AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

378.775
S67
411

University of Wisconsin - Madison

April 1997 **No.411**

THE SOURCE OF TECHNICAL CHANGE IN ITALIAN AGRICULTURE: A LATENT VARIABLE APPROACH

By

Roberto Esposti[*] and Pierpaolo Pierani[,***]**

AGRICULTURAL &

APPLIED ECONOMICS

STAFF PAPER SERIES

---

[*] *Ph.D. student at the Department of Economics, University of Trento (Italy) and visiting scholar at the Department of Agricultural and Applied Economics, University of Wisconsin, Madison (USA).*

[**] *Research Assistant at the Department of Economics, University of Siena (Italy).*

[***] *The authors thank Jean-Paul Chavas and Pierluigi Rizzi for their insightful and useful comments.*

THE SOURCE OF TECHNICAL CHANGE IN ITALIAN AGRICULTURE:
A LATENT VARIABLE APPROACH

By

Roberto Esposti and Pierpaolo Pierani

Abstract

An alternative approach to the measurement of technical change is proposed. It is based on the explicit introduction of the variable "state of technology" into the dual representation of production. A theoretical hypothesis about generation of technical progress in the agricultural sector is formulated. By adding measurement error equations the model can be viewed as a MIMIC model. A maximum likelihood technique involving the implicit covariance matrix provides the estimation of the parameters of the model. Moreover, a Bayesian estimation of the latent variable is obtained. This approach is applied to the Italian agricultural sector during the period 1961-1991. The results provide some evidence about the source and the nature of technical change.

Keywords*:* *Italian agriculture, technical change, latent variable, MIMIC model, cost function.*

Introduction

Economists are unanimously convinced that technical change is one of the most relevant growth engines. Nevertheless, they largely disagree about the correct way to represent and measure it. Different theoretical paradigms and approaches often differ deeply on this issue, and disapproval is sometimes expressed about the way the mainstream economic theory has dealt with the issue so far. Despite the relevance of the theoretical debate, what makes technical change one of the most studied subject in the literature of last decades is its empirical relevance. This relevance is particularly highlighted by the great amount of growth accounting exercises that can be found in the literature.

In this paper we try to reconcile empirical measurement and theoretical explanation of technical change in an unique analytic framework. The object of our analysis is technological growth in Italian agriculture. Starting from the end of the second world war, this sector has gained high output growth rates although labor has constantly decreased and the level of capitalization is commonly considered insufficient. In other words, output growth can be only partially explained by the growth in inputs use. Empirically, productivity growth due to technical progress is just a residual component of output growth. The issue is how we can give a theoretical economic content and explanation to this empirical measure.

In the traditional approach, this residual is considered itself an expression of technical change and its measure, known as Total Factor Productivity (TFP) growth, constitutes a natural way to measure technical change in a sector. Therefore, we would conclude that a high rate of technical progress has been achieved in Italian agriculture during this period. Unfortunately, although some studies were carried out to correctly measure the dimension of this TFP growth (Pierani and Rizzi, 1992 and 1994; Esposti and Pierani, 1995), no attempt was made to explain this high rate of growth. Actually, the traditional approach itself, being based on a residual measure, can not achieve an explanation of the phenomenon.

Main purpose of this paper is twofold: to provide a measure of technical change in Italian agriculture between 1961 and 1991; and to gain some insight on causes and processes that determined this growth. The traditional approach, does not seem to be ideal when the focus is both on the measure and on the representation of the processes that generates technical advance. We propose an alternative approach based on the concept of technology as a latent variable. Technological level explicitly enters the production process as a particular input, while the economic process generating it is formally specified. This theoretical framework can be represented in a unified structural form in the so called MIMIC (Multiple Indicators and Multiple Causes) model.

The paper is organized as follow. In the first section we briefly survey the relevant literature about measurement and representation of technical change, focusing on the traditional Solow approach, its recent evolution and the basic critique to this kind of framework. In the second section, we describe the theoretical model designed to represent the evolution of Italian agriculture. It is essentially a dual representation of the production technology. Due to the presence of the latent technology variable as an explicit argument, it can be viewed as a MIMIC model. Briefly we deal with the econometric implications and issues involved in the estimation of this kind of model. In the third section the data set is described. Finally, in the forth section and in the conclusions, we present the results of the estimation providing an interpretation of the most relevant empirical results.

1. What does "a theory of technical change" mean?

Robert Solow (1957) is usually acknowledged as the first who attempted to investigate technical change within an appropriate and compatible production theory. The result of that analysis was surprising: technical change, measured as an output growth residual in U.S. manufacturing between 1909 and 1949, turned out to explain more than 85% of the per man income growth. Actually, it was not an original result. Several other economists (Tinbergen, 1942; Schmookler, 1952) had previously attempted to measure the residual and all of them found out that component of growth was surprisingly high.

The reason why Solow work was considered a seminal one is that residual measure was coherently embedded in the neoclassical representation of production: from Solow upward, the measure of the residual is no more seen as a "measure of our ignorance"; it is "simply" the shift upward of the production frontier, that is technical change.

To a great extent, this representation of technical advance is intuitively appealing. It is generally accepted that technical progress generates an increase in factors productivity and therefore in the level of output that a given vector of inputs is able to produce. Nevertheless, some aspects of that analysis seemed to be critical from the very beginning. After all, if we measure technical change as a shift of production function we still have a problem of finding a porper representation of the production function.

A great effort and a lot of literature as focused on this issue. The basic idea is that residual measure can still be useful but we need to be careful in the representation of production condition. Flexible functional forms have been used and most of the initial Solow assumptions have been relaxed. Subequilibrium due to quasi-fixed factors, mark-up pricing, adjustment cost, non constant returns to scale and inefficiencies were introduced (Morrison, 1992). This kind of literature is really worthwhile in refining original residual measure. However, there is still some feeling that we are getting only a better "measure of our ignorance".

After all, increase in productivity is with no doubt a critical aspect of the growth of all economies and it is actually the fundamental outcome of technical advance but it can not be identified with technical change. As economists, to know how much total factor productivity increases is not a great achievement if we can not know how actually this is determined, what kind of process is working behind it.

This is the second, and to us more fundamental, critique to Solow approach: a residual measure of technical change means that it is exogenously determined, measured but essentially not explained. Even in this context a lot of literature was produced trying to partially explain technical change with the innovations embodied in new-generation capital (Salter, 1960; Solow, 1962) and with some additional variable as expenditures in R&D, accumulation in human capital, spillover effects (Griliches, 1964; Stoneman, 1983).

To a certain extent, our analysis refers to this kind of literature in which both the effort of explaining and the effort of measuring technical change are fulfilled. Basically, the claim is that an economic theory of technical change must necessarily attempt to represent the economic process that generates it and not only to capture its final result that is increase in TFP.

