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# TECHNOLOGY DIFFUSION, INTERNATIONAL SPILLOVERS AND HUMAN CAPITAL IN THE MEDITERRANEAN AGRICULTURAL SECTOR

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# Technology Diffusion, International Spillovers and Human Capital 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. Agricultural total factor productivity estimates are obtained from a random coefficients dynamic production function. The 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. 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. The regression results are robust to alternative productivity estimates and different growth regressions.

ملخص

تبحث هذه الورقة الأدوار التي يلعبها رأس المال البشري والانفتاح في عملية نشر التكنولوجيا وزيادة الإنتاجية في قطاع الزراعة في دول البحر المتوسط. فنطرح تقييما لتوصيف غير خطى لنمو الإنتاجية، بحيث يستطيع ذلك التوصيف أن يداخل بين الأشكال السوقية والتوابع الأسية المحدودة لنشر التكنولوجيا. وذلك باستخدام مجموعة من تسع دول في جنوب المتوسط بالإضافة إلى خمس دول من الاتحاد الأوروبي في الفترة ما بين 1990 و 2005. وقد استقينا تقديرات العامل الكلي للإنتاجية الزراعية من معاملات دالية عشوائية لديناميكية الإنتاج. وتفضل النتائج توصيفا ًأسيا محدودا، وتوصي بأن الحالة الثابتة هي أسلوب متوازن للنمو في كل البلدان ذات الاقتصاديات المتأخرة والتي تنمو بخطى يحددها الطرف الرئيسي. كما توضح النتائج الأدوار الإيجابية للانفتاح ورأس المال في تيسير نشر التكنولوجيا وتعزيز عملية النمو الزراعي. فهناك تأثيرات تكاملية بين التكنولوجيا الأجنبية المتمثلة في السلع الرأسمالية المستوردة وبين التحصيل العلمي الخاص بالأداء الزراعي. كما تنطبق نتائج الانحدار بقوة على تقديرات الإنتاجية البديلة وكذا كل انحدارات النمو المختلفة.

## I. Introduction

The role of technology diffusion in the process of economic development is an important consideration in the recent literature[1]. The diffusion of new technologies is regarded as a key driver of productivity growth for countries behind the frontier. In models of technology diffusion, the rate of productivity growth of relatively backward economies depends on the extent of the adoption of the leading countries technological knowledge. According to these models, countries that are falling farther behind the frontier would experience higher rates of productivity growth.

Technology diffusion can take place through various channels that involve the transmission of new technologies across countries. Recent studies have identified international economic activities such as trade, FDI or equipment imports as important pathways for international technology diffusion (Lichtenberg and Von Pottlseberghe de Potterie, 1996; Borensztein *et al*., 1998; Xu, 2000; Mayer, 2001; Keller, 2000, 2004; Xu and Chiang, 2005; Harding and Rattsø, 2006).

Advanced technologies might not however automatically affect the host country's productivity. The extent to which the recipient country will be able to benefit from the new technologies depends crucially upon its human capital capabilities. Thus, advanced technologies would prove ineffective without sufficient human capital to absorb the technology diffused. 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.

Several empirical analysis highlight the importance of openness and human capital for successful technology diffusion and find strong empirical evidence supporting the positive role of these two determinants in fostering productivity growth[2]. Though there exists an extensive empirical literature of international technology spillovers and their effects on productivity, most of the existing analyses use industry or aggregate country data, few researches have been applied to agriculture.

This analysis investigates the roles of both human capital and international economic activities in the process of technology diffusion and productivity growth in the Mediterranean agricultural sector. The interrelationship between trade, human capital and agricultural productivity is likely to be a major issue in the Mediterranean region. Countries in this area have been actively participating in the new wave of globalization. Exposure to international trade, through the diffusion of new technologies, opens great opportunities to enhance agricultural productivity growth.

These economies share some common features like the environmental conditions, and cropping patterns. They, nevertheless, differ in their resources endowments and institutional factors. They are expected to be affected in different ways by the free trade policy, as their capacity to benefit from opportunities arising from the new trade environment depends considerably upon their ability to adopt new knowledge. In this context, examining the

[1] Research on technology diffusion includes Barro and Sala-i-Martin (1997), Xu (2000), Benhabib and Spiegel (2002), Xu and Chiang (2005).

[2] These studies include Eaton and Kortum (1996), Borensztein *et al*. (1998), Xu (2000), Mayer (2001), Griffith *et al.* (2004), Xu and Chiang (2005), Teixeira and Fortuna (2006).

human capital-trade-agricultural growth nexus in the Mediterranean region and assessing the countries potential to achieve convergence in agricultural productivity growth with the technological leader may be a useful tool for policy analysis and decision making.

The approach used in exploring the combined role of human capital and international technology diffusion in agricultural growth is inspired by the modified Nelson-Phelps specification suggested by Benhabib and Spiegel (2002). As the implications of different technology diffusion specifications for the agricultural growth path may be quite divergent, we use an empirical specification which nests the most frequently used forms of technology diffusion namely, the exponential and the logistic models. We follow a somewhat similar approach to that of Benhabib and Spiegel (2002) in estimating a nonlinear model for productivity dynamics that nests these two specifications in a panel sample of Mediterranean countries involved in the Euro-Mediterranean partnership for the period from 1990 to 2005.

