PUBLIC AGRICULTURAL R&D DESIGN AND TECHNOLOGICAL SPILL-INS

A DYNAMIC MODEL

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Abstract
The paper presents a dynamic model for the analysis of the National Agricultural Research Systems (NARS) strategy. In a context of increasing globalisation, both intersectoral and international technology spill-ins may greatly affect the NARS design, and this paper proposes an analytical framework for its study when major spill-ins are present. These spill-ins are calculated by applying the Yale Technology Concordance (YTC) methodology. A VAR/VEC model is then specified to detect empirically, given the calculated spill-ins, what NARS design prevails in a dynamic framework. The model is estimated for the Italian agriculture data and provides evidence of close dependency on external R&D sources.

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1. Introduction

In the agricultural economics literature, numerous recent studies have focused on technological spillovers and their enhancement of agricultural productivity, the general conclusion being that in many cases their role is of particular importance (Johnson and Evenson 1997; Schimmelpfenning and Thirtle, 1997, Esposti, 2000a). There are also good reasons for attention to be paid to spillovers in the agricultural sector. Firstly, agriculture can be viewed as a supplier-dominated sector for the introduction of technological innovations (Pavitt, 1984; Esposti, 1999), so that we may expect spillovers to be very high. Secondly, most own agricultural research is financed by public investments, and we should consequently enquire how public decision-making takes these externalities into account.

International and intersectoral technological spillovers in favour of some national agriculture may also explain why some countries display good productivity performance despite their low levels of national research, this being also the case of Italian agriculture. One hypothesis in explanation of Italy's scant national research investment in a relatively rich agricultural system is that the country free-rides research efforts undertaken in other sectors and countries (Swinnen *et al.*, 2000), taking advantage of the consequent spillover and concentrating limited resources on country-specific programmes and on some phases of the innovation process (especially development).

This paper proposes a model for assessment of national public R&D strategies in the agricultural sector in the presence of substantial technological spillovers. An empirical application to the Italian case is also presented. Section 2 describes the analytical framework underlying the functional relationship between public agricultual R&D and the technological spillover. Section 3 shows how this technological transfer can be calculated applying the Yale Technology Concordance. Section 4 presents a dynamic model depicting the dynamic interaction between the sectoral technological stock supplied by public investments and the technological spillover. Application of this model may provide useful insights into national R&D strategies, as shown for the Italian case in section 5. Section 6 concludes.

2. Technological Spill-Ins and Agricultural Public R&D

2.1. The policy issues

The recent debate on the creation of scientific knowledge and technological innovations concentrates on two apparently conflicting aspects (Archibugi and Michie, 1997). On the one hand, increasing importance is given to so-called National Innovation Systems (NIS). This concept was introduced by Freeman (1987) to describe and interpret the nation-specific factors crucial in shaping technological change. On the other hand, there is an increasing evidence of the *globalisation of technology*, a concept which describes and explains how the process of economic and social globalisation closely affects the production and transfer of technology (Howells and Wood, 1993).

An agricultural "version" of this debate has also recently developed (Anderson, 1994) it being argued that the role of National Agricultural Research Systems (NARS) must be fashioned according to the opportunities available to exploit international and intersectoral technology transfer. Moreover, the agricultural sector and technology display peculiarities that make the case of agriculture to some extent different. First, very few agricultural firms (farms) undertake R&D, with the consequence that sectoral private research investments are negligible in many countries. However, numerous industrial and service firms (at both national and international level) provide farmers with new generation inputs embodying technological innovations, which gives rise to very intense spill-ins to agriculture, while spill-outs are usually considered to be very small.[1]

But agriculture also engages in substantial own research effort through public NARS. Most countries devote resources to public agricultural R&D and Extension. At the international level, some of these NARS may be leaders and dominate in technological fields highly specific to agricultural production: the creation of new varieties, soil science and agronomy, and so on (Evenson, 1994). Moreover, many International Agricultural Research Centres (IARC) have been created mainly in order to generate and transfer agricultural technology internationally, to the especial benefit of NICs and LDCs . Therefore, agricultural own R&D effort, too, is able to generate international, if not intersectoral, spill-outs. Each NARS consequently defines its strategy in the awareness that most innovations can directly or indirectly take advantage of spill-ins either from other sectors or/and from other dominating NARS or IARC. Indeed, every country has the option between either designing a comprehensive research programme for all commodities and ecological areas or focusing on site-specific commodities and/or areas while the others take advantage of massive spill-ins (Pardey and Wood, 1994).

[1] The terms 'spill-in', 'spill-out', 'spillover' are different names for technological transfer depending on the context. A research programme generates spill-in if seen from the point of view of the receiving sector, spill-out (spillover) if seen from the producing sector.

Although all NARS mix these two options to some extent, the relevant question is how they choose between them. This choice also closely influences the amount of public R&D expenditure and its potential spill-outs. On these premises, understanding how NARS design their own strategies is also crucial for explanation of the recent decline in national public R&D investments in agriculture despite the widely acknowledged high rates of return (Binswanger, 1994; Lipton, 1994; Huffman and Just, 1999). One possible explanation is that large intersectoral and international spill-ins induce non-leader NARS to restrict their effort to very specific commodities and agricultural technology fields, free-riding on other sectors and on other NARS (or IARC) R&D efforts.

If technological spillovers are acknowledged, any NARS should concern itself with the co-ordination of public and private research, of its own activities and the access to the pool of international knowledge (Fuglie and Schimmelpenning, 1999). Coordination between the NARS and private-public collaboration at the international level may also explain why some countries display technological proximity and also form convergence clubs in terms of higher productivity growth, thereby creating an international R&D hierarchy with a leading and a trailing group of countries (Schimmelpfenning and Thirtle, 1999; Quah, 1997).

Some empirical studies have already concentrated on rational co-ordination between NARS and IARC in the presence of strong international and intersectoral spill-ins (Evenson and Kislev, 1975; Davis, 1991; Englander, 1991). However, they are affected by two main methodological difficulties. First, calculation of spill-ins to a national (or local) agricultural sector at both international and intersectoral level always encounters the empirical problem of a paucity of data. Many published studies, indeed, restrict themselves to very limited contexts and only consider technological transfer between NARS or IARC and a very specific and localised ecological zone or commodity.

Second, they often disregard a main endogeneity problem (Griliches, 1995; Evenson and da Cruz, 1989): if there are large spill-ins, the NARS's R&D investment decision cannot be modelled as an exogenous variable because it depends on other R&D programmes and their transferability (spill-in potentials).

Section 3 and 4 will suggest possible empirical solutions to the spillover measurement and endogeneity problems respectively. Nevertheless, detailed analysis of the theoretical background is required if empirical modelling is to be possible.

2.2. Theoretical background and modelling strategy

In a seminal work, Cohen and Levinthal (1989) modelled the internal R&D efforts of a firm in terms of two 'faces': a firm's R&D both enables it to create new knowledge and enhances its ability to assimilate and exploit existing external knowledge. Cohen and Levinthal call this dimension the firm's "absorptive capacity". If we extend this basic intuition to NARS, we may conceive their strategy as a mix between these two faces of R&D effort.

According to the Cohen-Levinthan model, each firm decides the level of R&D investments with respect to those of its competitors on the basis of three crucial concepts. The first is the *technological opportunity* constituted by all the technological knowledge potentially spilling-in from other competing firms or sectors or countries. Technological opportunity increases a firm's R&D according to its *absorptive capacity*: that is, the ability to appropriate externally produced knowledge. This capacity is always endogenous because it increases with own R&D effort, but it also depends on the characteristics of the spilling-in knowledge. However, the incentive to increase own R&D arising from increased technological opportunity may be offset by a countervailing force: spillover reduces the *appropriability* of the results of own R&D

effort, discouraging it because of the new knowledge's prevalent nature as a public good. Different types of research programme (basic, applied, development) may involve different features of the three key concepts. Basic R&D provides greater technological opportunity (i.e. spillover), but it also requires higher absorptive capacity if it is to be exploited, and therefore greater own R&D investments; for the same reason, however, it also requires lower appropriability, which reduces the incentive to invest.

Given technological opportunity, the balance between the opposing forces of endogenous absorptive capacity and appropriability gives the R&D non-cooperative Nash equilibrium level between the firms. However, I shall not dwell further on the theoretical foundations of the Cohen-Levinthan model; here the focus is not on private R&D but on public research by NARS, whose aims and consequent behaviour may be much more complex than firm's profit maximisation. Therefore, observed R&D investments can be still viewed as a Nash equilibrium, but the outcome can hardly be predicted by the theory and can be only empirically analysed and revealed by data.

Specific details regarding agricultural research may help to outline a consistent empirical model. Following Evenson and Binswanger (1978), we can model NARS behaviour in a resource allocation framework which incorporates research spill-ins and spill-outs as a component integral to the design of the research programme. A country seeking to improve its agricultural productivity has three general research options: *direct technology transfer, adaptive research* and *comprehensive research*. Under the first option, a NARS screens new technologies from other sources, adopting the ones most appropriate to its requirements without spending effort on further research. However, this option still needs R&D capability to screen, select and test the improved technology (that is, to increase its absorptive capacity, according to Cohen-Levinthan). If a NARS also carries out its own research programmes to develop, modify and redesign technologies from other sources to suit its own needs, then it shifts to an adaptive research strategy. Finally, under the comprehensive research option, the NARS's strategy is to produce and develop its own own technologies while also generating the requisite pretechnology or scientific knowledge.