An interesting general view of the problem is provided by Nelson (1981): technical change can be represented in two distinct moments, a *change phase* and a *coordination phase*. In the first phase, innovations are generated and are introduced in a production system (like a firm or a sector); then, within the production context these innovations are selected, compared to the old ones and an observable outcome is determined. This outcome is Total Factor Productivity. The coordination process is actually the phase the traditional approach typically focuses on: innovations coming from the dark are suddenly available to producers that introduce them in their production process getting a new production frontier.

The usual representation of production technology can be therefore a useful tool if we combine it with a representation of the change process. In other words, we can still use a production function, or its dual, to define the final outcome of the innovation process but we need to express an hypothesis for the generation of this innovation. This is what we pursue in our model.

2. Measuring technical change with a MIMIC model

Following Jöreskog and Sörbom (1989), let's indicate with $\eta = (\eta_1, \eta_2, \ldots, \eta_m)$ a vector of endogenous latent variables describing the dynamics of the state of the agricultural sector and with $\xi = (\xi_1, \xi_2, \ldots, \xi_n)$ a latent vector of independent variables representing the exogenous evolution conditioning the state dynamics. At any time t, we can express analytically the relation between these two vectors with this system of *structural equations*:

(1) $\eta = B\eta + \Gamma\xi + \varsigma$

where B (mxm) and Γ (mxn) are two coefficient matrices and $\varsigma = (\varsigma_1, \varsigma_2,..., \varsigma_m)$ is a vector of stochastic disturbances. The elements of the Γ matrix take into account the impact of the exogenous variables on the state, while the elements in B express the feedback effect of each endogenous variable on the state vector excluding itself (i.e. all diagonal elements are zeros). Furthermore, we assume that ς and ξ are uncorrelated and that $(I-B)$ is a non-singular matrix.

In general, all or some of the elements of the η e ξ vectors cannot be directly observed. Actually, we can only observe vectors $y = (y_1,y_2,...,y_p)$ and $x = (x_1,x_2,...,x_q)$ related to the previous ones according to these *measurement equations*:

(2) $y = \Lambda_y\eta + \varepsilon$

(3) $x = \Lambda_x\xi + \delta$

where $\Lambda_{y,x}$ are coefficient matrices, the ε and δ error terms are reciprocally uncorrelated, and both are uncorrelated with ς and with respective latent vectors, while there can be correlation between disturbances of the respective system of equations.

The general model (1) can be effectively applied to technical change analysis. In fact, the evolution of the system, represented by the state vector, identifies what we called the coordination process. The vector of the exogenous variables represents in turn the change process that is the introduction of innovations in the system. More explicitly, in our case the state constitutes the production process in the agricultural sector: based upon exogenous market prices and level of technology, it defines the optimal combination of input and output in agricultural production.

We represent production technology from the dual with a long run cost function. Differently from the traditional approaches, technical change is identified neither with the TFP growth nor with the logarithmic derivative of the aggregate cost function with respect to time[1]. The *level of technology* Ξ is an explicit argument of the cost function that therefore is defined as follows:

(4) $C = C(p,q,\Xi)$

---

[1] *It can be shown that the use of a proxy instead of the latent variable determines biased and inconsistent parameter estimates whenever a significant measurement error is present (Gao, 1994; Gao and Reynolds, 1994).*

where C is the minimized total cost, q is the aggregate output level, p is the vector of inputs prices; in our case we consider these aggregate inputs: x_M = materials; x_L = labor; x_K = capital; x_T = land. Ξ represents the stock of knowledge: it enters the production process as the traditional physical inputs. Therefore, in this model, q, p and Ξ are given.

An analytical specification of the input demand system depends on the functional form of (4). In order to choose the cost function form, a main requirement is the ex-ante restrictions imposed on the substitution matrix. According to this, flexible functional forms are widely employed in the recent literature. But another important issue has recently risen. The wide use of flexible functional form relies on the implicit assumption that data series are stationary. Being the variables expressed in levels, we can't exclude in these cases inconsistent estimates of the parameters and spurious results (Clark and Younglblood, 1992; Granger and Newbold, 1981).

Considering that most of the variables of these models (prices, output level, R&D expenditures, education level, etc.) grow following clear time trends, one possible solution is to differentiate the series. Assuming trend-stationary processes, this solution avoids the risk of spurious regressions (Plosser and Schwert, 1978). Following Gao and Reynolds (1994), we adopt a differential demand system, an extended Rotterdam model, that can be viewed as a fist order Taylor series approximation of a general demand system (Barnett, 1979; Theil, 1980)[2].

In this case, we can formulate the following factor demand system:

$$(5) \qquad s_i d(\log x_i) = \Sigma_k \, \mu_{ik} d(\log p_k) + \omega\theta_i d(\log q) + \beta_i d(\log \Xi), \qquad i = 1, .., 4$$

where: s_i is the i-th input cost share; $d(\log x_i)$, $d(\log p_k)$ and $d(\log \Xi)$ represent, respectively, logarithmic variations of the i-th input quantity, of the k-th input price and of the state of technology; ω is the cost flexibility[3], while θ_i is the i-th input marginal cost share; μ_{ik} is the Slutsky coefficient; $\beta_i = s_i\tau_i$, where $\tau_i = \partial(\log x_i)/\partial(\log \Xi)$ represents the technological

---

[2] In Appendix 1 we report Dickey-Fuller tests for all data series employed in this study. The results highlight that for none of them we can reject the null hypothesis of unit root, that is of non- stationary series. Therefore, the choice of a differential demand system seems a sensible solution to avoid spurious results and inconsistent estimates.

[3] In this paper we assume $\omega = 1$ being the only value consistent with an aggregate cost function (Chambers, 1988).

elasticity of the i-th input. We observe neutral technical change for the i-th factor if $\beta_i = 0$ $\forall$i ; if this is true we can't reject the hypothesis of Hicks-neutral technical change.

The cost minimizing hypothesis implied by (5), imposes some restrictions on the parameters (Selvanathan, 1989). More specifically, symmetry ($\mu_{ik} = \mu_{ki}$), homogeneity of degree 0 of the demand functions with respect to prices ($\sum_{k=1}^{4} \mu_{ik} = 0,\ i = 1,\ldots,4$) and adding-up with respect to output and technology ($\sum_{i=1}^{4} \beta_i = 0,\ \sum_{i=1}^{4} \theta_i = 1$) are imposed.

The second task of the model is to specify the process that generates Ξ. First of all, we assume that the farmer is viewed as an adopter rather than a generator of innovations. This seems consistent with the basic feature of the Italian agricultural sector: prevalent small farms, price-taker behavior with farmers incapable of own innovative strategies. In this context, technological knowledge can be seen as a public good. Therefore, technical progress constitutes a Marshalian positive externality.

In this framework, technical change in agriculture can be modeled specifying the exogenous generation of innovations and his gradual adoption within the sector. Considering Italian agriculture most of the innovations are originally generated in other sector or/and in other countries. Then, these opportunities can be actually converted in actual and effective innovations for the farmers through an adaptation and a diffusion effort; both are basically carried on by public R&D and Extension expenditures. When feasible innovations are made available to correctly informed farmers, the extent and the speed of the adoption depends on their technical capability and innovative attitude. In short, we indicate this capability and attitude as the level of human capital within the sector.

