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Trade, human capital, and technology diffusion in the Mediterranean agricultural sector

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ABSTRACT. This paper investigates the roles of human capital and openness in the process of technology diffusion and productivity growth in the Mediterranean agricultural sector. We estimate a nonlinear productivity growth specification that nests the logistic and the confined exponential technology diffusion functional forms, using a panel of nine South Mediterranean countries and five European Union countries for the period 1990 to 2005. The estimation results suggest that the steady state is a balanced growth path, with all backward economies growing at the pace determined by the leading edge. The findings illustrate the positive roles of openness and human capital in facilitating technology diffusion and fostering agricultural growth. We find strong complementary effects between foreign technology embodied in imported capital goods and educational attainment on farming performance.

JEL Classification: C23; D24; O33; Q17.
Keywords: Human Capital; Openness; Technology Diffusion; Agricultural Productivity; Panel Data.

RÉSUMÉ. Cet article explore le rôle du capital humain et de l'ouverture des échanges dans le processus de diffusion technologique et de la croissance de la productivité dans le secteur agricole méditerranéen. Nous estimons une forme non linéaire de la croissance de la productivité qui combine les processus de diffusion logistique et exponentiel. Le modèle utilise les données de panel couvrant la période 1990-2005 pour neuf pays du Sud de la Méditerranée et cinq pays de l'Union européenne. Les résultats révèlent des effets de rattrapage des performances productives, les économies les moins performantes convergent vers le taux de croissance de la frontière technologique. L'étude montre que le capital humain et l'ouverture commerciale facilitent la diffusion technologique et stimulent la croissance agricole. L'analyse révèle une forte complémentarité entre le niveau d'éducation et l'importation des biens d'équipement.

Classification *JEL* : C23 ; D24 ; O33 ; Q17.
Mots-clefs : Capital humain ; ouverture commerciale ; diffusion technologique ; productivité agricole ; données de panel.

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INTRODUCTION

The role of technology diffusion in the process of economic development is an important consideration in the recent literature. The diffusion of new technologies from advanced economies to developing ones is regarded as a key driver of productivity growth for countries behind the technology leader (see for example, Grossman and Helpman, 1991; Barro and Sala-i-Martin, 1997; Benhabib and Spiegel, 2002; and Griffith *et al.*, 2004). In the models of technology diffusion, the rate of productivity growth of developing countries depends on the extent of the adoption of the leading economies technological knowledge. According to these models, countries lagging behind the technological frontier would experience faster productivity growth than the leading country and thereby would enjoy technological catch up (Benhabib and Spiegel, 2002; Griffith *et al.*, 2004; Cameron *et al.*, 2005).

Technology diffusion can take place through different channels that involve the transmission of advanced technologies across countries. Recent studies have identified international economic activities such as trade, FDI or equipment imports as important pathways for foreign knowledge spillovers.[2]

Advanced technologies might not however automatically affect the host country's productivity. The adaptability and local usability of foreign technologies depend on the skill content of the recipient country's workforce. Advanced technologies might prove ineffective in countries without sufficient educated labor force to absorb international knowledge (Xu, 2000; Das, 2002). In a seminal formalization of the catching up process, Nelson and Phelps (1966) pointed to the importance of human capital in promoting a country's absorptive capacity and in fostering the diffusion of technology. Benhabib and Spiegel (2002) investigate the Nelson and Phelps suggestion, presenting a generalized model, where human capital impacts productivity by stimulating innovation and by facilitating technology adoption. Using cross-country nonlinear regression that nests different technology diffusion specifications, they find evidence supporting the positive role of human capital in the growth process.

Many authors have emphasized the importance of international trade and human capital for successful technology diffusion. Aggregate-level as well as industry-level analyses have found strong empirical evidence supporting the positive role of these two determinants in fostering productivity growth through the speed of technology transfer. Using data on a panel of developed and developing countries, Xu (2000) finds that international technology diffusion contributes to the productivity growth in developed countries. He shows that developing economies need to reach a minimum human capital threshold level in order to benefit from the technology transfer. Xu and Chiang (2005) also report evidence of the positive impact of trade openness on productivity through bringing in capital goods that embody foreign technology, and through stimulating inflow of foreign patents. Their results provide

2. Influential empirical work includes Borensztein *et al.* (1998), Lichtenberg and van Pottelsberghe de la Potterie (1998), Xu (2000), Mayer (2001), Keller (2000, 2004), Xu and Chiang (2005), and Wang (2007).

support to the positive role of educational attainment in speeding the technology catch up process. Sectoral-level studies convey similar messages about the importance of trade and human capital for technology spillovers and productivity growth; see for example Das (2002) for a sample of developed and less developed countries, Cameron *et al*. (2005) for United Kingdom, Lai *et al*. (2006) for China, and Wang (2007) for developing countries.

So far, sectoral analyses are mostly applied to industrial sectors, with very little work on agriculture. The evolving concerns regarding food security and natural resources, along with the gradual opening of agricultural markets during the recent wave of globalization, has sparked a growing interest in examining the relationship between international trade, technology diffusion, and agricultural productivity. A large body of empirical literature has investigated agricultural technology diffusion and adoption.[3] Most of these studies are country specific, and focus on the typical agro-climatic and socio-economic operating conditions required for technology adoption. While this literature contributes to our understanding of the agricultural technology diffusion process, it is difficult to make generalizations about the nexus between new technology and productivity growth in the agricultural sector. Moreover, although some of these studies recognize the importance of trade for agricultural technology diffusion, few have empirically examined this linkage.

This paper tries to fill this gap by investigating the roles of international trade and human capital in the process of technology diffusion and productivity growth in the Mediterranean agricultural sector. The empirical analysis is conducted over a set of six agricultural product categories in a panel of nine South Mediterranean Countries (SMC) and five European Union (EU) countries for the period 1990 to 2005. The selected countries have taken steps towards greater integration in the global economy, their profile is commensurate with the paper objective in many respects. First, these countries are about to start implementing a new agreement on trade in agricultural products under the EU-Mediterranean partnership and the Doha round of the WTO agreement on agriculture. Secondly, agriculture is a major sector in these countries as it represents an important source of income and output and employs a large segment of impoverished population.

Agriculture in these countries was subject to various protection mechanisms that have distorted market incentives and resulted in inefficient allocations of resources. Reducing trade barriers through further market liberalization in the framework of the Barcelona Agreement offers interesting perspectives for the development of agricultural production. The further trade integration between the EU and the SMC may facilitate the transmission of technological knowledge, promote the modernization of the farming sector, and enhance productivity growth. It is difficult, however, to deny the production constraints and agricultural structures that could impede the most optimistic prospects. From a policy perspective, investigating whether trade promotes technology diffusion in the Mediterranean agricultural sector

3. See, for example, Feder *et al.* (1985), Foster and Rosenzweig (1995), Abdulai and Huffman (2005), Lee (2005), and Baerenklau and Knapp (2007).

and how important are labor skills for technology spillovers is critical for evaluating the potential gains for the region in the context of globalization.

To examine these issues, we follow a somewhat similar approach to that of Benhabib and Spiegel (2002) in estimating a nonlinear model for productivity dynamics that nests the exponential and logistic forms of technology diffusion. This enables us to explore the different implications of these specifications for the agricultural growth path.

We examine the robustness of the results to the use alternative measures of agricultural productivity. We estimate a dynamic Cobb Douglas production function using the system GMM approach and the random coefficients model to account for cross country heterogeneity in production technologies. Agricultural total factor productivity (TFP) indexes are measured using the residual method. These approaches are likely to be more appropriate than that widely used in the existing analysis and which obtain TFP from a constant returns to scale Cobb-Douglas production function with fixed input shares (see, among others, Benhabib and Spiegel, 1994, 2002; and Xu, 2000). The potential for technology transfer is proxied by a country's distance from the technological frontier where the leading edge is defined as the economy with the highest level of agricultural TFP.