The size and complexity of NARS investments increase from the first option to the third. It is the costs of the alternative options and the accessibility of technology from other sources that finally determine the most efficient choice among competitive strategies (Maredia and Byerlee, 2000). Although this choice may differ across commodities and regional specialities, economies of size and the potential of research spill-ins are often of such importance in agriculture that countries tend to design their NARS according to one dominant option. Which strategy prevails within a NARS is an empirical question which can be answered with appropriate modelling.

Figure 1 shows the traditional distinction of R&D stock into basic research, applied research and development, where some R&D stock depends on the past values of the others, and reformulates that relation in terms of the NARS's own R&D, intersectoral and international spill-ins. At least part of the R&D mix spills-in from other sectors and/or countries. This is the external technological opportunity of the Cohen-Levinthan model: absorptive capacity induces an increase in own R&D when spill-ins increase. The interaction and combination of own stock and spill-ins depend on the NARS design and its underlying strategy; we can restate the three options outlined above in terms of this dynamic combination and interaction. Figure 2 shows that a NARS chooses a direct transfer option when most of basic and applied R&D stock spills-in while own investments are only targeted on development.[2] According to which spill-in sources prevail, other sectors or countries will thus dominate technology creation and transfer. **A**

NARS adopts an adaptive strategy if its R&D combines with spill-ins at least in applied research. Finally, in the case of comprehensive research, own R&D assists spill-ins in all the phases of the sequence.

There is, therefore, a sequence and a dynamic causality between different research efforts; if there is some measure of own stock and of spill-ins, in principle one can study the dynamic relation between them and infer the NARS strategy. All three stocks participate in the creation of sectoral-national knowledge stock (figure 3). However, own stock will be affected by the others if a direct transfer is prevalent. There is a *one-way* (or "end of chain") transfer if no knowledge spills-out from the own research stock, and it will be the only endogenous one.

However, also spill-ins may be endogenous, and this renders the dynamic relation much more complicated. There are two opposite ways to endogenize spill-ins. Recalling figure 2, under direct transfer the NARS devotes R&D only, or mainly, to development free-riding on other sectors' and countries' basic and applied R&D. One may thus observe an increase in spill-ins induced by a reduction in own R&D. This I shall call the *free-riding pull effect* induced by the low level of Cohen-Levinthan 'appropriability'. This transfer mode implies that both own and spill-in R&D are endogenous and dynamic substitutes. Moreover, if adaptive research, and even more so comprehensive research, is chosen, then the transfer may be *two-way* (or symmetric) because the own R&D produces spill-outs, so that also the spilled-in knowledge stocks may be enhanced as a consequence (Evenson and Putnam, 1990). In this transfer mode, own and spill-in R&D are endogenous and dynamic complements.

These transfer modes (*one-way, two-way, free-riding pull effect*) may differ between international and intersectoral spill-ins and they may also exist between them. The idea

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[22] By 'development' is also meant screening and extension activities.

is that there is a causality relation between the stocks which makes them potentially endogenous; the prevailing transfer mode depends on the prevalent **designed** option underlying the NARS R&D investments. All possible relations must be modelled, as in figure 3, if we are to determine empirically how sectoral-national knowledge is formed and single out the prevalent transfer modes and the dominant stocks.

3. Measuring spill-ins: the YTC and Agricultural Technological Stocks

According to Evenson and Johnson (1997), the essential concern of spillover studies is to define an R&D stock variable for a sector in location i at time t. The R&D stock of a given sector in a given nation is defined by its own past R&D investments but also by spill-in stocks deriving from other national private sectors, other (non-agricultural) national public institutions, or other nations' private sectors-public R&D. Generally speaking, the problem is how to measure the diffusion across time, sectors, and nations of an initial R&D investment. Given the context (a i-th sector of a m-th country at time t) the knowledge stock R can be calculated as the sum of the three stocks: the own, the intersectoral spill-in, and the international spill-in stocks. These stocks can be calculated from the investment flows as follows (Fagerberg and Verspagen, 1998):

(1) $$O_{im,t} = \sum_s w_s \left(K_{im,t-s}\right), \quad \forall s=0,...,s,...,S$$

(2) $$S_{im,t} = \sum_j w_{ij} \sum_s w_s \left(K_{jm,t-s}\right), \quad \forall j=0,...,i,...,J ; \forall s=0,...,s,...,S$$

(3)

$$I_{im,t} = \sum_c \sum_j w_{cij} \sum_s w_s \left(K_{jc,t-s}\right), \quad \forall j=0,...,i,...,J ; \forall s=0,...,s,...,S; \forall c=0,..., c,...,C \text{ and } c \neq m;$$

where O_t, S_t, I_t are the own stock, the intersectoral spill-in stock, the international spill-in stock respectively. $K_{jc,s}$ is the R&D investment made in the period (t-s) in the c-th country, in the j-th sector, included the i-th sector of the m-th country in question. The sum $\sum_s w_s \left(I_{im,t-s}\right)$ cumulates past investments according to a given set of weights. This is therefore the usual calculation of R&D stock where the weights depend on the lag profile of the investment's effect. For simplicity, we assume that the lag profile is the same everywhere, so that we can calculate the own stock for any sector and nation given the series of past investments.

The lag profile is imposed and modelled using the perpetual inventory method (PIM) frequently used for physical capital stock. It follows that R&D capital stock is (Park, 1995):

(4) $$R_{t+1} = R_t\left(1-\delta\right)+K_{t+1\text{-}n}$$

where $K_{t\text{-}n}$ is a n-lagged R&D expenditure taking account of a gestation period from expenditure to effects (Schimmelpfenning and Thirtle, 1999),[3] and δ is the depreciation rate of the stock.[4] Therefore the w_s are:

(5) $$\begin{aligned} w_s &= 0 && if \quad s < n \\ w_s &= \left(1-\delta\right)^{s-n} && if \quad s \geq n \end{aligned}$$

However, once we have all the own stocks, we must calculate their spill-out. Calculating the technological flows between sectors and nations is a complex task which involves calculation of the weights w_{ij} and w_{cij} defining the so called spillover matrices (Pardey and Wood, 1994). Although different approaches have been proposed (Marengo and Sterlacchini, 1990), a recently developed technique has rapidly become prevalent in the applied literature on technology flows.

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[3] A value of the initial stock can be obtained by means o a backward recursive substitution: $R_0 = I_{\text{-}n}\left(1+g\right)/\left(g+\delta\right)$ where g is the average annual investment rate over the sample period.

[4] Following Park (1995) and Esposti (2000b) n is set equal to 4 years; following the Japan Economic Institute (1989) and Esposti (2000b) δ is set equal to 0.20 assuming that each R&D investment is a mixture of base research, applied research and development.

I refer to the so-called Yale Technology Concordance (Johnson and Evenson, 1997), which calculates the coefficients of the spillover matrix on the basis of patent data. Patent data are usually available according to the International Patent Classification (IPC), which distinguishes patented inventions by technological field. The YTC is a procedure which assigns, on a probability base, any patented invention to an industry of manufacture (IOM) and to a sector of use (SOU) according to the IPC designation of the invention.

Applying the YTC we can calculate the weights as follows:

(6) $w_{ij} = \left\{ \hat{s}_{ij}^{N} \right\}$ and $w_{ijc} = \left\{ \hat{s}_{ijc}^{N} \right\} q_{jcm}$

where $\hat{s}_{ij}^{N}$ is the i-th row and j-th column element of the Spillover Matrix normalised by the row's total.[5] In other words, it is the share of patents granted to the i-th IOM flowing to the j-th SOU. $\hat{s}_{ijc}^{N}$ differs from $\hat{s}_{ij}^{N}$ because the j-th IOM belongs to the c-th country, and the normalisation by the row's total is also multiplied by q_{jcm} i.e. the share of the total patents granted to the IOM by the own country also issued in the m-th country.[6] Calculating the elements of the spillover matrix by applying the YTC therefore requires data on granted patents by IPC field and by the applying and issuing country. From the assumed w_s we can calculate the own R&D stock for any IOM of any country. Then, by applying the w_{ij} and w_{ijc} weights from the YTC we can calculate the stock spilling-in to the i-th SOU and m-th country under study.[7]

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[5] Note that also intrasectoral spillover is permitted ($s_{ii} > 0$).

[6] In other words, the patents issued to a given IOM in its own country are used as an indicator of its total inventive output; calculated on this total is the share flowing to other sectors and countries.

