run partial equilibrium framework, fixing certain inputs such as capital, land and/or family labour. (Brown and Christensen, 1981 ; Kulatilaka, 1985 ; Hertel, 1987). Equally important fixities may exist among production outputs (Boyle and Guyomard, 1989). Consequently the first objective of this study is to show the importance of taking into account the quasi-fixity of some inputs and/or outputs (non-marginal tarification, production quotas) in order to estimate the patterns of technical change and total factor productivity (section 1). Furthermore the problem with defining and measuring technical change biases when some inputs are treated as being quasi-fixed is explored on the basis of a restricted (or short-run) cost function : the relevant concepts of biases are defined and related to different possible equilibria. This analysis is extended to technical change biases on the output side (section 2).

Sections 3 and 4 are devoted to econometric issues. In empirical works on technical change, one often encounters regression equations that include a linear time trend as a proxy for technical change. However, as was shown in several papers on non-stationarity, empirical results of such equations can be highly misleading and can be subject to the spurious regression phenomenon. As a result, the estimated coefficients of time and exogenous variables can widely overstate the size of autonomous and incorporated technical change. In order to avoid such problems, non-stationarity properties of time series data must be carefully examined. We show how standard estimation of regressions including a time trend can lead to erroneous conclusions on technical change if data series are not stationary around a function of time, but rather are stationary in first difference. Moreover, we show how the tests for stationarity in difference as opposed to stationarity around a trend line developed by Dickey and Fuller (1979, 1981) can be used to determine the appropriate transformation of time series data (section 3). Lastly we briefly review some recent developments on the analysis of persistence in time series process which can be used to measure the autonomous and stochastic component of technical change. These methods which come from the time series literarure are very different from standard analysis of technical change, and provide a complementary approach to the usual measure of technical change. As an example, these methods are applied to the comparison of the respective size of the autonomous and stochastic component of technical change in the French sector for wheat and corn (section 4).

1. TOTAL FACTOR PRODUCTIVITY GROWTH AND TECHNICAL CHANGE : THEORETICAL ANALYSIS AND EMPIRICAL IMPLICATIONS

1.1. Theoretical analysis

There is no single generally accepted way to measure productivity or productivity growth. Following Solow (1957) the more common procedure directly related to the structure of production begins with a production function representation of the input to output transformation process (Link, 1987) and total factor productivity is then defined in terms of the efficiency with which inputs are transformed into "useful" output, assuming that homogeneous inputs produce a homogeneous output. More precisely, in the context of a production function, it is tradional to measure total factor productivity growth by the residual method, that is the growth in output quantity minus the growth in input quantities. In other words the multifactor productivity residual measure is linked to outward shifts in product long-run isoquant whereas the input effect, that is the effect measured by weighted growth rates of inputs, is associated with substitution effects along the isoquant. Alternatively and equivalently under certain regularity conditions which will be specified below, in the context of a total or long-run cost function, the dual total factor productivity measure is defined by the growth rate of average total cost minus the Divisia index of input prices : this residual is linked to downward shifts in unit or average long-run cost curves.

In numerous empirical studies, the continuous growth rates are replaced by the annual differences in the logarithms of the variables and the shares used as weights are replaced by annual arithmetic averages. The resulting indexes are the Tornquist indexes of total factor productivity growth, primal and dual respectively (see, for example, Berndt and Fuss, 1986 ; Hulten, 1986).

$$(\dot{TFP}/TFP) = \dot{Y}/Y - \Sigma_i \ (w_i X_i / p\ Y)\ (\dot{X}_i / X_i) \qquad (P_1)$$

$$\approx \log Y(t) - \log Y(t-1) - \Sigma_i \ [M_i(t) + M_i(t-1)]/2 \ (\log X_i(t) - \log X_i(t-1)) \qquad (P_2)$$

$$(\dot{TFP}/TFP) = \dot{CT}/CT - \dot{Y}/Y - \Sigma_i \ (w_i \ X_i / CT)(\dot{w}_i / w_i) \qquad (D_1)$$

$$\approx (\log CT(t) - \log CT(t-1)) - (\log Y(t) - \log Y(t-1)) - \Sigma_i \ [S_i(t)+S_i(t-1)]/2.(\log w_i(t) - \log w_i(t-1)) \qquad (D_2)$$

where $Y \geq 0$ is the output with price $p \geq 0$, $X' = (X_1, \ldots, X_N) \geq 0$ the transposed vector of inputs with associated transposed price vector $w' = (w_1, \ldots, w_N) \geq 0$, CT the total cost function, M_i the income shares and S_i the cost shares. Dots over variables indicate derivatives with respect to time. P_1 (respectively D_1) is the primal (respectively dual) Divisia index of total factor productivity growth, P_2 (respectively D_2) its Tornquist approximation.

These residual measures of total factor productivity are called non-parametric insofar as P_2 or D_2 do not require an econometric estimation of the production function or of the cost function. Nevertheless, both measures are derived under the assumption of a competitive long-run equilibrium. More precisely firms seek to maximise long-run profit in the first case whereas they seek to minimise long-run cost in the second case. The assumption of long-run returns to scale is not necessary to develop formulae P_1 and P_2 if estimates of income shares are available. It is interesting to note that long-run cost minimisation is a weaker assumption implied by long-run profit maximisation. Nevertheless input and output markets must be competitive and in long-run Marshallian equilibrium in order to extend the dual representation of total factor productivity to the multioutput-multiinput case.

How such measures, easy to compute, of total factor productivity are related to technical change measured by the rate at which the production function shifts ? Solow has shown that technical change and total factor productivity primal measure are two equivalent concepts if the following assumptions are satisfied : constant returns to scale, Hicks neutral technical change and perfect competition in both output and input markets. Furthermore, under these three restrictive assumptions, Ohta (1974) has shown that primal and dual non parametric measures are negatives of one another. Assuming a translog representation of either the production function or the cost function, Berndt and Jorgenson (1975), Diewert (1976) have proved that the assumption of neutral technical change is not necessary to have this equivalence. In other words, the non-parametric measures of total factor productivity growth rates equal the rate of technical change (the rate at which the production function shifts or the rate at which the long-run total cost function shifts) if the three following assumptions are verified :

- constant returns to scale
- input and output markets are competitive
- inputs and outputs are in long-run Marshallian equilibrium.

When one of these assumptions is violated, simple corrections can be applied to relate the growth rate of total factor productivity non-parametric indexes to technical change. Assuming that some inputs are quasi-fixed, we partition the input vector X into a subvector X^o of variable inputs and a subvector X^1 of quasi-fixed inputs. Indeed, the hypothesis that all inputs instantaneously adjust to their long-run equilibrium levels seems restrictive, especially for the agricultural technology since certain factors cannot be freely varied within the single period of observation. The principal source of fixity is the lack of mobility of self-employed farm labour which is enhanced by high unemployment in other economic sectors (Brown and Christensen, 1981 ; Guyomard and Vermersch, 1989). At the farm level, available agricultural land is often fixed over short to medium adjustment periods (Shumway, Pope and Nash, 1984). At the macro-economic level, land can be considered as a fixed factor even over long adjustment periods (Mahe and Rainelli, 1987). A same partition applies to output vector $Y = (Y^o, Y^1)$ in order to take into account the quasi-fixity (cattle) or the fixity (production quotas) of some outputs and also in order to take into account the possibility of a non-marginal tarification of certain outputs. Furthermore, we do not assume long-run returns to scale.

Total costs are variable costs plus fixed costs, that is, $CD(Y^o,Y^1,w^o,w^1,X^1,t) = CR(Y^o,Y^1,w^o,X^1,t) + \Sigma^1{}_j\ w^1{}_j\ X^1{}_j$. The calculated rate at which total factor productivity primal measure changes is always equal to :

$$(\dot{TFP}/TFP)_P = \Sigma^o{}_r\ R_r\ \dot{Y}^o{}_r/Y^o{}_r + \Sigma^1{}_s\ R_s\ \dot{Y}^1{}_s\ /Y^1{}_s - \Sigma^o{}_i\ S_i\ \dot{X}^o{}_i/X^o{}_i$$
$$- \Sigma^1{}_j\ S_j\ \dot{X}^1{}_j/X^1{}_j\ .$$

Technical change is defined by - $\delta\log CD/\delta t$, that is the rate at which the disequilibrium total cost function CD shifts. Then, it can be shown that technical change and the traditional total factor productivity non-parametric measure are related by the following equation (see annex n°1).

$$- \delta\log CD/\delta t = \Sigma^o{}_r\ (p^o{}_r\ Y^o{}_r/CD - p^o{}_r\ Y^o{}_r/\ RT)\ \dot{Y}^o{}_r/\ Y^o{}_r$$
$$+ \Sigma^1{}_s(\hat{p}^1{}_s\ Y^1{}_s/CD - p^1{}_s\ Y^1{}_s/RT)\ .\ \dot{Y}^1{}_s/Y^1{}_s$$
$$- \Sigma^1{}_j\ \hat{w}^1{}_j\ X^1{}_j/CD\ .\ \dot{X}^1{}_j/X^1{}_j + \Sigma^1{}_j\ w^1{}_j\ X^1{}_j/CD\ .\ \dot{X}^1{}_j/X^1{}_j$$
$$+ (\dot{TFP}/TFP)_P \qquad [c]$$

