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Modelling technical change in Italian agriculture: a latent variable approach

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Abstract

This paper presents an alternative approach to the measurement of technical change. It is based on the latent variable *level of technology* that enters explicitly the input demand system and on a hypothesis about the innovation generating process. By adding measurement error equations, the behavioral system can be viewed as a Multiple Indicators/Multiple Causes (MIMIC) model. The parameter estimates are obtained with a maximum likelihood estimator which involves the implicit covariance matrix. The analysis refers to Italian agriculture and the results provide some evidence on the nature and level of technical change during the years 1961–1991. © 2000 Elsevier Science B.V. All rights reserved.

Keywords: Italian agriculture; MIMIC model; Total factor productivity (TFP); Technical change

1. Introduction

In this paper, we develop an econometric model to analyze the sources of growth of output and to estimate the rate of technical change in Italian agriculture for the period 1961–1991. Since World War II, agricultural output has risen at remarkable rates, labor has steadily diminished and capital has commonly been considered scarce. In other words, output growth can only be partly explained by changes in input use. One could therefore conclude that the agricultural sector in Italy registered sustained rates of technical progress, at least during the investigation period.

Though, it is generally accepted that technological innovation influences output growth enhancing total factor productivity (TFP), conventional TFP indexes often give an inadequate account of the real contribution of technical change. Solow (1957) is usually cited as the seminal study in this field. Nonetheless, some aspects of his elegant accounting framework appeared open to criticism right from the beginning. The residual measure implicitly assumes that technical change is exogenous which essentially amounts to leaving it unexplained. TFP growth can be viewed as the fundamental outcome of technical change but it cannot be identified with it. Not only can it be an erroneous measure of such change but, more fundamentally, it does not provide any information about how technical change is generated. A great deal of literature has focused on the explanation of technical change, in particular, trying to introduce so-called

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non-conventional inputs, such as R&D and Extension expenditure, human capital accumulation, spillover effects. Contributions can be divided into two big strands of literature. The first focuses on the theoretical aspects. In a general economic equilibrium framework, the idea is to model why some agents invest time or money in R&D, human capital accumulation, etc. thereby fostering technical change. This is substantially the approach of the so-called endogenous (or new) growth theory (Lucas, 1986; Jones, 1995).

A second research field is essentially empirical. It does not aim at explaining why technical change occurs; rather, it wants to provide empirical evidence of the link between technical change and its measured result (TFP) and the non-conventional inputs mentioned above. Although it may seem less ambitious and based upon ad hoc assumptions, it has attracted much attention. This paper is a contribution to this strand of literature.

In applied work, the crucial point is that we cannot observe the real technological level, and, consequently, the estimation of the relation between non-conventional inputs and technological change becomes problematic. To tackle it, three strategies have been proposed. The first assumes that non-conventional inputs (most frequently R&D) are good proxies of technological level and therefore introduces them explicitly into the aggregate production function (or dual functions) together with conventional inputs. Many results for the agricultural sector have been presented (Huffman and Evenson, 1989; Khatri and Thirtle, 1996; Mullen et al., 1996; Kuroda, 1997) also for the case of Italy (Esposti and Pierani, 1999). However, results using this approach are only reliable to the extent that non-conventional variables are good proxies of the underlying technological level.

A second approach is based upon the so-called TFP decomposition and it implies two stages. [1] In the first, TFP growth calculation is carried out, with technical change being approximated by the time trend. The productivity index is then regressed on non-conventional inputs to estimate their impact and contribution to technical change. Many results have also been produced for the agricultural sector using this approach (Thirtle and Bottomley, 1989; Evenson and Pray, 1991; Fernandez-Cornejo and Shumway, 1997; Alston et al., 1998a) including for the Italian case (Esposti, 1999). However, if TFP growth is a poor proxy of real technical change, this approach runs into econometric problems, due to the inconsistency of parameter estimates caused by measurement errors (Fuller, 1987).