[7] For instance, if the SOU being studied is Italian agriculture, we calculate the R&D own stock for any other national IOM sector. From the YTC we derive the share of total patents granted to this IOM flowing to Italian agriculture; the R&D spill-in stock will be the own IOM R&D stock multiplied by that share. By summing these spill-ins for any national IOM we obtain the intersectoral spill-in stock. We can also calculate the own R&D stock for any IOM of another country. Knowing how many patents have been issued by the Italian patent office to this foreign IOM, we can repeat the YTC analysis and calculate the

The use of patent data to calculate technological spillover is controversial. Firstly, such data are not always good indicators of real innovative activity or of the economic value of the innovations themselves (Griliches, 1994). Moreover, technological flow between sectors and nations may take many forms. Patents are only one such form, and they almost exclusively concern innovations embodied in some new input (new chemicals, new machinery, etc.). A large number of inventions are unable to flow in that form and, in any case, patenting activity may differ across sectors and countries due to the differing strategic behaviours of firms and to heterogeneous regulations and rules across countries.

The most serious drawback to patent data is that many major R&D investments do not imply patentable innovations (Keller, 1997). Basic research, especially by universities, and most public research, produce new scientific knowledge that is difficult to protect with property rights and is not embodied in a new good. Furthermore, in many countries certain kinds of innovation are given different forms of protection and are not collected in patent data (new varieties are a case in point for agriculture). Consequently, the use of patent data to calculate research spill-ins implies the assumption that the patent flow estimated by means of the YTC is a good proxy for the overall transfer of technology and knowledge among sectors and/or countries.

Under this assumption, we can use YTC to include public R&D investments in the spill-in stock calculation. We can assume that national non-agricultural public R&D spills-in to national agriculture with the same proportion of total patents granted in the country flowing to the SOU agriculture. According to the same argument, we can assume that public foreign R&D (included other NARS' investments) flows to the SOU agriculture under study with the same proportion of total patents granted in the foreign country also

spill-in using the share on total patents granted in its own country. Adding up the spill-ins for all countries issued in the country under examination. Thus, we can straightforwardly add spillovers from public R&D to intersectoral and international spill-in stocks.

Again, spill-in stock calculation on the depicted base and on patent data relies on assumptions that greatly simplify the complex, discontinuous and causal process of scientific and technological cross-insemination between periods, sectors and nations. Although recent empirical studies are willing to accept these strong assumptions (Johnson and Evenson, 1999), particular caution is required in interpreting the results.

4. A Dynamic Model

Once we have an appropriate calculation of the stocks, we may return to figure 3 and model it more formally and explicitly with the following system of equations:

$$\text{(7a)} \quad \begin{aligned} O_{t+1} &= c_1 + a_{11} O_t + a_{12} S_t + a_{13} I_t + \boldsymbol{e}_{1,t} \\ S_{t+1} &= c_2 + a_{21} O_t + a_{22} S_t + a_{23} I_t + \boldsymbol{e}_{2,t} \\ I_{t+1} &= c_3 + a_{31} O_t + a_{32} S_t + a_{33} I_t + \boldsymbol{e}_{1,t} \end{aligned}$$

which can be written in more compact form using matrices:

$$\text{(7b)} \quad \mathbf{R}_{\mathbf{t+1}} = \mathbf{C} + \text{\textbf{Ù}}\mathbf{R}_{\mathbf{t}} + \text{\textbf{å}}_{\mathbf{t}}$$

where $\mathbf{R}$ is the vector of research stocks, $\mathbf{C}$ is a vector of the constant terms, $\mathbf{e}$ is a vector of error terms and $\mathbf{W}$ is the matrix of coefficients. System (7b) formally expresses the logic behind figure 3 and the discussion in section 2.2. Any stock is potentially endogenous because it can be affected by the past values of all the others; the sign and magnitude of parameters can also indicate the interaction between the stocks. Assuming that $\mathbf{e}$ is a vector of serially uncorrelated white-noise disturbances with variances σ_1, σ_2 and σ_3 respectively, (7b) can be viewed as a VAR(1) model. Specifying only a one-year lag might seem too restrictive; yet according to the PIM described in the previous

gives the international spill-in stock.

section, many lagged R&D investments enter into calculation of the stocks, so that any one-year lagged stock in fact contains numerous past R&D investments.

Despite the controversy on the economic content of the VAR models (Canova, 1995; Sims, 1980; Runkle, 1987; Enders, 1995), here we can only appeal to the reduced form of the relation between the stocks given in equation (7b). Although hypotheses on how they interact dynamically are formulated in section 2.2, we do not know *a priori* which transfer mode is actually prevalent, and therefore which stock must be modelled as endogenous. However, our principle interest here is the structural linkages among the stocks, because they reveal the underlying NARS strategies that we are looking for. A VAR model like (7b) is able to yield much useful information about these underlying structural behaviours. Granger-causality testing and innovation accounting (impulse response functions and forecast-error variance decomposition) can yield empirical evidence of the prevalent dynamic relation between the three stocks.

However, innovation accounting cannot be carried out on the reduced form (7b); the VAR models in structural form are overparametrised and are therefore not identified unless some restriction is introduced (Enders, 1995). The structural form of the model is necessary because the error terms in (7b) may be correlated; if this happens, every variable has a simultaneous effect on the others: shocks on one variable, i.e. change in the error terms, also affect all the others. To obtain a structural form we must rewrite the model so that all the effects of one variable on the others is explicit and the error terms (innovations or shocks) are incorrelated.[8]

We can rewrite (7b) in structural form as follows:

(8a) $$\mathbf{R}_{t+1} = \mathbf{B}^{-1}\tilde{\mathbf{A}}_0 + \mathbf{B}^{-1}\tilde{\mathbf{A}}_1\mathbf{R}_t + \mathbf{B}^{-1}\mathbf{u}_t$$

[8] They are also called 'pure innovations' because they affect only the respective variable without affecting the others.

where $\mathbf{u}$ is a vector of pure shocks and $\mathbf{C}=\mathbf{B}^{-1}\tilde{\mathbf{A}}_{\mathbf{0}}$, $\grave{\mathbf{U}}=\mathbf{B}^{-1}\tilde{\mathbf{A}}_{\mathbf{0}}$, $\mathring{\mathbf{a}}_{\mathbf{t}}=\mathbf{B}^{-1}\mathbf{u}_{\mathbf{t}}$. To make the structural form more explicit, (8a) is rewritten as follows:

(8b) $\quad \mathbf{B}\,\mathbf{R}_{\mathbf{t+1}}=\tilde{\mathbf{A}}_{\mathbf{0}}+\tilde{\mathbf{A}}_{\mathbf{1}}\mathbf{R}_{\mathbf{t}}+\mathbf{u}_{\mathbf{t}}$

which is a structural VAR: unless $\mathbf{B}$ is a diagonal matrix, each variable simultaneously affects the others and the error terms are pure shocks. The equations in (8b) are therefore behavioural functions, the error terms being orthogonal. Following (8a) we can also rewrite the structural extensive form of the model (7b):

$$
\begin{aligned}
& O_{t+1}=b_{10}-b_{12}S_{t+1}-b_{13}I_{t+1}+g_{11}O_t+g_{12}S_t+g_{13}I_t+u_{1,t}\\
\text{(7c)}\quad & S_{t+1}=b_{20}-b_{21}O_{t+1}-b_{23}I_{t+1}+g_{21}O_t+g_{22}S_t+g_{23}I_t+u_{2,t}\\
& I_{t+1}=b_{30}-b_{31}O_{t+1}-b_{32}S_{t+1}+g_{31}O_t+g_{32}S_t+g_{33}I_t+u_{3,t}
\end{aligned}
$$

where:

$$
\mathbf{B}=\begin{bmatrix}1 & b_{12} & b_{13}\\ b_{21} & 1 & b_{23}\\ b_{31} & b_{32} & 1\end{bmatrix},\ \tilde{\mathbf{A}}_{\mathbf{1}}=\begin{bmatrix}g_{11} & g_{12} & g_{13}\\ g_{21} & g_{22} & g_{23}\\ g_{31} & g_{32} & g_{33}\end{bmatrix},\ \tilde{\mathbf{A}}_{\mathbf{0}}=\begin{bmatrix}b_{10}\\ b_{20}\\ b_{30}\end{bmatrix}.
$$

Writing model (7a) in structural form essentially means giving it an economic content. Here we are interested in finding what happens to the own stock when spill-in stocks increase, and in how it produces feed-back to spill-ins themselves.

Mainly, a VAR model can provide this kind of information by means of innovation accounting. Like any univariate autoregressive process, a VAR model has a moving average representation (VMA). The VMA version of (7b) is:

(7d) $\quad \mathbf{R}_{\mathbf{t}}=\overline{\mathbf{R}}+\sum_{i=0}^{\infty}\grave{\mathbf{U}}^{i}\ \mathring{\mathbf{a}}_{t-i}$

where $\overline{\mathbf{R}}$ is the vector of the unconditional means of the R&D stocks. Using transformations in (7c), (7d) can be written as follows:

(7e) $\quad \mathbf{R}_{\mathbf{t}}=\overline{\mathbf{R}}+\sum_{i=0}^{\infty}\grave{\mathbf{E}}^{i}\ \mathbf{u}_{t-i}$

where **È**^{i} is a 3x3 matrix whose elements depend on the elements of matrix **B** (Enders, 1995). (7e) describes how an exogenous shock (u) on one variable affects the movement of others around their unconditional means. Therefore, elements f_{jk} of the **È** matrix are also called impact multipliers and their change over time $f_{jk}(i)$ is the so called impulse response function. Developing the VMA in (7e) forwards rather than backwards, we can also calculate the so called forecast-error variance decomposition which calculates the proportion of the movement in a sequence due to its own shocks versus shocks to the other variables.