Equation [c] may be also written as.

$$.(TFP/TFP)_P = - \delta\log CD/\delta t$$
$$+(1-\mu)(\mu)^{-1}[\Sigma^o{}_r\ p^o{}_r\ Y^o{}_r/CD.\dot{Y}^o{}_r/Y^o{}_r + \Sigma^1{}_s\hat{p}^1{}_s Y^1{}_s/CD.\dot{Y}^1{}_s/Y^1{}_s]$$
$$+ \Sigma^o{}_r\ R_r\ .\ \dot{Y}^o{}_r/Y^o{}_r + \Sigma^1{}_s\ R_s\ .\ \dot{Y}^1{}_s/Y^1{}_s$$
$$- (\mu)^{-1}\ [\Sigma_r\ p^o{}_r\ Y^o{}_r\ /CD\ .\ \dot{Y}^o{}_r/Y^o{}_r + \Sigma^1{}_s\ p^1{}_s\ Y^1{}_s/CD\ .\ \dot{Y}^1{}_s/Y^1{}_s]$$
$$+ \Sigma^1{}_j\ (\hat{w}^1{}_j - w^1{}_j)\ X^1{}_j\ /CD\ .\ \dot{X}^1{}_j\ /X^1{}_j \qquad [d]$$

1.2. Consequences for empirical studies

Equations [c] and [d] show that when some netputs are in disequilibrium (quasi-fixities and/or non-marginal tarifications) the non-parametric measure of total factor productivity $\dot{TFP}/TFP$ does not equal the rate of technical change.

Nevertheless when all markets are in long-run Marshallian equilibrium and if returns to scale are constant, equations [c] and [d] collapse to the usual expression ;

$\dot{TFP}/TFP = - \delta \log CT/\delta t$; since in such a case

$CT = CD$, $p^1{}_s = \hat{p}^1{}_s$ for all s, $w^1{}_j = \hat{w}^1{}_j$ for all j,

$\mu = 1$ and $CT = RT$. In order to analyse the consequences of the simplifying assumptions allowing to show the equivalence between total factor productivity growth rate and technical change, we will consider successively three particular cases.

First, if all markets (inputs and outputs) are in equilibrium but if returns to scale are not constant, equation [c] reduces to :

$$(\dot{TFP}/TFP)_p = - \varepsilon_{CTt} + \Sigma_r \, p_r \, Y_r (1/RT - 1/CT) \, . \, \dot{Y}_r / Y_r \qquad [e]$$

If returns to scale are decreasing, RT > CT and therefore $(\dot{TFP}/TFP)_p < - \varepsilon_{CTt}$. Decreasing returns to scale will yield negative scale effects and the residual measure of total factor productivity will be underestimated as a measure of technical change. For increasing returns to scale, the bias is inverted. In the special case of a multiinput-monooutput technology or if outputs are separable with respect to inputs, the previous equation may be written as :

$$(\dot{TFP}/TFP)_p = - \varepsilon_{CTt} + (1 - \delta CT/\delta Y . \, Y/CT) . \, \dot{Y}/Y$$

$$= - \varepsilon_{CTt} + (1 - \mu^{-1}) \, . \, \dot{Y}/Y \qquad [f]$$

This equation shows that if the long-run cost function is linearly homogeneous with respect to Y, $\mu = 1$ and the term $(1-\mu^{-1})$. $\dot{Y}/Y$ is zero : in this case, $(\dot{TFP}/TFP)_p = - \varepsilon_{CTt}$. Under increasing (decreasing) returns to scale, $(\dot{TFP}/TFP)_p$ is greater (smaller) than $- \varepsilon_{CTt}$.

Second, consider the case where returns to scale are constant, all inputs variable (no quasi-fixity on the input side) but some output markets in disequilibrium. Equation [c] becomes, assuming that all outputs may be in disequilibrium.

$$(\dot{TFP}/TFP)_p = -\varepsilon_{CT t} + \Sigma_s\ (p_s Y_s/RT - \hat{p}_s Y_s/CT)\ .\ \dot{Y}_s/Y_s \qquad [g]$$

The direction of the bias induced by a non-marginal tarification of outputs depends on the gap between market output shares $p_s Y_s/RT$ and "marginal" output shares $p_s Y_s/CT$, where $p_s = \delta CT/\delta Y_s$ is the marginal cost of output Y_s. As an example, let us consider the case of the dairy quota which is binding since its implemantation in 1984 in EEC. Guyomard, Mahé, Tavéra and Trochet (1988) consider that from 1984 to 1986 the shadow price of milk decreases by 5 to 6 percent per year. More precisely, using a theoretical model developed by Mahé and Guyomard (1989) which links the endogeneous dual price of milk $\hat{p}^M{}_s$ to its determinants (output and variable input prices, quasi-fixed input levels and prices, milk-quota level and technical change) it is possible to calculate the dual milk price growth rate for each year. The results for France and Germany are presented in table 1.

Table 1. Observed and dual milk price growth rate, milk quota growth rate ; France and Germany, 1984 to 1988, %, national prices (provisional results)

FRANCE	dual price/	market price/	quota level
1984	-2.2	+4.1	-2.0
1985	-4.1	+4.1	+0.0
1986	-2.8	+3.0	+0.2
1987	-11.3	+1.3	-5.6
1988	-5.8	+2.5	-2.6

GERMANY	dual price /	market price/	quota level
1984	-3.3	-2.6	-6.7
1985	-1.0	-1.1	-0.3
1986	-3.5	+1.3	0
1987	-8.6	-0.2	-5.9
1988	-3.2	-0.03	-2.7

Assuming that dual and market prices are equal for the base period 1984, that is assuming that the milk market is in equilibrium in 1984, we can compute the dual price level of milk for each year and consequently we can calculate the bias induced by the milk quota system in measuring technical change by the traditional non-parametric total factor productivity index. As an example in 1984 the bias is equal to -0.031 % in

France and -0.017 % in Germany. The bias, which depends not only on the gap between dual and market prices but also on the milk quota growth rate, increases with time since the difference between dual and observed milk prices increases too (see table 1).

Third, let us consider the case where returns to scale are constant, all output markets competitive and in equilibrium but some inputs quasi-fixed. In such a case, equation (c) reduces to

$$(\dot{T}FP/TFP)_P = -\varepsilon_{CDt} + \Sigma^1{}_j\ [(\hat{w}^1{}_j - w^1{}_j)\ .(X^1{}_j/CD)].(\dot{X}^1{}_j/X^1{}_j) \qquad [h]$$

This equation is the counterpart of equation [g] established in the case of output disequilibrium. So the same reasoning applies. The magnitude and sign of the difference between $(\dot{T}FP/TFP)_P$ and $(-\varepsilon_{CD}t)$ depend on the gap between dual and market prices of quasi-fixed factors.

2. NEUTRAL OR BIASED TECHNICAL CHANGE : PROBLEMS OF DEFINITIONS AND PROBLEMS OF MEASUREMENT

2.1. Problems of definitions

Technical change is often characterized as neutral or biased. Based on original Hick's definition and assuming a two input - one output linearly homogeneous technology, technical change is said to be neutral if it leaves unchanged the marginal product of input X_1 to that of input X_2. However, as noted by Blackorby, Lovell and Thursby (1976), "to compare situations before and after technical change, something must be held constant. Exactly what is to be held constant has been the subject of some debate and constitutes the crux of the issue at hand". Kennedy and Thirlwall (1972) among others argue that factor endowments must be held constant at least at the macro level and consequently technical change effects must be measured along a ray where factor proportions remain unchanged. At the firm level and also at the macro level in a sector like agriculture where enterprises are more often assumed price-takers, it is most useful to define neutrality holding factor price ratio constant (Binswanger, 1974). Consequently in this study like in most studies applied to agricultural technologies (for a review, see Thirtle and Ruttan, 1987) biases and neutrality are defined along an expansion path, that is in terms of the proportional change in the input ratio holding factor price ratio constant. In other words,

$$\frac{\delta(X_1/X_2)}{\delta t} \cdot \frac{1}{(X_1/X_2)} \left| \begin{array}{l} > 0 \text{ input } X_2 \text{ saving} \\ = 0 \text{ neutral} \\ < 0 \text{ input } X_2 \text{ using} \\ \\ \text{factor price ratio } (w_1/w_2) \text{ constant.} \end{array} \right.$$