We examine the robustness of our results by using 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, and measure agricultural TFP indexes using the residual method. These approaches are likely to be more appropriate than other approaches used in the existing analyses and that obtain TFP from a constant returns to scale Cobb-Douglas production function with fixed input shares[3]. 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: Section 2 outlines the steady state implications of the exponential and logistic diffusion patterns. Section 3 presents the empirical model and the estimation methods. Section 4 provides an overview of the data used. Section 5 reports the main econometric results relating to the roles of human capital and openness and quantifies their economic importance. Section 6 summarizes the essential findings and concludes the paper.

## II. Human Capital, Economic Opening and Productivity Growth

Our approach to investigate the combined importance of international openness and human capital in stimulating foreign technology diffusion and productivity growth in the Mediterranean agricultural sector is based on the Benhabib and Spiegel (2002) and Stokke (2004) models. Benhabib and Spiegel (2002) adapt a modified specification of the catch-up model of technology diffusion introduced by Nelson and Phelps (1966) to explore the effect of human capital on productivity growth for a cross-section of countries. 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 considers the interaction between openness and human capital in the adoption function. The channels of foreign spillovers are measured by the trade share of GDP, trade restrictions, foreign direct investment (FDI) and agricultural machinery imports. We follow Stokke (2004) in using a productivity specification linking the economy's absorptive capacity to the degree of openness and human capital.

Productivity growth is assumed to be driven by domestic innovations and technology adoption, as in the Benhabib and Spiegel approach. The Innovation part is related to the level of human capital, while the adoption part is captured via a term comparing the degree of openness with the human capital and technology gap to the best practice frontier.

[3] See Benhabib and Spiegel (1994, 2002) among others.

Various functional forms for the technology diffusion pattern have been used in 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:

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

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. $g(H_i(t))$ is the contribution from innovation to productivity growth that depends on the level of human capital $H_i(t)$, and $f(H_i(t), Openness_i(t))\left[1 - \frac{A_i(t)}{T(t)}\right]$ 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 ( $g'_i(.) > 0$ and $f_i{}'(.) > 0$ ). 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 $g(H_L)$, 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 $g(H_L) > g(H_i) \quad \forall i$.

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:

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

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:

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

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

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

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

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

For the logistic case, we have:

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

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

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

with $s \in [-1, 1]$. Note that if $s$ = 1, the diffusion pattern is logistic, while if $s$ = −1, it is exponential[4].

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:

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

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

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

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

The equilibrium path of productivity is given by:

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

The country's levels of human capital and openness would be growth enhancing as they are expected to act as an engine of innovation as well as a stimulus to technology adoption respectively. The payoff to increased openness and higher educational attainment is greater

[4] See Benhabib and Spiegel (2002).

the more technologically progressive the leader nation is. However, it can be seen from the following equations that the smaller the gap in education between the leading country and the backward countries, the slighter the payoff is. Countries that are closer to the leader in terms of human capital and technology may therefore experience lower rates of productivity growth.

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

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

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 $s(g_i - g_L) + f_i < 0$ :

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

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:

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

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

The transition path is:

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

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

These results highlight the importance of the functional form of the technology diffusion pattern 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[5]. However, low-skilled economies may diverge relative to the frontier, since the level of education is not sufficiently high to allow for introducing foreign technology, $f(H_i, Openness_i) + g(H_i) - g(H_L) < 0$.

## III. 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 form, we measure total factor productivity (TFP) as the difference between gross output and the factor inputs. Modeling agricultural output as a function of labor, capital, land, water and fertilizers, our baseline production function can be written in log-linear form as:

$$y_{it} = \lambda y_{it-1} + (1-\lambda)[\beta_K k_{it} + \beta_N n_{it} + \beta_L l_{it} + \beta_W w_{it} + \beta_F f_{it}] + ln(A_{it}) + \omega_i + v_{it} \qquad (14)$$

Where $y_{it}$ indicates log output, $k_{it}$, $n_{it}$, $l_{it}$, $w_{it}$ and $f_{it}$ are log of capital, labor, land, water and fertilizers respectively. $A_{it}$ is total factor productivity; $\beta_k, \beta_n, \beta_l, \beta_w$ *and* $\beta_f$ denote parameters to be estimated representing factor share coefficients. The subscripts *i* and *t* make reference to the $i^{th}$ country and $t^{th}$ period respectively, $\omega_i$ 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 also represents a simple way of capturing the adjustment process associated with an increase of inputs, as expanding 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 fails however to account for the possibility of production heterogeneity since the specification is restricted to a representative homogenous producer. When the technological differences are insignificant, estimating a random effect 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 technological differences might be accommodated with a model that estimates different parameters for each country or group of countries. Among the models suggested in the literature, the random coefficients specification has been designed as well suited to deal with this problem as it allows the heterogeneity to take the form of continuous parameter variation across countries (Green, 2002, 2003; Hsiao and Pesaran, 2004).

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

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

[5] This specification is consistent with the S-shaped technology diffusion path, where productivity growth first rises and then falls.

where $y_{it}$ refers to log output and $x_{ijt}$ *(j: 1..4)* are log water, land, capital, labor and fertilizers respectively. $A_{it}$ is TFP and $u_{it}$ is the error term assumed to be independently, identically distributed over $t$ with mean zero and variance $\sigma_i^2$, and is independent across $i$. The $\beta_i$'s represent a variable elasticity of output with respect to each input $x$ and is specified as a Swamy (1970) type random coefficient models:

$$\beta_i = \beta + \alpha_i$$

where $\alpha_i$ 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 total factor productivity considering these two alternative models. We begin by estimating the dynamic production function in (14) allowing for fixed country 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), which 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 level and differenced equations to be identical. This approach uses lagged differences as instruments for contemporaneous levels, in addition to the usual lagged levels as instruments for first differences. The consistency of the system GMM estimator is checked by the Sargan test of over identifying restrictions.