This general representation of the innovation process can be synthetically modeled as follows. We assume that technological level in Italian agriculture is defined by this *technology generation function*:

(6) $\Xi = S\, g(R, I, H)$

where S is the international and intersectorial *spillover* on the Italian agricultural sector, that is technical knowledge generated in other countries and other sectors that can be potentially useful in the agricultural production[4]. R represents the public agricultural research; I expresses the diffusion of information within the sector determined by public extension services. Finally, H is the human capital. By assumption, S, R, I, and H are stock variables and they are exogenously determined[5].

Actually, what we are interested in is the variation in the level of technology (Ξ). Differentiating (6) with respect to time we get[6]:

$$(7) \qquad \dot{\Xi} = \dot{S} + (\partial \ln g / \partial \ln R)\dot{R} + (\partial \ln g / \partial \ln I)\dot{I} + (\partial \ln g / \partial \ln H)\dot{H}$$

where $\dot{\Xi} = \partial \ln \Xi / \partial t$[7]. If we indicate with ε_R, ε_I, e ε_H the elasticities with respect to Ξ, assuming them constant, we can rewrite (7) as follows:

$$(8) \qquad \dot{\Xi} = \dot{S} + \varepsilon_R \dot{R} + \varepsilon_I \dot{I} + \varepsilon_H \dot{H}$$

We can consider the potential spillover as a constant quota of the whole new technological knowledge produced at intersectorial and international level[8], therefore $\gamma_1 = \dot{S} / \dot{T}$. Then:

$$(9) \qquad \dot{\Xi} = \gamma_T \dot{T} + \gamma_R \dot{R} + \gamma_I \dot{I} + \gamma_H \dot{H}$$

Equation (9) defines the innovation process in the Italian agricultural sector. Adding (9) to the differential demand system representing the coordination process, the general model (1) can be expressed as follows:

---

[4] We separate explicitly this variable in the expression of the technology generation function being it a prerequisite to have innovative opportunities at sectorial level.

[5] The basic idea is that technology level is a stock of knowledge; this stock varies with the variations of the stocks that contributes to generate it.

[6] Therefore, we assume that $g(\cdot)$ is a continuous and differentiable function.

[7] Given the generic variable A, we denote $\dot{A} = \partial \ln A / \partial t$.

[8] Actually, not the whole new technological and scientific knowledge is potentially relevant for the agricultural sector. The S variable is an expression of this actual potential as a constant quota of the entire production of new knowledge.

$$\begin{pmatrix} \dot{\Xi} \\ s_M d\ln x_M \\ s_L d\ln x_L \\ s_K d\ln x_K \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 \\ \beta_M & 0 & 0 & 0 \\ \beta_L & 0 & 0 & 0 \\ \beta_K & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \dot{\Xi} \\ s_M d\ln x_M \\ s_L d\ln x_L \\ s_K d\ln x_K \end{pmatrix} + \begin{pmatrix} \gamma_T & \gamma_R & \gamma_I & \gamma_H & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mu_{MM} & \mu_{ML} & \mu_{MK} & \theta_M \\ 0 & 0 & 0 & 0 & \mu_{ML} & \mu_{LL} & \mu_{MK} & \theta_L \\ 0 & 0 & 0 & 0 & \mu_{MK} & \mu_{MK} & \mu_{KK} & \theta_K \end{pmatrix} \begin{pmatrix} \dot{T} \\ \dot{R} \\ \dot{I} \\ \dot{H} \\ d\ln(p_M/p_T) \\ d\ln(p_L/p_T) \\ d\ln(p_K/p_T) \\ d\ln q \end{pmatrix} + \varsigma$$

(10)

In eq. (10) the differential demand system is rewritten in terms of relative prices with land price (p_T) as the numeraire. Therefore, we drop the land demand equation and we estimate a system of three differential demand equations with symmetry imposed. Moreover, imposing homogeneity and adding-up restrictions allows to get the parameters of the equation dropped. It results: $\beta_T = -(\beta_M + \beta_L + \beta_K)$, $\mu_{MT} = -(\mu_{MM} + \mu_{ML} + \mu_{MK})$, $\mu_{LT} = -(\mu_{ML} + \mu_{LL} + \mu_{LK})$, $\mu_{KT} = -(\mu_{MK} + \mu_{LK} + \mu_{KK})$, $\mu_{TT} = \mu_{MM} + 2\mu_{ML} + 2\mu_{MK} + \mu_{LL} + 2\mu_{LK} + \mu_{KK}$, $\theta_T = 1 - (\theta_M + \theta_L + \theta_K)$.

As it should be clear, the only latent variable in η is the technical change $\dot{\Xi}$; all the other variables are observable. Various proxies for technical have been used in the literature. The more widely employed is the growth of TFP. Although we follow this stream, we emphasize that in our approach $\dot{\Xi}$ and TFP growth can not be considered equivalent due to the existence of measurement errors.

As in (2) and (3), the presence of unobservable variables requires the introduction of measurement equations. Through these equations, latent variable econometrics (Aigner and Deistler, 1989) describes the unobserved vector explicitly taking account of the error with which the proxy measures the phenomenon. In our model, the system of measurement equations results:

$$(11) \qquad \begin{pmatrix} \dot{TFP} \\ s_M d\ln x_M \\ s_L d\ln x_L \\ s_K d\ln x_K \end{pmatrix} = \begin{pmatrix} \lambda_{11} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \dot{\Xi} \\ s_M d\ln x_M \\ s_L d\ln x_L \\ s_K d\ln x_K \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

The model (10)-(11) is a special case of LISREL (Linear Structural Model with Latent Variables) model defined in (1), (2) and (3). It is usually called MIMIC model (*Multiple Indicators and Multiple Causes*) for the presence of only one latent vector η (Jöreskog and Goldberger, 1975; Bollen, 1989). In this case, in fact, we assume that $x = \xi$; exogenous variables are therefore observed without measurement errors.

Using LISREL 7.2 software, model (10)-(11) is estimated with a maximum likelihood procedure[9].

3. The Data Set

Prices and quantities for materials, land, capital and labor are Fisher aggregates based on elementary data of the AGRIFIT database (Caiumi *et al.*, 1995)[10]; the TFP growth data come from Pierani and Rizzi (1994)[11].

The variables of the eq. (9) are defined as follows. Concerning with the technology spillover ($\dot{T}$), we try to take into account all innovations produced at an intersectorial and international level to capture the idea of a spread technological advance. The only data series available for the period and that can represent this idea are the data about both domestic and foreign patent demands in United States. Even if patent data are often criticized as indicators of technological advance, we can agree with Griliches (1994) to consider the number of patent demands presented at a given time t as an effect of the recent R&D expenditures and all the past knowledge stock. In other words, we consider

---

[9] *A more detailed description of the applied econometric procedure is presented in Appendix 2. A complete analysis of the econometric and identification issues of the MIMIC model can be found in Bollen (1989).*

[10] *It is a recent database of the Italian agriculture from 1951 to 1991.*

[11] *It's a measure that explicitly takes into account the short-run subequilibrium due to quasi-fixity of some factors, in particular family labor and capital (Morrison, 1992).*

this variable a good proxy of the general technological knowledge that can potentially spill over the agricultural sector[12] (Griliches, 1994).