The previous definition can easily and equivalently in the two input case be transformed into a definition in terms of factor shares at constant factor price ratio. Furthermore the share approach generalizes immediatly to the many-input case. The measure of bias for each factor proposed by Binswanger is given by,

$$B_{it} = \frac{\delta S_i}{\delta t} \cdot \frac{1}{S_i} \left| \begin{array}{l} > 0 \text{ input } X_i \text{ using} \\ = 0 \text{ input } X_i \text{ neutral} \\ < 0 \text{ input } X_i \text{ saving} \\ \\ \text{factor price ratio } (w_i/w_j) \text{ constant.} \end{array} \right.$$

where S_i is the share of input X_i in total costs. Technical change biases are then defined on the basis of a dual representation of the technology, assuming that there exists a long-run total cost function $CT(Y, w, t)$ where all inputs are variable. It is interesting to note that if the long-run technology is not homothetic with respect to Y, it is necessary to hold constant not only relative factor prices but also output levels. Following Sato (1970), the bias B_{it} can be interpreted using the following decomposition

$$B_{it} = \delta S_i/\delta t \ . \ 1/S_i \Big|_{Y,\ w_i/w_1}$$
$$= \delta \log(w_i X_i(Y,w,t)/CT(Y,w,t))/\delta t$$
$$= \delta \log X_i(Y,w,t)/\delta t - \delta \log CT(Y,w,t)/\delta t$$
$$= \varepsilon_{it} - \varepsilon_{CTt}$$

Consequently the bias is the difference of two effects : the percentage change in demand for the input X_i minus the average percentage variation in inputs. The sign of this second effect is known unambiguously if technical change occurs ($\varepsilon_{CTt} < 0$). Then a technical change which is input X_i saving decreases expenditure on that factor because the reduction in X_i from a change in t is greater than average. This technical change is input X_i using when it increases expenditure on that factor, that is when the average effect is greater than the specific effect. An alternative interpretation perhaps less intuitive is given by Morrison (1988) : she notes that each technical change bias B_{it} may be expressed as $B_{it} = 1/S_i(\delta^2 \log CT/\delta \log p_i \delta t) = \delta \varepsilon_{CTt}/\delta \log p_i$ and consequently B_{it} measures also the effect on total cost diminution from a change in p_i. Finally, note that if there are n inputs, there will be n measured biases B_{it}. Nevertheless it may be useful to define biases as follows :

$$Q_{ij} = B_{it} - B_{jt} = \delta \log S_i/\delta t - \delta \log S_j/\delta t$$

In this case there will be n!/2(n-2)! measures. Q_{ij} greater than zero implies that technical change has resulted in using more of factor X_i relative to factor X_j.

The assumption that a long-run Hicksian equilibrium can be achieved by the observed technology is crucial to the development of the previous analysis in terms of total cost shares. However, we have shown that such an assumption is too restrictive and unrealistic. When one input is quasi-fixed it appears as an argument in the restricted cost function $CR(Y,w^0,X^1,t)$ and in the total disequilibrium cost function $CD(Y,w^0,w^1,X^1,t)$. Consequently two short-run measures of technical change may be defined,

$$B^{CR}_{it} = \delta \log S^{CR}_i / \delta t \,\Big|_{w^o_i / w^o_1,\ Y,\ X^1}$$

$$= \delta \log X^{oCR}_i \ (Y, w^o, X^1, t)/\delta t - \delta \log CR(Y, w^o, X^1, t)/\delta t$$

$$= \varepsilon^{CR}_{it} - \varepsilon_{CRt}$$

where S^{CR}_i is the restricted cost share of input X^o_i.

$$B^{CD}_{it} = \delta \log S^{CD}_i / \delta t \,\Big|_{w^o_i / w^o_1,\ w^1,\ Y,\ X^1}$$

$$= \delta \log X^{oCR}_i \ (Y, w^o, X^1, t)/\delta t - \delta \log CD(Y, w^o, w^1, X^1, t)/\delta t$$

$$= \varepsilon^{CR}_{it} - \varepsilon_{CDt}$$

where S^{CD}_i is the disequilibrium total cost share of input X^o_i.

Both derivations are based on constant relative variable input prices as well as output and quasi-fixed input levels. Furthermore the second definition implies also the constance of fixed input rental prices. B^{CR}_{it} and B^{CD}_{it} are linked by the following equality,

$$B^{CD}_{it} = \varepsilon^{CR}_{it} - \varepsilon_{CDt} = \varepsilon^{CR}_{it} - \varepsilon_{CRt} - (\varepsilon_{CDt} - \varepsilon_{CRt})$$

$$= B^{CR}_{it} - \varepsilon_{CRt} \ (CR/CD - 1)$$

$$= B^{CR}_{it} - \varepsilon_{CRt} (-\Sigma^1_j \ w^1_j \ X^1_j \ /CD)$$

Consequently, $B^{CD}_{it} \leq B^{CR}_{it}$. If technical change is short-run equilibrium input X^o_i saving, then it is also short-run disequilibrium input X^o_i saving. In the same way, if B^{CD}_{it} is superior or equal to zero, then B^{CR}_{it} is also superior to zero. Finally note that technical change can be short-run equilibrium input X^o_i using ($B^{CR}_{it} \geq 0$) and short-run disequilibrium input X^o_i saving ($B^{CD}_{it} \leq 0$). In such a case a change in t implies that $\varepsilon^{CR}_{it} \leq \varepsilon_{CDt}$ so that the specific effect of t on X^o_i is greater than the average effect measured with respect to the disequilibrium cost function but this specific effect is smaller than average measured with respect to the restricted cost function. This analysis shows that certain biases can be difficult to interpret and consequently that policy implications must be derived with caution.

Nevertheless it is more useful to analyse technical change biases defined in terms of disequilibrium cost shares because these definitions are more easily visualized and more directly comparable to long-run equilibrium biases. Finally note that if we define short-run biases in terms of differences, $Q^{CR}_{ij} = B^{CR}_{it} - B^{CR}_{jt} = B^{CD}_{it} - B^{CD}_{jt} = Q^{CD}_{ij}$, the previous difficulty of interpretation vanishes.

Short-run, equilibrium or disequilibrium, technical change biases do not take into account the ability to adjust the quasi-fixed inputs in the long-run. Consequently, these measures are not calculated along the global expansion path relative to all inputs insofar as the quasi-fixed factors are not necessarily initially at their optimal levels. In order to take into account the full response of variable and quasi-fixed inputs, we use the fact that long-run responses can be deduced solely from the estimated parameters of the short-run cost function. This property has been extensively used to derive long-run price elasticities from their short-run counterparts (Brown and Christensen, 1981 ; Kulatilaka, 1985, 1987 ; Guyomard, 1988 ; Guyomard and Vermersch, 1989). This property can easily be extended to technical change biases. As a consequence, long-run measures take into account the adjustment of quasi-fixed inputs induced by time.

$$
\begin{aligned}
B_{it} &= \delta \log S^{CD}_{i}(Y,w^{o},X^{1}(Y,w^{o},w^{1},t),t)/\delta t \Big|_{w^{o}_{i}/w^{o}_{1},\, w^{1}_{j}/w^{o}_{1},\; Y} \\
&= \delta \log X^{oCR}_{i}.(Y,w^{o},X^{1}(Y,w^{o},w^{1},t),t)/\delta t \\
&\quad - \delta \log CD(Y,w^{o},w^{1},X^{1}(Y,w^{o},w^{1},t),t)/\delta t \\
&= \varepsilon^{CR}_{it} + \Sigma^{1}_{j}\ \delta \log X^{oCR}_{i}/\delta \log X^{1}_{j}.\delta \log X^{1}_{j}(.)/\delta t \\
&\quad - (\varepsilon_{CDt} + \Sigma^{1}_{j}\ \delta \log CD/\delta \log X^{1}_{j}.\delta \log X^{1}_{j}(.)/\delta t) \\
&= B^{CD}_{it} + \Sigma^{1}_{j}\ (\delta \log X^{oCR}_{i}/\delta \log X^{1}_{j} - \delta \log CD/\delta \log X^{1}_{j}).\delta \log \\
&\quad X^{1}_{j}(.)/\delta t \\
&= B^{CD}_{it} + \Sigma^{1}_{j}\ (\varepsilon^{CR}_{ij} - \varepsilon_{CDj}).\delta \log X^{1}_{j}(.)/\delta t \\
&= B^{CD}_{it} + \Sigma^{1}_{j}\ \varepsilon^{CR}_{ij}\ \delta \log X^{1}_{j}(.)/\delta^{t}
\end{aligned}
$$

since in the long-run, $\delta CD/\delta X^{1}_{j} = 0$.

This equation shows that the long-run technical change bias B_{it} is the sum of two effects : the short-run disequilibrium bias and the "expansion" technical change bias. The signs of B_{it} and B^{CD}_{it} may differ depending on the relative magnitude of this "expansion" effect which can be either positive or negative. In other words, technical change may be input X^o_i long-run saving and short-run disequilibrium using.