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

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 $E(\alpha_i x_{it}') = 0$, we can no longer assume that $E(\alpha_i y_{it-1}) = 0$. The violation of the independence between the regressors and the individual effects $\alpha_i$ implies that the pooled least squares regression of $y_{it}$ on $y_{it-1}$, 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 $\theta_i$ 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[6] (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 $g(H_{it}) = \gamma_H h_{it}$ and $f(H_{it}, Openness_{it}) = \gamma_{op} op_{it} h_{it}$, where $h_{it}$ denotes the log of country *i's*

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

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 $GTFP_{it}$ is the growth rate of agricultural total factor productivity (TFP) of country *i* at time *t,* $\gamma$ is a constant and $\eta$ 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.

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[7]. For *s* being equal to -1 the specification is confined exponential, while with *s* equal 1 it is logistic[8]. 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 $\gamma$, $\gamma_H$, $\frac{\gamma_{op}}{s}$ 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. To test the robustness of the results, a set of institutional factors including investment in research and development, governance infrastructure and average agricultural holdings are added to the baseline specification.

Another challenge is the potential endogeneity of the technology gap since the productivity level investigated enters this variable[9]. We tempt 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 check for the robustness of the results. Second, we estimate different linear approximations to the nested specification in (16) with the instrumental variables estimator.

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

[7] See Benhabib and Spiegel (2002) for a similar procedure.

[8] When s tends to zero, the diffusion process converges to the Gompertz growth model and the technology gap *B* converges to $exp = \left( \frac{(g_i - g_L)}{f_i} \right)$.

[9] Another concern may be with measurement error in the explanatory variables.

[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.

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

where X is the vector of control variables that includes institutional factors, $\delta_{it}$ is a parameter that varies with country and time and $\upsilon_{it}$ 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 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.

## IV. 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, openness measures and countries characteristics. The data used are obtained from the FAO (FAOSTAT), World Bank (WDI), AOAD, Eurostat, CEPII, AMAD, ASTI, Barro and Lee (2000), Pardey *et al*. (2006), and Kaufmann *et al*. (2007) databases as well as from the different reports of the FEMISE, FAO, CIHEAM and ESCWA. The variables used in the empirical analysis are summarized as follows:

- **Output and input**: we consider six product categories: fruits (apricots, dates, figs, olives, peaches and nectarines, pears, apples, plums, grapes), shell-fruits (almonds, peanuts, hazelnuts, pistachios), citrus fruits (lemons, oranges, tangerines, grapefruits, other citrus fruits), vegetables (artichokes, carrots, cucumbers and pickles, strawberries, watermelons and melons, pepper, potatoes, tomatoes), cereals (rice, wheat, maize, barley) and pulses (beans, peas, chick-peas, lentils, vetches). Five inputs are included in the production function, namely land, irrigation water, fertilizers, labor and machines. The data for the input use by crop for each country is constructed according to the information collected from recently published reports from the sources above.
- We construct aggregate output and input indices for each product category using the Tornqvist and EKS indexes[11].

[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: $T_{ij}^k = \Pi_{h \in k} \left(\frac{y_{hi}}{y_{hj}}\right)^{(\omega_{hi}+\omega_{hj})/2}$ where $y_{hi}$ and $y_{hj}$ are outputs (or inputs) of *h-th* agricultural commodity in countries *i* and *j* respectively, and $\omega_{hi}$ and $\omega_{hj}$ 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: $Q_i^k = \Pi_{j:1}^{I} \left(T_{ij}^k\right)^{a_j}$ where $a_j$ is the share of country *j* in the total production of the *k-th* commodity (including countries *1,…,I* only).

- **Openness**: four variables are used as measures of openness, the ratio of agricultural exports plus imports to GDP, trade barriers that include ad-valorem tariffs and indices of non-tariff barriers[12], FDI net inflows measured in proportion to GDP, and the share of agricultural machinery and equipment imports in agricultural value added.
- **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.
- **Country characteristics**: these variables include observations on agricultural research and development (R&D) expenditures; infant mortality; land fragmentation, proxied by the percent of holdings under five hectares; average holdings, measured by the country's average farm size; and various institutional variables such as political stability, government effectiveness, regulatory quality, rule of law and control of corruption.

## V. Empirical Findings and Economic Implications

In this section 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.

### *1. Estimation of Agricultural Productivity*

We estimate the dynamic CD production function both by the system GMM method – fixed coefficient model in equation (14) – and the weighted MG estimator – random coefficient 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 therefore estimating a common production function may result in somewhat misleading productivity measurement.

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 also indicate the relative importance of capital and labor in agricultural production.

Cross country productivity estimates are then retrieved as a residual from the production functions. TFP estimates as well as mean rates of TFP growth by country are reported in Table A2 in the Appendix. The results indicate positive growth in the Mediterranean countries. South Mediterranean countries lie near the top in terms of agricultural growth. Morocco, Jordan, Syria, Tunisia and Israel have experienced important positive growth over the sample period, while France, Italy Greece and Turkey have fallen in the set exhibiting the lowest growth in farming productivity.

[12] Agricultural commodities are currently protected with a complex system of tariff and non tariff barriers – entry price system and tariff rate quotas. The determination of the appropriate level of protection is a fairly complex task. The method used here attempts to provide an aggregate measure of ad-valorem tariffs and the ad-valorem equivalent of specific tariffs and tariff quotas, taking into account preferential agreements. The obtained rates represent just an approximation of the real trade restrictiveness levels due to the absence of some observations.