Combining (7a) and (7c) and also considering variances and covariances of the error terms, it emerges that the reduced form estimation yields 18 parameters, while the structural form contains 21 unknown parameters. Therefore, the necessary, although not always sufficient, condition for the structural form to be exactly identifiable is to impose three restrictions on the parameters (Enders, 1995). Several identification restrictions of structural VARs have been proposed (Sims, 1986; Bernake, 1986; Blanchard and Quah, 1989; King *et al*., 1991). These restrictions are based on assumptions driven by the theory which impose restrictions on the simultaneous effect or the long-run relation (for instance, the money neutrality assumption in the long run) among the variables. Here, theoretical assumptions can be made according to the discussion in section 2.2.[9]

On the one hand, I am unwilling to impose restrictions on the long run relations between the stocks; after all, in the present model the long run equilibrium between the stocks defines precisely the NARS design that we are looking for. On the other hand, imposing short term restrictions in the structural model implies the constraining of some possible

[9] There are some empirical works on dynamic causality and cointegration involving R&D investments in the agricultural economics literature (Shalek, 1999; Zapata and Gil, 1999; Makki et al., 1999). However, all of them deal with analysis of the Granger causality between R&D, prices and TFP, for instance in

simultaneouus effects, as is clear in (7c) (Canova, 1995). On this ground, it must be considered that although a NARS may adopt a fully comprehensive research strategy, the agriculture sector is still a supplier-dominated sector. Therefore, although it may happen that own R&D affects intersectoral spill-in over time, this can only come about with a lag. We can therefore set $b_{21} = 0$. At the same time, the globalisation of technology can, in terms of agricultural innovations, marginalize a relatively small country with respect to international research advances. Again, own R&D may affect international spill-in, but this can happen only as a lagged effect; therefore $b_{31} = 0$. The same argument holds for I and S: in a small country, national spill-in to agriculture affects international spill-in only with a lag; then is $b_{32} = 0$. This set of restrictions allows identification of the VAR structural form, thus permitting innovation accounting.[10] Figure 3 shows how these restrictions work.

Besides identification of the structural form, another crucial issue for uncovering the long-run relations between the stocks in the VAR model is the stationarity of the variables in vector **R.**[11] If they are stationary, we can interpret (7b) as a long run stable dynamic system. Assume that stocks in (7b) grow at the same long run rate, which means that the sectoral-national knowledge stock in figure 3 grows at a constant rate. This assumption implies a long run balanced growth of the system in (7b). If we wish to study the interlinkage between the stocks under this long run condition, and if $\mathbf{C} = \mathbf{0}$, we can interpret system (7b) as a first order homogeneous difference equations system.

If long run balanced growth holds, we can write $\mathbf{R}_{t+1} = g\,\mathbf{R}_t$ and $\mathbf{R}_{t+n} = g^n\,\mathbf{R}_t$. We can straightforwardly obtain the growth rate γ by solving the (7b) system under $\mathbf{C} = \mathbf{0}$. If

order to test the induce innovation hypothesis. Identification of the underlying structural model and its economic content is not an issue addressed by these studies.

[10] It is easy to check that these restrictions allow structural decomposition through Choleski factorisation according to this ordering of variables: I, S and O.

the estimated $\mathbf{W}$ is a non-negative matrix, the Perron-Frobenius theorem holds and there exists a positive dominant eigenvalue λ_m of $\mathbf{W}$ associated with an eigenvector ν_m. Since λ_m is greater than any other eigenvalue of $\mathbf{W}$, it follows that in the long run (i.e. for t great) we can write $\mathbf{R}_t = l_m^t \mathbf{R}_0$ where $\mathbf{R}_0$ is the vector of the initial stocks (Tu, 1994) which can be calculated according to note 3. Therefore, $\lambda_m = \gamma$ and each stock will grow at the same rate; due to the stationarity of the stocks, we expect $\lambda_m<1$, that is, long-run stability (Enders, 1995; Tu, 1994). Finally, the associated eigenvector ν_m can be interpreted as the stable mix between the stocks. However, it should be emphasised that interpreting the model in terms of the long-term balanced growth of a stationary system is only a projection to the long run equilibrium, assuming it exists, not a forecast where this equilibrium is imposed. In other words, the long run relations are not estimated but only extrapolated from the estimated coefficients. Consequently, if this estimation is not efficient or consistent, this long run projection is potentially incorrect.

However, if the R&D stocks are not stationary in the levels,[12] balanced growth will be explosive, the VMA representation will fail because it does not allow innovation accounting, and the usual hypothesis testing cannot be performed; generally speaking, the VAR model cannot be properly estimated. Therefore, stationarity is a necessary condition for a VAR model to be meaningful. In this case of non stationarity, we have two alternatives. Suppose that the stocks are stationary in the first differences: that is, they are I(1) processes. If the stocks are not cointegrated, we can still apply the model outlined above to stocks' first differences. However, some authors (Sims, 1980; Doan, 1992) counsel against differencing also when variables in the levels contain a unit root.

[11] Innovation accounting requires the VAM form of the model, which is not possible if the process is not stationary.

[12] As in many studies (Shea, 1998), stock variables can be in the logarithm of levels but this do not affect the stationarity problem.

They argue that the goal of VAR analysis is not parameter estimation itself, but the interrelationships among variables, their co-movements also in the long run, which would be lost with differentiated variables.

But if they are cointegrated processes, CI(1), we have an alternative to first differencing, that is, writing equation 7(b) as a VEC model using the error correction mechanism:

(9) $$\Delta \mathbf{R}_{t+1} = \mathbf{C} + \boldsymbol{\alpha\beta'}\ \mathbf{R}_t + \boldsymbol{\Omega\Delta}\mathbf{R}_t + \boldsymbol{\varepsilon}_t$$

where $\boldsymbol{\beta}$ is the matrix of the cointegration vectors and $\boldsymbol{\alpha}$ is a matrix of corresponding weights indicating the adjustment speed to the long run equilibrium. Therefore, $\boldsymbol{\alpha\beta'}\ \mathbf{R}_t$ indicates a cointegrated stationary process defining the long run equilibrium between the stocks. The VEC representation implies that the movement of the stocks over time, although not stationary and behaving as a stochastic trend, is such that they do not drift too far apart because each responds to the deviation from a stable long-run equilibrium.

We can estimate this VEC model as a usual VAR because it contains both the long run relationship between the stocks given by the cointegrating relation and the short-run adjustment identified by the adjustment parameters. This implies that the structural form is still underindentified and that it is necessary to introduce the above-outlined restrictions on parameters. Note, however, that if there is a cointegrating relation between the stocks, and consequently (9) holds, then (5b) written in the first differences, although it is a solution to non-stationarity, may generate biased estimates due to mis-specification errors: the long term relations are, in this case, excluded from the estimated specification.

5. The Case of Italian Agriculture: Data and Results

The model is now applied to Italian agricultural data. There are specific reasons for focusing on the Italian case. According to the World Bank, in 1996 Italian agriculture ranked second in Europe for agricultural value added. But national agricultural research intensity (i.e. the ratio between agricultural research expenditure and agricultural gross domestic product) is low when compared to that of other developed countries (Alston and Pardey, 1998; Huffman and Just, 1999; OECD, 1995). Nevertheless, according to the traditional parametric estimation, public research in Italian agriculture displays a very high social rate of returns (Esposti, 2000b). Moreover, recent multilateral TFP comparisons (OECD, 1995) demonstrate that, although Italian agriculture in fact achieved significant TFP growth in the last decade, it cannot be placed in the high-productivity growth club of European countries (Schimmelpfenning and Thirtle, 1999). There is therefore enough empirical evidence to suggest underinvestment in R&D.

Furthermore, in Italy vegetables and fruit (including grapes and olives) account for about 40% of gross domestic agricultural product. These products are highly territorially specific and often require a national and regional research effort. We may therefore expect to find a public R&D closely and selectively targeted on these products. Recalling section 2.2, one suggested explanation for Italy's low research intensity in agriculture is that the country chooses the (less expensive) option of the *direct transfer* of foreign technology for most commodities, while it adopts a (much more expensive) *comprehensive research* programme only for national and regional-specific products (Maredia and Byerlee, 2000). The latter strategic option also requires large-scale public investments in Extension.

This selective research strategy enables Italian agriculture to free-ride technological spill-ins from other countries and sectors for undifferentiated products, concentrating most of its effort on producing its own technology for some specific products, thereby avoiding redundant research that would reduce the rates of return (Swinnen *et al.*, 2000). This strategic choice of the NARS, however, prevents Italian agriculture from joining the group of the most productive national agriculture sectors (USA, Netherlands, France for instance). There is an international R&D hierarchy comprising the high-productivity club integrated with the international system and a trailing group, which includes Italy, that can only partly catch-up through spill-in because technological distances may be too great (Schimmelpfenning and Thirtle, 1999).