The paper is organized as follows. The next section outlines the steady state implications of the exponential and logistic diffusion patterns. The third section presents the empirical model and the estimation methods. Section four provides an overview of the data used. Section five reports the main econometric results relating to the roles of human capital and openness and quantifies their economic importance. Finally, the essential findings and conclusions are summarized in the last section.

Human capital, economic opening and productivity growth

Our approach to investigate the importance of international trade and human capital in the process of technology diffusion and productivity growth is based on the work of Benhabib and Spiegel (2002). Using cross-country data, Benhabib and Spiegel (2002) estimate a nonlinear specification of TFP growth to test the Nelson and Phelps (1966) hypothesis that education speeds the process of technological diffusion. Their approach nests different forms of technology diffusion in a model where human capital affects growth through its effects on both the innovation ability and technology adoption.

We use an extended version of this baseline specification that includes trade openness as a channel for technology diffusion. We assume agricultural productivity growth to be driven by both domestic innovation and adoption of foreign technology. The innovation part is related to the level of human capital, while the adoption part is captured *via* a term interacting the degree of openness with human capital and the technology gap to the best practice frontier.[4]

4. Somewhat similar formulations can be found in Stokke (2004), and Xu and Chiang (2005).

Various functional forms for the technology diffusion pattern have been used in the empirical literature. The most commonly used specification is the exponential model. The leading alternate model is the logistic technology diffusion process. Our specification allows for these two types of diffusion processes and examines the implications of both forms for the agricultural productivity growth path. The growth rate of agricultural productivity in country *i* at time *t* is then given by:

$$\frac{\dot{A}_i(t)}{A_i(t)} = g\big(H_i(t)\big) + f\big(H_i(t), Openness_i(t)\big)\left[\frac{T(t)}{A_i(t)} - 1\right] \qquad (1),$$

where $A_i(t)$ and $T(t)$ represent agricultural TFP and the frontier level of productivity respectively, and $\frac{A_i(t)}{T(t)}$ is the technology gap. $g\big(H_i(t)\big)$ is the contribution from innovation to productivity growth that depends on the level of human capital $H_i(t)$, and $f\big(H_i(t), Openness_i(t)\big)\left[1 - \frac{A_i(t)}{T(t)}\right]$ represents the rate of technology diffusion. The dot indicates change from one period to the next.

The endogenous growth rate and the catch up coefficient are assumed to be increasing functions in all arguments $\big(g'_i(.) > 0 \text{ and } f_i'(.) > 0\big)$. Human capital enhances the country's innovative capacity as well as its ability to adopt foreign technology. The degree of openness also contributes positively to the catch up. Human capital and openness (and therefore, g_i and f_i) are supposed to be constant in the long run and then only affect productivity level and equilibrium gap. The technology level of the country leading in agricultural productivity and representing the technology frontier is taken to grow exponentially at the rate $g\big(H_L\big)$, so that $T(t) = T_0 e^{g(H_L)t}$. A country with a lower level of human capital may not overtake the technology level of a country having an educational advantage, thus $g\big(H_L\big) > g\big(H_i\big) \quad \forall i$.

The catch up process specified in equation (1) is also known as the confined exponential diffusion process (Banks, 1994; Benhabib and Spiegel, 2002). An alternative formulation is the logistic diffusion process given by:

$$\frac{\dot{A}_i(t)}{A_i(t)} = g\big(H_i(t)\big) + f\big(H_i(t), Openness_i(t)\big)\left[1 - \frac{A_i(t)}{T(t)}\right] \qquad (2).$$

In view to investigate the implications of these two types of diffusion processes for the productivity growth path, we follow Benhabib and Spiegel (2002) and derive a specification that nests the exponential and logistic technology diffusion functional forms. We define the technological distance between the best-practice level of technology and the current level of productivity as:

$$B_i(t) = \frac{A_i(t)}{T_0 e^{g(H_L)t}} \quad (3).$$

Differentiating equation (3) with respect to time, we have:

$$\frac{\dot{B}_i(t)}{B_i(t)} = \frac{\dot{A}_i(t)}{A_i(t)} - g(H_L) \quad (4).$$

Substituting (3) and (4) into (1) yields:

$$\frac{\dot{B}_i(t)}{B_i(t)} = g(H_i(t)) - g(H_L) + f(H_i(t), Openness_i(t))\left[B_i(t)^{-1} - 1\right] \quad (5).$$

For the logistic case, we have:

$$\frac{\dot{B}_i(t)}{B_i(t)} = g(H_i(t)) - g(H_L) + f(H_i(t), Openness_i(t))\left[1 - B_i(t)\right] \quad (6).$$

Using (5) and (6) we can specify a diffusion process that nests the exponential and logistic growth equations. More specifically:

$$\frac{\dot{B}_i(t)}{B_i(t)} = g(H_i(t)) - g(H_L) - \frac{f(H_i(t), Openness_i(t))}{s}\left[B_i(t)^s - 1\right] \quad (7).$$

with $s \in [-1, 1]$. Note that if s = 1, the diffusion pattern is logistic, while if s = –1, it is exponential.[5]

For H_i and $Openness_i$ constant, so that $g_i = g(H_i)$, $g_L = g(H_L)$ and $f_i = f(H_i, Openness_i)$, the solution to the technology diffusion equation is:

$$B_i(t) = \left(\frac{1 + \frac{s(g_i - g_L)}{f_i}}{\left(1 + \left(B_0^{-s}\left(1 + \frac{s(g_i - g_L)}{f_i}\right) - 1\right) e^{-(s(g_i - g_L) + f_i)t}\right)} \right)^{1/s} \quad (8).$$

Given that $g_L > g_i$, if either $s(g_i - g_L) + f_i > 0$, or if the diffusion pattern is exponential ($s < 0$):

$$\lim_{t \to \infty} B_i(t) = \left(1 + \frac{s(g_i - g_L)}{f_i}\right)^{1/s}$$

5. See Benhabib and Spiegel (2002).

There exists a stable steady state at $B=\left(\frac{f_i+s\left(g_i-g_L\right)}{f_i}\right)^{1/s}$ and countries would exhibit positive catch up in agricultural productivity with the technology leader. Despite educational differences, productivity growth in the backward economies responds to the productivity distance to best practice, and all countries can take benefit of the growth of the leader nation.

The equilibrium path of productivity is given by:

$$A_i^*\left(t\right)=\left(\frac{f_i+s\left(g_i-g_L\right)}{f_i}\right)^{1/s}T_0^*e^{g_Lt} \tag{9}$$

The country's levels of human capital and openness would be growth enhancing since they are expected to act as engines of innovation as well as stimulus to technology adoption. The payoff to increased openness, as well as to higher educational attainment, is greater the more technologically progressive is the leader nation. It can be seen, however, from the following equations that the smaller is the educational difference with the leading country, the slighter is the backward countries' payoff. Countries that are closer to the leader in terms of human capital and technology may, therefore, experience lower rates of productivity growth.

$$\frac{\partial A_i^*\left(t\right)}{\partial H_i}\frac{H_i}{A_i^*\left(t\right)}=\frac{H_i\left(f_{H_i}\left(g_L-g_i\right)+g_i{}'f_i\right)}{f_i\left(f_i+s\left(g_i-g_L\right)\right)} \tag{10}$$

$$\frac{\partial A_i^*\left(t\right)}{\partial Openness_i}\frac{Openness_i}{A_i^*\left(t\right)}=\frac{Openness_i f_{Openness_i}\left(g_L-g_i\right)}{f_i\left(f_i+s\left(g_i-g_L\right)\right)} \tag{11}$$

Where f_{H_i} and $f_{Openness_i}$ are the derivatives of f with respect to human capital and openness.