We first computed an ad-valorem equivalent for the tariff rate quotas (TRQ) as a trade-weighted average of inside- and outside-quota tariff rates (Bouët *et al*. 2004). Data on tariff quotas mainly comes from the AMAD and CEPII databases. Specific tariffs are converted into ad-valorem equivalents on the basis of the price wedges between the entry prices and unit value imports. The aggregate applied duties are obtained as a result of the calculation of the import-weighted average of ad-valorem and ad-valorem equivalent measures of applied protection.

### *2. Productivity Growth Regressions: The Nested Specification*

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. Our base specification nests the exponential and logistic diffusion patterns in a nonlinear regression equation. We use the non linear least squares approach to estimate equation (16). The regression results using TFPG1 and TFPG2 as dependent variables are reported in Tables 2 and A3, respectively. Models 1 to 4 examine the effects of openness using four alternative indicators, namely trade, tariff barriers, FDI and agricultural machinery imports.

As foreign technology diffuses mainly through capital goods, the productivity effects of openness might be better captured by the import of capital goods. Therefore, agricultural machinery import (*imach*) is our preferred measure of openness.

Table 2 reveals several interesting results for the effects of international activities on productivity growth. The interaction of openness with educational attainment is highly significant in all the models. The interaction term is positive for the logistic diffusion process and negative in the confined exponential specification as expected[13]. This result suggests strong complementary effects between openness and educational attainment on agricultural growth, and is consistent with the notion that countries with sufficient educational attainment benefit positively from advanced technology brought along by international activities. The interaction term between education, openness and relative productivity is negatively signed and highly significant, supporting the catch up effect. This implies that the further a country is from the frontier, the greater is the potential for openness combined with education to increase agricultural growth through the speed of technology diffusion. Human capital in log levels is rarely significant, providing little support to the role of human capital in enhancing innovation[14]. This result may however be explained by the fact that the education effect is captured indirectly through other variables.

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. The point estimate of *s* in model 4 (the regression using our preferred measure of openness) is -0.823. This value is lower than 0 but not significantly different from -1. Models 1 to 3 seem to favor the Gompertz growth model.

Model 5 interacts education *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 providing support for 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 an explanatory variable, faces problems of endogeneity

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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.

[14] 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…

since the productivity level investigated enters this variable[15]. 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[16]. The results are robust to the adjustment of the technology gap[17]. 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 Tables 2 and A3. 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 tempt to address this concern by extending our base specification to incorporate a number of conditioning variables.

The control variables we introduce include average holdings, research and development (R&D) expenditures, infant mortality, land fragmentation, rule of law, control of corruption, government effectiveness, political stability and regularity quality.

The estimation results with GTFP1 and GTFP2 as dependent variables are presented in Tables A4 and A5 respectively. In models 1 to 7 of these tables we replicate the results from Tables 2 and A3 but include the control variables in the base equation (16). Human capital is still statistically insignificant. The results reported here use average years of schooling as a proxy for human capital, but this finding is robust to alternative indicators such as the literacy rate, the secondary school attainment, HDI. The interaction term between education and agricultural machinery imports remain statistically significant at the 1% level, suggesting a strong complementary effect between human capital and foreign technology in enhancing agricultural growth. The findings regarding the role of human capital and openness in speeding technology diffusion are robust, as the catch up term enters significantly with the predicted sign at a one percent confidence level. The results still support the confined exponential diffusion process, as the point estimates of *s* are again close to -1 in our preferred models.

A number of interesting findings regarding the effect of the control variables on agricultural productivity growth emerge from tables A4 and A5. The results indicate a positive relationship between agricultural productivity and both R&D expenditure and average holdings. Infant mortality used as an indicator of health seems to impact negatively on farming performance. The results show a positive role of institutional quality in enhancing agricultural growth. Control of corruption, political stability and regularity quality enter with positive and statistically significant coefficients.

Note that the regression results are robust to the use of alternative measures of agricultural TFP growth, namely GTP1 and GTFP2. The findings with the regression using TFP growth estimates based on the fixed coefficients production function as a dependant variable are relatively close to those obtained with our preferred specification.

[15] The other explanatory variables may be also subject to endogeneity and measurement errors.

[16] The lagged *GAP* is highly correlated with the current *GAP*. The regression of *GAP* on lagged *GAP* has an $R^2$ of 0.98.

[17] A similar procedure was employed in Xu (2000).

## 3. Productivity Dynamics: The Linear Specification

Alternative productivity dynamics are investigated in equation (17), where the dependent variable is TFPG1, human capital is measured by the average years of schooling 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[18].

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 percent 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 hypothesis and show that the lagging economies that lie further behind the leading edge 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.

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[18] The instruments used include the lagged literacy rate, the predicted value of GAP, the lagged value of trade, $imach_{t-2}$, and $H_{t-2}$.

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 markedly 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 quite important education levels as well. 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 a significant technology gap compared 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.

## VI. Conclusion

There is an influential literature investigating the contribution of international technology diffusion to economic development. A wide range of empirical evidence suggests that engaging in international economic activity has important implications for a country's productivity growth through international knowledge spillovers. Many economists have emphasized the role of human capital in successful technology diffusion. Human capital in the form of educational attainment is associated with the notion of absorptive capacity, which captures the idea that the adoption and assimilation of innovation requires the presence of a sufficient level of qualified work force.

The empirical models of international technology spillovers so far rely generally on cross-country data or industry level data. There is little evidence on the technology diffusion effects in the agricultural sector.

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.

