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TRADE LIBERALIZATION, AGRICULTURAL PRODUCTIVITY AND POVERTY IN THE MEDITERRANEAN REGION

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Abstract

A widely held view in the economic literature is that productivity growth is an important pathway through which trade liberalization affects the poor. This paper explores the links between trade openness, agricultural productivity, growth and poverty reduction in a panel of Mediterranean countries involved in global market liberalization. The mpirical results lend strong support to the view that agricultural productivity is an important channel for poverty alleviation. The findings illustrate the positive effects of openness on the rate of farming productivity and the speed of catching up with the best practice technology. Overall, the findings support the benefits of trade liberalization in the Mediterranean region, but suggest that the positive outcomes are contingent on complementary efforts.

ملخص

ثمة اعتقاد شائع في الكتابات الاقتصادية بأن نمو الإنتاجية هي من الوسائل المهمة التي يمكن من خلاله أن تؤثر عملية تحرير التجارة على الفقراء. وتستكشف هذه الورقة الصلات بين التجارة المفتوحة والإنتاجية الزراعية والنمو وعملية تخفيف حدة حالات الفقر في مجموعة من دول البحر المتوسط التي شاركت في تحرير التجارة العالمية. تؤيد النتائج التجريبية وجهة النظر التي ترى أن الإنتاجية الزراعية من الوسائل المهمة لتخفيف حدة الفقر. وتدل النتائج على الآثار الإيجابية للانفتاح على معدل الإنتاجية الزراعية وعلى سرعة اللحاق بركب أفضل الوسائل التكنولوجية. وتؤيد النتائج إجمالاً فوائد تحرير التجارة في منطقة البحر المتوسط ولكنها توحي بأن تلك النتائج الإيجابية إنما تتوقف على جهود تكميلية.

I. Introduction

The impact of international trade on economic growth and poverty is a central issue in the debate surrounding globalization. Despite the controversy about the causal link between openness and economic performance in the literature, the benefit of trade to faster growth and poverty alleviation are generally recognized. More recently, the Uruguay Round commitments and the ongoing Doha Round of agricultural trade negotiations refocused attention on the economic linkages between trade, agricultural development, and poverty, providing a new impetus to the re-examination of these linkages.

The debate surrounding the role of agriculture in the development process has fueled a wealth of empirical studies (Datt and Ravallion 1998, 1999; Timmer 2002, 2005; Thirtle *et al*. 2003; Anderson 2004; Majid 2004; Rao *et al*. 2004; Bravo-Ortega and Lederman 2005; Christiaensen *et al*. 2006; and Ravallion and Chen 2007). The focus on agriculture is motivated by the importance of farming in many developing countries where it accounts for an important share of employment and export earnings. Most of the evidence lends support to the view that agricultural development is a potent factor in fostering economic growth and reducing poverty in countries with predominantly rural poverty profiles.

International trade can lead to enhanced farming productivity through the diffusion of new technologies that would, in turn, drive the pro-poor agricultural growth process. Despite extensive theoretical and empirical evidence on the positive impact of trade liberalization, the link between openness and agricultural performance has been rarely studied. In addition, the effects of agricultural productivity gains on income distribution are worthy of further investigation.

Agriculture remains an important sector in many countries in the Mediterranean. Nonetheless, agricultural resources in the region remain highly distorted by trade barriers and subsidies. Protection policies create perverse incentives for mismanagement and inefficiency. Several Mediterranean countries suffer from mounting pressure on their natural resource base as a result of rapid population growth and rising urbanization. Given limited resources, significant improvements are required in agricultural productivity through technological innovations and efficiency to achieve sustainable rural development and contribute to poverty alleviation. Exposure to international trade, through the diffusion of new technologies, opens great opportunities to enhance agricultural productivity that could prove beneficial to growth and poverty reduction in several Mediterranean countries.

Is agricultural productivity an important pathway through which liberalization affects the poor? The purpose of this paper is to address this issue by exploring the links between: (i) openness and agricultural productivity, and (ii) farming performance, economic growth, and inequality. The countries under investigation comprise a sample of Mediterranean countries that have taken steps towards greater integration in the global economy. More specifically, the profile of countries under investigation is commensurate with the paper objectives 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, although highly distorted due to trade barriers and protective policies.

As Mediterranean countries press ahead with liberalization within the framework of the Barcelona-Agreement, speculations have arisen regarding the impact of liberalization in accelerating agricultural development via technology transfer. Further, greater openness is likely to increase the country's welfare through the effect of higher agricultural productivity in enhancing growth and reducing inequality. Higher growth and less inequality are likely to contribute to poverty reduction.

To that end, the analysis embraces two main objectives: (i) estimating Technical Efficiency (TE) and Total Factor Productivity (TFP) in the Mediterranean agricultural sector, and (ii) investigating the simultaneous influence of agricultural productivity on income growth and income distribution towards analyzing implications on poverty. In the first step of econometric analysis, TE and TFP indexes are assessed using the latent class stochastic frontier model to account for cross country heterogeneity in production technologies. Second, the paper examines the relevance of farming performance to poverty reduction using a simultaneous dynamic model of panel data comprising agricultural productivity, growth and income distribution across countries.

The structure of the paper is as follows. Section II outlines the plan for empirical investigation and presents the procedure to measure agriculture productivity. Section III presents the methodology to explore the linkage between agricultural productivity and the incidence of poverty. Section IV reviews the data. Section V reports the empirical results. Finally, section VI synthesizes the main findings and draws some conclusions.

II. Empirical Plan

The analysis of international agricultural productivity and efficiency has been subject to extensive research. The conceptual approaches to measuring agricultural productivity rely on the Divisia index and the production frontiers, adopting alternative non-parametric and parametric techniques.[1] The parametric stochastic frontier models have the advantage of controlling for random events. Based on the econometric estimation of the production frontier, the efficiency of each producer is measured as the deviation from the best practice technology. Productivity change is computed as the variation over time of the producer's distance from the frontier and is decomposed into technology change, factor accumulation, and changes in efficiency (Sena 2003; Kumbhakar 2004). Comparisons of inter-country production functions require, however, controlling for technological differences in the stochastic frontier models (Green 2003; Kumbhakar and Tsionas 2003; Moutinho *et al*. 2003; Corral and Alvarez 2004; Kumbhakar 2004; Orea and Kumbhakar, 2004).

The latent class stochastic frontier models are better suited to modeling technological heterogeneity. These models combine the stochastic frontier approach with a latent sorting of individuals into discrete groups.[2] Cross country heterogeneity is accommodated through the simultaneous estimation of the probability for class membership and a mixture of several technologies.

The deviation of country-specific frontiers estimates from the best practice technology will measure the technological gap among the Mediterranean countries.[3] Assume a latent sorting of

[1] The Divisia index and the non-parametric methods have been challenged in the literature as the first does not provide sources of productivity growth, and the second is deterministic and does not allow for stochastic shocks in the production process (Kumbhakar 2004).

[2] For details, see (Green 2001b, 2002, 2003; Caudill 2003; Kumbhakar 2004; Orea and Kumbhakar 2004).

[3] This is defined as the metafrontier function; see Battese and Rao, (2002) and Khumbhakar, (2004).

producers in various countries into J discrete unobserved groups, each using a different production technology. The technology for the j^{th} group is specified as:

$$ln(y_{it}) = ln\, f(x_{it}, \beta_j) + v_{it}|_j - u_{it}|_j \qquad (1)$$

subscript i indexes producers (or countries) (i: $1 \ldots N$), t (t: $1 \ldots T$) indicates time and j (j: 1, …, J) represents the different groups. β_j is the vector of parameters for group j, and y_{it} and x_{it} are, respectively, the production level and the vector of inputs. For each class (or group), the stochastic nature of the frontier is modeled by adding a two-sided random error term $v_{it}|_j$, which is assumed to be independent of a non-negative inefficiency component $u_{it}|_j$.[4]

We adopt the scaled specification for $u_{it}|_j$ by writing it as[5]:

$$u_{it}|_j = exp\left(ln\left(z_{it}\right)'\delta_j\right)\omega_{it}|_j \qquad (2)$$

Where, z_{it} is a vector of country's specific control variables associated with inefficiencies, δ_j is a vector of parameters to be estimated, and $\omega_{it}|_j$ is a random variable with a half normal distribution.