For a logistic diffusion pattern (s > 0) and $s\left(g_i-g_L\right)+f_i<0$:

$$\lim_{t\to\infty}B_i\left(t\right)=0$$

There is no steady state with B > 0, the productivity growth rates diverge and the backward countries will not be able to catch up.

If H_i and/or $Openness_i$ vary with time equation (7) can be written as:

$$\dot{B}_i\left(t\right)=a\left(t\right)B_i\left(t\right)-c\left(t\right)B_i^{s+1}\left(t\right) \tag{12}$$

where $a\left(t\right)=g\left(H_i\left(t\right)\right)-g\left(H_L\left(t\right)\right)+\frac{f\left(H_i\left(t\right),Openness_i\left(t\right)\right)}{s}$

and $c\left(t\right)=\frac{f\left(H_i\left(t\right),Openness_i\left(t\right)\right)}{s}$

The transition path is:

$$B_i(t) = \left(B_0^{-s} e^{-\psi(t)} + s e^{-\psi(t)} \int_0^t c(\tau) e^{\psi(\tau)} d\tau \right)^{-1/s} \tag{13}$$

where $\psi(t) = \int_0^t sa(\tau) d\tau \cdot$

These results highlight the importance of the pattern of technology diffusion and its interaction with human capital and openness in fostering productivity growth. For the exponential diffusion process there exists a balanced growth path with backward economies growing at the rate determined by the best practice country. While if technology diffusion is of the logistic type, the country's ability to catch up with the technology leader will depend on the relative importance of technology adoption and innovation as sources of productivity growth. If the difference in human capital endowment between the best practice frontier and the follower allows the catch up rate to exceed the innovation differential growth rate, so that $f(H_i, Openness_i) + g(H_i) - g(H_L) > 0$, the backward economy tends to catch up with the leader nation and the productivity growth rates will converge.[6] Low-skilled economies may however diverge relative to the frontier, since the level of education is not sufficiently high, that $f(H_i, Openness_i) + g(H_i) - g(H_L) < 0$, to allow for introducing foreign technology.

Econometric framework

Productivity measurement

We begin the analysis by estimating productivity and changes in productivity in the Mediterranean agricultural sector. Assuming that a country-specific production function can be depicted by a Cobb-Douglas (CD) form, we measure TFP as the difference between gross output and the factor inputs. Modeling agricultural output as a function of a set of inputs, our baseline production function can be written in log-linear form as:

$$y_{it} = \lambda y_{it-1} + (1-\lambda) \sum_j \beta_j x_{ijt} + \ln(A_{it}) + \omega_i + v_{it} \tag{14}$$

where y_{it} and x_{ijt} denote respectively logs of output and inputs, A_{it} is total factor productivity, and β_j indicate parameters to be estimated. The subscripts *i:* 1,…,N*; t:* 1,…,T; and *j*: 1,…, *J* make reference to the i^{th} country, t^{th} period, and j^{th} input respectively. ω_i are unobserved country specific effects, v_{it} captures all other shocks to country productivity, and is supposed to be serially uncorrelated. Absence of serial correlation is assisted by the inclusion of dynamics in the form of a lagged dependent variable. This dynamic form represents also a simple way of capturing the adjustment process associated with an increase of inputs, as expanding

6. This specification is consistent with a S-shaped technology diffusion path, where productivity growth first rises and then falls.

production factors requires time for these factors to become fully operational and therefore for output to reach its new long-run level. The adjustment costs associated with inputs variations can be captured empirically through the parameter λ (Nickell *et al.*, 1992; Nickell, 1996).

The wide variation in economic characteristics of the Mediterranean countries produces a large amount of unmeasured heterogeneity in the data. The above model allows the incorporation of cross country heterogeneity in the simple form of a random effect. It ignores, however, the variations in the parameters of the core production frontier, which may better capture technological differences across producers (Tsionas, 2002).

When the technological differences are quite insignificant, estimating an error components model would be appropriate, while if the unobserved heterogeneity is important the estimate of the underlying technology may be biased (Green, 2003; Corral and Alvarez, 2004; Hockmann and Pieniadz, 2007). The random parameters model is likely to be better suited to accommodate technological differences across countries, as it allows the heterogeneity to take the form of continuous parameter variation (Hsiao and Pesaran, 2004; Green, 2003, 2005).

A more general alternative to the formulation in (14) would be to estimate productivity using the following dynamic random coefficients CD production function:

$$y_{it} = \lambda_i y_{it-1} + (1-\lambda_i)\sum_j \beta_{ij} x_{ijt} + \ln\left(A_{it}\right) + u_{it} \qquad (15)$$

where u_{it} is an error term assumed to be independently, identically distributed over t with mean zero and variance σ_i^2, and is independent across i. The $\beta_i^{'}s$ represents a variable elasticity of output with respect to each input x. It is specified as a Swamy (1970) type random coefficient models: $\beta_i = \beta + \alpha_i$, where α_i is a random variable distributed independently of the x_i's, with mean zero and a finite positive semi-definite covariance matrix.

We estimate agricultural TFP using the error components and the random parameters models. We begin by estimating the dynamic production function in (14) allowing for country specific effects that may be correlated with the factor inputs. Because the model contains a lagged dependent variable, estimation of the parameters poses several challenges including the possible correlation of the lagged dependent variable with the disturbance term. The conventional panel data estimators are likely to generate biased results. To alleviate endogeneity bias, we use the system GMM approach proposed by Blundell and Bond (1998). This approach involves estimating a two-equation system, consisting of the differenced equation and the original level equation, subject to appropriate cross-equation restrictions that constrain the coefficient vectors in the two equations to be identical. The system GMM method uses lagged differences as instruments for contemporaneous levels, in addition to the lagged levels as instruments for first differences. The consistency of the estimator depends on the validity of the instruments and the absence of serial correlation. The validity of the instrument variables is checked using the Sargan test of overidentifying restrictions.

The second alternative deals with the cross country heterogeneity problem using the random coefficients specification of production technology in (15) to measure agricultural TFP.

When the regressors are strictly exogenous and the errors, u_{it}, are independently distributed, the best linear unbiased estimator of the Swamy type model is the generalized least squares (GLS) estimator. However in a dynamic model, while we may maintain the assumption that $E\left(\alpha_i x_{it}'\right) = 0$, we can no longer assume that $E\left(\alpha_i y_{it-1}\right) = 0$. The violation of the independence between the regressors and the individual effects α_i implies that the pooled least squares regression of γ_{it} on γ_{it-1}, and x_{it} will yield inconsistent parameter estimates, even for sufficiently large panels.

Pesaran and Smith (1995) suggest a mean group (MG) estimator of $\bar{\theta}$ (with $\theta_i = (\lambda_i, \beta_i')'$) by taking the average of the OLS individual estimations $\hat{\theta}_i$ across *i*. This MG estimator can however be severely biased when the number of observations is small, a consistent estimator of θ_i would then be obtained using a weighted average of the least squares estimator of individual units with the weights being inversely proportional to individual variances[7] (Hsiao *et al.*, 1999).