A third alternative has recently been suggested (Gao, 1994; Gao and Reynolds, 1994). It uses the concept of technology as a latent variable. Both TFP and non-conventional inputs can be regarded as proxies but they measure it with errors that can greatly affect estimates, and this also partially explains why such different results can be found in the literature (Alston et al., 1998b). Moreover, while TFP is the observed effect of technical change, non-conventional inputs are observed possible causes of it. Latent variable models can handle these issues well: technological level explicitly enters the production process, while the economic process generating it and involving non-conventional inputs is formally specified. This structure can be represented in a unified analytic form and simultaneously estimated in the so-called Multiple Indicators/Multiple Causes (MIMIC) model.

This paper applies this latent variable approach to Italian agriculture. The main aim is to stress the differences that can emerge with respect to alternative methods. Moreover, some emphasis is also put on data sources and the construction of variables, as we think, these are crucial aspects that can highly affect latent variable estimates and explain the above-mentioned differences.

2. MIMIC model specification

Long run agricultural production in Italy is depicted from the dual by means of the differential approach (Theil, 1980). It consists of one aggregate output (q), four inputs (materials (x_{M}), labor (x_{L}), capital (x_{K}), land (x_{T})) and the unobservable technology level (Ξ). [2] The derived input demand function can be viewed as first-order Taylor series approximation to a

[1] It is also called two-stage approach while the first one-stage or integrated approach.

[2] The use of a poor proxy for the latent variable would result in biased and inconsistent parameter estimates due to measurement error (Gao, 1994; Gao and Reynolds, 1994).

general demand system and takes the form (Barnett, 1979; Gao and Reynolds, 1994): [3]

$$s_i\, \mathrm{d}(\log x_i) = \sum_k \mu_{ik}\, \mathrm{d}(\log p_k) + \omega\theta_i\, \mathrm{d}(\log q) + \beta_i\, \mathrm{d}(\log \Xi), \quad i = 1, \ldots, 4 \qquad (1)$$

where: s_i is the i-th cost share; d (log) represents a logarithmic change of relevant variables; ω is the cost flexibility; [4] θ_i indicates the i-th marginal cost share; μ_{ik} is the Slutsky coefficient; $\beta_i = s_i \tau_i$, and $\tau_i = \partial(\log x_i)/\partial(\log \Xi)$ is the technology elasticity of the i-th input. Technological change is defined to be input i-using, -saving or -neutral depending on whether β_i is positive, negative or nil, respectively. On the other hand, overall neutrality implies that $\beta_i = 0$ for all i.

Since Ξ is not observable, it is not possible to estimate directly from Eq. (1) with standard regression tools. We have to turn to latent variable econometrics. Following Jöreskog and Sörbom (1989), we indicate with $\eta = (\eta_1, \eta_2, \ldots, \eta_m)$ a latent vector of endogenous variables describing the state of agriculture and with $\xi = (\xi_1, \xi_2, \ldots, \xi_n)$ a vector of exogenous variables which have an influence on the state. Formally, each period relationship between the two vectors can be expressed by the following system of linear *structural equations*:

$$\eta = B\eta + \Gamma\xi + \zeta \qquad (2)$$

where, B ($m \times m$) and Γ ($m \times n$) are matrices of coefficients and $\varsigma = (\varsigma_1, \varsigma_2, \ldots, \varsigma_m)$ denotes a typical disturbance vector. It is assumed that ς and ξ are not correlated and the matrix (I–B) is nonsingular. By definition, the latent vector, usually only some element in it, is not observable. Instead, we can observe an indicator $y = (y_1, y_2, \ldots, y_p)$ which is related to η through *measurement equations*, such that:

$$y = \Lambda_y \eta + \varepsilon \qquad (3)$$

where, Λ_y ($p \times m$) is a matrix of parameters. The error term ε is assumed not to be correlated with ς and η, but there can be correlation within systems.

The equation system Eqs. (2) and (3) is often referred to as MIMIC model in that it may contain multiple indicators and multiple causes of the unobserved variables. In this study, technological progress is conceptualized as taking place in two separable stages: generating innovations potentially available to agriculture; selecting innovations and determining a measurable outcome, namely, productivity growth. The exogenous vector represents the generation and the introduction of innovations into the agricultural sector. The state vector describes the process in which the optimal combination of inputs is determined, conditional on the level of technology, output and factor prices.