In a latent class model, the unconditional likelihood for country i is obtained as a weighted average of its j-class likelihood functions, with the probabilities of class membership used as the weights:

$$LF_i = \sum_{j:1}^{J} LF_{ij} P_{ij} \qquad (3)$$

Where, LF_i and LF_{ij} are respectively the unconditional and conditional likelihood functions for country i, and P_{ij} is the prior probability of belonging to class j, as assigned by the researcher for this country.[6] To constrain these probabilities to sum to unity, we parameterize P_{ij} as a multinomial logit model:

$$P_{ij} = \frac{exp(\lambda_j' q_i)}{\sum_j exp(\lambda_j' q_i)} \qquad (4)$$

[4] In order to estimate (1) by the maximum likelihood method we assume that the noise term $v_{it}|_j$ follows a normal distribution $N(0,\sigma^2_{v_j})$ and the inefficiency term $u_{it}|_j$ is a non-negative normal random variable. The recent literature contains few applications of the latent class stochastic frontier model (Green 2001a, 2002; Caudill 2003; Corral and Alvarez 2004; Orea and Kumbhakar 2004; Takii 2004; El-Gamal and Inanoglu 2005). Most of these models specify the inefficiency component as i.i.d half normal and do not investigate the effect of the exogenous factors on technical efficiency. Orea and Kumbhakar (2004) suggest remedying this shortcoming by modeling the dependence of the efficiency term on a set of exogenous variables.

[5] See Wang and Schmidt, (2002) and Alvarez *et al*., (2006) for discussion of the practical advantages of models with the scaling property.

[6] The salient feature of the latent class model is that the class membership is unknown to the analyst; the probabilities in this formulation reflect the uncertainty that the researchers might have about the true partitioning in the sample.

Where, q_i is a vector of a country's specific and time-invariant variables that explain probabilities and λ_j are the associated parameters.

The overall log likelihood function for the sample is then given by:[7]

$$ln\,LF = \sum_{i:1}^{N} ln\,LF_i \qquad (5)$$

Using the parameters estimates and Bayes' theorem, we compute the conditional posterior class probabilities from:[8]

$$P_{j|\mathrm{i}} = \frac{LF_{ij}P_{ij}}{\sum_{j} LF_{ij}P_{ij}} \qquad (6)$$

The estimated posterior probabilities help to compute the efficiency scores. Given that there are *J* groups, the latent class model estimates *J* different frontiers using two methods that identify inefficiencies of the producers. The first method estimates technical efficiency using the most likely frontier (the one with the highest posterior probability) as a reference technology. This approach results in a somewhat arbitrary selection of the reference frontier that can be avoided by evaluating the weighted average efficiency score as follows:

$$ln\,TE_{\mathrm{it}} = \sum_{j:1}^{J} P_{j|\mathrm{i}}\, ln\,TE_{it|\mathrm{j}} \qquad (7)$$

Where, $TE_{it}\,|_j = exp(-u_{it}\,|_j\,)$ is the technical efficiency of country *i* using the technology of class *j* as the reference frontier.

The model can be fully specified by the selection of the appropriate number of classes. Since estimation with too few or too many classes may result in biased estimates, the Schwarz Bayesian Information Criteria (*SBIC*), and the Akaike Information Criteria (*AIC*) have been proposed in the literature to address the class size issue. These criterions are expressed as:

$$SBIC(J) = -2LF(J) + K(J)\ln(n) \qquad (8a)$$

$$AIC(J) = -2LF(J) + 2K(J) \qquad (8b)$$

Where, *LF(J)* is the value of the likelihood function with *J* classes, *K(J)* is the number of independent parameters to be estimated and *n* is the number of observations. The decision rule is to take the model with the lowest *AIC* or *SBIC*.

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[7] Various algorithms for the maximum likelihood estimation have been proposed. The conventional gradient methods and the expectation maximization (EM) algorithm are among the most used approaches (Greene 2001a; Caudill 2003; Kumbhakar 2004; Orea and Kumbhakar 2004).

[8] It appears from this setting that the sample is classified into different groups by using the goodness of fit of each estimated frontier, namely LF_{ij}, as additional information to identify which class generates each observation. Every country is assigned a specific class according to the highest posterior probability. For example, country *i* is classified into group *k* (:1…*J*) if $P_{k|\mathrm{i}} = \max_{j} P_{j|\mathrm{i}}$.

Once this model is estimated, it is possible to assess the rate of total factor productivity change from the results. The components of productivity can be identified from the parametric decomposition of stochastic output growth. The logarithmic differentiation of the conditional production function (1) with respect to *t* leads to the following decomposition:

$$\dot{y}_i\,|_j = \sum_k \varepsilon_{k|_j}\,\dot{x}_k + \frac{\partial ln\big(f(x_i,\beta_j)|_j\big)}{\partial t} - \sum_h \frac{\partial exp\big((ln\,z_{it})'\delta_j\big)}{\partial ln(z_{ih})}\dot{z}_{ih}\omega_i\,|_j - exp\big((ln\,z_{it})'\delta_j\big)\frac{\partial \omega_i\,|_j}{\partial t} \quad (9)$$

Total factor productivity (TFP) growth is defined as the difference between the rate of growth of output and the rate of growth in input use[9]:

$$\dot{TFP}_i\,|_j = \dot{y}_i\,|_j - \dot{x}_i = \frac{(\varepsilon|_j - 1)}{\varepsilon|_j}\sum_k \varepsilon_k\,|_j\,\dot{x}_k + \frac{\partial ln\big(f(x_i,\beta_j)|_j\big)}{\partial t} - \sum_h \frac{\partial exp\big((ln\,z_{it})'\delta_j\big)}{\partial ln(z_{ih})}\dot{z}_{ih}\omega_i\,|_j - exp\big((ln\,z_{it})'\delta_j\big)\frac{\partial \omega_i\,|_j}{\partial t} \quad (10)$$

Where, $\varepsilon_{k|_j} = \frac{\partial ln\big(f(x_i,\beta_j)|_j\big)}{\partial ln\,x_{ik}}$ are the elasticities of output with respect to each input and $\varepsilon|_j$ is the sum of all the elasticities. The dot indicates the growth rate.

Equation (10) decomposes TFP growth into a scale component, which measures a scale effect when inputs expand over time; a technology component, which measures the rate of outward shift of the conditional best-practice frontier; and two additional terms which capture the efficiency change induced by a set of exogenous factors z_i and the contribution of technical efficiency change over time[10].

In the latent class stochastic frontier model each observation has a probability of class membership, thus the decomposition of TFP in equation (10) must be adjusted to this framework. Following a similar procedure used in the computation of individual inefficiencies, the TFP growth of each country in each year is determined by:

$$\dot{\mathrm{TFP}}_i = \sum_{j:1}^{J} P_{j|i}\,\dot{TFP}_{i|_j} \quad (11)$$

In order to explain the cross-country productivity growth, we use the metafrontier approach. The advantage of this approach is that it allows comparison of the individual technologies to the best practice technology or metafrontier to appraise technology gaps between countries. We use the estimated country-specific frontiers to construct the metafrontier function that envelopes all the individual technologies and which is expressed by:

$$y^*_{it} = f(x_{it},\beta^*) = \max_j f\big(x_{it},\beta_j\big) \quad (12)$$

[9] See Orea and Alvarez (2005) for a similar specification.

[10] This specification assumes that producers are allocatively efficient (see Kumbhakar 2004).

The technology gap ratio is then measured as the deviation of country frontiers from the metafrontier[11]:

$$TGR_{it}^{j} = \frac{f(x_{it}, \beta_j)}{f\left(x_{it}, \beta^*\right)} \tag{13}$$

Countries with a higher TGR are technologically more advanced and, therefore, a positive growth rate of TGR is a sign of catching-up with the technological leader.

It is helpful to expand this analysis by investigating the determinants of the technological catching up process across countries and over time. In particular, we examine the effect of trade openness, measured by trade volumes and protection barriers, on accelerating the catching-up process and filling the technological gap. This is done by regressing the TGR growth rate on trade and a set of institutional factors such as governance, infrastructure, human capital and investment in research and development. Trade measures are included to accommodate the role of technology diffusion, while the institutional variables would capture the economies' ability to take advantage of foreign sources of growth and to avoid overstating the effects of international linkages.

Accordingly, the estimable equation takes the following form:

$$\hat{\mathrm{TRG}}_{\mathrm{it}} = \alpha_0 + \sum_h \alpha_h W_{hit} + \varepsilon_i + \gamma_t + \upsilon_{it} \tag{14}$$

Where, $\hat{\mathrm{TRG}}_{\mathrm{it}} = \dfrac{\mathrm{TRG}_{\mathrm{it}} - \mathrm{TRG}_{\mathrm{it-1}}}{\mathrm{TRG}_{\mathrm{it-1}}}$ is the rate of change in the technology gap ratio, W_{hi} are trade and institutional variables, ε_i unobserved country effect and γ_t time shocks.

III. Linkages between Agricultural Productivity, Growth and Poverty

This section investigates the contribution of the agriculture sector to poverty reduction.[12] The effect of agriculture-driven growth on poverty depends nevertheless on income distribution (Chen and Ravallion, 2004). Hence is the need to study the link between agricultural productivity, growth, inequality and poverty.

To address this issue, we provide an empirical evaluation of the impact of agricultural productivity on growth, inequality and poverty. Our procedure follows the framework established in Lopez (2004); it takes into account the simultaneous influence of agricultural productivity on growth and income distribution in a dynamic panel setting, and infers their combined effects on poverty.