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 emphasized the interactions between human capital and international trade, and found 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 that help with 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 used 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 a significant technology gap in comparison to 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 markedly slower rates. However, from the southern panel Jordan, followed by Lebanon and Syria, seem to experience significantly fast technology transfer.

This analysis provides interesting insights into the agricultural productivity dynamics and sheds light on the benefits of economic openness in the Mediterranean region. Further research is still needed to investigate country specific determinants of advanced technology adoption in agriculture – new technologies might be geo-climatic and land-specific – and then using diffusion models which allow for country specific environmental and climatic conditions within their analysis decision. In turn, this may allow for a better understanding of technology transfer within Mediterranean countries.

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**Table 1: Input Elasticities**

| Variables | Fixed Coefficients | Random Coefficients Model | |
|---|---|---|---|
| | | **Mean Response Coefficients** | **Range Of Elasticity Coefficients** |
| $y_{t-1}$ | 0.394** | 0.241** | 0.168-0.426 |
| | (3.3) | (4.52) | |
| Land | 0.247** | 0.279** | 0.223-0.373 |
| | (4.78) | (3.58) | |
| Water | 0.132** | 0.236** | 0.188-0.334 |
| | (3.26) | (2.99) | |
| Capital | 0.116** | 0.194** | 0.097-0.296 |
| | (2.97) | (2.82) | |
| Labour | 0.108* | 0.142* | 0.088-0.238 |
| | (1.97) | (2.09) | |
| Fertilizers | 0.008 | 0.033* | 0.009-0.049 |
| | (1.48) | (1.62) | |
| M1[a] | z = -4.9 | | |
| M2[b] | z = 1.09 | | |
| Sargan[c] | Chi2(116) = 78.45 | | |
| | (p= 0.997) | | |
| No. of observations | 1260 | 1260 | |

Notes:
a: 1st order serial correlation,
b: 2nd order serial correlation,
c: Sargan test of the over identifying restriction, degrees of freedom are under brackets.
Numbers in parenthesis are t-statistics. The significance at the 10% and 1% levels is indicated by * and ** respectively.

## 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 | -0.033 | -0.06 | -0.04 | -0.07 | -0.07 | -0.098 | -0.085 |
| | (-0.46) | (-0.8) | (-0.54) | (-0.91) | (-0.88) | (-1.37) | (-1.2) |
| lnH | 0.013 | 0.02 | 0.015 | 0.021 | 0.031 | 0.033 | 0.04 |
| | (0.34) | (0.5) | (0.39) | (1.54) | (1.62) | (0.85) | (0.94) |
| lnH*trade | 0.04** | | | | | | |
| | (2.96) | | | | | | |
| lnH*ltrade*$GAP^s$ | -0.04** | | | | | | |
| | (-2.96) | | | | | | |
| lnH*FDI | | -0.08 | | | | | |
| | | (-1.44) | | | | | |
| lnH*FDI*$GAP^s$ | | 0.08 | | | | | |
| | | (1.44) | | | | | |
| lnH*tariff | | | -0.035* | | | | |
| | | | (-2.41) | | | | |
| lnH*tariff*$GAP^s$ | | | 0.035* | | | | |
| | | | (2.41) | | | | |
| lnH*imach | | | | -0.184** | | -0.12** | |
| | | | | (-3.43) | | (-3.98) | |
| lnH*imach*$GAP^s$ | | | | 0.184** | | 0.12** | |
| | | | | (3.43) | | (3.98) | |
| lnH*imach*NM | | | | | -0.32* | | -0.264* |
| | | | | | (-2.05) | | (-2.24) |
| lnH*imach*$GAP^s$*NM | | | | | 0.26* | | 0.188* |
| | | | | | (1.91) | | (2.41) |
| lnH*imach*SM | | | | | -0.18** | | -0.144** |
| | | | | | (-3.22) | | (-3.18) |
| lnH*imach*$GAP^s$*SM | | | | | 0.15** | | 0.105** |
| | | | | | (2.82) | | (3.42) |
| s | 0.07 | -0.64* | 0.07 | -0.823** | -0.95** | -1 | -1 |
| | (0.8) | (-1.69) | (0.42) | (-2.8) | (-2.82) | | |
| Number of observations | 1177 | 1177 | 1177 | 1177 | 1177 | 177 | 1177 |
| $R^2$ adjusted | 0.284 | 0.27 | 0.29 | 0.48 | 0.49 | 0.513 | 0.522 |

Notes:

The dependant variable is TFP growth measured using the random coefficients model (GTFP1). *GAP* is the ratio of the sample country's agricultural TFP to the highest level of TFP. *imach* is the ratio of agricultural machinery imports to agricultural value added. *NM* and *SM* are dummies for north and south Mediterranean countries respectively.