The rational for assuming Ξ exogenous has to do with one of the main features of agriculture in Italy, namely, the prevalence of small farms and price-taker behavior. Incapable of their own innovative strategies farmers adopt rather than produce innovations. An important issue is the specification of the influences thought to affect the technological level but beyond the control of farmers. A number of exogenous shifters are considered including public R&D and Extension expenditures, human capital, and international and intersectoral *spillover*. Though in applied work, the choice of these cause variables and methods of construction are still subject to debate, there is widespread recognition that knowledge capital approximated by public R&D and Extension variables is pivotal. Being quantitatively negligible, private research does not play a relevant role and it is not considered. [5] When innovations are made available to properly informed farmers, the extent and speed of their adoption depend on the skill and innovative attitude of the farmers. The human capital variable synthesizes this capability. In fact, agricultural innovations mostly originate from outside the sector, at least in Italy. The importance of intersectoral and international spillovers of technology have been well emphasized in literature (Bouchet et al., 1989) and demonstrated for Italian agriculture (Esposti, 1999). Accordingly, we have modelled the innovation process with the following exogenous *generating function*:

[3] The augmented Dickey–Fuller test is performed to test the stationarity. The results indicate that all variables used in the analysis are nonstationary since we cannot reject the null hypothesis of unit root. Assuming trend-stationary processes, the differential approach seems a sensible solution to avoid spurious results and inconsistent estimates (Plosser and Schwert, 1978; Granger and Newbold, 1981; Clark and Youngblood, 1992).

[4] We set $\omega = 1$, as this is the value consistent with an aggregate cost function (Chambers, 1988).

[5] Fernandez-Cornejo and Shumway (1997) makes an analogous choice for Mexican agriculture.

$$\Xi = Sg(R, I, H) \tag{4}$$

where S is the international and intersectoral technology *spillover*.[6] R and I indicate public agricultural research and extension services, respectively, and H, human capital. All explanatory variables in Eq. (4) are treated as predetermined stocks. This equation is simply a descriptive device motivated by heuristic arguments. Log differentiating Eq. (4) with respect to time yields:

$$\dot{\Xi} = \dot{S} + \varepsilon_R \dot{R} + \varepsilon_I \dot{I} + \varepsilon_H \dot{H} \tag{5}$$

where $\dot{\Xi} = \partial \ln \Xi / \partial t$, $\varepsilon_R = \partial \ln g(.)/\partial \ln R$, and so on. In addition, if we are willing to assume that the ratio of the potential spillover to the whole new international and intersectoral technological knowledge[7] is constant ($\gamma_T = \dot{S}/\dot{T}$), then:

$$\dot{\Xi} = \gamma_T \dot{T} + \gamma_R \dot{R} + \gamma_I \dot{I} + \gamma_H \dot{H} \tag{6}$$

Combining the demand system Eq. (1) with Eq. (6), we get the latent variable model to be estimated. Structural equations can be represented as follows:

$$\begin{pmatrix} \dot{\Xi} \\ s_{\mathrm{M}}\,\mathrm{d}\ln x_{\mathrm{M}} \\ s_{\mathrm{L}}\,\mathrm{d}\ln x_{\mathrm{L}} \\ s_{\mathrm{K}}\,\mathrm{d}\ln x_{\mathrm{K}} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ \beta_{\mathrm{M}} & 0 & 0 & 0 \\ \beta_{\mathrm{L}} & 0 & 0 & 0 \\ \beta_{\mathrm{K}} & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \dot{\Xi} \\ s_{\mathrm{M}}\,\mathrm{d}\ln x_{\mathrm{M}} \\ s_{\mathrm{L}}\,\mathrm{d}\ln x_{\mathrm{L}} \\ s_{\mathrm{K}}\,\mathrm{d}\ln x_{\mathrm{K}} \end{pmatrix}$$
$$+ \begin{pmatrix} \gamma_T & \gamma_R & \gamma_I & \gamma_H & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mu_{\mathrm{MM}} & \mu_{\mathrm{ML}} & \mu_{\mathrm{MK}} & \theta_{\mathrm{M}} \\ 0 & 0 & 0 & 0 & \mu_{\mathrm{ML}} & \mu_{\mathrm{LL}} & \mu_{\mathrm{MK}} & \theta_{\mathrm{L}} \\ 0 & 0 & 0 & 0 & \mu_{\mathrm{MK}} & \mu_{\mathrm{MK}} & \mu_{\mathrm{KK}} & \theta_{\mathrm{K}} \end{pmatrix}$$
$$\times \begin{pmatrix} \dot{T} \\ \dot{R} \\ \dot{I} \\ \dot{H} \\ \mathrm{d}\ln(p_{\mathrm{M}}/p_T) \\ \mathrm{d}\ln(p_{\mathrm{L}}/p_T) \\ \mathrm{d}\ln(p_{\mathrm{K}}/p_T) \\ \mathrm{d}\ln q \end{pmatrix} + \varsigma \tag{7}$$