For R&D and extension expenditures in the Italian agricultural sector (R and I variables) we use public expenditures as reported by Ministries accountings. These are data about research funding by the Italian Ministry of Agriculture and Forestry, about expenditures of the specialized public research institutes and expenditures of public University Faculties of Agriculture and Animal Science. Extension expenditures are obtained both from the Ministry of Agriculture and Forestry accounting and from public local extension services. All these expenditure data are expressed in billions of constant price Italian lira.

As previously emphasized, we need stock data to estimate the model presented. To convert expenditure data into stock data we adopted the method proposed by Park (1995)[13]. It is basically an application of the perpetual inventory method to R&D expenditure. The only difference is that a three years lag is considered before the new expense is recorded.

Finally, concerning with human capital variable (H), we follow the methodology in Gao and Reynolds (1994) using the average years of schooling of agricultural workers. These data allowed us to define stock series starting from 1961 to 1991. Therefore, our analysis refers to this period[14].

4. Estimation results

Parameter estimates of the MIMIC model are reported in matrix form in table 1; in table 2 respective elasticities are reported. Matrix $\boldsymbol{B}$ estimates provide information about the bias of technological change. While materials and capital bias seem to be not statistically significant, we observe a technical change clearly labor using. Therefore, the

---

[12] *We choose US patents being the only ones available for a long period. Moreover, due to its technological leadership and its open economy, US patents can be considered good indicators of technological advance over countries.*

[13] *We apply a depreciation rate of 0,3 for the R&D, as in Park, and of 0,5 for the stock relative to extension expenditures.*

[14] *More information about data series can be obtained by contacting us.*

empirical evidence rejects the hypothesis of Hicks-neutral technical change and indicates a bias toward labor and against land. This result is somewhat surprising if compared to previous studies (Gao and Reynolds, 1994) where, whenever neutrality is rejected, labor saving and capital using technical change is frequently observed.

Nevertheless, these results often refer to structural agricultural conditions deeply different from Italian agriculture. In the Italian case, in fact, small family farms are predominant and excess labor and capital and land scarcity is indeed the rule. Therefore, what we observe is a technological path consistent with these structural constraints. This path allows to detain labor force in the sector rising its productivity with respect to the other factors. Looking at the literature, this technological evolution seems to be quite original. However, there is no economic reason to think that technical evolution in the agricultural sector should be inevitably oriented toward an increasing level of capitalization. A higher level of capital per worker is indeed observed but this is above all an effect of relative prices change rather than of technological change.

According to these results, however, it is not easy to conclude if this kind of path is actually an optimal one. In other words, a labor using technical change can be due to the labor excess constraint itself. Family farms may select innovations that allow to increase labor productivity, being not easy for family labor force to be employed in other sectors. According to this scenario, the observed technological path is the only feasible, while potentially better technological solutions can't be actually afforded.

Moreover, according to the exogeneity of innovations we assumed in our analysis, we could legitimately claim that this technological path is determined by voluntary choices of the institutional agents. In our hypothesis, they have under control the variables we considered as causes of technical change, and in particular R&D and Extension services.

Some useful information about the institutional explanation of technical change can be derived from estimates of matrix Γ. Both variations in spillover and extension stocks turn out to be not statistically significant. Therefore, their marginal impact on the Italian agricultural sector seems unclear. On the contrary, R&D and human capital stocks result to have a positive and significant marginal impact on the sectorial technological level.

These results suggest that R&D and agricultural worker education have been important growth factor in Italian agriculture during this period.

Conventional information about production technology can be obtained by the estimates of μ_{ij} and θ_i, and by factor demand elasticities in tab.2[15]. Most of the price coefficients are statistically significant. The signs of direct price effects are correctly negative for materials, labor and capital, although not significant for the latter, while it turns out to be positive for land. However, it is not possible to check if this result is statistically relevant lacking an estimate of standard error for this parameter.

Cross price coefficient estimates provide empirical evidence of complementarity between materials and capital, material and land, labor and land. Moreover, labor is substitute of both materials and capital. Therefore, the conventional alternative between an intensive use of a capital and materials and an intensive use of labor emerges. In this sense, our results seem to confirm what came out in previous analyses (Pierani and Rizzi, 1992; Gao and Reynolds, 1994).

Some useful information can be obtained looking at elasticities (table 2). Compensated price elasticities are quite small with respect to output and technology elasticities. This would confirm that in the long run factors demands are only partially determined by evolution of relative prices. In particular, looking at the demand of labor, it results that marginal impact of technological change is the most important factor while output and relative prices have relatively small impacts.

This result seems to be quite relevant in the explanation of the structural evolution of the Italian agriculture. In fact, the share of labor constantly decreased during this period having been substituted by materials and capital. According to our results, this effect is entirely determined by the great increase in labor relative price (fig.1), while technological bias is working on the other direction. Therefore, observed technological path worked in opposition to relative prices change controlling the progressive reduction of agricultural working force. Clearly, these results substantially reject the traditional hypothesis of induced innovation.

---

[15] *Elasticities are calculated using sample averages of factor shares.*

As shown in fig.1, relative price of labor increased during the entire period. If the induced innovation hypothesis was working for the case under study, we should observe a labor saving technical change. So, we can conclude that for Italian agriculture induced innovation hypothesis is inconsistent. Actually, other empirical evidence of the failure of the hypothesis can be found in the literature (Olmstead and Rhode, 1993). However, this is not entirely surprising. Induced innovation hypothesis requires precise conditions to work. On the market side, it requires the existence of active and competitive markets in which prices can effectively signal relative factors scarcity. In the case of Italian agriculture, increase of relative price of labor doesn't seem to be an effect of endogenous labor scarcity in the sector but the effect of exogenous forces[16].

Moreover, even if markets correctly signaled relative scarcity, there should still be research and extension activities to provide innovations in the direction required. In our case, these activities are prevalently provided by public institutions. Therefore, it is essentially a political choice that determines the direction of innovative activities. Agricultural policies biased toward small family farms can indeed promote labor using innovations despite the market signaling.