Following the common practice, poverty measures are characterized in terms of average income with the Lorenz curve representing the relative income distribution in the following setting:

$$P = P\left(Y, L\left(p\right)\right) \tag{15}$$

[11] See Kumbhakar (2004).

[12] Previous evidence suggests that agriculture significantly contributes to pro-poor growth through its spillovers to the rest of the economy (Timmer 2005; Bravo-Ortega and Lederman 2005; Christiaensen *et al*. 2006).

Where, P denotes the poverty measure which we assume to belong to the Foster-Greer-Thorbecke class (1984)[13], Y is per capita income and $L(p)$ is the Lorenz curve. Following Lopez (2004), we decompose the change in poverty into a growth component and an inequality component. This can be written as:

$$\frac{dP}{P} = \eta \frac{dY}{Y} + \kappa \frac{dG}{G} \tag{16}$$

We refer to the first term in (16) that relates P to Y as the growth effect and the second term that relates P to G as the inequality effect. The parameter $\eta = \frac{\partial P}{\partial Y}\frac{Y}{P}$ denotes the growth elasticity of poverty, and the parameter $\kappa = \frac{\partial P}{\partial G}\frac{G}{P}$ designates the inequality elasticity of poverty, where G represents the income Gini Index.

The inequality elasticity of poverty is expressed as the elasticity of poverty with respect to the Gini index according to the assumption of the log-normality of the income distribution[14] (Lopez 2004; Lopez and Servén 2006).

The effect of agricultural productivity on poverty variation can be expressed as:

$$\frac{\partial LnP}{\partial LnTFP} = \eta \frac{\partial LnY}{\partial LnTFP} + \kappa \frac{\partial LnG}{\partial LnTFP} \tag{17}$$

Equation (17) indicates that the effect of agricultural productivity variation on poverty depends on the impact of farming productivity on growth, and the effect of growth on poverty reduction. However, there is evidence that growth may result in a wider income disparity in some countries. Hence, we study the impact of farming productivity on inequality and the effect of inequality on poverty.

The elasticities η and κ can be computed following the procedure in Lopez and Servén (2006) under the hypothesis of lognormality of per capita income. Their exact expressions are given in the appendix A.

The contribution of agricultural productivity gains to both growth and inequality is estimated using the following dynamic simultaneous model:

$$y_{it} - y_{it-1} = \delta y_{it-1} + \beta' x_{it} + \gamma g_{it} + \varepsilon_i + \xi_t + \zeta_{it} \tag{18}$$

$$g_{it} - g_{it-1} = \alpha g_{it-1} + \lambda' x_{it} + \chi y_{it-1} + \upsilon_i + \varsigma_t + \nu_{it} \tag{19}$$

Where, y is the log of per capita income, g is the log of the Gini coefficient, x represents the set of explanatory variables including agricultural productivity, ε and υ are unobserved country-

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[13] $P_\theta = \int_0^z \left(\frac{z-x}{z}\right)^\theta f(x)dx$, where θ is a parameter of inequality aversion, z is the poverty line, x is income, and $f(.)$ is the density function of income. P_0, P_1 and P_2 are the headcount ratio, the poverty gap and the squared poverty gap respectively.

[14] $\log(Y)$ is distributed as $N(\mu,\sigma)$ with , $\sigma = \sqrt{2}\Phi^{-1}\left(\frac{G+1}{2}\right)$ where Φ denotes the cumulative normal distribution.

specific effects, ξ and ς are time-specific effects, and ζ and ν are the error terms. The subscripts *i* and *t* represent country and time period.

Equations (18) and (19) can be employed to obtain estimates of how poverty changes would be associated with a change in agricultural productivity. The dynamic structure of the system differentiates between the short and long-run impacts of agricultural productivity on growth, inequality and poverty. The contribution of farming productivity to poverty changes in the short-term is given by:

$$\frac{\partial LnP}{\partial LnTFP} = \left(\beta_j + \gamma\lambda_j\right)\eta + \kappa\lambda_j \tag{20}$$

While in the long-run it is measured by:

$$\frac{\partial LnP}{\partial LnTFP} = -\frac{\left(\alpha\beta_j - \gamma\lambda_j\right)}{\left(\delta\alpha - \gamma\chi\right)}\eta - \frac{\left(\delta\lambda_j - \gamma\chi\right)}{\left(\delta\alpha - \gamma\chi\right)}\kappa \tag{21}$$

Estimating equations (18) and (19) is potentially biased by endogeneity arising from correlation between the explanatory variables and unobserved country-specifics. The widely used estimator in this context is the generalized method of moments (GMM).[15]

IV. Data

The application is based on panel data at the national level for agricultural production in nine Southern Mediterranean Countries (SMC) involved in partnership agreements with the European Union (EU) such as: Algeria, Egypt, Israel, Jordan, Lebanon, Morocco, Syria, Tunisia and Turkey; and five EU Mediterranean countries with demonstrated performance in agricultural production: France, Greece, Italy, Portugal and Spain during the period 1990-2005. Our data set includes observations on the main crops grown in these countries, inputs use, trade openness, agricultural research effort, land distribution, land quality, climatic conditions, human capital, institutional factors, per capita income, and income inequality using the Gini index. These variables are grouped in five sets to estimate the stochastic production function in (1); the parametric function of the inefficiency component in (2); the class probabilities in (4); the technology gap in (14); and the growth and inequality equations in (18) and (19). The data is from the FAO (FAOSTAT), World Bank (WDI), AOAD, Eurostat, CEPII, AMAD, ASTI, UN-WIDER, Dollar and Kraay (2002), Pardey *et al*. (2006), and Kaufmann *et al*. (2007), as well as from the different reports of the FEMISE, FAO, CIHEAM and ESCWA. Appendix A summarizes the variables used in the empirical analysis:

[15] The procedure takes first differences to eliminate the fixed effects and uses lagged instruments to correct for simultaneity (Arellano and Bond, 1991). First difference transformation wipes out the time-invariant variables that might be of interest, since it purges the model of all cross-country differences. Blundell and Bond (1998, 2000) suggest estimating the differenced equations simultaneously with the original level equations, subject to appropriate cross-equation restrictions that constrain the coefficient vectors in the level and differenced equations to be identical. This approach, system GMM, uses lagged differences as instruments. Blundell and Bond (1998) indicate that the system GMM estimator performs much better than the standard differenced GMM estimator when the data are highly persistent. In our application, we check the consistency of the system GMM using two specification tests. The first tests for serial correlation, and the second addresses the instrument validity issue using the Sargan test of over-identifying restrictions.

- Factors influencing the catching up process:

  We investigate the determinants of the catching up process by regressing the TGR growth rate on a set of explanatory variables including trade openness, agricultural research effort, human capital, foreign direct investment, other institutional factors, namely voice and accountability, political stability, government effectiveness, regulatory quality, rule of law and control of corruption.
- Variables used to estimate the growth and inequality equations:

  In addition to income and inequality data, we need to calculate poverty measures as well as the elasticities of poverty with respect to growth and inequality to assess the respective contributions of growth and inequality to poverty changes. Under the assumption of a log normal income distribution, we can derive simple expressions for these variables which depend only on the prevailing degree of inequality, and on the poverty line relative to mean per capita income (Lopez 2004; Lopez and Servén 2006).[16]

V. Estimation Results

This section summarizes the main results derived using the empirical application of the methodologies described in sections III and IV.

1. The Latent Class Model

This empirical application involves basically a three-step analysis of agricultural productivity performance across Mediterranean countries. First, a Cobb Douglas parameterization of the technology frontier is employed and the latent class model of equation (1) is estimated using maximum likelihood via the EM algorithm[17]. Second, efficiency and productivity levels and growth are computed for each country. Third, the technology gap among the different countries is measured and the determinants of technological catch up are investigated focusing on the role of trade openness in speeding the catch up process.

We estimated several groups. First, we started by appraising the results for each group. Second, we stacked the different groups in one model and reported the results.

In estimating the latent class model, we begin by examining the class selection issue. The *SBIC* and *AIC* test results, displayed in table B2 in Appendix B, support the segmentation of the model and indicate that the model with four classes is preferred for citrus fruits and for the pooled model, while the preferred number of classes for the remaining product categories is three.

Thus, we limit the discussion to the results of estimating a mixture of stochastic frontiers to these numbers of classes.

Table 1 presents the results of estimating the input elasticities of the production frontier. In the interest of space limitation, we describe the results using pooled data and report the results for

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[16] The choice of the poverty line is nevertheless problematic, given that our study includes some countries of the European Union. Applying a developing Mediterranean country poverty line to the EU will imply very low poverty rates in that region; while an EU poverty line will give very high poverty rates in many low-income countries. Our analysis reports the results for the poverty measures and the growth and inequality elasticities of poverty using two specific poverty lines, set at 50% of the mean per capita GDP (at constant 2000$ prices) and the mean income of the three first quintiles in each country. We compute three common poverty measures: the headcount index, the poverty gap index, and the squared poverty gap index.