Empirical specification of technology diffusion

The catch up model of technology diffusion in equation (7) can be tested empirically using a panel data regression specification in which the endogenous growth component $g(H_i)$ and the catch-up coefficient $f(H_i, Openness_i)$ enter in log-linear form. Following the approach of Benhabib and Spiegel (2002), we assume that $g\left(H_{it}\right) = \gamma_H h_{it}$ and $f\left(H_{it}, Openness_{it}\right) = \gamma_{op} op_{it} h_{it}$, where h_{it} denotes the log of country *i's* levels of human capital and op_{it} represents openness. The exponential and logistic models of technology diffusion, discussed in the previous section, are nested in the subsequent non linear specification:

$$GTFP_{it} = \gamma + \gamma_H h_{it} + \frac{\gamma_{op}}{s} op_{it} h_{it} - \frac{\gamma_{op}}{s} op_{it} h_{it} \left(\frac{A_{it}}{A_{Lt}} \right)^s + \eta_{it} \qquad (16)$$

where $GTPF_{it}$ is the growth rate of agricultural total factor productivity (TFP) of country *i* at time *t,* γ is a constant and η is an error term. A_{it} represents the country *i*'s agricultural TFP level, we term the economy with the highest level of TFP at time *t* the frontier ($i = L$) and denote this A_{Lt}. Human capital is measured by average years of schooling in the population over age 25. The channels of foreign technology spillovers are captured by four alternative variables: total agricultural trade as a share of agricultural value added, tariff barriers, foreign direct investment (FDI) over GDP, and the share of agricultural machinery and equipment imports in agricultural value added.

7. This estimator is asymptotically equivalent to the MG estimator for sufficiently large time series (Hsiao and Pesaran, 2004).

The estimation of equation (16) allows the data to determine the appropriate value of the parameter s and to distinguish between the two diffusion patterns discussed previously.[8] For s being equal to –1 the specification is confined exponential, while with s equal 1 it is logistic. When s tends to zero, the diffusion process converges to the Gompertz growth model and the technology gap converges to[9]: $B = \exp\left(\frac{(g_i - g_L)}{f_i}\right)$.

We therefore estimate the above nested model in a panel of Mediterranean countries using the nonlinear least squares approach, where the coefficients to be estimated are γ, γ_H, $\frac{\gamma_{op}}{s}$ and s respectively. The computational difficulties of the nonlinear fixed effect models preclude the introduction of individual specific effects to control for the differences between the countries. We add a set of institutional factors, including investment in research and development, governance infrastructure, and average agricultural holdings, to the baseline specification. This strategy enables us to control for heterogeneity in certain observed variables and to check the robustness of the results.

Another econometric concern is that measurement error and endogeneity of some explanatory variables, such as technology gap, could lead to bias in the estimated coefficients. We tempted to deal with this problem using two methods. First, we regress the technology gap against the lagged gap and use the predicted value as an alternative to the technology gap in equation (16) to examine the robustness of the results. Second, we estimate different linear approximations to the nested specification in (16) using the instrumental variables estimator.

As an alternative to the nonlinear model we also investigate the following linear specification, in which human capital and openness enter separately and in interaction with the technology gap[10]:

$$\begin{aligned} GTFP_{it} = {} & \delta_{it} + \beta\Delta\ln\left(A_{Lt}\right) + \alpha_1 h_{it-1} + \alpha_2 op_{it-1} - \theta_1 \ln\left(\frac{A_i}{A_L}\right)_{t-1} - \theta_2 h_{it-1}\ln\left(\frac{A_i}{A_L}\right)_{t-1} \\ & - \theta_3 op_{it-1}\ln\left(\frac{A_i}{A_L}\right)_{t-1} + \kappa X_{it-1} + \upsilon_{it} \qquad (17). \end{aligned}$$

where X is vector of control variables, which includes institutional factors, δ_{it} is a parameter that varies with countries and time and v_{it} is an error term. This specification allows the contemporaneous agricultural TFP growth rate in the leader country to directly affect TFP growth in the follower countries. The speed of technology transfer in equation (17) is given by $\theta_1 + \theta_2 h_{it-1} + \theta_3 op_{it-1}$, while the full effects of human capital and of openness on farming performance are measured by $\alpha_1 - \theta_2 \ln\left(\frac{A_i}{A_L}\right)_{t-1}$ and $\alpha_2 - \theta_3 \ln\left(\frac{A_i}{A_L}\right)_{t-1}$ respectively.

8. See Benhabib and Spiegel (2002) for a similar procedure.
9. See Benhabib and Spiegel (2002).
10. Griffith *et al.* (2004) used a similar specification to investigate the role of R&D in stimulating innovation and technology adoption in OCDE countries.

Data

The empirical application in this study considers panel data at the national level for agricultural productions in nine south Mediterranean countries involved in the partnership agreements with the UE such as: Algeria, Egypt, Israel, Jordan, Lebanon, Morocco, Syria, Tunisia and Turkey; and five UE Mediterranean countries presenting a strong potential in agricultural production as: France, Greece, Italy, Portugal and Spain for the period 1990-2005. Our data set includes observations on the main crops grown in these countries, inputs use, trade openness measures, and countries characteristics. The variables used in the empirical analysis are summarized as follows.

i) Outputs and inputs: we consider six agricultural product categories: fruits, shell-fruits, citrus fruits, vegetables, cereals, and pulses. Five inputs are included in the production function, namely land, irrigation water, fertilizers, labor and machines. Data on crop production and input use are taken from the FAOSTAT database. The data for the input use by crop for each country are constructed according to the information collected from recently published reports by FAO, FEMISE, ESCWA, and CIHEAM. We construct aggregate output and input indices for each product category using the Tornqvist and EKS indexes.[11]

ii) Openness: four variables are used as measures of openness, namely the ratio of agricultural exports plus imports to GDP, agricultural trade barriers, FDI net inflows measured in proportion to GDP, and the share of agricultural machinery and equipment imports in agricultural value added. Data on agricultural trade and on agricultural machinery and equipment imports come from FAOSTAT database. The source for the data on FDI net inflows is the World Development Indicators (WDI) published by the World Bank. Our data on agricultural trade barriers are drawn from the MacMaps database constructed by the CEPII.[12]

iii) Human capital: we use the average years of schooling in the population over age 25 from the updated version of Barro and Lee (2000) data set as a proxy for human capital. Several alternative proxies including the percentage of adult population with secondary education, the literacy rate and the human development index were also considered. These data are drawn from WDI.

11. For each country i and in each product category k, we compute tornqvist output and input indexes, taking alternatively all the countries j (j ≠ i) as numeraire, using the following formula: $T_{ij}^{k} = \prod_{h \in k} \left(\frac{y_{hi}}{y_{hj}} \right)^{(\omega_{hi}+\omega_{hj})/2}$ where y_{hi} and y_{hj} are outputs (or inputs) of *h-th* agricultural commodity in countries i and j respectively, and ω_{hi} and ω_{hj} are the *h-th* output (input) shares. We use the Eltetö-Köves-Szulc (EKS) procedure which defines the quantity index for product k and country i as the geometric weighted average of these indices: $Q_{i}^{k} = \prod_{j:1}^{I} \left(T_{ij}^{k} \right)^{a_j}$ where a_j is the share of country j in the total production of the *k-th* commodity (including countries *1,…,I* only).

12. Available at http://wits.worldbank.org/witsweb/default.aspx.

iv) Country characteristics: these include an array of variables representing agricultural research effort, land holdings, health indicators, and institutional quality.
Data on agricultural R&D expenditures are obtained from Pardey *et al*. (2006). Land fragmentation is proxied by the percent of holdings under five hectares, and average holdings is controlled for by country's average farm size. These data are constructed from the decennial agricultural censuses of the FAO.

Health is proxied by infant mortality obtained from WDI.

Institutional quality includes various institutional variables considered as indicators of a country's governance, namely, political stability, government effectiveness, regulatory quality, rule of law and control of corruption. Data on these variables are drawn from Kaufmann *et al*. (2007).