At the bottom of tab.1 we report some statistical indicators of the goodness of fit of the model (Jöreskog and Sörbom, 1989; Bollen, 1989; Bollen and Long, 1993). First of all, the estimate of the variance of the error term ε_1 turns out to be significantly different from 0. Actually, this is an important result; it shows that we can't 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 *goodness of fit indices (GFI)*[17] provide information about the fit of the whole MIMIC model (that is (10) and (11)). They can be considered the analogues of the R^2 in

---

[16] *Due to increasing Unions bargaining power and income distribution policies, the increase of labor price in Italy during the considered period was actually a generalized phenomenon involving all sectors not only agriculture.*

[17] *Goodness of fit indices are obtained as complement to 1 of the ratio between the value of the Fitting Function of the specified model and the value obtained without assuming any a priori specification. The Adjusted index corrects for the degrees of freedom (Jöreskog e Sörbom, 1989).*

the classical regression model. On the contrary, *Squared Multiple Correlation for* $\dot{TFP}$ and *Total Coefficient of Determination of structural equations* provide only partial information about the fit of the model; the former refers only to measurement equations (11), the latter to the system of structural equations (10). So they can signal what component of the MIMIC model more affects the GFI. It turns out that the variation of TFP seems to be not a very good proxy of unobserved technical change. However, it is still the best proxy that is available. After all, it is just the consciousness our proxies are not so good that makes the use of a latent variable model a sensible alternative.

4.1. Technical change measurement

The second part of the estimation procedure (see appendix 2) involves estimation of the latent variable $\dot{\Xi}$. In table 3 we present the results obtained with the MIMIC model in comparison with two measures of TFP growth: the traditional one and a corrected version (Pierani and Rizzi, 1994) indicated as *TFPcorr*[18]. In fig.2 these three indexes are drawn and in table 4 subperiods averages are reported.

As can be easily noticed, the MIMIC estimate of the rate of technical change shows interesting differences with respect to the TFP measures. In the MIMIC case, the yearly average rate in the period is about 3,1%; this measure is higher than the conventional ones (1,9% and 2,3% respectively). Therefore, according to our results we can conclude that traditional technical change measure through TFP growth rates tends to underestimate technical progress.

However, the most interesting differences emerge considering the subperiod averages. In the MIMIC results a sort of cyclical behavior in the long term seems to emerge. We observe high technological growth rates in the sixties, clear slow down in the seventies and the highest rates in the eighties. This result for the last subperiod can be partially explained by the definitive substitution of traditional agricultural organization

[18] *This TFPcorr is the variable actually employed as indicator of technical change in the MIMIC model.*

with more rational and modern systems even in the backward regions of the country (Esposti and Pierani, 1995).

As in analogous studies (Gao and Reynolds, 1994), the MIMIC measure of technical change seems to be more smooth and regular in the short run. This is, in fact, one of the properties of this method. Due to the explicit presence of measurement errors, 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 price shocks can affect TFP measurement).

Being smoother in the short run, the MIMIC measure more clearly reveals the long run behavior of technology. As can be seen in fig.1, in the long run the MIMIC measure differs from a linear trend more than TFP measures. Therefore the latent variable approach seems to be a good solution whenever the research goal is to highlight long run behavior rather then short run shocks.

5. Conclusions

The model presented in this paper appeals to the latent variable concept to represent and measure technological growth in the Italian agricultural sector. It is presented as an alternative approach with respect to the traditional TFP measure. It allows to get a measure of technical change partially distinguished from productivity growth. Theoretically these two concepts are linked, being higher productivity the final outcome of a technical advance, but they can't be considered perfectly corresponding, as the traditional approach does. Technical change is a complex economic and institutional process and understanding this process is at least as important as measuring the final result.

A MIMIC model turns out to be useful being able to satisfy both these requirements: representing the generation process and measuring technical change. Its estimation is quite straightforward and provides consistent estimates of the structural parameters. It is even quite flexible allowing for dynamic and endogenous specification of the generation process. However, these alternatives have not been explored in this study.

The empirical results provide some evidence of the positive impact of public R&D expenditure on the agricultural technological level. Also relevant seems to be the increase of human capital expressed by education level.

The most interesting empirical result seems to be the role played by technical progress in the structural evolution of the sector. Being labor using, technical advance partially compensate for the tendency to substitute labor with capital and materials due to their relatively lower market prices.

MIMIC quantification of technical change turns out to be different from the TFP measures that seem to underestimate technological advance. The behavior of different measures over time is itself quite different. MIMIC result reveals a cyclic behavior in the long run. Particularly intense is the technological growth that emerges in the eighties, probably caused by declining of traditional and inefficient agricultural systems.

A latent variable approach provides more information on the causes of technical change and seems to guarantee a more reliable measure in the long run. However, even in these models TFP measures are still necessary as proxies. Moreover, TFP measures are still relatively easier and less computationally expensive. Essentially, the choice between these alternative approaches depends on the final objective of the research project.

Table 1 - Parameter estimates of the MIMIC model (standard errors in parenthesis)

B

	$\dot{\Xi}$	$s_M\Delta\log(x_M)$	$s_L\Delta\log(x_L)$	$s_K\Delta\log(x_K)$
$\dot{\Xi}$	0,0000	0,0000	0,0000	0,0000
$s_M\Delta\log(x_M)$	-0,0765 (0,1756)	0,0000	0,0000	0,0000
$s_L\Delta\log(x_L)$	0,8289*** (0,2918)	0,0000	0,0000	0,0000
$s_K\Delta\log(x_K)$	-0.2903 (0,1810)	0,0000	0,0000	0,0000

Γ

	$\dot{T}$	$\dot{R}$	$\dot{I}$	$\dot{H}$	$\Delta\log(p_M/p_T)$	$\Delta\log(p_L/p_T)$	$\Delta\log(p_K/p_T)$	$\Delta\log(q)$
$\dot{\Xi}$	-0,0364 (0,141)	0,3644** (0,159)	-0,0759 (0,129)	0,2909* (0,149)	0,0000	0,0000	0,0000	0,0000
$s_M\Delta\log(x_M)$	0,0000	0,0000	0,0000	0,0000	-0,0699*** (0,0177)	0,0927*** (0,0178)	-0,0143** (0,0077)	0,6114*** (0,1949)
$s_L\Delta\log(x_L)$	0,0000	0,0000	0,0000	0,0000	0,0927*** (0,0178)	-0,0857*** (0,0232)	0.0207** (0,0104)	0,1194 (0,2365)
$s_K\Delta\log(x_K)$	0,0000	0,0000	0,0000	0,0000	-0,0143** (0,0077)	0,0207** (0,0103)	-0,0137 (0,009)	0,2645 (0,2241)

Θ_{ε}[19]

ε_1	ε_2	ε_3	ε_4
0,0004*** (0,0001)	0.0000	0.0000	0.0000

Squared Multiple Correlation of $\dot{\mathrm{TFP}}$	0,335
Total Coefficient of Determination of structural equations	0,842
Goodness of Fit Index	0,790
Adjusted Goodness of Fit Index	0,389