[17] The estimation procedure was programmed in Stata 9.2.

specific crops, namely fruits, citrus, cereals, shell fruits, pulses, and vegetables in Table B3 in Appendix B.

For the production function, we obtain fairly reasonable estimates. The input elasticities are globally positive and significant at the 10% level. The differences of the estimated factor elasticities among classes seem to support the presence of technological differences across the countries. Water and cropland have globally the largest elasticity, indicating that the increase of Mediterranean agricultural production depends mainly on these inputs.

Water appears among the most important production factors in the pooled crop production model and in the commodity models, indicating that Mediterranean crops are highly water intensive and water is the most limiting and precious input in this region. Labour and machinery also seem to be important factors in crop production. Fertilizers, although significant in some specific commodity models, appear to have a limited effect on Mediterranean production. This may be explained by the fact that farmers in some regions tend to use fertilizers as complementary input to organic manure which is much less expensive.[18]

In addition to production elasticities, the estimated technology frontiers provide a measure of technical change. A positive sign on the time trend variable reflects technical progress. Significant shifts in the production frontier over time were found in the pooled and specific commodity models, indicating gains in technical change for the selected countries.

The investigation of the behavior of production efficiency in Table 1 (and Appendix Table B3) shows the presence of significant technical inefficiency effects in the model. The variance ratio $\gamma \equiv \sigma_u^2 \big/ \left(\sigma_u^2 + \sigma_v^2\right)$ exceeds 60% in the different panels, suggesting that farmers from the Mediterranean countries operate beneath the frontier function and inefficiencies in production are the dominant source of random errors since they explain more than 60% of the variation in the Mediterranean crop yields. The generalized likelihood ratio test confirms the presence of one-sided error component in the specified model at the 1% level, supporting the relevance of a stochastic parametric production function. The traditional average production function would then be an inadequate representation of the data. The hypothesis that inefficiency effects have half normal distribution is also strongly rejected.

The estimated coefficients of the inefficiency function provide some explanation of the efficiency differentials among the selected countries. All the variables proved significant at the 10% level and have globally the expected signs. Irrigation, average farm size, machinery equipment and education have a positive impact on the efficiency of resources use, while land fragmentation is associated with more inefficient behavior.

The examination of the estimation results of the latent class probability functions shows that the coefficients are globally significant, indicating that the variables included in the class

[18] The choice of the poverty line is nevertheless problematic, given that our study includes some countries of the European Union. Applying a developing Mediterranean country poverty line to the EU will imply very low poverty rates in that region; while an EU poverty line will give very high poverty rates in many low-income countries. Our analysis reports the results for the poverty measures and the growth and inequality elasticities of poverty using two specific poverty lines, set at 50% of the mean per capita GDP (at constant 2000$) and the mean income of the three first quintiles in each country. We compute three common poverty measures: the headcount index, the poverty gap index, and the squared poverty gap index.

probabilities provide useful information in classifying the sample. We had no prior expectation about the signs of these coefficients, as positive values on the separating variables' coefficients in one class indicate that higher values of these variables increase the probability of assigning a country into this class, while negative parameters suggest that the probability of class membership decreases with an increase of the corresponding variables. For example, a higher inequality in operational holdings, measured by land Gini, increases the probability of a country to belong to class two, while wider irrigated areas decrease the probability of membership in the three first classes.

Table 2 summarizes the estimated prior and posterior class probabilities as well as the grouping of countries between the different classes in the pooled and specific commodity models. The posterior class probabilities are, on average, very high (70 percent or more). The classification resulting from these probabilities show globally that Algeria, Israel, Jordan, Lebanon, Portugal and Tunisia belong to the same group characterized by relatively low agricultural production levels, a similar pattern of specialization based on a strong presence of fruits and vegetables, significant land inequality and high fragmentation of holdings. The second group formed by Greece, Morocco and Syria shows higher production levels and more equitable land distribution. The remaining groups include Egypt, France, Italy Spain and Turkey. The average production level of these countries is significantly larger than that in other classes, while land fragmentation and land inequality are much lower. These countries show a common cropping pattern in which cereal crops account for an important part.

The efficiency scores by class are summarized in Table B4, and average efficiency scores and TFP changes, estimated using equations (7) and (11) respectively, are reported in Table B5 in Appendix B. The results show consistent productivity increases in the Mediterranean agricultural sector on average, with Turkey registering the best average rate of productivity gain (8.31%). Significant differences in technical efficiency and productivity performance are, however, apparent among commodity groups and countries. On average, over the period under consideration, EU countries exhibited better efficiency levels and higher productivity growth rates than SMC.

Variation of performance across countries opens the possibility of investigating the factors contributing to productivity improvement and facilitating the catching up process between high-performing and low-performing countries. To tackle this issue, we first measure the technology gap ratio (TGR) using equation (13) and then estimate the model in equation (14) that links the TGR growth rate to a host of variables, including trade openness, FDI, R&D, human capital and institutional factors.

Table 3 reports in its first and second columns the estimation results, considering two measures of international openness, namely trade volumes and trade barriers.

Across the two models, the TGR growth rate increases with human capital, proxied by the literacy rate, tertiary education and HDI, R&D, FDI, rule of law, voice and accountability. In contrast, TGR growth decreases with mortality and regulatory quality. It is interesting to note the robust effects of openness on TGR growth, regardless of the openness measure. TGR growth increases with higher trade shares and decreases with more trade barriers.

The regression results lend support to the view that FDI and trade openness are predominant channels of technology transfer and point to their importance in accelerating the catching up process. Human capital and R&D, which capture the domestic ability to absorb foreign technology, seem to contribute significantly to reducing the technology gap between the selected countries. The empirical findings show evidence of the positive effects of openness on productivity improvement (possibly through technological advancement), and suggest that international trading opportunities would have larger benefits in countries with favorable internal factors relating to higher human capital endowments, significant R&D expenditures and positive institutional conditions.

2- The Poverty-Agricultural Productivity Nexus

Assessing the role of agricultural productivity gains in alleviating poverty requires the empirical evaluation of the impact of productivity on growth and distributional change, as well as measuring the elasticity of poverty with respect to each of them. We first compute the growth and inequality elasticities of poverty for two different poverty lines, using the three FGT poverty measures. Second, we estimate equations (18) and (19) to investigate the impact of agricultural TFP on growth and inequality. Finally, we gauge the short and long run poverty outcomes using equations (20) and (21).

The estimation results of the equations for real per capita GDP growth and inequality are reported in Table 4. The elasticities of poverty with respect to growth, inequality and productivity are presented in Tables B6 and B7 of Appendix B.

The regression performs quite well in conventional statistical terms. Consistent with the evidence from the serial correlation and the Sargan tests, the assumptions of no second order serial correlation and of the validity of the instrument set are not rejected.

A number of significant results emerge from the empirical analysis. First, the findings indicate that inequality would positively affect growth, while income levels may adversely increase inequality. The point estimates of the coefficients for these variables suggest, however, small potential impacts.

Agricultural productivity is a key factor to economic growth and income distribution in developing countries. This is evident by the positive and statistically significant coefficient of TFP, 0.081, in the per capita real GDP growth equation and the significantly negative coefficient, -0.121, in the inequality changes equation.

A more open trade regime seems as well to be positively related to growth and negatively associated with inequality. Our results suggest that reducing the tariffs restrictions on trade is likely to lead to faster growth as well as to reduction in inequality.

On the other hand, we find that research effort, as computed by R&D expenditures, would contribute to growth, but increase inequality.

Factors such as farm fragmentation and inequality of land holdings appear to thwart economic growth and to accentuate income disparity. The point estimates of the coefficients of these variables indicate that increasing average farm sizes and reducing disparities in land ownerships would strongly help to close the income inequality gap.

The results for human capital indicate that higher literacy rates would enhance growth, as evident by the positive and significant coefficient, 0.012 in the per capita GDP growth equation. This variable however enters positively and significantly the inequality equation, indicating that countries with better education would be less equal. Human development, as measured by the

HDI index education, appears on the other hand to support both higher growth and lower inequality.

A number of institutional quality measures are taken into consideration. The results are very assuring regarding the positive effects of institutional quality on real per capita GDP growth. Control of corruption, government effectiveness, and political stability has positive and significant effects, indicating an increase in real per capita GDP growth with improvement in these institutional indicators.

Surprisingly, however, improvement in the institutional quality indicators does not appear to have a significant bearing on inequality changes. Another surprising result is that improvement in law enforcement does not appear to have the expected effect on growth and inequality. This may be explained by the co-linearity between the institutional factors.