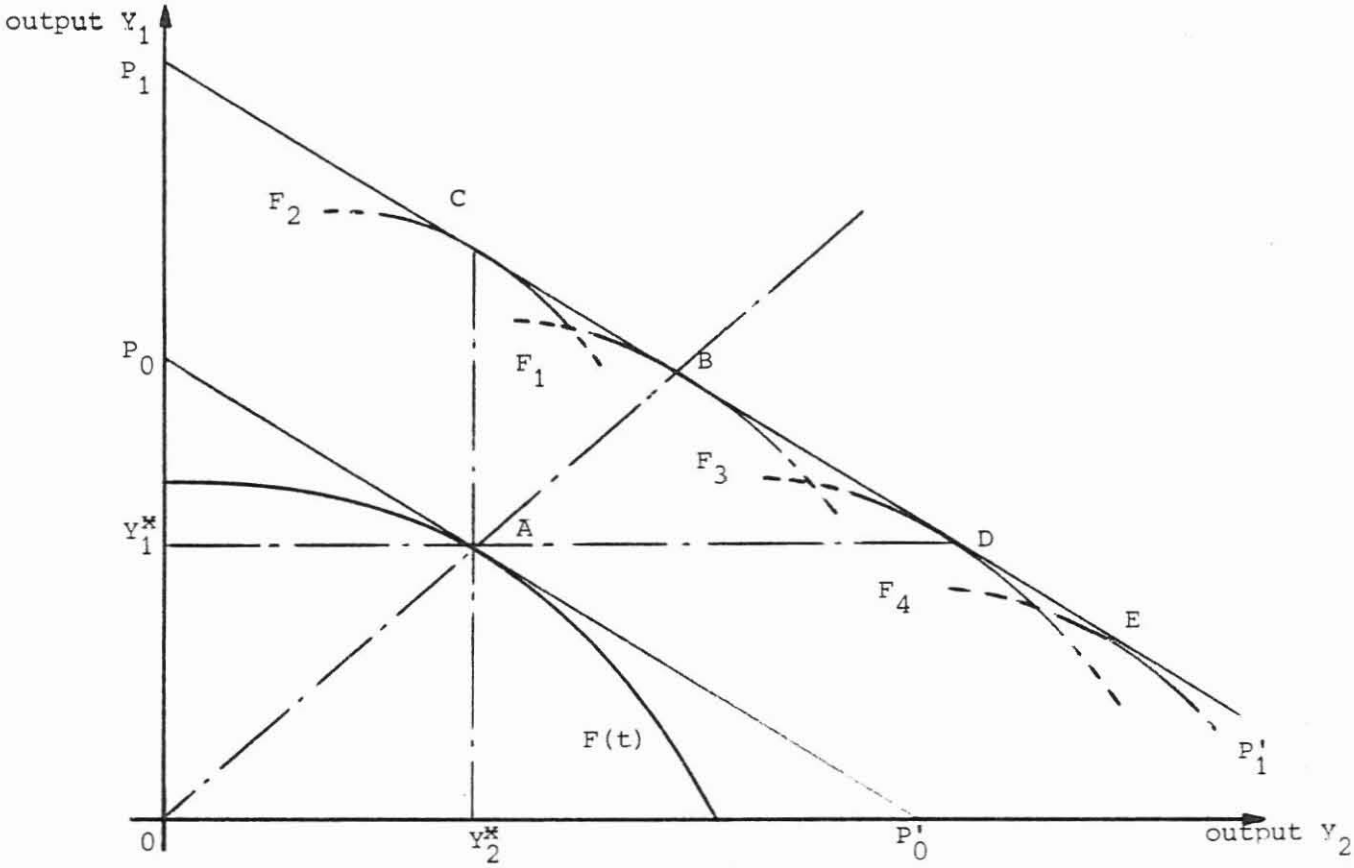
In the multioutput case, technical change biases may also be defined for outputs. Assuming that farmers are long-run profit maximisers and using the property that maximisation of profits may be broken into two parts, maximisation of revenue and minimisation of costs (Sakai, 1974), we will define technical change biases on the output side in terms of long-run revenue output shares holding relative output prices and input levels constant. More specifically, the total or long-run revenue function is defined by $R(p,X) = Max_Y(\Sigma_r p_r Y_r \ ; \ Y_r \varepsilon Y(X))$, where $Y(X)$ is the output possibility set, Y the vector of m outputs with prices $p' = (p_1,...,p_m) \geq 0$. The total profit function is then defined by $\Pi(p,w) = Max_{Y,X}(\Sigma_r p_r Y_r - \Sigma_i w_i X_i \ ; \ (-X,Y)\varepsilon T) = R(p,X(p,w)) - CT(w,Y(p,w))$, where T is the production possibility set. Consequently a measure of bias for each output is given by ,

$$B_{rt} = \frac{\delta S_r}{\delta t} \cdot \frac{1}{S_r} \Bigg|_{\text{input levels, relative output prices.}}$$

where S_r is the total revenue share of output Y_r. A positive value of B_{rt} implies that technical change is biased toward output Y_r (or relatively rth output using), while a negative value of B_{rt} implies that technical change is biased against output Y_r (or relatively rth output saving). Finally, $B_{rt} = 0$ implies neutrality with respect to Y_r.

This definition can be illustrated geometrically. The curve F(t) (figure 1) represents the product transformation frontier for a single hypothetical industry, which produces only two outputs Y_1 and Y_2 given the levels of inputs. The slope of the tangent to this transformation curve indicates relative commodity prices : given prices p_1 and p_2, the firm faces an isorevenue line $PP':R = p_1Y_1 + p_2Y_2$ which has slope $-p_1/p_2$. Consequently, with relative output prices depicted by p, the optimal production combination is at point A = (Y^*_1, Y^*_2). The direct effect of technical change would result in a shift of the product transformation curve. The curves F_1, F_2, F_3 and F_4 represent four alternative possibilities. For technologies F_1, F_2 and F_3, the proportional "using" in outputs is equal to P_0P_1/OP_0, but the output using biases differ. In the first case (technology F_1), technical change uses both outputs in the same proportion as before : the new tangency point is B and technical change will be said to be neutral with respect to both outputs ($B_{1t} = B_{2t} = 0$). On contrary, if the new equilibrium is at point C on curve F_2, the output Y_2 level remains unchanged but technical change is output Y_1 using. By the same way, on curve F_3 at point D, technical change is output Y_2 using but neutral with respect to Y_1. These three possibilities are limiting cases insofar as technical change is defined as neutral and/or purely output using. If the technical change effects are more favorable to Y_2 relative to Y_1, the new curve will be skewed toward Y_2 so that the new equilibrium point is E where $Y_2 > Y^*_2$ and $Y_1 < Y^*_1$: in such a case, technical change is output Y_2 using and output Y_1 saving. In other words, technical change is biased toward output Y_2 and against output Y_1.

Figure 1. Neutrality and biases of technical change in output space at constant factor levels and constant output prices.



Output biases B_{rt} can interpreted using the same decomposition as in the input-bias case :

$$B_{rt} = \delta S_r / \delta t .\ 1/S_r \Big|_{X,\ p_r/p_s}$$

$$\begin{aligned} s &= \delta \log(p_r Y_r(p,t,X)/R(p,t,X))/\delta t \\ &= \delta \log Y_r(p,t,X)/\delta t - \delta \log R(p,t,X)/\delta t \\ &= \varepsilon_{rt} - \varepsilon_{Rt} \end{aligned}$$

Consequently, each bias B_{rt} is the difference of two effects : the percentage change in supply for the output Y_r minus the average percentage variation in outputs. The sign of this second effect is positive if technical change occurs. Then a technical change which is biased toward output Y_r increases revenue on that output because the rise in Y_r from a change in t is greater than average. An alternative interpretation may be proposed using the following derivation ; $B_{rt} = 1/S_r (\delta^2 \log R$

$/\delta \log p_r \delta t) = (\delta \varepsilon_{Rt} / \delta \log p_r).1/S_r$; and consequently B_{rt} measures also the effect on total revenue increase from a change in p_r.

Important fixities exist among production outputs. The example that springs to mind immediately is that of cattle output in the agricultural sector (Boyle and Guyomard, 1989). When some outputs are considered as quasi-fixed, they appear as arguments in the restricted revenue function $RR(p^o, Y^1, X, t)$ and in the total disequilibrium revenue function $RD(p^o, Y^1, p^1, X, t)$. This last function represents the maximum attainable revenue given the vector of variable output prices p^o, the vector of production inputs X, time t and with some outputs as quasi-fixed $Y^1{}_s$. This function is defined by : $RD(p^o, Y^1, X, t, p^1) = RR(p^o, Y^1, X, t) + \Sigma^1{}_s p^1{}_s Y^1{}_s$. Consequently two short-run measures of technical change biases on the output side may also be defined, in terms of restricted revenue shares or in terms of disequilibrium revenue shares, respectively. The analysis which is analogous to that proposed in the input bias case will not be developed in this paper (for more details, see Boyle and Guyomard, 1989).