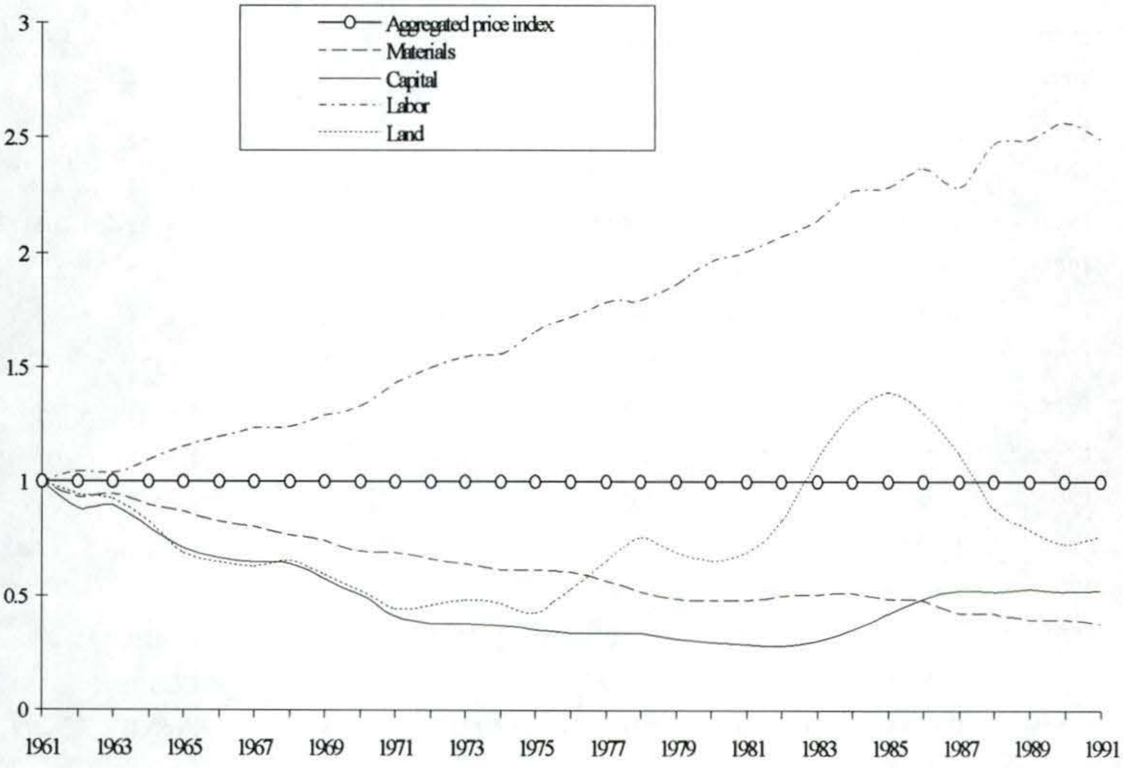
*, **, *** : parameters statistically different from zero respectively at 10%, 5%, 1% significance level

[19] *It is the estimate of the variance of error terms of the measurement equations.*

Table. 2 - Compensated price, output and technological elasticities[20]

	P_M	P_L	P_K	P_T	*Output*	*Technology*
Materials (M)	-0,2947	0,3903	-0,0602	-0,0358	2,5750	-0,3221
Labor (L)	0,1878	-0,1736	0,0419	-0,0561	0,2419	1,6796
Capital (C)	-0,0688	0,1000	-0,0659	0,0307	1,2734	-1,3976
Land (T)	-0,1386	-0,4518	0,1190	0,4713	0,0766	-7,5365

Figure 1 - Relative prices of inputs



[20] *Elasticities with respect to land are calculated obtaining land parameters from restrictions described in section 2. However, lacking estimates of their standard errors we can not have information about their statistical significance.*

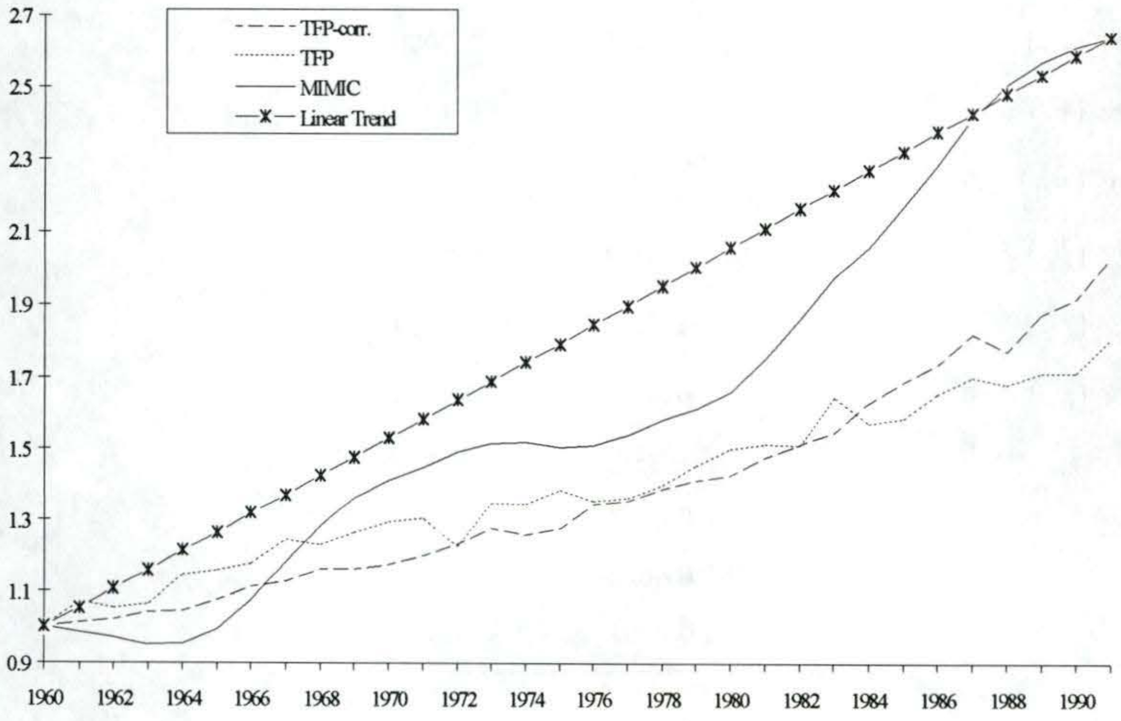
Table 3 - Technical change rates and technology indices: a comparison between different approaches