To evaluate the impact of agricultural productivity on poverty, Tables B6 and B7 summarize the elasticity of poverty with respect to growth, inequality and productivity. Three measures of poverty are considered: poverty headcount, poverty gap and squared poverty gap. Each measure is computed for two benchmarks. PL1 assumes the poverty line is 50% of mean GDP per capita income. PL2 assumes the poverty line is the mean income of the three first quintile shares.

A review of Table B6 confirms the well-known result that poverty, regardless of its measure, decreases with real growth. The impact of growth on poverty seems stronger in Mediterranean EU countries than in the south side. Countries such as Lebanon, Syria and Turkey, where the growth elasticity is low in absolute value, will find it harder than France, Italy, Spain and Greece to achieve fast poverty reduction. In line with the evidence in the empirical literature, we also find that inequality, as measured by the income Gini coefficient, is positively related to poverty. In general, the evidence is robust. Regardless of the poverty measure and benchmark, the results indicate that income inequality exacerbates and perpetuates poverty.

Poverty seems to react positively to inequality and negatively to growth, and where the positive impact of the Gini coefficient on poverty is the lowest, the negative impact of growth on poverty is small[19]. On average, both growth and inequality have smaller effects on poverty in SMC. The growth and inequality elasticities of poverty appear also to be greater, in absolute values, for the PL2 benchmark.

Overall, our results suggest that policies supporting both higher growth and lower inequality would induce poverty reduction. However, policies worsening income distribution may have ambiguous poverty outcomes. As inequality hampers the poverty-reducing effects of the pro-growth policies, poverty could increase unless the poverty-reducing effects of growth outweigh the poverty-raising effects of inequality.

The findings of Table 4 indicate that several pro-growth policies, such as international trade openness, agricultural productivity growth, sustainable human development and more equitable land distribution would reduce inequality and are therefore pro-poor.

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[19] It is interesting to note however that the distribution of the elasticity coefficient is not robust to the various measures of poverty. The distribution of the squared poverty gap is in sharp contrast to the distribution of the headcount and poverty gap. The squared poverty gap measures the variance from the specified benchmark. This variance is pronounced using the squared poverty gap that increases largely with the inequality Gini coefficient in Lebanon.

On the other hand, education and R&D expenditures possibly increase inequality and thus present a trade-off between their growth and inequality outcomes. Some countries may be willing to tolerate modest deteriorations in income equality in exchange for faster growth. Such trade-off is problematic in countries such as Lebanon and Syria, where the small positive growth impact would not be enough to offset the inequality poverty-raising effect.

We next compute the elasticity of poverty with respect to agricultural productivity using the benchmark PL1. The presence of dynamics allows us to assess the potential short and long run poverty alleviating effects of farming productivity growth. The results are reported in Table B7. As expected, agricultural productivity has an important role to eradicate poverty. Improving farming performance appears to strongly benefit the poor in the long run. Using the headcount measure, poverty decreases with an elasticity ranging from a low of -0.068 in Lebanon to a high of -0.236 in France, in the short run. While the long run productivity elasticity of poverty ranges from -1.83 in Lebanon to -0.64 in France. The results suggest that agricultural growth tends to play a more prominent role in reducing poverty in EU countries in the short run. Conversely, poverty alleviation should be expected to be much higher in SMC in the long run[20].

VI. Summary and Conclusion

Advocates of globalization identify strong benefits from trade liberalization in terms of resource allocation, economic growth and poverty alleviation. Despite the controversy that surrounds the trade issues, there is widespread acceptance that relatively open policies contribute significantly to development.

The existing empirical literature has been relatively successful in examining the association between trade openness, growth and poverty; it has however much less to say about the link to agricultural productivity gains. For poverty reduction, however, even if the effects of trade on industry and economic growth are important, agricultural productivity would have the most direct effect.

The analysis of this paper has focused on the impact of trade liberalization on agricultural productivity and poverty in the Mediterranean region. Agriculture is a vital sector in the Mediterranean economies as it represents an important source of income and output and employs a large segment of impoverished population. The critical rural dimension of poverty in the Mediterranean region, points to a central role for the agricultural sector in poverty eradication.

Agriculture was subject to various protection mechanisms that have distorted market incentives and resulted in inefficient allocations of resources. As the Mediterranean region proceeds with more plans for trade liberalization, attention has focused on the potential effects on agricultural productivity and poverty reduction towards evaluating the potential gains for the region in the context of globalization.

To that end, our analysis examines the effects of trade openness on agricultural productivity in the Mediterranean basin, and assesses how farming performance impinges on poverty through the projected interaction with growth and inequality.

The distinguishing aspect of this study is the attempt to account for heterogeneity in cross country agricultural production in the estimates of technical efficiency and productivity change. The methodology follows the latent class stochastic frontier models where output includes thirty six

[20] The evidence is robust with respect to the PL2 benchmark. We didn't however report the results to save space.

agricultural commodities and five input variables: crop land, irrigation water, fertilizers, labor and machines. Estimates support the presence of technological differences across countries. Mediterranean crops appear to be highly water intensive which limits productive capacity given the scarcity of water in the region. Labor, machinery, and to a lesser extent, fertilizer, seem also to be important factors for agricultural production. While there are important inefficiencies in Mediterranean agricultural production, the evidence reveals positive rates of productivity growth in most of the selected countries.

One of the salient features of the regression results is that trade openness exerts a significant ameliorating influence on the incidence of poverty in Mediterranean countries. We find evidence that severe trade restrictions may increase income inequality and adversely affect growth. Through this channel, higher trade liberalization has direct effects on decreasing poverty.

The impact of openness on poverty is further reinforced through the indirect channel. Opening up to foreign trade and direct investment seems to facilitate catching up with the best practice technology, providing substantial support for the view that openness promotes productivity growth through technology transfers. Agricultural productivity gains would lead to both faster growth and lower income inequality. Agricultural development seems, therefore, to have positive effects on the society as a whole but, given high concentration of poverty in rural areas, the poor would benefit more than proportionately. Our findings indicate that farming performance tends to play a more prominent role in reducing poverty in advanced countries, in the short run, while its poverty alleviating effects in Mediterranean developing countries are enhanced in the long run. Underlying the difference is a larger incidence of poverty in developing countries that necessitates a longer path of sustained improvement in agricultural productivity before a significant effect on poverty alleviation is realized.

To sum, the paper’s results support the benefits of trade liberalization on agricultural growth and poverty reduction in the Mediterranean region. As the agriculture sector is likely to reap the benefits of liberalization and trade openness, the income inequality gap is likely to shrink and the incidence of poverty is likely to decrease. Such added benefits provide direct testimony that developing countries in the Mediterranean basin should be more actively pursuing efforts to increase trade linkages and integration.

It is necessary to emphasize, however, that the added benefits of trade liberalization are contingent on complementary efforts that would reinforce the positive effects on per capita income growth and poverty reduction. The paper’s evidence provides a menu of complementary structural, policy and institutional measures that should be in place to ensure the maximum added benefits of trade liberalization on growth and welfare in the Mediterranean economies.

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Appendix A:

Poverty Measures, Growth and Inequality Elasticities

The growth and inequality elasticities of the Foster-Greer-Thorbecke class poverty measures are computed using the following procedure:

$P_\theta = \int_0^z \left(\frac{z-x}{z}\right)^\theta f(x)dx$, where θ $\in \{0,1,2\}$ is a parameter of inequality aversion, *z* is the poverty line, *x* is income, and *f(.)* is the density function of income. When *x* follows a lognormal distribution with mean μ and variance σ², we can respectively express the headcount, the poverty gap and the squared poverty gap indexes as[21]:

$$P_0 = \Phi\left(\frac{\log\left(z/y\right)}{\sigma} + \frac{\sigma}{2}\right)$$

$$P_1 = \Phi\left(\frac{\log\left(z/y\right)}{\sigma} + \frac{\sigma}{2}\right) - \frac{y}{z}\Phi\left(\frac{\log\left(z/y\right)}{\sigma} - \frac{\sigma}{2}\right)$$

$$P_2 = \Phi\left(\frac{\log\left(z/y\right)}{\sigma} + \frac{\sigma}{2}\right) - 2\frac{y}{z}\Phi\left(\frac{\log\left(z/y\right)}{\sigma} - \frac{\sigma}{2}\right) + \left(\frac{y}{z}\right)^2 e^{\sigma^2}\Phi\left(\frac{\log\left(z/y\right)}{\sigma} - \frac{3\sigma}{2}\right)$$

Where Φ denotes the cumulative normal distribution and *y* the average per capita income. The standard deviation of the lognormal distribution is given by $\sigma = \sqrt{2}\Phi^{-1}\left(\frac{G+1}{2}\right)$, with *G* the Gini index.

The growth elasticities are given by:

$$\eta_0 = \frac{\partial \log(P_0)}{\partial \log(y)} = -\frac{1}{\sigma}\lambda\left(\frac{\log\left(z/y\right)}{\sigma} + \frac{\sigma}{2}\right)$$

[21] See Lopez and Servén, (2006) for details.