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

**Table 3: Agricultural TFP Linear Growth Regressions**

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| $\Delta lnA_L$ | 0.72 | 0.704 | 0.606 | 0.707 |
| | (11.45) | (14.78) | (14.35) | (14.89) |
| lnH | 0.06* | 0.037 | | 0.063** |
| | (2.38) | (1.39) | | (2.62) |
| imach | 0.12 | | 0.18* | 0.121* |
| | (1.06) | | (2.09) | (1.64) |
| lnGAP | -0.062** | -0.054** | -0.013* | -0.084* |
| | (-5.48) | (-7.66) | (-1.96) | (-1.91) |
| lnH*lnGAP | | -0.17* | | -0.169** |
| | | (-1.73) | | (-2.88) |
| imach*lnGAP | | | -0.269** | -0.267** |
| | | | (-3.01) | (-3.15) |
| Average holding | 0.017** | 0.017** | 0.016** | 0.017** |
| | (3.17) | (3.16) | (3.12) | (3.29) |
| Land fragmentation | -0.002* | -0.001 | -0.002** | -0.022* |
| | (-1.74) | (-0.91) | (2.6) | (-2.22) |
| R&D | 0.03** | 0.026* | 0.026** | 0.028** |
| | (2.88) | (2.43) | (2.54) | (2.59) |
| Mortality | -0.003** | -0.0032** | -0.006 | -0.0023* |
| | (-2.85) | (-3.03) | (-1.05) | (-2.28) |
| Control of Corruption | 0.0002 | 0.0002 | 0.0001 | 0.002* |
| | (1.21) | (1.18) | (0.67) | (1.75) |
| Gov. effectiveness | -0.0006 | -0.0006 | -0.0005 | -0.004 |
| | (-1.37) | (-1.33) | (-1.26) | (-0.65) |
| Political stability | 0.0002* | 0.0002* | 0.0002* | 0.0002* |
| | (2.1) | (2.01) | (1.83) | (2.06) |
| Regularity quality | 0.0004* | 0.0004* | 0.0003* | 0.0003* |
| | (2.17) | (2.12) | (1.62) | (2.01) |
| N. of observations | 1177 | 1177 | 1177 | 1177 |
| $R^2$ adjusted | 0.92 | 0.904 | 0.906 | 0.919 |

Notes:
Regression results for GTFP1, panel data, *H*, *GAP* and *imach* are instrumented. Numbers in parentheses are *t*-statistics. * and ** denote statistical significance at the 10% and 1% levels respectively.

**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 | 0.859 | 0.184 | 0.275 |
| Egypt | 0.59 | 0.286 | 0.467 |
| Israel | 0.946 | 0.104 | 0.184 |
| Jordan | 3.891 | 0.077 | 0.143 |
| Lebanon | 1.744 | 0.149 | 0.249 |
| Morocco | 1.119 | 0.162 | 0.264 |
| Syria | 1.345 | 0.111 | 0.196 |
| Tunisia | 1.237 | 0.144 | 0.245 |
| Turkey | 0.888 | 0.085 | 0.155 |
| France | 4.173 | 0.077 | 0.142 |
| Greece | 2.029 | 0.140 | 0.241 |
| Italy | 1.914 | 0.099 | 0.177 |
| Portugal | 2.934 | 0.142 | 0.243 |
| Spain | 2.063 | 0.112 | 0.197 |

## Appendix

### Table A1: Some Summary Statistics

| | | Mean | St. dev. | Min | Max |
|---|---|---|---|---|---|
| GAP | $TFP/TFP_L$ | 0.722 | 0.198 | 0.22 | 1 |
| Human capital | Av. Years of schooling in the population over 25 years. | 6.11 | 1.78 | 3.01 | 9.4 |
| Trade | Total agricultural trade (% of GDP) | 5.08 | 12.2 | 0.122 | 132.6 |
| FDI | Foreign direct investment, net inflows (% of GDP). | 1.45 | 1.396 | -0.61 | 9.47 |
| Imach. | Agricultural machinery and equipment imports (% of agricultural value added). | 5.57 | 4.4 | 0.44 | 19.78 |

### Table A2: Agricultural Total Factor Productivity Estimates

| Country | Random coefficients model | | Fixed Coefficients model | |
|---|---|---|---|---|
| | TFP1a | TFPG1b | TFP2 | TFPG2 |
| Algeria | 1.48 | 0.063 | 1.596 | 0.098 |
| | (0.273) | (0.398) | (0.35) | (0.545) |
| Egypt | 1.56 | 0.043 | 1.503 | 0.044 |
| | (0.208) | (0.327) | (0.236) | (0.326) |
| Israel | 1.950 | 0.113 | 1.970 | 0.147 |
| | (0.314) | (0.669) | (0.342) | (0.804) |
| Jordan | 1.714 | 0.111 | 1.746 | 0.15 |
| | (0.468) | (0.548) | (0.524) | (0.63) |
| Lebanon | 1.680 | 0.04 | 1.725 | 0.037 |
| | (0.221) | (0.382) | (0.23) | (0.373) |
| Morocco | 1.693 | 0.191 | 1.652 | 0.282 |
| | (0.454) | (0.966) | (0.49) | (0.835) |
| Syria | 1.707 | 0.14 | 1.689 | 0.131 |
| | (0.311) | (0.609) | (0.3) | (0.579) |
| Tunisia | 1.738 | 0.124 | 1.628 | 0.137 |
| | (0.431) | (0.698) | (0.38) | (0.735) |
| Turkey | 2.04 | 0.005 | 2.62 | 0.012 |
| | (0.082) | (0.143) | (0.123) | (0.179) |
| France | 2.43 | 0.026 | 2.535 | 0.025 |
| | (0.154) | (0.269) | (0.275) | (0.242) |
| Greece | 2.190 | 0.013 | 2.198 | 0.012 |
| | (0.127) | (0.212) | (0.128) | (0.209) |
| Italy | 2.271 | 0.019 | 2.312 | 0.017 |
| | (0.14) | (0.217) | (0.147) | (0.209) |
| Portugal | 2.031 | 0.037 | 1.852 | 0.028 |
| | (0.185) | (0.311) | (0.152) | (0.297) |
| Spain | 2.312 | 0.051 | 2.266 | 0.045 |
| | (0.22) | (0.393) | (0.206) | (0.366) |

Notes:
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.
Numbers in parenthesis are standard deviations.