The parameter restrictions implied by symmetry ($\mu_{ik}=\mu_{ki}$), homogeneity of degree 0 of the demand functions $\left(\sum_k \mu_{ik} = 0, \forall i\right)$ and adding-up of the system $\left(\sum_i \beta_i, \sum_i \mu_{ik} = 0, \forall k, \sum_i \theta_i = 1\right)$ are imposed in estimation (Selvanathan, 1989). In our case, the land share equation is omitted and the remaining three input demands are expressed in terms of relative prices, with land as numeraire.[8]

All cause variables in Eq. (6) are observable. However, the presence of unobserved technical change requires measurement equations. Through them, we represent the latent variable with the growth rate of TFP explicitly taking into account the error with which the indicator measures the unobserved variable (Aigner and Deistler, 1989).

In our model, the system of measurement equations takes the form:

$$\begin{pmatrix} T\dot{F}P \\ s_{\mathrm{M}}\,\mathrm{d}\ln x_M \\ s_L\,\mathrm{d}\ln x_L \\ s_K\,\mathrm{d}\ln x_{\mathrm{K}} \end{pmatrix} = \begin{pmatrix} \lambda_{11} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \times \begin{pmatrix} \dot{\Xi} \\ s_{\mathrm{M}}\,\mathrm{d}\ln x_{\mathrm{M}} \\ s_{\mathrm{L}}\,\mathrm{d}\ln x_{\mathrm{L}} \\ s_{\mathrm{K}}\,\mathrm{d}\ln x_{\mathrm{K}} \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{8}$$

where, ε_1 denotes a typical disturbance term. The MIMIC model (Eq. (7)–(8)) is a special case of Linear Structural Model with Latent Variables (LISREL) for the presence of only one endogenous latent vector (Jöreskog and Goldberger, 1975; Bollen, 1989). The parameters are estimated using LISREL 7.2 software with a maximum likelihood procedure.[9]

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[6] We separate explicitly this variable in the expression of the technology generation function as it is a prerequisite to have innovative opportunities at sectoral level.

[7] As also indicated in Khatri and Thirtle (1996), not all new technological and scientific knowledge is potentially relevant for agriculture. S expresses this potential as a constant share of the entire production of new knowledge represented by the T variable.

[8] Indirect estimates of the other parameters in the omitted land share equation can be obtained rearranging the restrictions of the demand system in terms of the directly estimated parameters as follows: $\beta_T=-(\beta_{\mathrm{M}}+\beta_{\mathrm{L}}+\beta_{\mathrm{K}})$, $\mu_{MT}=-(\mu_{\mathrm{MM}}+\mu_{\mathrm{ML}}+\mu_{\mathrm{MK}})$, $\mu_{LT}=-(\mu_{\mathrm{ML}}+\mu_{\mathrm{LL}}+\mu_{\mathrm{LK}})$, $\mu_{KT}=-(\mu_{\mathrm{MK}}+\mu_{\mathrm{LK}}+\mu_{\mathrm{KK}})$, $\mu_{TT}=\mu_{\mathrm{MM}}+2\mu_{\mathrm{ML}}+2\mu_{\mathrm{MK}}+\mu_{\mathrm{LL}}+2\mu_{\mathrm{LK}}+\mu_{\mathrm{KK}}$, $\theta_T=1-(\theta_{\mathrm{M}}+\theta_{\mathrm{L}}+\theta_{\mathrm{K}})$.