Where $\lambda = \dfrac{\phi(.)}{\Phi(.)}$ and ϕ the standard normal density. For the poverty gap and the squared poverty gap $\eta_\alpha = \dfrac{\alpha(P_\alpha - P_{\alpha-1})}{P_\alpha}$, $\alpha \in \{1,2\}$[22] .

The Gini elasticities with respect to the three poverty indexes are given by:

$$\kappa_0 = \frac{\partial \log(P_0)}{\partial \log(G)} = \lambda \left(\frac{\log\left(z/y \right)}{\sigma} + \frac{\sigma}{2} \right) \left(\frac{\sigma}{2} - \frac{\log\left(z/y \right)}{\sigma} \right) / \left(\sqrt{2}\sigma\phi\left(\sigma/\sqrt{2} \right) / G \right)$$

$$\kappa_1 = \frac{\partial \log(P_1)}{\partial \log(G)} = \left(\frac{\phi(a)(-b) - y/z\, \phi(b)(-a)}{P_1} \right) / \left(\sqrt{2}\sigma\phi\left(\sigma/\sqrt{2} \right) / G \right)$$

$$\kappa_2 = \frac{\partial \log(P_2)}{\partial \log(G)} = \left(\frac{\phi(a)(-b) - 2y/z\, \phi(b)(-a) + \left(\frac{y}{z} \right)^2 e^{\sigma^2} \left(2\sigma^2 \Phi(c) + \phi(c) \left(\frac{-\log\left(z/y \right)}{\sigma} - 3\sigma \right) \right)}{P_2} \right) / \left(\sqrt{2}\sigma\phi\left(\sigma/\sqrt{2} \right) / G \right)$$

With: $a = \left(\dfrac{\log\left(z/y \right)}{\sigma} + \dfrac{\sigma}{2} \right)$, $b = \left(\dfrac{\log\left(z/y \right)}{\sigma} - \dfrac{\sigma}{2} \right)$, and $c = \left(\dfrac{\log\left(z/y \right)}{\sigma} + \dfrac{3\sigma}{2} \right)$

[22] See Kakwani, (1990); Bourguignon, (2003); and Lopez and Seven, (2006).

Appendix B:

Detailed Variables for Investigation

Variables Used to Estimate the Stochastic Production Frontier:

- Outputs: we consider thirty six agricultural commodities belonging to six 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). These commodities count among the main produced and traded products in the Mediterranean region. Important trade restrictions are currently imposed on most of these goods that are considered to be sensitive.
- Inputs: given difficulty in collecting data on input requirement by crop and by country, this study opts to consider only five input variables: cropland, irrigation water, fertilizers, labor and machines. The data for the input use by crop for each country are 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[23].
- Factors Influencing Technical Efficiency:

  The inefficiency effect model incorporates an array of control variables representing: irrigation, defined as the percent of land under irrigation; land fragmentation, which is controlled for by the percent of holdings under five hectares; average holdings, measured by the country's average farm size, machinery equipment, measured by the total number of wheeled and crawler tractors used; and educational attainment approximated by tertiary schooling.
- Determinants of the Latent Class Probabilities:

  The separating variables employed are related to input and climate endowments and to geographic features. We consider country averages of: percent of land under irrigation, total number of wheel and crawler tractors, total applied fertilizers, land quality approximated by the part of agricultural area incurring severe and very severe degradation, inequality in

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[23] 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 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: $Q_i^k = \Pi_{j:1}^{I} \left(T_{ij}^{k} \right)^{a_j}$ where a_j is the share of country *j* in the total production of the *k-th* commodity (including countries *1,…,I* only). See Hallak (2003) and Rao *et al*. (2004) for a similar procedure.

operational holdings measured by the land Gini coefficient and human capacities approximated by the human development index.

- Factors Influencing the Catching up Process:

  We investigate the determinants of the catching up process by regressing the TGR growth rate on a set of explanatory variables including:

  - Trade openness: two variables are used as measures of openness, the standard ratio of exports plus imports to GDP and trade barriers that include ad-valorem tariffs and indices of non-tariff barriers[24].
  - Agricultural research effort: data on agricultural R&D expenditures include public and private R&D efforts. As data are available on a limited basis between the years 1990 and 1995, the expenditure observations were interpolated to obtain a larger panel.
  - Human capital: the Human capital indicators include the percentage of adult population with tertiary education, the literacy rate and the human development index as proxy of educational attainment as well as infant mortality as a measure of health.
  - Foreign direct investment: FDI, measured in proportion to GDP per capita, is included to accommodate the role of technological spillovers.
  - Other institutional factors: various institutional variables are considered as indicators of a country's governance, namely, voice and accountability, political stability, government effectiveness, regulatory quality, rule of law and control of corruption.

- Variables Used to Estimate the Growth and Inequality Equations:

  Income and inequality data are taken from the latest available date within the period 1990 to 2005. We approximate mean income by per capita GDP in 2000 international dollars, drawn from the World Development Indicators (WDI). Data on income distribution are from Dollar and Kraay's (2002) and UN-WIDER World Income Inequality Databases.

- Although these datasets contain a large amount of information about the distribution of income within many countries, they form however unbalanced and irregularly spaced panel of observations. We approximate the missing values using a simple linear time-trend forecast[25].
- To assess the respective contributions of growth and inequality to poverty changes, we need to calculate poverty measures as well as the elasticities of poverty with respect to growth and inequality. Under the assumption of a log normal income distribution, we can derive simple

[24] 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 (Bureau and Salvatici 2002). Data on entry prices come from the FEMISE, CIHEAM and ESCWA reports. We use a four-year average of unit values and of imports to reduce the variability due to climatic effects.

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.

[25] A similar approximation has been used in Sala-i-Martin (2002).

expressions for these variables which depend only on the prevailing degree of inequality, and on the poverty line relative to mean per capita income (Lopez 2004; Lopez and Servén 2006).

The choice of the poverty line is nevertheless problematic, given that our study includes some countries of the European Union. Applying a developing Mediterranean country poverty line to the EU will imply very low poverty rates in that region; while an EU poverty line will give very high poverty rates in many low-income countries. Our analysis reports the results for the poverty measures and the growth and inequality elasticities of poverty using two specific poverty lines, set at 50% of the mean per capita GDP (at constant 2000$) and the mean income of the three first quintiles in each country. We compute three common poverty measures: the headcount index, the poverty gap index, and the squared poverty gap index.

Table 1: Latent Class Model Parameter Estimates: Total pool

	CLASS 1	CLASS 2	CLASS 3	CLASS4
	Production Frontier			
Land	0.184**	0.174**	0.192*	0.131**
Water	0.377**	0.235**	0.187**	0.188**
Labor	0.162*	0.347**	0.152*	0.239*
Fertilizers	0.036*	0.045	-0.006	0.195*
Capital	0.041*	0.018*	0.19**	0.196**
Time	0.023*	0.036**	0.071**	0.088*
Intercept	0.97*	1.766*	1.98*	2.91*
	Efficiency term			
Irrigation	-0.133*	-0.015	-0.105**	-0.123*
Land fragmentation	0.028**	0.0302*	0.053**	0.024*
Average holding	-0.0215*	-0.011*	-0.015*	-0.012*
Machinery	-0.047*	-0.063**	-0.105**	-0.097*
Tertiary	-0.026**	-0.047**	-0.0127*	-0.019*
σ^2	0.258	0.64	0.55	0.33
$\gamma = \sigma_u^2/\sigma^2$	0.67	0.86	0.87	0.82
	Probabilities			
Irrigation	-0.075*	-0.117*	-0.029*	
Total fertilizers	-0.011*	0.011**	-0.0068*	
Total machinery	-0.074*	-0.133*	0.0129**	
HDI	0.113**	0.021*	-0.0237**	
Land GINI	-0.091	0.022**	-0.026**	
Intercept	0.96*	1.359*	1.042*	
Log-likelihood	-179.75			
Number of Obs.	1344			

Notes: the variables in the production frontier and efficiency function are in natural logarithm. The significance at the 10% and 1% levels is indicated by * and ** respectively. A negative sign in the inefficiency model means that the associated variable has a positive effect on technical efficiency.