The model outlined above is able to provide insights and empirical evidence regarding this hypothesis on Italian NARS design and its dynamic dependence on intersectional and international spill-ins. Spill-ins are calculated by applying the YTC as presented in section 3. Patent data are taken from the CRENoS database of the University of Cagliari[13]. Reliable data cover the period 1972-1991;[14] they refer to patent applications in Italy (to either the Italian Patent Office or the European Patent Office) by both national and international inventors. The database contains patent applications by inventors in the following foreign countries: USA, UK, Netherlands, Germany, France, Japan. During the period in question, patent applications from these countries accounted for about 85% of total applications in Italy; they therefore exhaustively represent overall international technological transfer to Italy.

Italian agriculture, too, displays a very marked concentration of intersectoral and international dependency in few sectors.[15] Table 1 sets out the YTC evidence on dominant sectors and countries in the creation of technical change in Italian agriculture. Most agricultural innovations produced by domestic inventors concern three sectors; mainly Machinery and, to a much lesser extent, Chemicals and Drugs. These are also

[13] For more details and explanation see Paci *et al*. (1996).

[14] This is admittedly a limited and insufficiently updated period. However, patent data always raise problems of updating, also in view of the lag, quite long in the Italian case, between application for a patentand its granting. This problem is stressed in many studies. Also Johnson and Evenson (1999) reports problem with Italian records and patent data updating; their empirical analysis applies to the period 1973-1987.

[15] 81% of patented innovations used by Italian agriculture is produced by foreign inventors.

the prevailing sectors of foreign inventors; however, in this case the share of Chemicals is as high as Machinery. American and German inventors account for more than 60% of the foreign patented innovations used by Italian agriculture, while the proportion of French, British and Japanese inventors is less than 15%. Moreover, innovations originating in the USA, Germany and France mainly concern the Machinery sector, while inventions from Japan and UK mainly concern Chemicals, and also show an higher share of the Drugs sector.

The results provide substantial empirical support for the restrictions on the simultaneous effect between stocks: foreign invention activity dominates the national and, in turn, other national sectors dominate agriculture. Consequently, it seems legitimate to assume that agriculture R&D does not have a contemporaneous effect on spill-in stocks and the intersectoral national spill-in has no contemporaneous effect on the international one.

The weights of the spillover matrix, once they have been calculated by means of the YTC,[16] can be applied to own R&D stocks. National (both private and public) and sectoral R&D investments are taken from OECD databases (OECD, 1994 e 1997). The own (Italian) agricultural R&D stock is calculated using public R&D expenditure. In Italy, private agricultural R&D is negligible, while public agricultural Extension amounts to about 75% of public R&D on average. Therefore, in calculating own R&D stock both R&D and Extension public investments are considered (see Esposti and Pierani, 2000a for details). The R&D stocks, own (*O*), intersectoral spill-in (*S*) and international spill-in (*I*), are expressed in 1985 PPP USA dollars.

First, the presence of an unit root is detected for the three stocks. This also requires testing for the presence of a drift and/or of a trend. Inappropriate testing may confuse (especially in the presence of smoothed series) a stochastic trend (therefore a unit root) with a process with a deterministic trend or with a stationary process with a drift and a strong (although less than unit) autoregressive coefficient. The appendix (table A.1) reports unit root tests under several assumptions. Three unit root tests are calculated: the Adjusted Dickey-Fuller (ADF) test, the Perron-Philips (PP) test and the Weighted Symmetric (WS) test (Pandula *et al.*, 1994). It is not always easy to interpret the results of this set of unit root tests, partly owing to the small sample size and to the well known low power of these tests with respect to the alternative hypothesis. However, the presence of a unit root is never rejected for any stock. The lower part of table A.1 reports tests on the presence of both a deterministic trend and a drift; moreover, a structural break in 1980 through a time dummy is tested (Perron, 1989). Following the procedure suggested by Dolardo *et al.* (1990), the data reject the presence of a deterministic time trend, of a drift and of a structural change in 1980.[17] We may therefore conclude that all the stocks are not stationary. Table A.2 reports ADF unit root tests on the first differences. We can reject the presence of an unit root at the 90% confidence interval; considering that the test has low power with respect to the alternative hypothesis of no unit root, we are willing to accept the hypothesis that the stocks are stationary in the first differences. Consequently, we can conclude that the three stocks move over time around a stochastic trend (Esposti, 2000b).

Table A.3 reports the Engle-Granger and Johansen cointegration tests. According to the Engle-Granger test, null hypothesis of no cointegration can be rejected at 85% significance level. The test is not particularly powerful with respect to the alternative hypothesis, given that it is based on a ADF test where unit root means no cointegration. Moreover, the Johansen trace test suggests that the hypothesis that the cointegrating

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[16] See Esposti (2000a) for more details.
[17] Other years of the early eighties have been considered for structural change obtaining the same results.

matrix (**ð** = **áâ'**) has rank lower or equal to one can be accepted at 95% level while the hypothesis that it has rank zero is rejected at the 95% critical value but not at the 90% one. In other words, cointegration tests suggest that the stocks are not stationary but either the hypothesis of one cointegrating vector or of no cointegration could be accepted.

Since the cointegration tests are inconclusive with respect to the real underlying data generation process, we can accordingly follow two distinct modelling strategies. If the stocks are difference stationary and not cointegrated, we can estimate a VAR model in the differences, whereas if they have one cointegrating vector a VEC model like (7) holds. The structural form, and therefore innovation accounting, of both models can be identified through the restrictions on simultaneous effects outlined above.

Tables 2 and 5 report the estimated parameters of the VAR and VEC models respectively.[18] Although reduced form parameters are difficult to interpret economically, the estimates show that introducing an error correction term in a VAR model in the first differences may affect the results. Note that according to the AIC there is no significant advantage in extending the model to two or three lags; in the case of the VEC model one lag is the optimal solution. Therefore, a one-lag specification is mantained for both models. Considering that only one cointegrating vector is present, and despite the risk of small size bias, the VEC model is estimated using the Engle-Granger two-steps procedure (Engle and Granger, 1987).[19] This estimation procedure is used by Makki *et al*. (1999) on a similar subject and it provides efficient estimation of the unrestricted VEC; it does not rely on any distributional assumption required by the

[18] According to previous tests, constant terms, deterministic trends and time dummies are excluded from the estimated model.

[1919] The normalisation is made with respect to the own R&D stock (O). However, normalisation in the other stocks does not change the results significantly. Moreover, we are assuming that O depends on

MLE estimation of the VEC, according to the Johansen (1988) and Stock and Watson (1993) alternative approach (Canova, 1994).

Two parameters of the estimated VAR show a negative sign; however, they are not statistically different from 0. The equation of the Own R&D stock (O) shows the lowest goodness of fit. Only one parameter is significant and the R^2 is clearly the lowest. However, it is also the only stock for which the hypothesis of Granger-causation by the other two stocks can be accepted. Indeed, the spill-in stocks afford a better goodness of fit due to an higher impact of own lagged values, while we may accept that they are not Granger-caused by the other VAR variables.

The dependence of the own stock on spill-ins is confirmed by the innovation accounting. Table 3 reports 10-years variance decomposition of the forecast error while table 4 and figure 4 report the impulse response function to one standard deviation pure shocks. Forecast-error variance decomposition suggests that the own R&D stock closely depends on international spill-in; in a 10-year horizon, after 5 years the effect of shocks in international spill-in equals the effect of an own shock. Also the national intersectoral spill-in is strongly affected by the international one, while the impact of a shock on the own R&D stock is negligible. As a consequence, the international stock is mostly exogenous in the estimated system: in a ten-year horizon at least 80% of the forecast-error variance can be attributed to its own pure shock.

The impulse response functions confirm the previous interpretation. A few years after the pure shock, the impulse in the international spill-in is dominating for all stocks. The effect of an own R&D shock is always almost negligible from the second year after the impulse onwards. More marked and persistent is the response of the intersectoral spill-in to its own shock, but this almost vanishes at a 10-year horizon. It must also be

contemporaneous values of both I and S, whereas the reverse does not hold. Therefore, this restriction on considered that this impulse response concerns shocks in the first differences, not in the levels. Therefore, cumulating the response at any year provides the impulse response in the stock levels to a single period shock (Enders, 1995) (table 4). Shocks in the international spill-in greatly increase the levels of both own and intersectoral spill-in stocks. Shocks on the others have a positive and significant effect on themselves but not on the other shocks; moreover, an impulse on the intersectoral spill-in has an overall reducing effect on the others.

As said, the estimation of the VAR model in the first differences may miss important information about the long run equilibrium between the stocks; this equilibrium is of main interest to recover the NARS strategy according to the discussion in section 2.2. The results may be a mixture of both the movement around the long term relation and the short term adjustment to a previous disequilibrium. Without a cointegrating relation to separate these distinct effects in a ECM, representation is not possible; moreover, it may also happen that no cointegration and no stable long run equilibrium between the stocks exists. However, we can still use the estimated VAR parameters to derive some information on long term behaviour. Setting the negative not significant parameters equal to zero, and assuming balanced growth of the dynamic system generating the sectoral-national knowledge stock, we can calculate the dominant eigenvalue and the associated eigenvector of the non negative matrix of coefficients. Projecting the system in the long run, we can interpret the eigenvalue as the balanced growth rate and the eigenvector as the long term stable distribution between the three stocks.[20]

Table 2 reports the calculated eigenvalue and eigenvector. The system is stable because the eigenvalue is inside the unit circle. This implicitly confirms the stationarity of the series' first differences. However, the eigenvalue is very close to unity, which suggests

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the contemporaneous effects makes less critic the choice of normalisation.

that the first differences show strong persistence and may be easily confused with random walks. The stable distribution between the stocks attributes the highest share to own stock with respect to spill-ins. This may seem to contradict previous results. However, as shown, the own stock has a limited impact on itself and on the other shocks; therefore, to have balanced growth, relatively more investments in own R&D are required.