## Table A3: 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 | 0.045 | -0.08 | 0.28** | 0.12 | -0.041 | -0.13* | -0.008 |
| | (0.7) | (-1.15) | (5.01) | (1.7) | (-0.6) | (1.86) | (-0.14) |
| lnH | 0.13** | 0.15** | 0.034 | 0.02 | -0.051 | -0.013 | -0.016 |
| | (3.64) | (3.98) | (1.11) | (0.52) | (-1.26) | (-1.14) | (-0.35) |
| lnH*trade | 0.04** | | | | | | |
| | (6.1) | | | | | | |
| lnH*ltrade*$GAP^s$ | -0.04** | | | | | | |
| | (-6.1) | | | | | | |
| lnH*FDI | | 0.06** | | | | | |
| | | (12.9) | | | | | |
| lnH*FDI*$GAP^s$ | | -0.06** | | | | | |
| | | (-12.9) | | | | | |
| lnH*tariff | | | 0.02 | | | | |
| | | | (1.497) | | | | |
| lnH*tariff*$GAP^s$ | | | -0.02 | | | | |
| | | | (1.497) | | | | |
| lnH*imach | | | | -0.19** | | -0.15** | |
| | | | | (-2.9) | | (-11.9) | |
| lnH*imach*$GAP^s$ | | | | 0.19** | | 0.15** | |
| | | | | (2.9) | | (11.9) | |
| lnH*imach*DC | | | | | -0.46** | | -0.37** |
| | | | | | (-5.2) | | (4.57) |
| lnH*imach*$GAP^s$*DC | | | | | 0.42** | | 0.25** |
| | | | | | (4.9) | | (5.42) |
| lnH*imach*LDC | | | | | -0.22** | | -0.17** |
| | | | | | (-11.31) | | (-11.2) |
| lnH*imach*$GAP^s$*LDC | | | | | 0.19** | | 0.12** |
| | | | | | (10.92) | | (13.2) |
| s | -1.1 | -1.44** | -0.61 | -0.68* | -0.89* | -1 | 1 |
| | (-1.22) | (-12.92) | (-1.19) | (2.28) | (-2.1) | | |
| Number of observations | 1177 | 1177 | 1177 | 1177 | 1177 | 1177 | 1177 |
| $R^2$ adjusted | 0.21 | 0.26 | 0.28 | 0.31 | 0.29 | 0.373 | 0.396 |

Notes*:*
The dependant variable is TFP growth measured using the fixed coefficients model (GTFP2).
(.) t-statistics. * and ** denote significance at the 1% and 10% level, respectively.

**Table A4: 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 | 0.025 | 0.06 | 0.031 | -0.034 | -0.005 | 0.021 | 0.0542 |
| | (0.76) | (0.39) | (0.2) | (-0.17) | (-0.3) | (0.15) | (0.37) |
| lnH | 0.037 | 0.023 | 0.036 | 0.09 | 0.009 | 0.017 | 0.009 |
| | (0.85) | (0.28) | (0.43) | (0.91) | (0.81) | (1.26) | (0.14) |
| lnH*trade | 0.039** | | | | | | |
| | (2.88) | | | | | | |
| lnH*ltrade*GAP$^s$ | -0.039** | | | | | | |
| | (-2.88) | | | | | | |
| lnH*FDI | | -0.08 | | | | | |
| | | (-1.43) | | | | | |
| lnH*FDI*GAP$^s$ | | 0.08 | | | | | |
| | | (1.43) | | | | | |
| lnH*tariff | | | -0.0362* | | | | |
| | | | (-2.47) | | | | |
| lnH*tariff*GAP$^s$ | | | 0.0362* | | | | |
| | | | (2.47) | | | | |
| lnH*imach | | | | -0.172** | | -0.13** | |
| | | | | (-3.22) | | (-4.36) | |
| lnH*imach*GAP$^s$ | | | | 0.172** | | 0.13** | |
| | | | | (3.22) | | (4.36) | |
| lnH*imach*DC | | | | | -0.423* | | -0.417** |
| | | | | | (-2.47) | | (-2.67) |
| lnH*imach*GAP$^s$*DC | | | | | 0.289* | | 0.259** |
| | | | | | (2.14) | | (2.78) |
| lnH*imach*LDC | | | | | -0.151** | | -0.146** |
| | | | | | (-2.59) | | (-3.05) |
| lnH*imach*GAP$^s$*LDC | | | | | 0.131** | | 0.117** |
| | | | | | (2.57) | | (3.64) |
| Average holding | 0.0025* | 0.0016* | 0.0027* | 0.0015* | 0.0013* | 0.0014 | 0.0016 |
| | (1.65) | (1.92) | (1.79) | (1.79) | (1.82) | (1.38) | (1.4) |
| R&D | 0.0025* | 0.0014* | 0.0025* | 0.002* | 0.0036* | 0.0018* | 0.0046** |
| | (1.7) | (2.37) | (1.88) | (1.82) | (1.99) | (1.92) | (2.84) |
| Mortality | -0.002* | -0.002* | -0.0018* | -0.0011* | -0.0013* | -0.0015* | -0.002* |
| | (-1.98) | (-1.94) | (-1.99) | (-1.63) | (-1.73) | (-2.07) | (-1.94) |
| Rule of law | 0.0008* | 0.0008* | 0.0009* | 0.0011* | 0.0012 | 0.001* | 0.0013* |
| | (1.96) | (1.92) | (1.69) | (2.23) | (1.43) | (1.93) | (1.65) |
| Control of Corruption | 0.00047* | 0.0004* | 0.00053* | 0.0006* | 0.0007* | 0.0005* | 0.0006* |
| | (1.86) | (1.78) | (1.96) | (2.16) | (2.26) | (1.94) | (1.73) |
| Government effectiveness | 0.0002* | 0.0002* | 0.00019 | 0.0003 | 0.0002 | 0.0002 | 0.0001 |
| | (1.92) | (2.04) | (1.35) | (1.5) | (1.29) | (1.3) | (1.19) |
| Political stability | 0.0002* | 0.0002* | 0.0002* | 0.0002* | 0.0001* | 0.0003* | 0.0001 |
| | (1.83) | (1.85) | (1.79) | (2.09) | (1.94) | (2.06) | (1.36) |
| Regularity quality | 0.0005* | 0.0007* | 0.0005* | 0.004 | 0.0004* | 0.0004* | 0.0004* |
| | (1.99) | (1.85) | (1.93) | (1.04) | (1.83) | (1.94) | (1.91) |
| s | 0.083 | -0.584* | 0.095 | -0.893** | -0.972** | -1 | -1 |
| | (0.75) | (-1.63) | (0.46) | (-3.84) | (-2.79) | | |
| Number of observations | 1177 | 1177 | 1177 | 1177 | 1177 | 177 | 1177 |
| $R^2$ adjusted | 0.428 | 0.427 | 0.43 | 0.586 | 0.592 | 0.616 | 0.618 |