Table 2: Prior and Posterior Probabilities

CLASS	COUNTRIES	PRIOR PROB.	POST. PROB.
	FRUITS		
1	Algeria, Egypt, Jordan, Morocco, Portugal, Syria, Tunisia, Turkey	0.696	0.765
2	France, Greece, Italy	0.748	0.849
3	Spain, Israel, Lebanon	0.589	0.747
	CITRUS		
1	France	0.926	0.994
2	Algeria, Portugal, Jordan, Lebanon, Tunisia	0.826	0.843
3	Greece, Morocco, Syria	0.785	0.806
4	Egypt, Italy, Israel, Spain, Turkey	0.827	0.98
	SHELL FRUITS		
1	Egypt, Greece, Israel, Jordan, Lebanon, Morocco, Portugal	0.76	0.796
2	Algeria, France, Syria, Tunisia	0.653	0.658
3	Italy, Spain, Turkey	0.844	0.937
	VEGETABLES		
1	Jordan, Lebanon, Portugal	0.784	0.853
2	Algeria, Egypt, Greece, Israel, Italy, Morocco, Spain, Syria, Turkey	0.604	0.7
3	France, Tunisia	0.627	0.809
	CEREALS		
1	Algeria, Israel, Jordan, Lebanon, Portugal, Tunisia	0.813	0.817
2	Greece, Morocco, Syria	0.889	0.92
3	Egypt, France, Italy, Spain, Turkey	0.849	0.893
	PULSES		
1	Israel, Jordan, Lebanon	0.739	0.966
2	Algeria, Greece, Italy, Portugal, Morocco, Syria, Spain, Tunisia, Egypt	0.629	0.921
3	France, Turkey	0.924	0.994
	TOTAL POOL		
1	Israel, Jordan	0.439	0.627
2	Morocco, Portugal, Syria, Tunisia	0.583	0.727
3	Algeria, Greece, Lebanon	0.429	0.651
4	France, Egypt, Italy, Turkey, Spain	0.656	0.851

Table 3: Determinants of TGR Growth

	TRADE VOLUMES		TRADE BARRIERS	
	COEFFICIENTS	T-VALUES	COEFFICIENTS	T-VALUES
Literacy	2.11*	2.53	2.15*	1.73
Tertiary	1.02**	2.79	1.03**	2.82
HDI	0.52	1.62	0.47*	1.75
Mortality	-1.76*	-1.91	-1.24**	-2.64
Trade volumes	0.82**	2.87		
Trade barriers			-0.35*	-2.19
R&D	0.41*	2.17	0.36*	1.81
FDI	3.31**	3.56	3.05**	3.62
Rule of law	0.33*	1.91	0.37*	2.14
Control of corruption	0.075	0.85	0.07	0.7
Government effectiveness	0.017	0.4	0.014	1.11
Political stability	0.038*	1.79	0.032	1.19
Regularity quality	-0.86**	-8.02	-0.85**	-7.91
Voice and accountability	0.27**	2.67	0.28*	2.07
R^2	0.532		0.529	

Table 4: Determinants of Growth and Inequality

VARIABLES	COEFFICIENT	T-RATIO
	GROWTH EQUATION	
Lagged income	-0.0143*	-2.03
Gini	0.0108*	2.39
TFP	0.08107*	2.6
Trade barriers	-0.0324*	-2.68
R&D	0.0309*	2.03
Land fragmentation	-0.0195	-1.19
Land Gini	-0.0341*	-1.78
HDI	0.0131**	3.36
Literacy	0.0118*	2.13
Control of corruption	0.0187**	3.74
Government effectiveness	0.0222*	2.78
Political stability	0.0384*	2.04
Rule of law	-0.0035*	-2.9
Regularity quality	-0.0097*	-2.42
M1: First order serial correlation	z = -2.36 p = 0.018	
M2: Second order serial correlation	z = -1.57 p = 0.117	
Sargan instrumental validity test	$\chi^2(78) = 74.06$ p = 0.605	
	INEQUALITY CHANGES EQUATION	
Lagged Gini	-0.0258**	-2.94
Lagged income	-0.016*	-2.09
TFP	-0.121**	-4.17
Tariff barriers	0.0347**	3.29
R&D	0.0162**	3.07
Land fragmentation	0.0692*	2.85
Land Gini	0.0665*	2.42
HDI	-0.0229**	-2.94
Literacy	0.0141**	3.14
Control of corruption	0.0056	0.56
Government effectiveness	0.00766	1.19
Political stability	0.00307	1.22
Rule of law	-0.0347*	-1.84
Regularity quality	0.0151	1.73
M1: First order serial correlation	z = -2.39 p = 0.017	
M2: Second order serial correlation	z = 0.15 p = 0.884	
Sargan instrumental validity test	$\chi^2(79) = 64.8$ p = 0.875	
Number of observations	224	

The models are estimated with time dummies using the Blundell and Bond (1998) GMM estimator. The significance at the 10% and 1% levels is indicated by * and ** respectively.

Appendix C: Summary Statistics and Estimation Results

Table B1: Descriptive Statistics

COUNTRY		GDPCAP	AGRVA	GINI	PHEAD1	PHEAD2	QUAL.	IRR.	AGLAND	FERTCONS	AGMACH	RAIN	LANDGINI	AVHOLD	LFRAG
Algeria	**Mean**	1758.58	10.78	34.07	21.51	9.32	21	6.83	16.61	127.92	1.26	211.50	67	2.76	55
	Std. Dev.	135.02	1.00	2.33	5.77	3.62	0	0.27	0.21	33.20	0.04	0.00	0	0.00	0
Spain	**Mean**	13349.63	5.142	32.69	20.02	10.35	38	19.08	60.25	1460.86	6.04	321.70	86	1.13	63
	Std. Dev.	1495.92	1.042	2.78	6.68	4.57	0	1.33	0.44	201.72	0.79	0.00	0	0.15	1
France	**Mean**	21140.55	3.10	28.73	14.72	6.72	9	12.83	54.47	2522.83	7.15	478.00	54	4.76	24
	Std. Dev.	1731.34	0.35	1.67	5.31	3.33	0	1.03	0.55	322.90	0.39	0.00	0	0.00	5
Greece	**Mean**	9909.64	8.97	33.69	21.45	9.72	48	35.70	68.57	1794.52	8.71	86.10	57	0.60	76
	Std. Dev.	1238.74	1.65	0.78	5.86	3.42	0	2.64	2.62	288.75	0.66	0.00	0	0.00	1
Italy	**Mean**	17759.61	3.17	32.70	19.65	8.66	28	24.28	53.04	2030.19	18.79	250.80	78	0.55	77
	Std. Dev.	1187.47	0.35	1.58	4.08	2.55	0	0.95	1.55	224.22	1.71	0.00	0	0.10	1
Portugal	**Mean**	9478.10	5.10	36.27	24.41	8.82	21	24.26	42.12	1206.13	8.22	78.60	73	0.38	80
	Std. Dev.	890.24	1.59	0.49	4.38	2.24	0	2.99	1.46	75.45	1.87	0.00	0	0.02	1
Israel	**Mean**	16815.06		37.24	25.37	10.69	6	45.38	26.27	2854.41	7.32	9.20	80	3.91	92
	Std. Dev.	1276.56		4.66	5.01	4.60	0	1.32	0.30	418.00	0.20	0.00	0	0.00	0
Jordan	**Mean**	1759.70	4.36	37.79	26.15	9.96	31	18.65	13.20	850.96	2.24	9.90	68	0.85	79
	Std. Dev.	152.46	2.24	2.62	6.32	4.25	0	0.90	0.19	225.71	0.33	0.00	0	0.00	0
Lebanon	**Mean**	4774.73	8.64	54.94	45.73	22.83	25	32.10	32.22	2474.03	3.40	6.90	67	1.12	97
	Std. Dev.	630.79	2.41	0.03	5.43	4.45	0	2.55	0.96	691.33	1.28	0.00	0	0.00	0
Morocco	**Mean**	1199.09	16.42	38.50	27.06	10.72	14	13.86	68.58	392.09	0.50	154.70	67	1.96	71
	Std. Dev.	95.31	1.83	1.36	2.74	1.47	0	1.23	0.57	61.37	0.06	0.00	0	0.00	0
Syria	**Mean**	1080.36	26.79	43.32	32.83	15.74	60	20.66	74.62	705.90	1.89	46.70	67	2.26	78
	Std. Dev.	84.17	2.90	1.68	3.77	2.70	0	3.76	0.53	57.71	0.36	0.00	0	0.00	0
Tunisia	**Mean**	1889.59	13.25	39.90	29.41	12.19	79	7.72	60.76	348.83	1.15	33.90	65	2.37	53
	Std. Dev.	293.65	1.83	0.19	7.21	4.22	0	0.46	1.84	35.63	0.15	0.00	0	0.00	0
Turkey	**Mean**	2815.62	15.50	43.16	32.51	13.46	89	16.94	51.25	765.15	3.57	459.50	59	1.07	66
	Std. Dev.	256.20	1.85	3.55	7.45	5.52	0	2.12	0.56	85.42	0.54	0.00	0	0.29	1
Egypt	**Mean**	1392.57	16.94	35.37	23.48	12.07	9	99.69	3.24	4050.50	2.93	51.40	55	1.10	87
	Std. Dev.	172.29	0.88	3.60	3.81	2.86	0	1.32	0.26	433.79	0.25	0.00	0	0.04	12