2.2. Problems of measurement

The traditional framework for analysing technical change biases on the input-side is generally based on a multifactor-monooutput long-run translog cost function with a time trend representation of technical change. Since the translog is now standard and familiar in the literature, we do not discuss its properties in this paper (see, for example, Berndt and Christensen, 1973 ; Christensen, Jorgenson and Lau, 1975). Nevertheless, it is useful to note that this specification allows technical change to vary at a non-constant rate, to be scale varying or to change with input prices through the introduction of a quadratic term in time and interactions of the time trend with input prices and output level. In the multioutput case, technical change may be also output mix varying. Using Shephard's lemma, one obtains the cost share equations ; $S_i = a_i + \Sigma_k a_{ik} .\log p_k + a_{iY} .\log Y + a_{it} . t$;

which together with the total cost function itself provide the basis for estimation. Given estimated parameters of this system, it is possible to compute the rate of technical change and long-run equilibrium technical change biases as :

$$- \delta \log CT/\delta t = - (a_t + a_{tt} . t + \Sigma_i a_{it} . \log p_i + a_{Yt} . Y)$$

$$B_{it} = a_{it} / (a_i + \Sigma_k a_{ik} . \log p_k + a_{iY} . \log Y + a_{it} . t)$$

From these equations, we observe that the sign of B_{it} depends upon the sign of a_{it} (the total cost function being non-decreasing in p, estimated input shares are non-negative). Consequently, a qualitative bias of technical change is obtained as the sign of the parameter a_{it} in each share equation. Berndt and Wood (1985) have discussed in details the constraints linked with such a model. In particular, they have shown that since the a_{it} are constant they do not vary in response to relative input price changes. Nevertheless it is easy to verify that long-run equilibrium technical change biases, defined as $\delta \log S_i/\delta t$, vary with input prices since $\delta^2 \log S_i/\delta t\, \delta \log p_k = - a_{it} .a_{ik}/ (a_i + \Sigma_k a_{ik}.\log p_k + a_{iY} .\log Y + a_{it} .t)^2$.

When time is included as an explanatory variable in the cost function, we implicitely assume that all coefficients are constant over time. An alternative specification proposed by Stevenson (1980) is to specify a model such that parameters may change over time. More specifically all coefficients are assumed to vary, linearly or log-linearly, with time so that long-run cost shares may now be written as ; $S_i = \ddot{a}_i + \Sigma_k \ddot{a}_{ik} .\log p_k + \ddot{a}_{iY} .\log Y = (a_i + \Sigma_k a_{ik} .\log p_k + a_{iY} .\log Y) + (a^*_i + \Sigma_k a^*_{ik} .\log p_k + a^*_{iY} . \log Y) . f(t)$. Whereas the traditional specification of technical change cannot be used to assess directly the validity of the induced innovation hypothesis, this modified model allows to specifically test for price-induced technical biases. Following Stevenson, "the extent to which factor-share bias is induced by factor price shifts is given by, $\delta^2 S_i /\delta t\, \delta \log p_k = a^*_{ik}$ (I think that equation (14) in Stevenson (1980, p. 166) should read as this equation) where we expect $a^*_{ik} > 0$ for $k \neq i$ and $a^*_{ik} < 0$ for $k = i$. In the spirit of Hicks (1932), technological change requires time. Consequently any index of technology depends on past values of the variables relevant to the investment technical process. For this reason, lagged variables may be used in state of instantaneous variables : in this case, long-run factor shares may be written as ; $S_i = (a_i + \Sigma_k\ a_{ik}\ .\log p_k + a_{iY}\ .\log Y) + B_{it}$; with $B_{it} = g\ (p_{-\infty},\ldots,p_{-1},Y_{-\infty},\ldots,Y_{-1},t)$. Unfortunately, such a cost share equation, estimated successfully by Gatien, Lassere and Ouelette (1987) for the asbestos industry in Canada cannot be derived from a parametric cost function considered as a local approximation around an expansion point to the true but unknown cost function. The second possibility, proposed by Binswanger (1978) in the case of a tradional translog specification is to use a two step procedure. In a first step, the cumulated technological change biases are calculated as follows : $B_{it}^{CUM} = S_{it=0} + \Sigma_t\ \delta S_{it}/\delta_t$, where $S_{It=0}$ represents the cost share of input i in the first time period. In a second step, these cumulative biases are compared to corresponding changes of relative input prices.

A third specification of technical change is the factor augmenting form or, from the point of view of the dual, the price diminishing form (Berndt and Wood, 1985 ; Wills, 1979). In this case, input prices are written as : $p^*_{it} = p_{it} - \exp(-\Theta_i t)$ where p^*_{it} and p_{it} are efficient and observed prices, respectively, associated with augmented (X^*_{it}) or observed (X_{it}) input levels. The estimating equations become : $S_{it} = a_i + \Sigma_k\ a_{ik}\ .\log p^*_k + a_{iY}\ .\log Y = a_i + \Sigma_k\ a_{ik} \log p_k + a_{iY}\ .\log Y + \Sigma_k\ (-a_{ik}).\ \Theta_k\ .\ t$. Note that a negative augmentation rate is not only counter-intuitive but also ruled out by economic theory (Kohli, 1981).

In order to illustrate the qualitative and quantitative relevance of the foregoing analysis, table 2 presents differents technical change biases on the input side derived from various models of the French agricultural sector (provisional results).

Table 2 : Technical change biases on the input side. (French agriculture, period 1959-1984)

Models	Biases (expansion point 1970, %)			
1) long-run translog cost function				
four inputs : K, N, S, CI				
one output : Y				
non-neutral technical change (model I)	long-run equilibrium biases Bit			
	K	N	S	CI
- static long-run equilibrium	3.79	-4.20	-1.55	5.75
- dynamic long-run equilibrium (multivariate adjustement)	5.07	-7.80	0.87	9.91
2) Long-run translog cost function				
four inputs : K, N, S, CI				
one output : Y	long-run equilibrium biases Bit			
non-neutral technical change (model II)	K	N	S	CI
static long-run equilibrium	5.15	-3.95	-3.01	5.24
3) Short-run translog cost function	short-run equilibrium biases Bit^{cq}			
four variable inputs A, F, NS, O	A	F	NS	
three quasi-fixed inputs : K, N, S	-5.98	5.82	13.07	
one output Y	short-run disequilibrium biases Bit^{cr}			
non-neutral technical change (model I)	A	F	NS	
static short-run equilibrium	-8.75	3.04	10.30	

Note : model I corresponds to a time trend representation of technical change, model II is estimated assuming that the different parameters, vary linearly with time. K = capital, N = family and hired labour, S = land, CI = raw materials, which can be desagregated in three components : A = animal feed, F = fertilizers, O = other raw materials, NS : hired labour.

3. SOME REMARKS ON THE USE OF TIME TREND AS A PROXY FOR TECHNICAL CHANGE

Lots of applied empirical works on technical change use a time trend as a proxy for technical change (or, more precisely, for the autonomous component of technical change) in regressions such as :

$$Y_t = \alpha + \beta t + \sum_{i=1}^{K} \delta_i Z_{it} + e_t \tag{1}$$

where Y_t is the log of output, $Z_t = (Z_{1t}, \ldots, Z_{Kt})$ is a set of K exogenous variables (each taken in log), t is a linear time trend and e_t is a series of white noise (o, σ^2_e) residuals.

In equation (1), the effect of the Stochastic Component of Technical Change (SCTC) is captured through the effect of the exogenous variables Z while the time trend is used to represent the effect of the Autonomous Component of Technical Change (ACTC). Such a formulation amounts to implicitely assume that the ACTC is purely deterministic : it has evoluated at a constant growth rate in the past and it will keep on evoluating at the same rate in the future independently of all shocks affecting the economy or the sector under consideration. Recently several papers on non-stationarity have shown that results from the estimation of equation (1) are strongly subject to the spurious regression phenomenon and have to be taken with caution if Y_t and the Z_{it} ; i=1,...,K; are non-stationary.

3.1. Some remarks on non-stationarity

Many economic time series are characterized by non-stationarities such as a changing mean and variance over time[1]. There is obviously an unlimited number of possibilities that can account for non-stationary behaviour but lots of

1 In applied empirical analysis, only weak stationarity is required which is equivalent to $E(X_t)$ = constant and $Cov(X_t, X_{t-s}) = \delta^2$ if $S = 0$ and $= 0$ if $S \neq 0$.

authors have recently reexamined two widely used procedures to model changing means over time. Let X_t be a logarithmic non-stationary time series.