We can also explicitly introduce a long run equilibrium between the stocks assuming that a cointegrating vector exists. In this case, to prevent omission of a relevant regressor, an error correction term must be introduced. This has also an important economic interpretation. It allows the separation of the short and long term relations between the stocks, thereby avoiding the mixture of results that could potentially affect the previous estimated model. In the VEC model, through the error correction term, part of the stocks' movement is an adjustment to disequilibrium; the rest of the movement is a response to change in the stocks according to the long term equilibrium.

The lower part of table 5 reports the estimated cointegrating vector and the speed of adjustment vector. Note that the signs of the elements of both vectors β and α are consistent with cointegration, that is, with a long run equilibrium, and a consequent error correction term in the model. β expresses the long run distribution between the stocks; the stable combination implies that 0.64 and 0.28 units of the intersectoral and international spill-ins respectively correspond to an unit of the own stock. This is a proportion which is not very different from the eigenvector calculated in the previous VAR model as a balanced growth projection of the estimated matrix of coefficients. The estimated elements of the vector β statistically differ from 1; this implies that the long run equilibrium implied by the cointegrating relation does not mean that the stocks

[20] See section 4 for details.

move around a common stochastic trend; rather, that they move around stochastic trends maintaining a stable proportion in the long run.

The signs of the elements in the β vector express the adjustment with respect to the short run disequilibrium; if the own stock is greater than the long run proportion the error correction term should downward adjust the variation of the stock itself. Therefore, the adjustment parameter in α corresponding to the own stock is expected to be negative; following the same argument, the adjustment coefficients are expected to be positive for the spill-in stocks. Estimated parameters are fully consistent with these theoretical expectations. The own stock adjusts much more quickly than the spill-in stocks; in the case of the international spill-in the coefficient is even not statistically different from 0. This result has a clear economic interpretation; the own stock is under the control of the NARS and it can adjust rapidly to its own long run equilibrium, whereas it cannot affect the adjustment process of the spill-ins. It also implies that the error correction term may be quite relevant in the case of the O equation, while it is less important for the S and almost negligible for the I equations of the VEC model.

By means of the error correction term, VEC estimated parameters can significantly differ with respect to the previous VAR. First of all, note that now also the intersectoral spill-in is clearly endogenous. The hypothesis of no Granger causality by the other stocks can be accepted only for the international spill-in, which is further evidence that it tends to be mostly exogenous and not under NARS control. Moreover, the goodness of fit of the O stock increases slightly, although it is still quite slow. In any case, more significant parameters are found and they clearly affect both the O and the S equations. As explanatory variables, O is never significant while S shows negative and significant effects with respect to the other stocks. Although these estimates are hardly directly interpretable, they significantly affect the innovation accounting and the consequent economic meaning.

Table 6 reports the forecast-error variance decomposition. A shock in the own stock explains very little of the stocks' movement, while an important role is played by the international spill-in. The novelty is that also the shocks of the intersectoral spill-in explain a large proportion of the system's entire movement. The impulse response functions (figure 5 and table 7) confirm the role of O and I: a single-year pure shock of own stock has a little impact and vanishes quite rapidly in a 10-year horizon. A single-year impulse in international spill-in always has a positive impact, vanishing quite slowly over the years. The effect of one pure shock on intersectoral spill-in is only partly surprising. It determines a negative effect on the other two stocks and, via its endogeneity, this negative response also affects the S stock itself over the years. However, the cumulated effect of the pure shocks finally confirms what partially emerged in the VAR model: the S impulse has a negative feedback on the entire system. An impulse on the own stock has a very limited effect, except on itself, while the most relevant enhancing role on the entire sectoral-national knowledge stock is induced by a positive shock in the international spill-in.

6. The Underlying NARS Design: Some Final Comments

How can the results of the VAR/VEC models be reconciled with the analysis of the NARS in section 2? The small sample size and the low power testing make it difficult to detect the real underlying data generation process. In particular, if a cointegrating relation existed, the VAR estimates would mix the long and short run movements, making the results difficult to interpret. However, the VAR and VEC models yield largely concordant results. A first important finding from the estimation is the role played by own R&D effort in designing the NARS in the case of Italian agriculture. It depends dynamically to a great extent on spill-ins, while its own effect on the spill-ins themselves is quite limited. This confirms that a "one way" transfer mode prevails in the case of Italian agriculture, which suggests the prevalence of a direct transfer strategy. However, this conclusion may not be not entirely correct.

In fact, although strongly endogenous, the own R&D stock must constitute the largest proportion in the long run equilibrium between the stocks. This is explained by its narrow multiplying impact on the entire system implied by the "end of chain" transfer, but also by the fact that substantial own effort is needed. In other words, the NARS seemingly requires an adaptive effort, rather than a pure direct transfer, also because many agriculture products and techniques are highly country or regional specific. Therefore, even in the case of a trailing country and/or sector from a technological point of view, and in which spill-ins predominate, the specific characters of agricultural production always require an adaptive R&D effort to some extent (Evenson, 1994).

Also of particular interest is the role that emerges for the two spill-ins. International spill-in is mostly exogenous and plays a crucial leading role in increasing and orienting the NARS. Its powerful multiplying effect influences both own R&D and intersectoral (national) spill-in. However, it is negatively affected by an increase in the latter, which also shows a negative impact on own stock. Evidently, there is a free-riding effect between national non-agricultural research and the effort spent by the national agricultural (public) research and the inventions produced by foreign countries. In economic terms, intersectoral spill-in is a substitute for, and not a complement of, both own and international spill-in stocks. We can also infer that this substitution holds because research is at least partially conducted on the same ground at the conjunction between the international spill-in and the agricultural national effort: that is, at the level of applied research.

This result confirms the findings of previous studies (Esposti, 2000a), and it also suggests the need for close co-ordination within the NARS between non-agricultural and agricultural research efforts, given international spill-ins. A more radical change in NARS strategy would also be possible, affecting the relation between own and international spill-in stocks. Selecting a comprehensive research strategy would make own R&D and international spill-in substitutes to some extent. This would greatly increase own R&D effort, but it might also enable Italian agriculture to move out of the group of technological followers into the club of leaders.

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Figure 1 – The research sequence in the creation of the sectoral (agricultural) and national knowledge stock with spill-ins

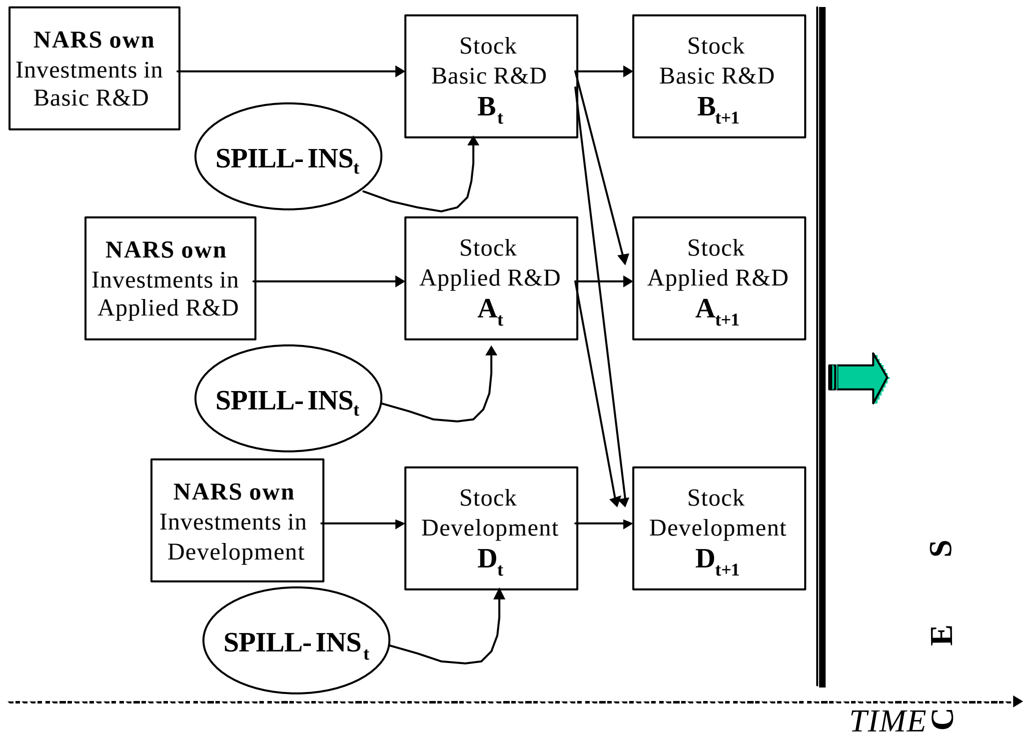
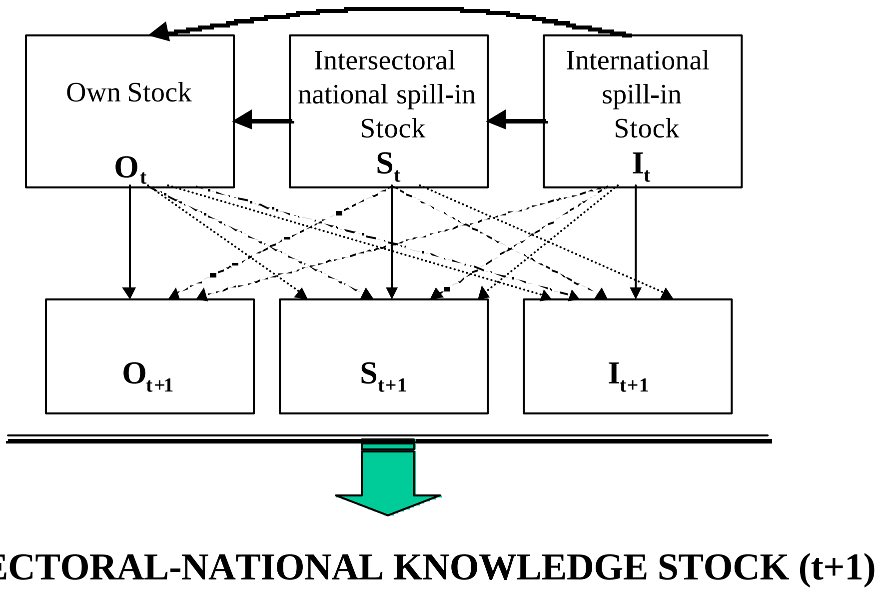