TABLE A1.1 provides summary statistics of the variables used in the regression analysis (APPENDIX 1).

Empirical findings and economic implications

The ambition of our empirical investigation is to explore the roles of both human capital and openness in the international diffusion of technology and to estimate their effects on agricultural productivity growth. We start by estimating the production functions in (14) and (15) to measure agricultural TFP, and then use these estimates to explore the roles of both human capital and openness in technology diffusion and agricultural productivity growth.

Estimation of agricultural productivity

We estimate the dynamic CD production function both by the system GMM method (random components model in eq. (14)) and the weighted MG estimator (random coefficients model in eq. (15)). The results presented in TABLE 1 show that the numerical values of the input elasticities are relatively close in both methods. The variation in the country level elasticity coefficients obtained in the Random Coefficient model is however quite substantial, thus vindicating the varying coefficient approach. This suggests that Mediterranean farmers employ different technologies, and that heterogeneity should be controlled to obtain consistent productivity estimates.

The estimated elasticities in TABLE 1 are positive and globally significant at the 1% level. Mediterranean crops appear as cropland and water intensive. The results indicate also the relative importance of capital and labor in agricultural production.

Cross country productivity estimates are retrieved as a residual from the production functions. TFP estimates as well as mean rates of TFP growth by country are reported in TABLE A1.2 (APPENDIX 1). It is noteworthy that the TFP measures from both models are fairly close, suggesting that these models perform well with regard to heterogeneity bias. The results indicate that controlling for correlations between the unobserved country-specific effects and the explanatory variables reduces heterogeneity bias and hence ensures consis-

Table 1 - Input elasticities

Variables	Error components model	Random coefficients model	
		Mean response coefficients	Range of elasticity coefficients
y_{t-1}	0.324**	0.241**	0.168-0.426
	(3.14)	(4.52)	
Land	0.227**	0.279**	0.223-0.373
	(4.37)	(3.58)	
Water	0.203**	0.236**	0.188-0.334
	(3.06)	(2.99)	
Capital	0.113**	0.194**	0.097-0.296
	(2.94)	(2.82)	
Labor	0.114*	0.142*	0.088-0.238
	(2.07)	(2.09)	
Fertilizers	0.075*	0.033*	0.009-0.049
	(1.82)	(1.62)	
M1[a]	Z = -4.55		
M2[b]	Z = 1.14		
Sargan[c]	Chi2(85) = 82.91		
	(p = 0.554)		
No. of observations	1,260	1,260	

Notes: For the model in the first column the instruments used in each equation are γ_{it} and X_{ij} (j: 1, …, 4) lagged t-3 to t-10 for the first differenced equations, as well as Δy_{it} and Δx_{ijt} lagged t-3 for the levels equations.
The results are quite robust to the use of alternate subsets of instruments. The use of only certain lags of the instruments is justified by the fact that too many instruments potentially lead to invalid results, while the overidentification test appears valid (Roodman, 2007). Numbers in parenthesis are t-statistics.
The significance at the 10% and 1% levels is indicated by * and ** respectively.
a: 1st order serial correlation.
b: 2nd order serial correlation.
c: Sargan test of the overidentifying restriction, degrees of freedom are under brackets.

tent productivity estimates. However, accounting for parameter variation did not seem to greatly influence productivity.

The results in TABLE A1.2 indicate positive growth in the Mediterranean countries. The ordering of countries by productivity growth rates is potentially interesting for policy purposes. The ranking helps to verify the hypothesis according to which developing countries tend to experience higher rates of productivity growth. South Mediterranean countries appear to lie near the top in terms of agricultural growth. Morocco, Jordan, Syria, Tunisia and Israel experienced important positive growth over the sample period, while France, Italy Greece and Turkey lie in the set exhibiting the lowest growth in farming productivity.

Productivity growth regressions: the nested specification

Our base specification in equation (16) nests the exponential and logistic diffusion patterns in a nonlinear regression equation. We estimate this equation using the non linear least squares approach. The regression results are reported in TABLE 2, where the dependent variable is TFP growth rate measured using the error components model (*GTFP1*). The fact that productivity measures do not seem to be sensitive to the specification of variations in the technology parameters and that the system GMM method allows to better handle the endogeneity issue, suggests that *GTFP1* may be a better measure of agricultural productivity change. For robustness check, we also run the regression using the TFP growth rate estimate from the random parameters model (*GTFP2*) as a dependent variable. The results are not reported here in the interest of space limitation.

Models 1 to 4 in TABLE 2 examine the effects of openness using four alternative indicators, namely trade, tariff barriers, FDI and agricultural machinery imports (*imach*). As foreign technology diffuses mainly through capital goods, the productivity effects of openness might be better captured by the import of capital goods. Therefore *imach* is our preferred measure of openness.

Several interesting results are displayed in this table regarding the effects of international activities on productivity growth. The interaction of *imach* with human capital is negatively signed and highly significant.[13] This result suggests strong complementary effects between the import of capital goods and educational attainment on agricultural growth, and is consistent with the notion that greater endowment of skilled labor helps to embody technological benefits. The interaction term between human capital, *imach* and relative productivity is positively signed and highly significant. Thus education and international trade spur faster growth in the agricultural sector through the speed of technology transfer. The further a country lies behind the frontier and the greater the potential for international trade combined with education to increase agricultural growth. The productivity effects of trade, FDI and tariff barriers are small, indicating that import of capital goods is the dominant channel for agricultural technology diffusion.[14]

Human capital in log levels is statistically significant only in models 1 and 2, providing little support to the role of human capital in enhancing own innovation.[15] This result may however be explained by the fact that the education effect is captured indirectly through other variables.

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13. The negative interaction term between human capital and openness in the exponential specification is consistent with the theoretical predictions as the combined effect of human capital and openness on productivity growth, measured by $\left(\gamma_{op}\left(\frac{A_{it}}{A_{Lt}}\right)^{-1} - \gamma_{op}\right)$, is positive. The interaction term is expected to be positive for the logistic diffusion process.
14. The productivity effect of trade is incorrectly signed.
15. Human capital is proxied here by the average years of schooling in the population above 25. This result is robust to alternative human capital indicators such as the literacy rate, HDI index, secondary education…

Table 2 - Impact of human capital and openness on agricultural TFP growth

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	0.043	–0.08	0.28**	0.15*	–0.05	–0.16*	–0.085
	(0.6)	(–1.18)	(4.95)	(1.76)	(–0.71)	(–1.87)	(–0.51)
lnH	0.126**	0.16**	0.036	0.021	–0.049	–0.016	–0.014
	(3.49)	(3.95)	(1.26)	(0.57)	(–1.34)	(–1.17)	(–0.44)
*LnH*trade*	0.042**						
	(6.59)						
*LnH*trade*GAP^s*	–0.042**						
	(–6.59)						
*LnH*FDI*		–0.067**					
		(–12.74)					
*LnH*FDI*GAP^s*		0.067**					
		(12.74)					
*LnH*tariff*			0.023				
			(1.52)				
*LnH*tariff* GAP^s*			–0.023				
			(–1.52)				
*LnH*imach*				–0.196**		–0.18**	
				(–3.12)		(–12.23)	
*LnH*imach*GAP^s*				0.196**		0.18**	
				(3.12)		(12.23)	
*LnH*imach*NM*					–0.49**		–0.392**
					(–5.94)		(–4.63)
*LnH*imach*GAP^s*NM*					0.47**		0.291**
					(5.19)		(5.91)
*LnH*imach*SM*					–0.28**		–0.184**
					(–12.03)		(–11.85)
*LnH*imach*GAP^s*SM*					0.22**		0.131**
					(11.18)		(13.77)
S	–1.15	–1.52*	–0.64	–0.769*	–0.92**	–1	–1
	(–1.18)	(–12.95)	(–1.39)	(–2.55)	(–2.64)		
Number of observations	1,177	1,177	1,177	1,177	1,177	1,177	1,177
R^2 adjusted	0.24	0.28	0.28	0.35	0.37	0.42	0.465

Notes: *NM* and *SM* are dummies for north and south Mediterranean countries respectively.
Numbers in parenthesis are t-statistics.* and ** denote significance at the 1% and 10% level, respectively.
For the variables definition see the TABLE A1.1 (APPENDIX 1).