- The first procedure is to assume that X is explained by a linear dependence on time, with the remaining variation in X being due to a stationary cyclical component ε_t. In this case X_t is modeled as :

$$X_t = a + bt + \varepsilon_t$$
$$\text{and } \phi(L)\varepsilon_t = \Theta(L)\eta_t \qquad (2)$$

where $\phi(L)$ and $\Theta(L)$ are polynomials in the lag operator L ($L^k X_t = X_{t-k}$) of respective order p and q ; ε_t is a stationary and invertible process and η_t a white noise process $(0, \sigma^2_\eta)$. The most noteworthy characteristics of model (2), which Nelson and Plosser (1982) dub the Trend Stationary (TS) model, are that the trend incorporated in X_t is completely deterministic and that all shocks to X are temporary or cyclical. Thus, the path of X in the long-run is completely deterministic and is not altered by current or past events. A related issue is that uncertainty on forcasting error is bounded since :

$$Var(X_t - a - bt) = Var(\varepsilon_t) = \sigma^2_\varepsilon \qquad (3)$$

- The second procedure maintains that X contains one unit root[2] and differencing of the data is therefore the correct way to remove non-stationarities. The adequate model, which Nelson and Plosser (1982) call the Difference Stationary (DS) model, is :

$$X_t - X_{t-1} = b + u_t$$
$$\text{and } \Omega(L)u_t = \Gamma(L)v_t \qquad (4)$$

2 Let X_t follow a stochastic difference equation model of the form : $(1-\delta_1 L..-\delta_r L^r)X_t=(1-d_1 L..-d_r L^r)W_t$, where W_t is a series of iid random shocks with mean o and variance σ^2 w. Let Z denote a complex variable and consider the function $\delta(Z)=(1-\delta_1 Z\cdot\cdot-\delta_r Z^r)$. If μ is a root of $\delta(Z)=0$ with $|\mu|=1$, then μ is called a unit root of $\delta(Z) = 0$.

where u_t is a stationary ARMA process, $\Omega(L)$ and $\Gamma(L)$ are lag polynomials of respective order r and s, v_t is a white noise process $(0, \sigma^2{}_v)$. A particular case of the DS model is the random walk model in which u_t does not follow an ARMA process but is instead an identically independent distributed (iid) white noise process $(0, \sigma^2{}_u)$.

Since data are in logs, $(X_t - X_{t-1})$ is the growth rate of X_t. Furthermore the mean growth rate b is theoritically the same as the coefficient on t in model (2). The great difference between DS and TS models lies in the fact that in the DS model the impact of a shock on X_t embodied in the innovations v_t is to shift the level of X upward or downward permanently.

In order to rapidely compare the properties of the DS and TS process, the first equation of model (4) is rewritten as :

$$X_t = X_0 + b\ t + \sum_{j=1}^{t} u_{t-j} \tag{5}$$

by accumulating changes in X from any initial value, say X_0. Although (5) has the same form as (1), we see that the intercept is no more a fixed parameter but rather depends on the initial value X_0. Furthermore the disturbance is no more stationary and the variance-covariance matrix depends on time.

Another point is that whereas the width of a confidence interval for future values of X in (2) is limited by the finite dispersion of ε_t, in (5) it increases without bound with time :

$$\mathrm{Var}\ (X_t - X_0 - bt) = \mathrm{Var}\ (\sum_{j=1}^{t} u_{t-j}) = t\sigma^2{}_u \tag{6}$$

3.2. Econometric Problems due to non-stationary disturbances

Model (1) implicitely assumes that the ACTC which can be written as :

$$ACTC_t = Y_t - \sum_{i=1}^{K} \delta_i Z_{it} = \alpha + \beta t + e_t \qquad (7)$$

follows a TS process. In this case the ACTC is assumed deterministic. Forecasts made with such a model are thus based on the hypothesis that only the SCTC can be altered by a given policy in the long-run since

$$\hat{Y}_{T+m} = \alpha + \sum_{i=1}^{K} \delta i \, \bar{Z}_{i\,T+m} + \beta.(T+m) \qquad (8)$$

where $\hat{Y}_{T+m}$ is the forecast of Y_{T+m} made at time T and $\bar{Z}_{i\,T+m}$ the value taken for $Z_{i\,T+m}$.

However if the ACTC is not a TS variable but instead a DS variable according to :

$$ACTC_t = Y_t - \sum_{i=1}^{K} \delta_i Z_{it} = ACTC_{t-1} + \beta + e_t' \qquad (9)$$

then first differencing of the relationship (1), that is,

$$(Y_t - Y_{t-1}) = \beta + \sum_{i=1}^{K} \delta_i \, .(Z_{it} - Z_{i\,t-1}) + e_t' \qquad (10)$$

would put it in the form suitable for estimation. This is due to the fact that if the ACTC is DS, then estimating a relationship such as (1) amounts to estimate a relationship similar to :

$$Y_t = Y_o + \beta t + \sum_{i=1}^{K} \delta_i Z_{it} + \sum_{j=1}^{t} e_{t-j}' \qquad (11)$$

with non-stationary residuals.

Nelson and Kang (1984) have discussed the consequences of estimating the relationship in levels (1) when the differenced relationship (10) is in fact the one with stationary disturbances. Their main results can be summarized as follows :

a) OLS estimates of $\delta'=(\delta_1, \ldots, \delta_K)$ and β in (11) are unbiased but inefficient since the disturbances in (11) are correlated across time periods.

b) As already discussed by Granger and Newbold (1974), estimation of δ' by OLS in levels is subject to the spurious regression phenomenon. That is, conventional t and R^2 tests are biased in favour of indicating a relationship between the variables when none is present. This is due to the fact that an OLS estimation of δ' in (11) can be thought as regression of detrented Y on detrended Z according to :

$$Y^*_t = \sum_{i=1}^{K} \delta_i Z^*_{it} + e^*_t \qquad (12)$$

where stars denote detrented variables.

However if Z_t and e_t are both DS process in equation (1) then Y_t is also DS. In this case relation (12) shows that estimating δ' by OLS in (11) is equivalent to a regression where the independent variable and the error term are both detrented random walks and thus have the same autocorrelation function (Chan-Hayya and Ord, 1977)[3]. The effect of autocorrelation in regression errors will be to inflate the variance of the OLS coefficients. In this respect, the precision of the estimate of δ' will be greatly overstated if serial correlation in the regression errors is ignored : conventional standard errors and t statistics will mislead by overstating significance of coefficient estimates.

3 Chan-Hayya and Ord (1977) show that when the true model of a time series is a random walk (or more generally a DS model), the use of a linear deterministic time trend to eliminate a suspected trend will produce large spurious positive autocorrelation in the first few lags.

c) A related issue is that correspondingly, R^2 will exagerate the extend to which movement of the data is actually accounted for by time and exogenous Z variables. Using a Monte Carlo experiment, Nelson and Kang show that time and a random walk will tipically explain about 50 % of the variation in a random walk that is in fact unrelated to either.

d) Estimating a relationship similar to (11) leads to spurious sample autocorrelations of residuals which exponentialy decline as it is the case in a first order autoregressive process. If the investigator believes the regression disturbances to be stationary then he can use the value of autocorrelation at lag one f_1 as an estimate of the autoregressive coefficient in the following transformed regression equation :

$$(Y_t - f_1 Y_{t-1}) = \alpha . (1-f_1) + \beta . (t - f_1(t-1)) + \sum_{i=1}^{k} \delta_i . (Z_{it} - f_1 Z_{it-1}) + (e_t - f_1 e_{t-1})$$

Regression (13) would be properly specified if f_1 were set at unity. Only in this case (which is equivalent to taking first differences of equation (1)) residuals $(e_t - e_{t-1})$ would be random. However as was pointed out in Nelson-Kang the empirical standard deviation of f_1 is only 0.064 around the mean of 0.852 and sample values of f_1 are thus rarely close to unity. The problem of non-random and non-stationary disturbances is still present in (13). It can be shown that the problem of spurious relationship of Y to time is partly alleviated by the transformation but it is still very strong. Lastly, continued iteration of the Cochrane-Orcutt procedure improves the properties of estimates but only first-differencing is the correct and adequate procedure.

3.3. Testing for the incorporation of a linear time trend

Several tests for stationarity have recently been proposed in the literature on time series models. The tests for stationarity in differences as opposed to stationarity around a trend line developed by Dickey and Fuller (1981) and largely applied in papers such as Nelson-Plosser (1982) seem to be a useful preliminary to analysis of non-stationary series. The Dickey-Fuller likelihood ratio statistic is based on the hypothesis that stationary time series can always be written as an autoregressive (AR) model. In order to test for the hypothesis that the series X_t follows a TS model with a m^{th} order AR process against the alternative that X_t follows a DS model with a $(m-1)^{th}$ order AR process, the testing procedure is to nest the TS and DS models in a more general model as follows :

$$X_t = \mu + \sum_{i=1}^{m} d_i \, . \, X_{t-i} + pt + \eta_t \qquad (14)$$

where η_t is a sequence of normal independent random variables $(0, \sigma^2_\eta)$ and $\sum_{i=1}^{m} d_i = 1$ and $p = 0$ in the case of the DS model.

By rearranging the terms X_{t-i}, the relationship (14) can be rewritten :

$$X_t = \mu + (\sum_{i=1}^{m} d_i)\, X_{t-1} + (-\sum_{i=2}^{m} d_i)\, . \,(X_{t-1} - X_{t-2}) + \ldots.$$

$$\ldots.+(-d_m)\, . \,(X_{t-m-1} - X_{t-m}) + pt + \eta_t$$

$$= \mu + D_1 \, X_{t-1} + \sum_{i=2}^{m} D_i \, . \,(X_{t+1-i} - X_{t-i}) + pt + \eta_t \qquad (15)$$

In equation (15) the null hypothesis of a DS model is equivalent to $D_1 = 1$ and $p = 0$. Two likelihood ratio tests ϕ_2 and ϕ_3 are developed by Dickey and Fuller. ϕ_2 is the usual regression F test of the null hypothesis H_o : $(\mu, D_1, p) = (0,1,0)$ against the alternative that X_t is TS ; while ϕ_3 is the usual regression F test of the null hypothesis H_0 : (μ, D_1, p) = (μ, 1, 0) against the alternative that X_t is TS. Although both ϕ_2 and ϕ_3 are conventional F statistics, the usual significance values are inappropriate if unit roots are present and must be replaced by the test statistics given in Dickey-Fuller (1981) - table V (test ϕ_2) and table VI (test ϕ_3).