Notes:
The dependant variable is TFP growth measured using the random coefficients model (GTFP1).
(.) t-statistics. * and ** denote significance at the 1% and 10% level, respectively.

**Table A5: 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 | 0.15 (1.12) | 0.24* (1.62) | -0.009 (-0.8) | -0.02 (-0.13) | 0.09 (0.45) | 0.179 (1.23) | 0.24 (1.36) |
| lnH | 0.06 (0.83) | -0.07 (-0.86) | 0.06 (0.97) | -0.145 (-1.05) | -0.13 (-1.25) | -0.005 (-0.7) | -0.09 (-1.09) |
| lnH*trade | -0.041** (-6.3) | | | | | | |
| lnH*ltrade*$GAP^s$ | 0.041** (6.3) | | | | | | |
| lnH*FDI | | 0.07** (13.6) | | | | | |
| lnH*FDI*$GAP^s$ | | -0.07** (13.6) | | | | | |
| lnH*tariff | | | 0.027* (1.68) | | | | |
| lnH*tariff*$GAP^s$ | | | -0.027* (-1.68) | | | | |
| lnH*imach | | | | -0.29** (-7.84) | | -0.174** (-12.8) | |
| lnH*imach*$GAP^s$ | | | | 0.29** (-7.84) | | 0.174** (12.8) | |
| lnH*imach*DC | | | | | -0.39** (-3.37) | | -0.38** (-3.37) |
| lnH*imach*$GAP^s$*DC | | | | | 0.36** (5.19) | | 0.25** (5.84) |
| lnH*imach*LDC | | | | | -0.19** (-5.91) | | -0.17** (-11.2) |
| lnH*imach*$GAP^s$*LDC | | | | | 0.18** (7.68) | | 0.13** (13.31) |
| Average holding | 0.0053* (1.85) | 0.0035* (1.93) | 0.0022* (1.74) | 0.0031* (1.66) | 0.005 (1.13) | 0.0079* (2) | 0.0052 (1.29) |
| R&D | 0.0033* (1.88) | 0.005* (1.82) | 0.0048* (1.96) | 0.0017* (1.65) | 0.0017* (2.39) | 0.0043** (3.07) | 0.0014* (1.94) |
| Mortality | -0.0024* (-1.78) | -0.0051** (-3.12) | -0.0017* (-2.14) | -0.002 (-1.96) | -0.0023 (-1.2) | -0.0025** (-2.68) | -0.0026* (-1.96) |
| Rule of law | 0.0005* (1.69) | 0.0001 (1.02) | 0.0005** (1.72) | 0.0018* (1.83) | 0.0017* (1.86) | 0.0004 (1.48) | 0.0001 (1.17) |
| Control of Corruption | 0.0004* (1.86) | 0.0005* (1.97) | 0.0001** (2.65) | 0.0014* (2.37) | 0.0013* (2.24) | 0.0003 (1.48) | 0.0013* (1.75) |
| Government effectiveness | 0.0003* (1.78) | 0.0007 (1.14) | 0.0003* (1.79) | 0.0004* (1.79) | 0.0002 (1.36) | 0.0005* (1.86) | 0.0003 (1.53) |
| Political stability | 0.0003* (1.73) | 0.0002* (1.81) | 0.0006 (1.32) | 0.0004 (1.3) | 0.0002 (1.48) | 0.0001 (1.39) | 0.00053 (1.59) |
| Regularity quality | 0.0003* (1.81) | 0.0011** (3.15) | 0.0002* (1.73) | 0.0003* (1.74) | 0.0005* (1.88) | 0.0005* (1.98) | 0.0003* (1.64) |
| s | -1.06 (-1.43) | -1.42** (-13.71) | -0.53 (-0.93) | -0.99** (-3.27) | -0.83** (-8.06) | -1 | -1 |
| Number of observations | 1177 | 1177 | 1177 | 1177 | 1177 | 177 | 1177 |
| $R^2$ adjusted | 0.387 | 0.41 | 0.395 | 0.428 | 0.4 | 0.484 | 0.493 |

Notes:
The dependant variable is TFP growth measured using the fixed coefficients model (GTFP2).
(.) t-statistics. * and ** denote significance at the 1% and 10% level, respectively.