[9] A detailed analysis of the econometric and identification issues of the MIMIC model can be found in Bollen (1989) and Jöreskog and Sörbom (1989).

3. Data sources and methods of construction

Annual time series for conventional inputs and output have been obtained as Fisher indexes of relevant prices and quantities from the AGRIFIT database of Italian agriculture which is described more fully in Caiumi et al. (1995). Agricultural output aggregates 52 products, but it does not comprise self produced inputs while it includes deficiency payments and other production subsidies. Four conventional inputs are considered in the analysis: intermediate consumption, labor, land and capital. The latter put together three broad categories: machinery and durable equipment, non-residential structures and livestock. Labor consists of self employed farmers and hired workers. Intermediate consumption includes purchased feeds, fertilizer, pesticides, seed, energy, repair and maintenance, etc. The TFP index comes from Pierani and Rizzi (1994). [10]

We next look at the way the exogenous influences are specified in the generating function in Eq. (6). Among the causes that may influence the unobserved technological level, we have considered public R&D and Extension expenditures, human capital, and international and intersectoral *spillover*. These are briefly discussed in turn.

The intersectoral and international technological stock (T) is captured by the number of domestic and foreign patent demands in United States. The extent to which this data can act as a good indicator of technological advance is often criticized. However, with Griliches (1994), we argue that the number of annual patent demands is the result of both recent R&D investment and cumulated knowledge stock. In other words, we consider it a good proxy of all technological knowledge. The spillover variable (S) represents the percentage of T which can potentially benefit agricultural productivity; hence, we expect that $0 < \gamma_T < 1$.

The substitution of US patents for international knowledge capital is common practice. In their study of UK agriculture, Khatri and Thirtle (1996) justify adopting them because they seem to perform better in term of explanatory power than EU patents. However, they consider only patents for agricultural chemicals and machinery. In Italy, there is some evidence that patented innovations useful for agriculture originate from different sectors and technological fields (Esposti, 1999) so we consider all patents and let the data determine the percentage actually relevant for agriculture. [11] Instead, Fernandez-Cornejo and Shumway (1997) have chosen US agricultural TFP as proxy for international knowledge capital. This variable might turn out to be a poor alternative when the study concerns agricultural sectors whose structures are markedly different from US agriculture as is the case of Italy.

An important issue which arises when using patent data is that values change over time as consequence of economic growth and cycle. Empirically, their market valuations are not observed, hence we adjusted US patent data for the long-run OECD-countries pro capite GDP growth (Griliches, 1994).

Public R&D and Extension (R and I variables) expenditures are obtained from Italian Ministry of Agriculture and Forestry, public local extension services and the accounts of other relevant Institutions. A list of specific sources, and a detailed explanation of the data and construction of the variables used in this study can be found in Esposti (1999). The data refers to research funding by the Ministry of Agriculture and Forestry, and expenditure by both specialized public research institutes and public University Faculties of Agriculture and Animal Science. Expenditure is expressed in billions of 1985 Italian lire.

To convert time series of R&D and Extension expenditures into stocks we follow the perpetual inventory method as slightly modified by Park (1995). The stock of research (similarly for extension) accumulates according to the following expression: $R_t = I^R_{t-m_R} + (1-\delta^R)R_{t-1}$, where I^R_t is gross investments. A number of alternatives exist regarding either the length or the shape of the lag profiles. Unfortunately, with few exceptions (Nadiri and Prucha, 1993), the assumptions underlying this conventional procedure

[10] This measure explicitly accounts for quasi-fixity of some factors, namely, family labor and capital. The authors use a Generalized Leontief form (Morrison, 1992). Their restricted cost function consists of one aggregate output three variable inputs, two quasi fixed factors and time trend.

[11] We do not apply perpetual inventory method to patent series as Khatri and Thirtle (1996). According to Griliches (1994), patents series are already stock variables being the result of all past R&D effort; moreover, the extinction and substitution of patents by themselves represent R&D depreciation well.

have not been statistically tested. Typically, one has to assume more or less arbitrary values for both the initial gestation lag (m), before investments become effective, and the (constant) rate of depreciation (δ). We set δ^R=0.1, m_R=4 (Park, 1995; Kuroda, 1997). Given that Extension programs have faster and shorter-lived impacts than R&D (Evenson and Westphal, 1995), we set δ^I=0.3 and m_I=3.