Our results favour the confined exponential specification, suggesting that the steady state is a balanced growth path, with all backward economies growing at the pace determined by the leading edge. The point estimate of *s* in model 4 (the regression using our preferred measure of openness) is –0.769. This value is lower than 0 but not significantly different from –1. As discussed in the theoretical section above, for *s* equal to –1 the specification of the diffusion process collapses to confined exponential. Models 1 and 3 seem to favour the Gompertz growth model, as *s* is not statistically different from zero.

Model 5 interacts *lnH*imach and lnH*imach *GAP* with dummies for north and south Mediterranean countries. The results remain robust to both groups of countries. The import interaction terms are smaller in magnitude for the south group, suggesting that the impact of international technology spillovers varies across these two regions. This may be explained by the fact that except for Israel, the level of educational attainment is higher in the north side, thus confirming the importance of human capital in adopting new knowledge.

These estimates provide interesting insights into the agricultural productivity dynamics, there are however some challenges to the general robustness of the results. The first is that introducing the technology gap as explanatory variable, faces problems of endogeneity since the productivity level investigated enters this variable.[16] The second derives from the omission of the country specific effects. We tempted to deal with the first problem by employing two methods. First, we regress the technology gap against the lagged gap and use the predicted value as an alternative to the relative TFP.[17] The results are robust to the adjustment of the technology gap.[18] Second, we repeat the base specification with *s* constrained to equal –1, and estimate the linear specification using the instrumental variables method. The regression results are reported in models 6 and 7 in TABLE 2. The coefficient estimates are still consistent with catch up being facilitated by the interaction of equipment imports with education. The parameter estimates remain of a similar magnitude and statistically significant at the 1% level, suggesting a limited effect of the endogeneity problem.

The regressions reported here do not formally accommodate cross country differences. As estimating nonlinear model with fixed effects panel data is computationally difficult, we tempted to address this concern by extending our base specification to incorporate a number of conditioning variables.

The control variables introduced include average holdings, land fragmentation, R&D expenditures, infant mortality, and institutional quality factors such as rule of law, control of corruption, government effectiveness, political stability and regularity quality.

Average holdings and land fragmentation capture the differences in the scale of agricultural holdings across countries and distinguish countries with important small farms. These vari-

16. The other explanatory variables may be also subject to endogeneity and measurement errors.
17. The lagged *GAP* is highly correlated with the current *GAP*. The regression of *GAP* on lagged *GAP* has an R^2 of 0.98.
18. A similar procedure was employed in Xu (2000).

ables are often cited as impeding productivity growth in agriculture (Vollrath, 2007). R&D captures technological change resulting from domestic agricultural research efforts. Infant mortality is included to control for the effect of the health care environment on agricultural productivity. Institutional quality factors reflect the ability of the government to provide sound macroeconomic policies and impartial authority which protects property rights and enforces contracts. Improved institutional quality is thought to enhance farming productivity (Self and Grabowski, 2007).

Broadening the baseline specification to control for these variables allows for distinguishing the productivity enhancing effects of technology diffusion from other sources of productivity variation. This is likely to provide a more general explanation of cross country productivity differentials. This will also serve as a test of the robustness of the results to model specification.

The estimation results are presented in TABLE A1.3 (APPENDIX 1). In models 1 to 7 of TABLE A1.3 we replicate the results from TABLE 2 but include the control variables in the base equation (16). The results are robust to the inclusion of these variables. The findings highlight the significance of the combined effects of education and international trade in stimulating foreign technology diffusion and agricultural productivity growth in the Mediterranean countries. Trade openness appears to substantially improve agricultural TFP through increasing imported capital equipments. Foreign trade seems to generate significant technology spillovers and to bring large productivity gains in North and South Mediterranean countries, but less in the South.

TABLE A1.3 reveals also several interesting results regarding the effect of the control variables on agricultural productivity growth. As can be seen, agricultural research efforts and larger farm sizes contribute to productivity improvement, infant mortality impacts negatively on farming performance. Control of corruption, political stability and regularity quality enter with positive and statistically significant coefficients, indicating a positive role of institutional quality in enhancing agricultural growth.

The regression using TFP growth estimates from the random coefficients model (*GTFP2*) also testify to the robustness of the statistically significant and positive impact that international technology diffusion has on agricultural productivity.[19]

Productivity dynamics: the linear specification

Alternative productivity dynamics are investigated in equation (17), where the dependent variable is *GTFP1*, and the openness indicator is proxied by the agricultural equipment imports share. This specification includes unobservable individual fixed effects and a set of institutional factors; we estimate it using the instrumental variables approach.[20] The estimation results are presented in TABLE 3.

19. These results are available upon request.
20. The instruments used include the lagged litracy rate, the predicted value of GAP, the lagged value of trade, $imach_{t-2}$, and H_{t-2}.

Table 3 - Agricultural TFP linear growth regressions

	Model 1	Model 2	Model 3	Model 4
ΔlnA_L	0.69	0.66	0.577	0.681
	(10.72)	(14.01)	(13.82)	(13.97)
lnH	0.066*	0.041		0.065**
	(2.47)	(1.46)		(2.71)
imach	0.16		0.186*	0.129*
	(1.38)		(2.27)	(1.68)
lnGAP	–0.069**	–0.059**	–0.015*	–0.082*
	(–5.76)	(–7.96)	(–2.16)	(–1.97)
*LnH*lnGAP*		–0.19*		–0.173**
		(–1.82)		(–2.96)
*Imach*lnGAP*			–0.274**	–0.275**
			(–3.28)	(–3.44)
Average holding	0.018**	0.017**	0.017**	0.017**
	(3.29)	(3.21)	(3.25)	(3.29)
Land fragmentation	–0.002*	–0.001	–0.002**	–0.022*
	(–1.81)	(–1.08)	(2.66)	(–2.27)
R&D	0.032**	0.029**	0.026**	0.027**
	(2.94)	(2.52)	(2.74)	(2.54)
Mortality	–0.0035**	–0.0031**	–0.0005	–0.0025*
	(–2.98)	(–3.21)	(–1.01)	(–2.36)
Control of corruption	0.0002	0.0002	0.0001	0.0002*
	(1.29)	(1.2)	(0.69)	(1.79)
Gov. effectiveness	–0.0005	–0.0005	–0.0005	–0.0004
	(–1.25)	(–1.38)	(–1.27)	(–0.97)
Political stability	0.0002*	0.0002*	0.0002*	0.0002*
	(2.17)	(2.14)	(1.87)	(2.18)
Regularity quality	0.0004*	0.0004*	0.0003*	0.0003*
	(2.32)	(2.26)	(1.67)	(2.14)
N. of observations	1,177	1,177	1,177	1,177
R^2 adjusted	0.92	0.904	0.906	0.919

Notes: Numbers in parentheses are t-statistics.
* and ** denote statistical significance at the 10% and 1% levels respectively.

A review of TABLE 3 confirms the previous results that foreign technology embodied in imported capital goods and human capital play a significant positive role in speeding the catch up to the technology frontier and in boosting agricultural productivity in the Mediterranean region.