	Technical Change Rate			**Technology Index**		
	MIMIC	*TFP*	*TFPcorr.*	*MIMIC*	*TFP*	*TFPcorr.*
1960	-	-	-	1	1	1
1961	-0,0144	0,0740	0,0139	0,9855	1,0740	1,0139
1962	-0,0151	-0,0185	0,0058	0,9706	1,0541	1,0198
1963	-0,0210	0,0096	0,0191	0,9501	1,0643	1,0393
1964	0,0065	0,0760	0,0053	0,9564	1,1451	1,0448
1965	0,0387	0,0112	0,0292	0,9935	1,1580	1,0753
1966	0,0835	0,0175	0,0322	1,0765	1,1782	1,1099
1967	0,0966	0,0557	0,0164	1,1805	1,2439	1,1281
1968	0,0885	-0,0112	0,0298	1,2850	1,2299	1,1617
1969	0,0595	0,0268	0,0002	1,3615	1,2629	1,1619
1970	0,0375	0,0268	0,0108	1,4127	1,2967	1,1745
1971	0,0243	0,0043	0,0206	1,4470	1,3023	1,1987
1972	0,0299	-0,0594	0,0299	1,4903	1,2249	1,2345
1973	0,0158	0,0976	0,0345	1,5139	1,3445	1,2771
1974	0,0027	-0,0027	-0,0147	1,5181	1,3409	1,2584
1975	-0,0089	0,0333	0,0138	1,5044	1,3855	1,2757
1976	0,0016	-0,0215	0,0516	1,5069	1,3557	1,3415
1977	0,0193	0,0035	0,0087	1,5360	1,3605	1,3532
1978	0,0284	0,0296	0,0278	1,5797	1,4007	1,3908
1979	0,0206	0,0372	0,0155	1,6123	1,4529	1,4124
1980	0,0289	0,0304	0,0073	1,6591	1,4970	1,4227
1981	0,0575	0,0084	0,0377	1,7546	1,5096	1,4763
1982	0,0614	-0,0026	0,0223	1,8623	1,5057	1,5093
1983	0,0615	0,0905	0,0237	1,9769	1,6419	1,5450
1984	0,0418	-0,0451	0,0525	2,0598	1,5679	1,6261
1985	0,0543	0,0109	0,0383	2,1717	1,5850	1,6884
1986	0,0524	0,0418	0,0256	2,2856	1,6512	1,7317
1987	0,0555	0,0284	0,0500	2,4125	1,6981	1,8182
1988	0,0383	-0,0110	-0,0243	2,5050	1,6794	1,7740
1989	0,0256	0,0193	0,0564	2,5692	1,7119	1,8741
1990	0,0153	-0,0015	0,0241	2,6086	1,7093	1,9193
1991	0,0113	0,0577	0,0580	2,6380	1,8079	2,0306

Table 4 - Technical change yearly averages by subperiods

	MIMIC	*TFP*	*TFPcorr.*
1961-1991	0,0312	0,0193	0,0231
1961-1971	0,0342	0,0243	0,0166
1972-1981	0,0138	0,0149	0,0211
1982-1991	0,0431	0,0165	0,0294

Figure 2 - Technology Index in different approaches



Appendix 1

A 1. Dickey-Fuller tests

Variable	DF	Significance Level
S_M *(Materials share)*	-0.5705	0.2259
S_L *(Labor share)*	-3.1732	0.1065
S_K *(Capital share)*	-2.3309	0.2986
S_T *(Land share)*	-2.1948	0.3424
$log(q)$	-2.6189	0.2174
$log(x_M)$	-1.8004	0.4862
$log(x_L)$	-2.4134	0.2737
$log(x_K)$	1.4147	1.0000
$log(x_T)$	-1.5250	0.5961
$log(p_M)$	-0.8439	0.8535
$log(p_L)$	-1.8968	0.4491
$log(p_K)$	-2.2236	0.3329
$log(p_T)$	-1.8695	0.4596
R	-0.3595	0.9717
T	0.0454	1.0000
I	0.4666	1.0000
H	0.4991	1.0000

Appendix 2

In this appendix we briefly describe the estimation procedure we adopted. MIMIC model is a special case of the broader LISREL model A LISREL model is usually estimated appealing to the concept of *implicit covariance matrix* (Jöreskog and Sörbom, 1989; Bollen 1989). We follow a two-stages procedure: first we estimate structural parameters of the model (10)-(11); then, we employ a Bayesian estimator to estimate rates of technical change (Jöreskog e Sörbom, 1989) [21].

The implicit covariance matrix approach differs substantially from the traditional estimation of linear equations. In this case we don't look for parameters that minimize some function of the residuals, but we look for parameters that minimize the "difference" between the sample variance-covariance matrix of the observed variables and the covariance matrix implied by the specified model. Therefore the underlying hypothesis is that the covariance matrix is function of the parameters of the model. If the model was correctly specified and parameters were known, we could express the population covariance matrix as follows:

$$\text{(A.1)} \quad \Sigma = \Sigma(\theta)$$

where Σ is the covariance matrix at population level, θ is the vector of the parameters of the model and $\Sigma(\theta)$ is the covariance matrix expressed as function of the parameters of the specified model under the hypothesis the model is correct.

More concretely, Σ matrix represents variances and covariances of the vectors of observed variables in the LISREL model (1)-(3), that is y e x. Therefore, $\Sigma(\theta)$ can be expressed as follows (Bollen, 1989):

$$\text{(A.2)} \quad \Sigma(\theta) = \begin{bmatrix} \Sigma_{yy}(\theta) & \Sigma_{yx}(\theta) \\ \Sigma_{xy}(\theta) & \Sigma_{xx}(\theta) \end{bmatrix}$$

In the MIMIC special case (A.2) becomes (Bollen ,1989):

$$\Sigma(\theta) = \begin{bmatrix} \Lambda_y(\mathrm{I}-\beta)^{-1}(\Gamma S_{xx}\Gamma' + \Psi)\left[(\mathrm{I}-\beta)^{-1}\right]'\Lambda_y + \Theta_\varepsilon & \Lambda_y(\mathrm{I}-\beta)^{-1}\Gamma S_{xx} \\ S_{xx}\Gamma'\left[(\mathrm{I}-\beta)^{-1}\right]\Lambda'_y & S_{xx} \end{bmatrix}$$

where S_{xx} is the covariance matrix of the exogenous variables x, Θ_ε is the covariance matrix of the error terms ε, Ψ is the covariance matrix of the error terms ς. Expressed in this way, Σ matrix is the *implicit covariance matrix* of the MIMIC model.
Therefore, under the hypothesis:

$$\Sigma = \Sigma(\theta)$$

---

[21] *More traditional estimation procedures for the MIMIC case can be found in Zellner (1970), Goldberger (1972), Jöreskog and Goldberger (1975). A different estimation approach considers the MIMIC model a particular state-space model; so estimation is achieved applying the methodologies usually adopted in these cases (Watson and Engle, 1983).*

we can estimate parameters looking for the values that minimize the "difference" between this $\Sigma(\theta)$ matrix and the sample covariance matrix S actually observed.

However, we need a criterion to define what we mean by 'difference". This criterion is the so called *Fitting Function (FF)*. It is a function of $\Sigma(\theta)$ and S to minimize with respect to the parameters. Various *FF*'s can apply; each of them gives parameter estimates with different properties (Bollen, 1989). In our case, we use the maximum likelihood fitting function F_{ML} : its minimization gives maximum likelihood estimates of the parameters of the model[22]. This function is expressed as follows (Anderson, 1989):

$$\text{(A.4)} \quad F_{ML} = \frac{T}{2} \cdot \log \left| \Sigma\left(\hat{\theta}\right) \right| + \frac{T}{2} \cdot tr\left(S\Sigma^{-1}\left(\hat{\theta}\right)\right)$$

where T is the number of observations.