Finally, concerning human capital (H), we proxy it with farmers education. Following analogous studies (Gao and Reynolds, 1994), we measure farmers education by their average years of schooling.

Given the assumed parameters, the final sample ranged from 1961 to 1991.

4. Empirical results and discussion

The results of estimation of model (Eq. (7)–(8)) are presented in Table 1. The upper part of the table sets out estimates of the input demand system. The empirical evidence seems to reject the hypothesis of Hicks neutrality, to support the evidence of labor-using technical change, and to be inconclusive with respect to materials and capital whose coefficients are not statistically significant. This picture is something of a novelty if compared to the application of an analogous methodology to US agriculture (Gao and Reynolds, 1994) and to other approaches applied to the Italian case (Pierani and Rizzi, 1991) where labour saving and capital and materials using biases are frequently registered.

On one hand, we can think the differences are real. Indeed, Italian and US agriculture present deep structural differences. In Italy, very small family farms are predominant and excess of labor, and capital and land scarcity are the norm. What we observe then is a bias consistent with these structural constraints, which allow labor to be retained within the sector by raising its productivity relative to the other factors. This pattern looks quite original, although there is no economic reason to think that agriculture should inevitably move toward capital intensification. An increase of capital intensity is indeed observed but it is mainly due to relative prices rather than technological change. If this is so, however, our results contrast with the induced innovation hypothesis.

On the other hand, this real explanation still leaves the question open as to why different results are obtained for Italian agriculture using different methodologies and model formulation. In particular, the ways of representing technical change appear to be crucial. Usually, the technological level it is approximated by a time trend, while here the trend variable does not play any role as the technological change is entirely determined by the dynamics of non-conventional inputs, that can drive and also invert technological biases. Consequently, the choice of the data and the construction of the variables are crucial and can greatly affect results. In particular, the definition of R&D and Extension stocks is a well-known open question in the literature (Alston et al., 1998a).

The lower part of Table 1 reports estimates of the generating function. It further reveals how the selec-

Table 1
Parameter estimates of the MIMIC model (standard errors in parenthesis)[a]

Demand system (Eq. (3))	$d\log(p_M/p_T)$	$d\log(p_L/p_T)$	$d\log(p_K/p_T)$	$d\log(q)$	$\dot{\Xi}$
Materials (M)	−0.0699	0.0927	−0.0143	0.6114	−0.0765
	(0.0177)	(0.0178)	(0.0077)	(0.1949)	(0.1756)
Labor (L)	0.0927	−0.0857	0.0207	0.1194	0.8289
	(0.0178)	(0.0232)	(0.0104)	(0.2365)	(0.2918)
Capital (K)	−0.0143	0.0207	−0.0137	0.2645	−0.2903
	(0.0077)	(0.0103)	(0.009)	(0.2241)	(0.1810)
Generating function (Eq. (6))	$\dot{T}$	$\dot{R}$	$\dot{I}$	$\dot{H}$	
Technical change ($\dot{\Xi}$)	−0.0364	0.3644	−0.0759	0.2909	
	(0.141)	(0.159)	(0.129)	(0.149)	

[a] Variance of ε_1=0.0004, (0.0001); squared multiple correlation of TFP=0.335; coefficient of determination of structural equations=0.8422.

Table 2
Price, output and technology elasticities [14]

Factor input	Prices of				Output	Technology
	Materials	Labor	Capital	Land		
Materials	−0.295	0.390	−0.060	−0.036	2.575	−0.322
Labor	0.188	−0.174	0.042	−0.056	0.242	1.680
Capital	−0.069	0.100	−0.066	0.031	1.273	−1.398

tion and definition of non-conventional inputs can be critical. According to the estimated parameters, extension (I) and technological spillover (T) growths turn out to be not statistically significant while research (R) and human capital (H) have positive and significant impacts. Gao and Reynolds (1994) found similar results. The null impact of I can be explained by the difficulty in separating Extension and R&D effects due to their high collinearity (Mullen et al., 1996). The result of T suggests that a more detailed and precise definition of intersectoral and international technological spillover is needed; in fact, the present estimate indicates that this variable is not well approximated by a simple constant share of total US patents. R is the most relevant and significant variable in determining a labor-using technical change. We can interpret this result as the consequence of a conscious political behavior to direct public agricultural research programs towards labor-intensive techniques and products. Alternatively, it could also be that an inappropriate definition of the R&D stock determines such an unusual labor-using bias.