The frontier agricultural TFP growth shows a strong positive effect at the 1 per cent statistical significance in all regressions, supporting the positive long run association between a lagging economy's productivity and the leader nation TFP.

In model 1 the three variables human capital, machinery imports and technology gap are entered separately. Human capital positively influences TFP growth, although significant the estimated effect is relatively small. The import level term is positively signed but statistically insignificant at conventional levels. The relative productivity enters with a significantly negative sign, indicating that countries with a larger technology gap against the frontier experience higher rates of productivity growth.

Model 2 examines the linear impact of human capital as well as its interactive effect with relative TFP. Human capital becomes statistically insignificant, while the interaction term is negative and statistically significant at the 10 percent level. Thus, the level of education seems to enhance farming performance through its impact on the speed of technology catch up, but not through rates of innovation.

Model 3 considers both the level of *imach* and the interaction between *imach* and the gap. The coefficient on agricultural equipment imports is significantly positive, while the import interaction term is negative and highly significant. This finding provides strong evidence on the importance of international trade for technology diffusion.

Model 4 reports the results including *imach* and human capital. These variables are entered individually alongside their interaction with relative TFP. The evidence lends strong support to the positive effects of both human capital and equipment imports on agricultural productivity growth through their contribution to technology diffusion. Positive externalities to higher educational attainment and more open regime in the form of a higher rate of innovation are confirmed by the empirical findings.

The effects of the control variables are relatively similar to those estimated with the nonlinear model in terms of their magnitudes and statistical significance.

In summary, the regression results support the catch up hypothesis. The countries that are further behind the technological frontier will experience higher growth rates in their agricultural sector. Human capital and international trade in the form of agricultural equipment imports appear to play a substantial role in the speeding up of the catch up process and then in boosting farming performance. The point estimates show that the influence of international trade on agricultural TFP growth is more important than that of human capital.

We further investigate this issue by quantifying the economic importance of these effects.

In section II, we have shown that the full effects of human capital and equipment imports on agricultural TFP growth may be captured by, $\alpha_1 - \theta_2 \ln\left(\frac{A_i}{A_L}\right)_{t-1}$ and $\alpha_2 - \theta_3 \ln\left(\frac{A_i}{A_L}\right)_{t-1}$ respectively, while the speed of technology diffusion is given by, $\theta_1 + \theta_2 \ln H_{it-1} + \theta_3 imach_{it-1}$. We use the parameter estimates of model 4 in TABLE 3 to evaluate these effects in each of the 14 countries in our dataset.

Column 1 of TABLE 4 evaluates the speed of technology diffusion using the average human capital and the average equipment imports ratio. The results indicate that globally the European Union countries lie notably near the top with France exhibiting the higher speed rate, while South Mediterranean countries display marked slower rates. One important result is that Jordan and to a lesser extent Lebanon and Syria, seem to experience significantly fast technology transfer. This may be explained by the fact that Jordan has a particularly important ratio of agricultural equipment imports. The level of education in this country is also relatively high. Lebanon and Syria have as well quite important education levels. The countries with the slower rates are Turkey, Algeria and Egypt. Technology transfer in Egypt appears to be substantially slow due to the very low machinery import ratio and the relatively weak education level in this country.

The full productivity effects of human capital and agricultural equipment imports are reported in columns 2 and 3 of TABLE 4 respectively. These effects are computed using the average relative agricultural TFP. As predicted by the model, the impacts of both educational attainment and international trade would be higher in countries with important technology gap to the leader. These productivity effects are significantly important in Egypt, and to a lesser extent in Algeria, Morocco and Lebanon. The impacts of human capital and openness on agricultural productivity are relatively low in France, Italy, Jordan, and Turkey, given that these countries lie in the frontier edge.

These empirical findings provide strong evidence regarding the impact of educational attainment and foreign technology spillovers on agricultural productivity growth through increasing the absorptive capacity. The international trade externalities in the process of technology diffusion seem relatively more important in magnitude than the human capital externalities.

Conclusion

The adoption of advanced agricultural technologies can be a powerful force in boosting farming productivity growth and in fostering economic development. The empirical investigation of the productivity effects of agricultural technology transfer is becoming an appealing question with the gradual opening of agricultural markets under the EU-Mediterranean partnership and the WTO Agreement on Agriculture.

Table 4 - Measurement of the speed of technology diffusion and of the full productivity effects of human capital and openness

	Speed of technology diffusion	Productivity effect of human capital	Productivity effect of equipment imports
Algeria	0.889	0.187	0.284
Egypt	0.605	0.293	0.492
Israël	0.977	0.107	0.188
Jordan	4.07	0.079	0.152
Lebanon	1.815	0.153	0.264
Morocco	1.162	0.166	0.273
Syria	1.398	0.115	0.208
Tunisia	1.286	0.148	0.259
Turkey	0.919	0.089	0.168
France	4.365	0.079	0.151
Greece	2.114	0.148	0.261
Italy	1.994	0.107	0.195
Portugal	3.066	0.145	0.257
Spain	2.151	0.115	0.208

In this paper we tempted to explore the implications for agricultural productivity growth of international technology diffusion in the Mediterranean region. The analysis highlights the roles of human capital and international activity in the technology catch up process.

A distinctive feature of our study was to allow for different diffusion patterns, namely the logistic and the confined exponential models. We estimate a nonlinear productivity growth specification that nests these technology diffusion functional forms using a panel of nine South Mediterranean Countries and five European Union Countries for the period 1990 to 2005.

Our results favor the confined exponential specification, suggesting that the steady state is a balanced growth path, with all backward economies growing at the pace determined by the leading edge.

We found robust results regarding the importance of international trade in the form of agricultural equipment imports and human capital in the speeding up of the catch up process and in boosting farming performance. The analysis emphasize the interactions between human capital and international trade, and find that educational attainment is important for successful adoption of advanced agricultural technology. This suggests that the Mediterranean integration process may yield larger benefits with the implementation of domestic policies of qualifying the farming labor force.

These results are robust to a number of sensitivity checks, including the use of alternative measures of agricultural TFP, the inclusion of institutional control variables, the use of alternative openness indicators and the estimation of alternative productivity growth specifications.

We use the parameter estimates to assess the full agricultural productivity effects of human capital and international trade as well as to evaluate the speed of technology diffusion in each country in our sample.

We found relatively important productivity effects in Egypt, and to a lesser extent in Algeria, Morocco and Lebanon, as these countries have somewhat important technology gap with the leading economy. The impacts of human capital and openness on agricultural productivity are relatively low in France, Italy, Jordan, and Turkey, given that these countries lie in the frontier edge.

The results relating to the speed of diffusion indicate that the European Union countries lie notably near the top with France exhibiting the higher speed rate, while South Mediterranean countries display marked slower rates. In the south panel, Jordan followed by Lebanon and Syria seem however to experience significantly fast technology transfer.

This analysis provides interesting insights into the agricultural productivity dynamics and allows shedding some lights on the benefits of economic opening in the Mediterranean region. Further research is still needed to investigate the countries' specific determinants of advanced technology adoption in agriculture. An interesting avenue for future work would be to examine the effects of the socioeconomic and structural factors such as climatic conditions, soil quality and credit constraints, on the Mediterranean farmers' decisions to adopt technological innovations.