Once we get ML estimates of the parameters, we can move to the second stage of the estimation procedure, that is the estimation of the latent variable $\dot{\Xi}$. Again, the basic idea is to express this variable explicitly as a function of the parameters of the model through its reduced form. Using the estimates previously obtained for these parameters, we can get $\dot{\Xi}$ through this Bayesian estimator (Thompson, 1951; Gao and Reynolds, 1994)[23]:

$$\text{(A.5)} \quad \dot{\Xi} = \mathrm{x}_t \hat{\Gamma} + \hat{\Psi} \hat{\Lambda}' \left(\hat{\Lambda} \hat{\Psi} \hat{\Lambda}' + \hat{\Theta}_{\varepsilon} \right)^{-1} \cdot \left(\mathrm{y}_t - \hat{\Lambda} \mathrm{x}_t \hat{\Gamma} \right)$$

From the $\dot{\Xi}$ estimates we can easily obtain an index of the level of technology represented by Ξ . This is just the cumulative index of the estimated annual rates of technical change.

---

[22] *This approach requires multinormality assumption for the* y *and* x *variables (Bollen, 1989). However this assumption can be partially relaxed (Anderson, 1989).*

[23] *This expression is not generally valid; it is specific for the MIMIC case and it is correct only for the estimation of the latent variable* $\dot{\Xi}$ *, not of the entire* η *vector .*

REFERENCES

Aigner, D.J. and M. Deistler (a cura di), 1989, *Latent variable models*, Annals of the *Journal of Econometrics*, 41.

Anderson, T.W., 1989, Linear latent variable models and covariance structures, *Journal of Econometrics* 41, 91-119.

Barnett, W.A., 1979, Theoretical foundations for the Rotterdam model, *Review of Economic Studies*, 50, 109-130.

Bollen, K.A., 1989, Structural equations with latent variables, John Wiley & Sons, New York.

Bollen, K.A. and J.S. Long, eds, 1993, *Testing structural equation models*, Sage Publications, Newbury Park California.

Caiumi, A., Pierani, P., Rizzi, P. and N. Rossi, 1995, *AGRIFIT: una banca dati del settore agricolo (1951-1991)(AGRIFIT: An Agricultural Sector Database (1951-1991))*, Franco Angeli, Milano.

Chavas, J.P. and T.L. Cox, 1992, A nonparametric analysis of the influence of research on agricultural productivity, *American Journal of Agricultural Economics* 74, 583-591.

Chambers, R.G., 1988, *Applied production analysis*, Cambridge University Press.

Clark, J.S. and Youngblood, 1992, Estimating duality models with biased technical change: a time series approach, *American Journal of Agricultural Economics*, 74, 353-360.

Esposti, R. and P. Pierani, 1995, Capacità utilizzata e produttività dei fattori. Il caso di una impresa ex-mezzadrile (Capacity Utilization and Factors Productivity. The Case of a Sharecropping Farm), *La Questione Agraria,* 60, 71-99.

Fuller, W., 1987, *Measurement error models*, John Wiley & Sons, New York.

Gao, X.M., 1994, Measuring technical change using a latent variable approach, *European Review of Agricultural Economics*, 21, 113-119.

Gao, X.M. and A. Reynolds, 1994, A structural equation approach to measuring technological change: an application to southeastern U.S. agriculture, *The Journal of Productivity Analysis* 5, 123-139.

Goldberger, A.S., 1972, Maximum likelihood estimation of regression models containing unobservable variables, *International Economic Review*.

Granger, C.W.J. and Newbold, 1981, Spurious regression in econometrics, *Journal of Econometrics*, 55, 121-130.

Griliches, Z., 1964, Research expenditures, education and the aggregate agricultural production function, *American Economic Review* 54, 961-974.

Griliches, Z., 1994, Productivity, R&D e data constraint, *American Economic Review*, 84, 1-23.

Griliches, Z. and D.W. Jorgenson, 1967, The explanation of productivity change, *Review of Economics and Statistics* 34.

Jöreskog, K.G. and A.S. Goldberger, 1975, Estimation of a model with multiple indicators and multiple causes of a single latent variable, *Journal of the American Statistical Association* 70, 631-639.

Jöreskog, K.G. and D. Sörbom, 1989, *LISREL 7: user's reference guide*, Scientific Software Inc., Mooresville, USA.

Morrison, C.J., 1992, *A micreconomic approach to the measurement of economic performance*, Springer-Verlag, New York.

Nelson, R.R., 1981, Research on productivity growth and productivity differences: dead ends and new departures, *Journal of Economic Literature*, 19, 1029-1064.

Olmstead, A.L. and P. Rhode, 1993, Induced innovation in american agriculture: a reconsideration, *Journal of Political Economy*, 101, 100-118.

Park, W.G., 1995, International R&D spillovers and OECD economic growth, *Economic Inquiry*, 33, 571-591.

Pierani, P. and P. Rizzi, 1994, *Equilibrio di breve periodo, utilizzazione della capacità e produttività totale dei fattori nell'agricoltura italiana (1952-1991)(Short-Run Equilibrium, Capacity Utilization e Total Factor Productivity in Italian Agriculture (1951-1991)),* Discussion Paper n.13, Dipartimento di Economia Politica, Università degli Studi di Siena.

Pierani, P. and P. Rizzi, 1992, *Produttività totale dei fattori e progresso tecnico* *nell'agricoltura italiana: un confronto Nord-Sud (Total Factor Productivity and Technical Change in Italian Agriculture: A North-South Comparison),* Quaderni del Dipartimento di Economia Politica n.130, Università degli Studi di Siena.

Plosser, C.I. and G.W. Schwert, 1978, Money, income and sunspots: measuring economic relationships and the effects of differencing, *Journal of Monetary Economics*, 4, 637-660.

Salter, W.E.G., 1960, *Productivity and technical change*, Cambridge University press, Cambridge.

Schmookler, J., 1952, The changing efficiency of the american economy, 1869-1938, *Review of Economics and Statistics*, 34, 214-231.

Selvanathan, E.A., 1989, Advertising and consumer demand: a differential approach, *Economics Letters*, 31, 215-219.

Solow, R.M., 1957, Technical change and the aggregate production function, *Review of Economics and Statistics*.

Solow, R.M., 1962, Technical progress, capital formation, and economic growth, *American Economic Review*, 52, 76-86.

Stoneman, P., 1983, *The economic analysis of technical change*, Oxford University Press, Oxford.

Tinbergen, J., 1959, On the theory of trend movements, tradotto in Klassen, L.H., Koyck, L.M. and H.J. Witteveen (eds.), *Jan Tinbergen, selected papers*, North Holland, Amsterdam [original version 1942].

Theil, H., 1980, *The system-wide approach to microeconomic*, Chicago: The University of Chicago Press.

Thompson, G.H., 1951, *The factor analisys of human ability*, London: London University Press.

Watson, M.W. and R.F. Engle, 1983, Alternative Algorithms for the estimation of dynamic factor, MIMIC and varying coefficient regression models, *Journal of Econometrics* 23, 385-400.

Zellner, A., 1970, Estimation of regression relathionships containing unobservable variables, *International Economic Review*, 11, 441-454.