The Dickey-Fuller testing procedure is applied to French data for production and yields for wheat and corn. Data are annual and for the period 1940-1988. Tests are based on estimates of equation (15). All series are taken in logarithms and the order of autoregressive process is determined after examination of the partial autocorrelation function of deviations from trend. Empirical results are reported in Table 3.

Table 3. Dickey-Fuller tests ϕ_2 and ϕ_3 : wheat and corn production and yields, French agriculture, 1940-1988

	Production		Yields	
	wheat	corn	wheat	corn
m	1	2	1	1
μ	12.315	1.206	2.371	1.089
D_1	-0.187	0.835	-0.116	0.374
p	0.045	0.016	0.039	0.029
ϕ_2	24.05*	3.08	21.13*	7.80*
ϕ_3	35.01*	1.20	29.96*	11.30*

* indicates rejection of the null hypothesis at the 5 % level(critical values are 5.13 for ϕ_2 and 6.73 for ϕ_3).

The null hypothesis of a DS model is rejected for wheat and corn yields data but is not rejected for corn production. Thus, wheat production and wheat yields data series both seem to incorporate a deterministic time trend. These results are compatible with the common idea that the increase in the French wheat production is mainly attributable to the regular improving of producing technics and to technical change. While corn yields seem to be distributed according to a TS process, corn production seems to be non stationary due to the presence of a unit root. Therefore, results of regressions such as (1) where corn production is the endogenous variable can be subject to the spurious regression phenomenon and have to be considered with caution. Such a regression should be taken in difference before estimation.

4. APPLICATION OF TIME SERIES METHODS TO THE MEASURE OF STOCHASTIC AND DETERMINISTIC COMPONENTS OF TECHNICAL CHANGE

Time series methods are only rarely used to measure technical change. However some recent developments of time series analysis - the theory of persistence - provide interesting procedures for decomposing technical change into a permanent, or secular component, on one hand, and a temporary component, on the other.

4.1. Definition of persistence

Let X_t be a given non-stationary logarithmic time series which can be made stationary with a first order difference. The Wold (1938) theorem shows that $(X_t - X_{t-1})$ can be written as an infinite moving average model according to :

$$X_t - X_{t-1} = (1-L)\, X_t = M(L)\, w_t \qquad (16)$$

where $M(L) = (1+M_1 L + M_2 L^2 + \ldots)$ is an infinite polynomial in the lag operator and w_t is white noise $(o,\ \sigma^2{}_w)$. The impact of a shock in period t on the growth rate in period t+k is M_k. The impact of the shock on the level of X_t is given by $P(L) = (1-L)^{-1} .\ M(L)$ which is equal to $P_k = 1 + M_1 + \ldots + M_k$ in period t+k. The total effect of the shock on the level of X_t is given by the infinite sum of the moving average coefficients, which is :

$$M(1) = \lim_{i \to \infty} P_i = 1 + \sum_{i=1}^{\infty} M_i$$

The value of M(1) is thus a measure of persistence. It indicates the extent to which the long run path of Xt deviates from its past trend after a once for all unit shock.

If X_t is a TS process, fluctuations in the series are stationary around a deterministic time trend and after a shock, the series always returns to its trend in the long-run. In this case, the persistence is thus zero (M(1)=0). At the opposite, if X_t is distributed according to a DS model, fluctuations in the series are permanent. For instance, if a unit shock makes the series decrease from its previously expected value ($E_t(X_t/X_{t-1},\ldots)$) by one unit, then expected future values of X_t ($E_t(X_{t+j})$) definitively decrease by one unit. In this case persistence equals one (M(1)=1). In the general case, M(1) can take any value between zero and one. This indicates that fluctuations in the series X_t are partly temporary and partly permanent and the value of M(1) is an estimate of the size of the permanent component. Lastly, if M(1) is greater than one, the series X_t indefinitively deviates from its trend after a given shock. This case being of limited interest, it is not retained in this paper.

There are several approaches to estimating persistence. Two of them, the Campbell-Mankiw and the Cochrane proceduces, are briefly presented in this paper. The theory of persistence provides a useful method to measure the relative size of the random walk and stationary components. Beveridge and Nelson (1981) show that any first-difference stationary process X_t can be represented as the sum of stationary or temporary (T_t) and random walk or permanent (P_t) components. It can be shown that long-term forecasts of X_t are unaffected by the transitory component whereas the permanent component shifts from period to period in response to current innovation. Beveridge and Nelson call P_t the stochastic trend of the series X_t. In other words the theory of persistence indicates which part of the process is TS and which part is DS.

4.2 Methods to estimate persistence

The first approach is based on ARMA methods and is proposed by Campbell and Mankiw (1987). Let X_t be the log of the economic time series under consideration. The change in X_t is first written as a stationary ARMA process :

$$C(L)\ (X_t - X_{t-1}) = D(L)\ w_t \qquad (17)$$

where C(L) and D(L) are finite polynomials in the lag operator. The moving-average representation M(L) equals $C(L)^{-1}D(L)$ since :

$$(X_t - X_{t-1}) = \frac{D(L)}{C(L)}\ w_t = M(L)\ w_t \qquad (18)$$

Campbell and Mankiw propose to use M(1) which equals D(1)/C(1) as a measure of persistence.

Cochrane (1988) proposes another measure of persistence which can be written as a ratio of variances[4] :

$$V(k) = 1/k.\ Var(X_t - X_{t-k})\ /\ Var(X_t - X_{t-1}) \qquad (19)$$

If X_t is a pure DS process, then the variance of the k-lagged difference is k times the variance of the once-lagged difference :

$$Var(X_t - X_{t-k}) = k.Var(X_t - X_{t-1}) \qquad (20)$$

4 As shown in Cochrane (1988) the value of V(k) can also be written as a function of autocorrelation of $(X_t - X_{t-1})$:

$$V(k) = 1 + 2 \sum_{j=1}^{k-1} (1-j/k).\ g_j$$ where g_j is the estimated j^{th} autocorrelation of $(X_t - X_{t-1})$

Hence, equations (19) and (20) show that for a DS model, the measure of persistence V(k) equals one. For any TS model, the variance of the k lagged difference tends toward a constant which equals twice the variance of the series (σ^2_X)

$$Var\ (X_t - X_{t-k}) \to 2\ \sigma^2_X \qquad (20)$$

In this case, the measure of persistence V(k) approaches zero for large k : $\lim_{k\to\infty} V(k) = 0$ (21)

Following Cochrane, the limit V of the variance ratio V(k) is a measure of persistence : $V = \lim_{k\to\infty} V(k)$.

For the two polar cases, both measures of persistence produce the same number : V = M(1) = 0 if X_t is a pure TS and V=M(1)=1 if X_t is a pure DS model. In the more general case, that is when X_t includes a permanent and a stationary component, the two measures are not the same. However they are not independent since it can be shown that

$$M(1) = [V/(1-R^2)]^{1/2} \qquad (23)$$

where R^2 is defined as $[1 - Var\ (w)/Var(X_t - X_{t-1})]$.

As suggested in Campbell-Mankiw and Cochrane, an approximate estimate of M(1), called $M^*_k(1)$, can be estimated nonparametrically as :

$$M^*_k(1) = [\ \hat{V}_k/(1-\hat{p}^2_1)]^{1/2}$$

by replacing R^2 in equation (23) with the square of the first autocorrelation p_1. However, note that since p^2_1 underestimates R^2 (except for an AR(1) process), $M^*_k(1)$ tends to understate M(1).

4.3. Application of Cochrane and Campbell-Mankiw procedures

When data series on technical change are available, the theory of persistence can be used to measure the relative sizes of the ACTC and SCTC. However data series on technical change are rarely available or are subject to lots of problems (see Section 1 and 2). In this sub-section, we assume that along the long-run or equilibrium path, production grows at the same rate as technical change. Thus the measure of persistence in production is a proxy for pesistence in technical change. The Cochrane and Campbell-Mankiw methods are thus applied to the previously defined French data series for production and yields for wheat and corn. The Cochrane measure in estimated with k = 30 which amounts to assume that temporary shocks have disappeared after 30 years. Empirical estimates of V^*_k and M(1) are reported in table 4.