Figure 2 – The NARS options according to the research sequence with spill-ins

TIME →

sequence / *option*	Stock Basic R&D **B** →	Stock Applied R&D **A** →	Stock Development **D**
1. Direct Transfer	SPILL-INS	SPILL-INS	SPILL-INS + OWN
2. Adaptive Research	SPILL-INS	SPILL-INS + OWN	SPILL-INS + OWN
3. Comprehensive Research	SPILL-INS + OWN	SPILL-INS + OWN	SPILL-INS + OWN

Figure 3 – Causality direction and sign under different technology transfer modes and with structural restrictions on contemporaneous effects (VAR model structural form)



Legend:

One-way ("end of chain") transfer (national and/or international) **(+)**

Two-way ("symmetric") transfer (national and/or international) **(+)**

"Free-riding" pull effect (national and/or international) **(-)**

Contemporaneous effects (identifying restrictions)

Table 1 – YTC patens count by IOM and SOU (1972-1991): contribution of sectors and countries to Italian agricultural (SOU) innovations

Main IOMs	
Domestic Patents	
Branch	*Share*
(Other) Machinery[21]	64%
Chemicals	12%
Drugs	5%
Total	81%
Foreign Patents	
Branch	*Share*
(Other) Machinery	39%
Chemicals	39%
Drugs	7%
Total	85%

Share of foreign patents for Italian agriculture (SOU)

	France	Germany	Japan	United Kingdom	USA	Total
Livestock	17%	28%	9%	14%	32%	100%
Crops and combo farms	13%	30%	11%	13%	33%	100%
Fruits and vegetables	15%	28%	11%	13%	33%	100%
Horticulture	26%	29%	6%	12%	28%	100%
Services to livestock	16%	20%	13%	15%	35%	100%
Services to crops	15%	30%	9%	12%	34%	100%
Other	20%	27%	9%	12%	31%	100%
Total Italian agriculture	15%	28%	10%	13%	33%	100%
Share of agriculture (SOU) on total patent applications in Italy	2.3%	1.7%	2.5%	2.4%	1.9%	2.0%

Foreign countries of sector shares in patenting for Italian agriculture (SOU)

France		Germany		Japan		United Kingdom		USA	
Machinery	49%	Machinery	44%	Chemicals	58%	Chemicals	44%	Machinery	40%
Chemicals	25%	Chemicals	38%	Machinery	21%	Machinery	32%	Chemicals	37%
Drugs	6%	Drugs	4%	Drugs	10%	Drugs	10%	Drugs	8%
Total	79%	Total	86%	Total	89%	Total	86%	Total	85%

[21] This branch identifies all the production of machinery highly user-specific and that can not be aggregated into otherwise classified machinery production. Agricultural machinery is included in this branch (Esposti, 2000a).

Table 2 – Estimated parameters of the VAR model in the differences (1 lag; no drift, no trend assumed; t-values in parentheses)

Dependent Variable	*O*	*Regressors* *S*	*I*	R^2
O	.175	.421	.818**	0.31
	(1.68)	(1.22)	(2.66)	
S	-.014	.866**	.133	0.66
	(-0.18)	(7.89)	(1.35)	
I	.118	-.153	.760**	0.60
	(1.31)	(-1.07)	(4.41)	

		1 lag	*2 lags*	*3 lags*
AIC values		28.41	27.91	28.99

		O	*S*	*I*
Granger causality: block exogeneity test		5.36*	2.43	4.16

	Dominant Eigenvalue	*(normalised) Dominant Eigenvector*		
		O	*S*	*I*
Long-run balanced growth	0.96	1.00	0.76	0.57

* Statistically significant at 90%; ** Statistically significant at 95%

Table 3 – Innovation accounting of the VAR model in the differences: 10 years forecast-error variance decomposition

Forecast Error Variance Decomposition of O			
Year	*O*	*S*	*I*
1	79	3	17
2	67	3	30
3	60	3	37
4	55	3	42
5	52	3	45
6	50	3	47
7	49	2	49
8	48	2	50
9	47	3	50
10	47	3	51
Forecast Error Variance Decomposition of S			
Year	*O*	*S*	*I*
1	0	66	34
2	0	61	39
3	0	57	43
4	0	53	47
5	0	49	51
6	0	46	54
7	1	43	56
8	1	41	58
9	1	40	59
10	1	38	60
Forecast Error Variance Decomposition of I			
Year	*O*	*S*	*I*
1	0	0	100
2	5	2	93
3	7	3	90
4	9	4	87
5	9	5	85
6	10	7	84
7	10	8	82
8	10	8	81
9	11	9	80
10	11	10	80

Table 4 – 10 year cumulative effect of shocks in the R&D stocks (VAR model in the differences)

Cumulative effects on	*Shocks in* *O*	*S*	*I*
O	72,7	-9,8	173,0
S	10,9	72,8	107,2
I	36,9	-37,7	96,9

Table 5 – Estimated parameters of the VEC model (1 lag; no drift, no trend assumed; t-values in parentheses)

Dependent Variables	*Regressors* *O*	*S*	*I*	R^2
O	.090	-.614**	2.570**	0.33
	(1.05)	(-2.34)	(3.16)	
S	-.040	0.571**	.634**	0.87
	(-1.14)	(3.72)	(2.58)	
I	.109	-.317*	1.041**	0.80
	(1.21)	(1.85)	(3.38)	

	O	*S*	*I*
Cointegrating vector	1.000	-0.635	-0.275
(β = long term relationship)		(.212)	(.328)
(standard errors in parentheses)[22]			
Speed adjustment vector	-.898**	.165*	.071
(α = short term adjustment)	(-2.28)	(1.77)	(1.43)
	1 lag	*2 lags*	*3 lags*
AIC values	25.78	27.26	27.61
	O	*S*	*I*
Granger causality: block exogeneity test	7.26**	5.21*	3.89

* Statistically significant at 90%; ** Statistically significant at 95%

[22] Due to non-normal distribution, traditional t-testing does not hold; therefore, only standard errors are reported (Enders, 1995)

Table 6 – Innovation accounting of the VEC model: 10 years forecast-error variance decomposition

Forecast Error Variance Decomposition of O			
Year	*O*	*S*	*I*
1	53	36	11
2	26	20	54
3	18	21	61
4	14	25	61
5	12	30	59
6	11	34	55
7	10	38	52
8	10	42	49
9	9	44	46
10	9	46	44
Forecast Error Variance Decomposition of S			
Year	*O*	*S*	*I*
1	0	71	29
2	0	41	59
3	0	24	75
4	1	18	81
5	2	18	80
6	3	22	76
7	3	26	70
8	4	31	65
9	4	35	61
10	4	39	57
Forecast Error Variance Decomposition of I			
Year	*O*	*S*	*I*
1	0	0	100
2	2	6	92
3	3	13	84
4	3	20	76
5	4	26	70
6	4	32	64
7	4	36	59
8	5	40	55
9	5	43	52
10	5	45	50

Table 7 – 10 year cumulative effect of shocks in the R&D stocks (VEC model)

Cumulative effects on		*Shocks in*	
	O	*S*	*I*
O	137,8	-340,7	310,3
S	45,0	-101,2	194,1
I	46,4	-138,9	145,3