Other information on agricultural technology can be obtained looking at the estimated price and output coefficients in Table 1 and at the compensated elasticities in Table 2. [12] Most of the price coefficients are statistically significant and the own-price effects on the main diagonal are correctly signed with the exception of land. Unfortunately, it is not possible to check whether the land price is statistically relevant as an estimate of its standard error is missing. Cross-price coefficients suggest complementarity between materials and capital, whereas, labor is a substitute for both materials and capital. Therefore, the known dichotomy between an intensive use of capital and materials and that of labor emerges. In this respect, our results confirm previous analyzes (Pierani and Rizzi, 1991).

Price responses are quite unelastic and smaller than output and technology elasticities. As a consequence, long-run factor demands are only partially determined by relative price changes. For instance, with respect to labor, the technical change elasticity is the highest while output and relative prices have smaller impacts. In fact, labor share has been constantly decreasing during the estimation period in favor of materials and capital. Such a transformation is entirely due to the increase of the relative price for labor, as technological bias works in the opposite direction. These contrasting effects resulted in a progressive reduction of the number of agricultural workers.

At the footnote of Table 1, we report some statistical indicators of the model (Bollen, 1989; Jöreskog and Sörbom, 1989). First of all, the estimate of the variance of the error term ε_1 turns out to be significantly different from zero. This result shows that we cannot substitute the latent variable with the indicator variable without introducing a bias due to measurement errors (Fuller, 1987). In other words, introducing TFP measure in the demand system would eventually give inconsistent estimates. The *squared multiple correlation* and the *total coefficient of determination* give an idea of the performance of each component block: the former refers to measurement Eq. (8), the latter to the structural Eq. (7). It turns out that the variation of TFP seems to be a poor proxy of the unobservable technical change. Nonetheless, it remains the best proxy available. After all, it is just the awareness of the inadequacy of our proxies that makes the latent variable model a sensible alternative.

Finally, it is necessary to comment on the estimation of the latent variable as compared with two alternatives: the conventional full-equilibrium measure of TFP growth and an adjusted version which considers

[12] Elasticities are calculated at the normalization point of data.