Table 4. Cochrane and Campbell-Mankiw measures of persistence :

Product	k	Production		Yields	
		V^*_k	M(1)	V^*_k	M(1)
Wheat	10	0.16	0.47	0.14	0.42
	15	0.10	0.38	0.09	0.35
	20	0.12	0.41	0.13	0.41
	25	0.11	0.39	0.12	0.39
	30	0.12	0.41	0.08	0.32
Corn	10	0.72	0.93	0.32	0.67
	15	0.55	0.81	0.21	0.54
	20	0.46	0.75	0.19	0.52
	25	0.43	0.71	0.19	0.51
	30	0.31	0.61	0.12	0.41

A shown by equation (23) the two measures take different values depending on the size of R^2. However results are fully compatible with those obtained with the Dickey-Fuller tests ϕ^2 and ϕ^3. Wheat production, wheat yields and corn yields include rather small permanent component (respectively 0.12, 0.08 and 0.12 as measured by V^*_k and 0.41, 0.32 and 0.41 as measured by M(1)). This is in harmony with ϕ_2 and ϕ_3 previous results that these series are TS. The greatest part of technical change seems to be deterministic in the French wheat and corn sector. In these sectors, technical change is thus only little affected by temporary shocks. A given shock has only a minor impact on the long-run behaviour of technical change in those sectors. Both the permanent and transitory components of corn production are important. This is consistent with estimated ϕ_2 and ϕ_3 statistics which showed that this series is DS. This apparent contradiction between results obtained with corn production and yields series can be attributable to fluctuations in planted acreages for corn during the period of analysis[5] while, at the opposite, planted acreages for wheat are rather constant all along the period. Thus, taken as a whole, results in table 2 seem consistent with the idea that the greatest part of technical change is deterministic and autonomous in the French wheat and corn sectors with the smallest SCTC in the wheat sector.

5. CONCLUDING REMARKS

Although a great deal of empirical research on productivity and technical change measurement has taken place in the last decade, some important problems, which have been reviewed in this paper, have not been treated in a completely satisfactory manner. As an example, the existence of the dairy quota in the EC requires further analysis in order to correctly measure the impact of this policy instrument on the traditional index of total factor productivity. More generally, lessons derived from economic theory and time series analysis can contribute to a better understanding of the sources of variations in the patterns of productivity growth and technical change.

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5 Planted acreages for corn increase with a relatively constant growth rate until 1973, then decrease in a chaotic way.

ANNEX 1. TECHNICAL CHANGE AND TOTAL FACTOR PRODUCTIVITY GROWTH RATE : THEORETICAL BACKGROUND

The analysis presented in this annex is similar to that developed by Morrison (1986) or Slade (1986), which in turn is heavily derivative of the pionering work of Berndt and Fuss (1981, 1986). The formula we propose is more general insofar as the technology is multiinput-multioutput with some outputs as "quasi-fixed". The basic notations are the following :
Y^o is the vector of variable outputs with typical price element given by $p^o{}_r$; Y^1 is the vector of quasi-fixed outputs with typical price element given by $p^1{}_s$.
X^o is the vector of variable inputs ($w^o{}_i$) ; X^1 is the vector of quasi-fixed inputs ($w^1{}_j$)
CD (Y^o, Y^1, w^o, w^1, X^1, t) is the disequilibrum total cost function (Berndt and Fuss, 1981), that is the total cost of producing Y when some inputs are fixed ; CR (Y^o, Y^1, w^o, X^1, t) is the corresponding restricted or variable cost function.
$(\dot{TFP}/TFP)_p = \Sigma^o{}_r\ R_r . \dot{Y}^o{}_r/Y_r + \Sigma^1{}_s\ R_s . \dot{Y}^1{}_s/Y_s - \Sigma^o{}_i\ S_i . \dot{X}^o{}_i/X_i - \Sigma^1{}_j\ S_j\ \dot{X}_j/X_j$, where R_r, R_s are long-run revenue output shares and S_i, S_j disequilibrium total cost input shares.

A logarithmic differential of CD(.) can be written as,

$$
\begin{aligned}
d \log CD/dt &= \delta \log CD/\delta t \\
&+ \Sigma^o{}_r\ \delta CR/\delta Y^o{}_r . Y^o{}_r/CD . \dot{Y}^o{}_r/Y^o{}_r \\
&+ \Sigma^1{}_s\ \delta CR/\delta Y^1{}_s . Y^1{}_s/CD . \dot{Y}^1{}_s/Y^1{}_s \\
&+ \Sigma^o{}_i\ \delta CR/\delta w^o{}_i . w^o{}_i/CD . \dot{w}^o{}_i/w^o{}_i \\
&+ \Sigma^1{}_j\ \delta CR/\delta X^1{}_j . X^1{}_j/CD . \dot{X}^1{}_j/X^1{}_j \\
&+ \Sigma^1{}_j\ w^1{}_j\ X^1{}_j/CD . \dot{X}^1{}_j/X^1{}_j + \Sigma^1{}_j\ w^1{}_j\ X^1{}_j/CD . \dot{w}^1{}_j/w^1{}_j \qquad [a]
\end{aligned}
$$

By Shephard's lemma ; $\delta CR/\delta Y^o{}_r = p^o{}_r\ \hat{V}r$; $\delta CR/\delta\ w^o{}_i = X^o{}_i\ \hat{V}i$; $\delta CR/\delta Y^1{}_s = p^1{}_s\ \hat{V}s$; $\delta CR/\delta X^1{}_j = -\ w^1{}_j\ V_j$, where $\hat{p}^1$ and w^1 are the vectors of dual or shadow prices for "quasi-fixed" outputs and inputs respectively.

Then, we can rewrite expression [a] as,

$$d \log CD/dt = \delta \log CD/\delta t$$

$$+ \Sigma^o{}_r\ p^o{}_r\ Y^o{}_r/CD.\ \dot{Y}^o{}_r/Y^o{}_r + \Sigma^1{}_s\ \hat{p}^1{}_s\ Y^1{}_s\ /CD.\ \dot{Y}^1{}_s\ /Y^1{}_s$$

$$+ \Sigma^o{}_i\ X^o{}_i\ w^o{}_i/CD.\ \dot{w}^o{}_i/w^o{}_i - \Sigma^1{}_j\ \hat{w}^1{}_j\ X^1{}_j\ /CD.\ \dot{X}^1{}_j\ /X^1{}_j$$

$$+ \Sigma^1{}_j\ w^1{}_j\ X^1{}_j/CD.\ \dot{X}^1{}_j/X^1{}_j + \Sigma^1{}_j\ \hat{w}^1{}_j\ X^1{}_j\ /CD.\ \dot{w}^1{}_j\ /w^1{}_j \qquad [b]$$

Differentiating the alternative definition of CD with respect to time ($CD = \Sigma^o{}_i\ w^o{}_i\ X^o{}_i + \Sigma^1{}_j\ w^1{}_j\ X^1{}_j$) and simplifying, we obtain the following relationship between technical change ($-\delta \log CD/\delta t$) and the traditional index of total factor productivity,

$$- \delta \log CD/\delta t = \Sigma^o{}_r\ (p^o{}_r\ Y^o{}_r/CD - p^o{}_r\ Y^o{}_r/\ RT)\ \dot{Y}^o{}_r/\ Y^o{}_r$$

$$+ \Sigma^1{}_s\ (\hat{p}^1{}_s\ Y^1{}_s/CD - p^1{}_s\ Y^1{}_s/RT)\ .\ \dot{Y}^1{}_s/Y^1{}_s$$

$$- \Sigma^1{}_j\ \hat{w}^1{}_j\ X^1{}_j/CD\ .\ \dot{X}^1{}_j/X^1{}_j + \Sigma^1{}_j\ w^1{}_j\ X^1{}_j/CD\ .\ \dot{X}^1{}_j/X^1{}_j$$

$$+ (\dot{TFP}/TFP)_p \qquad [c]$$

Finally, using the measure of long-run returns to scale proposed by Caves, Christensen and Swanson (1981) ; $\mu = [1-\Sigma^1{}_j\ \delta \log CR/\delta \log X^1{}_j]/[\Sigma^o{}_r\ \delta \log CR/\delta \log Y^o{}_r + \Sigma^1{}_s\ \delta \log CR/\delta \log Y^1{}_s]$; and substituting this expression into [c] we obtain,

$$(\dot{TFP}/TFP)_p = - \delta \log CD/\delta t$$

$$+(1-\mu)(\mu)^{-1}[\Sigma^o{}_r\ p^o{}_r Y^o{}_r/CD.\ \dot{Y}^o{}_r/Y^o{}_r + \Sigma^1{}_s\ \hat{p}^1{}_s\ Y^1{}_s/CD\ .\ \dot{Y}^1{}_s/Y^1{}_s]$$

$$+ \Sigma^o{}_r\ R_r\ .\ \dot{Y}^o{}_r/Y^o{}_r + \Sigma^1{}_s\ R_s\ .\ \dot{Y}^1{}_s/Y^1{}_s$$

$$- (\mu)^{-1}\ [\Sigma_r\ p^o{}_r\ Y^o{}_r\ /CD\ .\ \dot{Y}^o{}_r/Y^o{}_r + \Sigma^1{}_s\ p^1{}_s\ Y^1{}_s/CD\ .\ \dot{Y}^1{}_s/Y^1{}_s]$$

$$+ \Sigma^1{}_j\ (\hat{w}^1{}_j - w^1{}_j)\ X^1{}_j\ /CD\ .\ \dot{X}^1{}_j\ /X^1{}_j \qquad [d]$$

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