Figure 4 – 10 years impulse response functions of the estimated VAR model

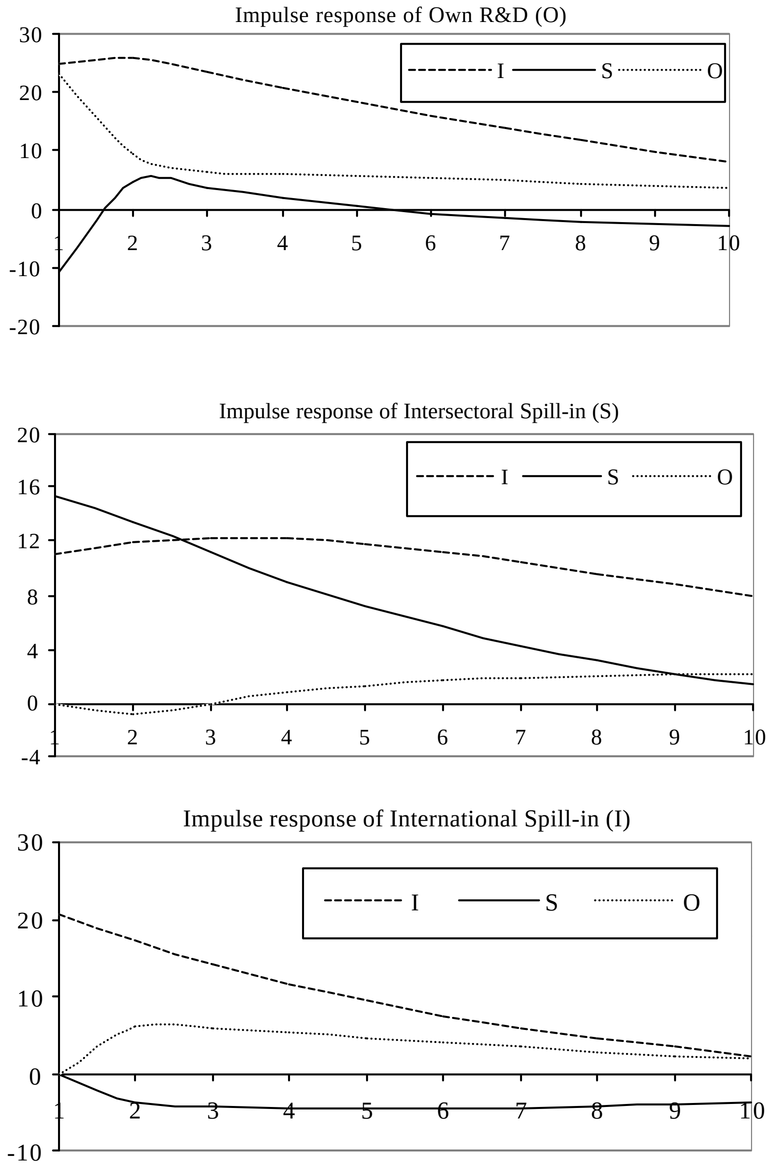
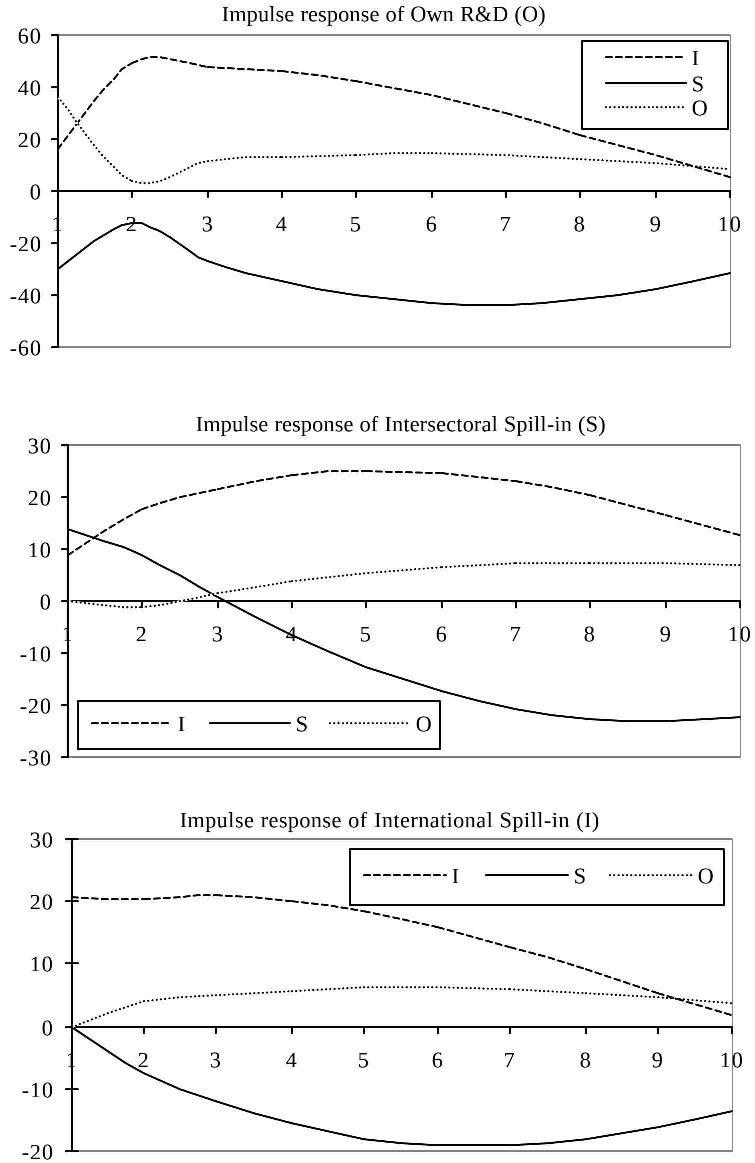


Figure 5 – 10 years impulse response functions of the estimated VEC model



APPENDIX

Table A.1 – Unit root tests on the stock levels (test statistics are reported; p-values in parentheses; distributions taken from MacKinnon, 1994, and Pantula et al., 1994)

Stock	*No trend No drift*			*No trend With drift*			*With trend With drift*			*With time dummy (structural break in 1980)*		
	ADF	*PP*	*WS*	*ADF*	*PP*	*WS*	*ADF*	*PP*	*WS*	*ADF*	*PP*	*WS*
O	2.52 (.99)	1.43 (.96)	NA	1.40 (.99)	0.49 (.98)	0.31 (.99)	-1.09 (.93)	-2.20 (.96)	-1.48 (.0.89	-2.82 (0.18	-10.8 (.38)	-2.82 (.13)
S	1.26 (.95)	0.64 (.84)	NA	-1.79 (.38)	-1.68 (.81)	-0.09 (0.99	-0.08 (.99)	-2.53 (.95)	0.83 (.99)	-1.21 (0.90	-3.87 (.89)	-1.65 (.83)
I	1.00 (.92)	0.70 (.85)	NA	0.82 (.99)	3.42 (.99)	0.24 (.99)	1.93 (.99)	2.57 (.99)	-0.10 (.99)	-2.22 (.47)	-9.15 (.49)	-2.41 (.34)

	No trend No drift			*No trend With drift*			*With trend With drift*			*With time dummy (structural break in 1980)*		
	O	*S*	*I*	*O*	*S*	*I*	*O*	*S*	*I*	*O*	*S*	*I*
AIC Optimal lag	2	4	3	2	3	3	2	4	4	2	2	2

Restriction Testing (Enders, 1995; page 257) (critical values in parentheses taken from Dickey and Fuller, 1981; Perron, 1989; 95% confidence interval)[23]

	O	*S*	*I*
No trend, No drift, No unit root (critical value = 5.68)	0,47	0,69	0,38
No trend, No unit root (deterministic drift) (critical value = 7.24)	0,17	0,28	0,07
No constant, No unit root (trend stationary process) (critical value = 5.18)	0,14	0,28	0,09
$\tau_{\alpha\tau}$ (critical value = 3.20)	0.15	0.30	2.01
$\tau_{\beta\tau}$ (critical value = 2.85)	1.04	0.43	1.78
$\tau_{\alpha\mu}$ (critical value = 2.61)	1.95	1.97	2.63
Perron's test of structural change (critical value = -3.94)	1.42	1.32	1.03

[23] For the tests taken from Dickey and Fuller (1981), critical values for sample size n = 25 are considered; for the Perron's test $\lambda = 0.4$ is assumed.

Table A.2 – ADF unit root tests on the stock first differences (no trend, no drift admitted)

Stock	*Test statistics* t	*90% Critical values*	*95% Critical values*
O	-2.29	-1.60	-1.95
S	-1.75	-1.60	-1.95
I	-1.66	-1.60	-1.95

Table 5 – Cointegration tests; 1 lag, no costant, no trend, no dummy assumed (test statistics are reported; p-values and critical values taken from Engle and Yoo, 1987, and Johansen and Juselius, 1990)

	Test statistics	*p- value*	
Engle-Granger t test	-3.67	0.14	
Johansen (trace) test:	*Test statistics*	*90% Critical values*	*95% Critical values*
Rank = 0	29.38	28.43	31.25
Rank ≤ 1	11.75	15.58	17.84
Rank ≤ 2	2.88	6.69	8.08