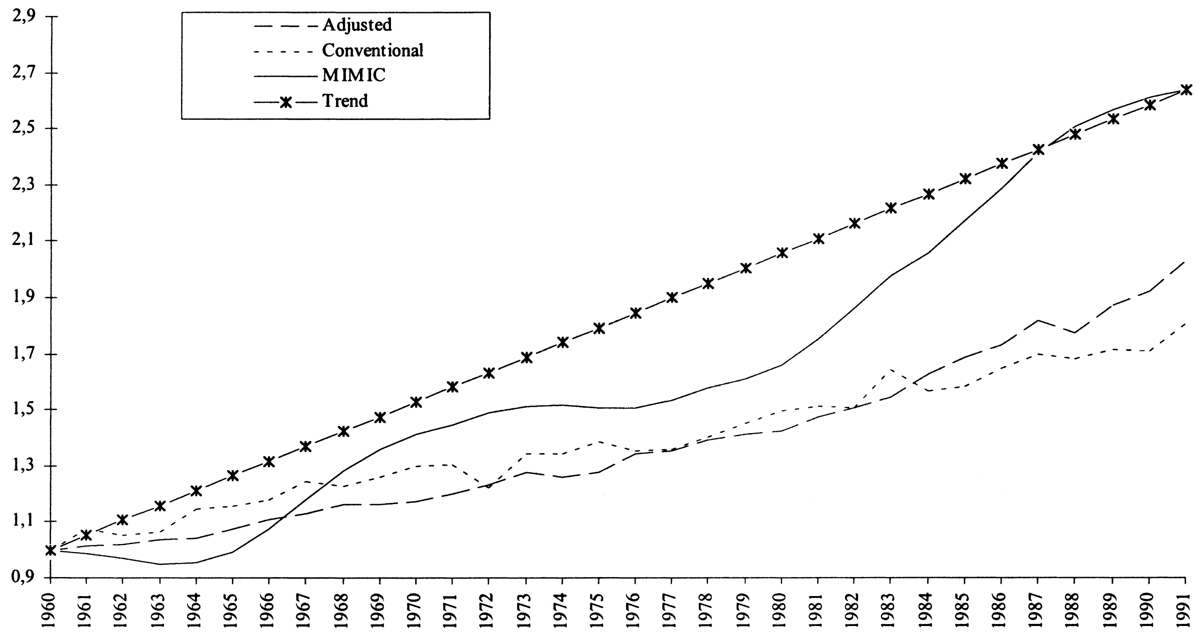

Fig. 1. Technology indexes over time.

Table 3
Technological change indexes (computed at the period means)

Period	MIMIC $\dot{\Xi}$	Conventional TFP	Adjusted TFP
1961–1991	0.031	0.019	0.023
1961–1971	0.034	0.024	0.017
1972–1981	0.014	0.015	0.021
1982–1991	0.043	0.016	0.029

the quasi-fixity of some input[13] (Pierani and Rizzi, 1994). The profiles of the three indices are drawn in Fig. 1, whereas, sub-period averages are reported in Table 3. The MIMIC estimate of technical change shows differences with respect to the TFP measures. In the MIMIC case, the average rate of growth over the whole period is 3.1%; this measure is higher than the conventional and the adjusted ones, 1.9 and 2.3%, respectively. According to our model, therefore, full- and/or sub-equilibrium TFP growth measures tend to underestimate technical progress.

Looking at the subperiod averages, the MIMIC results seem to show a sort of medium-term cyclical behavior: fast growth in the 60's, a remarkable slow down during the seventies and the highest rates in the eighties. Considering Fig. 1, one can see that the MIMIC measure shows a more regular path, too (Gao and Reynolds, 1994). This feature is due to the explicit presence of measurement errors, so that the latent variable estimation can take into account variations in the indicator variables that are not related to technology (particularly in agriculture, short-run factors like weather and other shocks can affect TFP measurement). This smoothness can also allow MIMIC measure to detect long or medium term cyclical patterns of agricultural technical change better. Therefore, the latent variable approach seems to be recommendable whenever the interest focuses on long run behavior rather than short run response.

5. Summary and concluding remarks

The MIMIC model uses the latent variable concept to depict technological growth in Italian agriculture. This alternative approach contrasts with the accounting procedure as it permits a measure of technical change partially distinguished from productivity

[13] This is the variable actually used as indicator of technical change in the MIMIC model.

growth. Theoretically, the two concepts are linked, as higher productivity is the final outcome of a technical advance, but they cannot be confused as is the case in the traditional approach. Technical change is a complex economic and institutional process and its comprehension is at least as important as its measurement. The MIMIC representation turns out to be useful in both respects: representing the generation process and measuring technical change. The model provides consistent estimates of the structural parameters and is flexible enough to allow potentially for a dynamic specification of the generating process. However, this alternative has not been explored in this study.

The empirical results provide some evidence of the positive impact of public R&D expenditure on the technological level in agriculture and also the increase of human capital expressed by education level seems significant. These variables play a relevant role in the structural transformation of the sector. As it is labor-using, technical change partially compensates for the tendency to substitute labor with capital and materials due to their relatively lower prices.

The MIMIC measure of technical change turns out to be different both from the conventional and adjusted TFP measures that appear to underestimate such change. Their profiles over time are also quite different. The MIMIC results reveal a cyclical behavior in the medium-long run along with a particularly intense technological growth in the 80’s, probably caused by the declining of traditional and inefficient agricultural systems.

The latent variable approach can outperform traditional approaches also providing empirical information about the causes of technical change. However, even the MIMIC model requires TFP measures as proxies. On the other hand, TFP measures are still relatively easier and less computationally expensive. Essentially, the choice between the alternative approaches depends on the objective of the research project.

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