N. B. H.[21]

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Appendix 1
Summary statistics and estimation results

Table A1.1 - Summary statistics

		Mean	St. Dev.	Min	Max
y	Crop output (quant. of selected commodities Mt)	0.85	2.61	0.0004	39.81
Land	Cropland (in Mha)	0.35	1.94	0.00018	39.55
Water	Irrigation water (in Mn3)	347.5	1,944.5	0.206	37,953
Labor	Labor (in Mdays)	6.1	19.4	0.0001	296.7
Fertilizers	Applied fertilizers (in tons)	888.9	3,178.3	0.14	49,288
Capital	Agricultural machinery and tractors (Mhours)	6.84	22.7	0.0012	278.8
GAP[a]	TFP/TFP_L	0.722	0.198	0.22	1
H	Av. years of schooling in the population over 25 years	6.11	1.78	3.01	9.4
Trade	Total agricultural (% of GDP)	5.08	12.2	0.122	132.6
FDI	Foreign direct invest., net inflows (% of GDP)	1.45	1.396	–0.61	9.47
Tariff	Agr. Tariffs and *ad-valorem* equiv. of non tariffs	12.1	6.7	2.4	27.8
Imach	Agr. mach. and equip. imports (% of agr. VA)	5.57	4.4	0.44	19.78
Average holding	Average farm size in Ha	3.06	3.48	0.25	20.22
Land fragmentation	Holdings under five hectares (in %)	71.3	18.3	15	98.2
R&D	Pub. and priv. R&D expenditures (in 2000 int. $)	316.3	723.2	8.7	3,100
Mortality	Infant mortality (per 1000 live births)	23.76	18.49	3.2	76
Rule of law	Contract enforcement, property rights etc.	40.91	66.6	–110	162
Cont. of corruption	Cont. of corrup. among officials, bribery etc.	36.5	72.9	–88	169
Gov. effectiveness	Bureaucracy, public infrastructure etc.	43.4	81.6	–128	195
Political stability	Unlikelihood of armed conflict, terrorist threats …	–22.6	90.97	–292	128
Regularity quality	Gov. intervention, trade policy, etc.	35.64	66.4	–122	145

a: TFP is agricultural TFP and TFP_L is the highest level of agricultural TFP.

Table A1.2 - Agricultural total factor productivity estimates

	Error components model		Random coefficients model	
	TFP1[a]	*GTFP1*[b]	*TFP2*	*GTFP2*
Algeria	1.601	0.099	1.48	0.063
	(0.36)	(0.542)	(0.273)	(0.398)
Egypt	1.507	0.046	1.56	0.043
	(0.234)	(0.328)	(0.208)	(0.327)
Israel	1.974	0.149	1.950	0.113
	(0.347)	(0.812)	(0.314)	(0.669)
Jordan	1.751	0.152	1.714	0.111
	(0.521)	(0.636)	(0.468)	(0.548)
Lebanon	1.728	0.038	1.680	0.04
	(0.237)	(0.375)	(0.221)	(0.382)
Morocco	1.656	0.281	1.693	0.191
	(0.494)	(0.834)	(0.454)	(0.966)
Syria	1.692	0.135	1.707	0.14
	(0.35)	(0.581)	(0.311)	(0.609)
Tunisia	1.632	0.135	1.738	0.124
	(0.387)	(0.731)	(0.431)	(0.698)
Turkey	2.674	0.011	2.04	0.005
	(0.127)	(0.177)	(0.082)	(0.143)
France	2.539	0.027	2.43	0.026
	(0.279)	(0.24)	(0.154)	(0.269)
Greece	2.224	0.011	2.190	0.013
	(0.132)	(0.211)	(0.127)	(0.212)
Italy	2.312	0.017	2.271	0.019
	(0.147)	(0.209)	(0.14)	(0.217)
Portugal	1.852	0.028	2.031	0.037
	(0.152)	(0.297)	(0.185)	(0.311)
Spain	2.266	0.045	2.312	0.051
	(0.206)	(0.366)	(0.22)	(0.393)

Notes: Numbers in parenthesis are standard deviations.
a: *TFP1* and *TFP2* are agricultural total factor productivity measures based on the random coefficients production function in (15) and the fixed coefficients model in (14) respectively.
b: *GTFP1* and *GTFP2* are the mean annual growth rates of *TFP1* and *TFP2* respectively.

Table A1.3 - Impact of human capital and openness on agricultural TFP growth: Model with countries' characteristics

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	0.13	0.22*	–0.062	–0.024	0.09	0.191	0.22
	(1.08)	(1.65)	(–0.77)	(–0.15)	(0.47)	(1.45)	(1.33)
lnH	0.07	–0.05	0.052	–0.131	–0.18	–0.026	–0.11
	(0.88)	(–0.81)	(0.91)	(–1.22)	(–1.19)	(–0.77)	(–1.02)
*LnH*trade*	–0.047**						
	(–6.38)						
*LnH*trade*GAP*^{S}	0.047**						
	(6.38)						
*LnH*FDI*		–0.067**					
		(–13.6)					
*LnH*FDI*GAP*^{S}		0.067**					
		(13.6)					
*LnH*tariff*			0.03*				
			(1.74)				
*LnH*tariff*GAP*^{S}			–0.03*				
			(–1.74)				
*LnH*imach*				–0.31**		–0.252**	
				(–7.95)		(–13.1)	
*LnH*imach*GAP*^{S}				0.31**		0.252**	
				(7.95)		(13.1)	
*LnH*imach*DC*					–0.41**		–0.4**
					(–3.45)		(–3.56)
*LnH*imach*GAP*^{S}**DC*					0.37**		0.31**
					(5.61)		(6.08)
*LnH*imach*LDC*					–0.22**		–0.19**
					(–6.04)		(–11.6)
*LnH*imach*GAP*^{S}**LDC*					0.2**		0.141**
					(7.78)		(13.85)
Average holding	0.0053*	0.0038*	0.0028*	0.0037*	0.004	0.0066*	0.006
	(1.85)	(1.97)	(1.81)	(1.72)	(1.2)	(2.4)	(1.37)
R&D	0.0036*	0.005*	0.005*	0.0026*	0.002*	0.004*	0.003*
	(1.91)	(1.85)	(2.01)	(1.69)	(2.48)	(2.97)	(2.01)
Mortality	–0.0025*	–0.005**	–0.0021*	–0.003*	–0.003	–0.003**	–0.003*
	(–1.81)	(–3.25)	(–2.24)	(–2.04)	(–1.35)	(–2.56)	(–2.05)
Rule of law	0.0006*	0.0001	0.0005**	0.002*	0.002*	0.0003	0.002
	(1.72)	(1.08)	(1.79)	(1.89)	(1.94)	(1.42)	(1.23)
Control of Corruption	0.0005*	0.0005*	0.0002*	0.0021*	0.0018*	0.0003	0.001*
	(1.89)	(1.95)	(2.6)	(2.41)	(2.51)	(1.4)	(1.82)
Government effectiveness	0.0004*	0.0006	0.0004*	0.0004*	0.0003	0.0005*	0.0003
	(1.79)	(1.13)	(1.79)	(1.89)	(1.39)	(1.89)	(1.59)
Political stability	0.0003*	0.0003*	0.0005	0.0004	0.0002	0.0001	0.0005
	(1.75)	(1.84)	(1.38)	(1.4)	(1.24)	(1.42)	(1.6)
Regularity quality	0.0003*	0.0012*	0.0002*	0.0003*	0.0004*	0.0004*	0.0003*
	(1.84)	(3.18)	(1.76)	(1.76)	(1.9)	(1.96)	(1.72)
s	–1.12	–1.45**	–0.59	–1.03**	–0.88**	–1	–1
	(–1.47)	(–13.8)	(–1.06)	(–3.36)	(–8.29)		
Number of observations	1,177	1,177	1,177	1,177	1,177	1,177	1,177
R^2 adjusted	0.39	0.43	0.4	0.44	0.44	0.49	0.51

* and ** denote significance at the 1% and 10% level, respectively. (.) t-statistics.

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