COUNTRY		LITRACY	TERTIARY	HDI	MORT	R&D	FDI	TRADE	RLAW	CORR	GOVEFF	POLSTAB	REGQUAL	VOICE
Algeria	**Mean**	62.59	14.58	68	41.81	95.19	0.71	0.03	-0.81	-0.64	-0.74	-2.00	-0.85	-1.21
	Std. Dev.	5.83	2.98	3	6.23	2.15	0.68	0.08	0.17	0.17	0.28	0.63	0.26	0.23
Spain	**Mean**	97.25	51.43	91	5.09	476.50	2.73	9.06	1.19	1.38	1.65	0.54	1.16	1.14
	Std. Dev.	0.61	10.24	2	1.45	43.48	1.61	2.23	0.10	0.22	0.21	0.27	0.18	0.09
France	**Mean**	99.70	48.75	92	5.18	2885.00	1.97	3.07	1.34	1.44	1.53	0.64	0.93	1.18
	Std. Dev.	0.00	5.83	1	1.17	136.48	0.91	0.53	0.14	0.17	0.19	0.26	0.22	0.14
Greece	**Mean**	96.13	51.11	89	6.73	63.40	0.85	1.93	0.66	0.64	0.75	0.42	0.85	0.95
	Std. Dev.	0.72	15.22	2	2.03	8.00	0.35	0.46	0.07	0.17	0.10	0.22	0.16	0.09
Italy	**Mean**	98.18	45.66	91	5.82	113.80	0.65	1.12	0.81	0.71	0.83	0.62	0.82	1.09
	Std. Dev.	0.27	10.43	2	1.44	9.08	0.43	0.33	0.16	0.18	0.14	0.31	0.22	0.09
Portugal	**Mean**	90.81	40.55	88	6.81	70.15	2.33	0.61	1.17	1.31	1.15	1.05	1.12	1.33
	Std. Dev.	2.29	12.13	2	2.27	9.68	1.81	0.18	0.12	0.12	0.17	0.22	0.19	0.07
Israel	**Mean**	94.09	46.06	89	6.64	21.01	1.75	2.73	0.92	1.13	1.02	-0.97	0.82	0.82
	Std. Dev.	1.87	8.19	2	1.65	2.60	1.16	1.11	0.13	0.27	0.22	0.37	0.17	0.22
Jordan	**Mean**	86.93	28.22	72	27.45	10.14	2.41	9.87	0.45	0.16	0.34	-0.14	0.36	-0.36
	Std. Dev.	3.07	5.39	3	3.37	1.67	2.83	3.85	0.16	0.15	0.18	0.21	0.23	0.30
Lebanon	**Mean**	84.54	39.40	72	29.09	11.47	0.91	1.49	-0.16	-0.44	-0.17	-0.75	0.04	-0.60
	Std. Dev.	2.66	4.35	3	1.79	0.96	0.63	0.64	0.22	0.12	0.18	0.24	0.35	0.17
Morocco	**Mean**	46.10	9.98	58	50.68	138.54	1.07	3.65	0.22	0.06	0.02	-0.21	0.10	-0.51
	Std. Dev.	4.57	0.56	3	11.11	25.79	1.31	0.87	0.25	0.20	0.15	0.24	0.27	0.18
Syria	**Mean**	72.17	17.69	68	23.78	65.36	0.86	0.28	-0.43	-0.64	-0.99	-0.48	-0.96	-1.61
	Std. Dev.	4.82	0.00	3	6.33	6.96	0.62	0.20	0.09	0.16	0.24	0.28	0.17	0.16
Tunisia	**Mean**	67.64	16.85	70	28.75	58.85	2.33	0.42	0.32	0.29	0.71	0.32	0.28	-0.86
	Std. Dev.	5.16	6.89	4	7.27	10.64	1.05	0.11	0.24	0.28	0.27	0.27	0.31	0.21
Turkey	**Mean**	82.98	20.22	71	45.85	233.75	0.65	0.74	-0.03	-0.21	-0.10	-0.97	0.32	-0.55
	Std. Dev.	3.18	5.59	3	12.65	19.01	0.46	0.24	0.07	0.21	0.24	0.27	0.29	0.34
Egypt	**Mean**	55.60	27.57	62	48.93	185.45	1.15	0.26	0.07	-0.25	-0.13	-0.45	-0.16	-0.90
	Std. Dev.	7.89	6.74	3	16.02	7.71	0.51	0.15	0.08	0.16	0.23	0.37	0.29	0.17

Table B2: Selection Statistics

Classes	Fruits		Citrus		Shell fruits		Vegetables		Cereals		Pulses		Total Pool	
	AIC	**SBIC**	**AIC**	**SBIC**	**AIC**	**SBIC**	**AIC**	**SBIC**	**AIC**	**SBIC**	**AIC**	**SBIC**	**AIC**	**SBIC**
1	744	750.8	779.54	786.4	934.6	941.4	657.8	664.7	981	987.9	895.7	902.5	5302	5384
2	718.7	735.8	718	735	918.1	935.2	638.2	655.3	930.9	947.9	863.1	880.1	5218	5287
3	667.8	695.1	706.8	734.1	771.4	839.6	531	578.8	828.1	886.1	841.6	879.1	5160	5235
4	673.6	711.2	680.1	717.6	837.9	916.4	608.6	646.2	876.9	945.2	855.2	903	5058	5173

Table B3: Latent Class Model Parameter Estimates: Commodity Groups

	Fruits			Citrus				Cereals			Shell Fruits			Pulses			Vegetables		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 4	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Production frontier																			
Land	0.425**	0.561**	0.439**	0.044	0.27*	0.397**	0.285*	0.251**	0.489**	0.142*	0.251*	0.63**	0.21**	0.478**	0.472**	0.51**	0.21**	0.22**	0.361*
Water	0.773**	0.578**	0.159**	0.041	0.126**	0.657**	0.795**	0.184**	0.163**	0.145*	0.504*	0.176*	0.174**	0.152**	0.046*	0.14*	0.559**	0.603**	0.305**
Labor	0.14*	0.244**	0.09	0.17*	0.182**	0.149**	0.089*	0.073*	0.044	0.122*	0.153*	0.124**	0.295*	0.195*	0.192**	0.163*	0.343**	0.131*	0.147**
Fertilizers	0.079*	0.314**	0.217**	0.036*	0.11*	0.221*	0.195*	0.054*	0.101	0.033*	0.202**	0.11*	0.209*	0.034*	0.18*	0.251**	0.021*	0.018*	0.089*
Capital	0.065*	0.446*	0.341**	0.014*	0.131*	0.265**	0.692**	0.263**	0.459*	0.286**	0.163**	0.105*	0.239**	0.113*	0.245**	0.265**	0.035*	0.145*	0.175**
Time	0.21**	0.045*	0.0029	0.047*	0.022**	0.012*	0.084*	0.059**	0.016*	0.052**	0.034**	0.085*	0.011	0.04*	0.018*	0.089**	0.016*	0.026*	0.051**
Intercept	0.99**	1.14*	1.45**	0.86*	3.71*	3.85*	3.45*	1.15**	2.21*	3.49*	0.97*	1.91*	1.83*	1.08*	2.4*	2.34*	1.52*	2.52*	0.18*
Efficiency term																			
Irrigation	-0.03**	-0.18**	-0.017	-0.094*	-0.022*	-0.025**	0.036	-0.02**	0.029	-	-0.04**	-0.027*	-0.086*	-0.03**	-0.029*	-0.017*	0.097	-0.09**	-0.021*
Land fragm.	0.071**	0.252**	0.009	0.021*	0.011**	0.0197**	0.024*	0.042*	0.313**	0.043**	0.018*	0.18**	0.071**	0.0122**	0.043**	0.022**	0.045*	0.071**	0.125**
Av. holding	-0.12**	-0.048*	-	-	-	-	-	-0.24**	-0.148*	-0.081*	-	-	-	-0.451*	-0.361*	-0.068*	-0.023*	-0.011	-0.018*
Machinery	-0.08**	-0.35**	-0.12**	-0.096*	-0.06**	-0.069**	-0.071*	-0.16**	-0.35**	-0.09**	-0.03**	-0.054*	-0.143*	-0.097**	-0.21**	-0.36**	-0.05**	-0.01**	-0.003**
Tertiary	0.0827	-0.039*	-0.04**	-0.011*	-0.014*	-0.017*	-0.015*	-	-0.017*	-0.009*	-0.047*	-0.07**	-0.09**	-0.042*	-0.012*	-0.017*	-0.012*	-0.032*	-0.037*
σ²	0.132	0.136	0.132	0.143	0.593	0.359	0.539	0.544	0.739	0.72	0.425	0.5	0.78	0.273	0.349	0.754	0.337	0.49	0.729
γ= σ_u^2/σ^2	0.81	0.87	0.82	0.89	0.574	0.782	0.94	0.87	0.94	0.91	0.778	0.624	0.89	0.594	0.84	0.91	0.791	0.81	0.94
Probabilities																			
Irrigation		-0.39**	-0.47**	-	-	-			-0.297*	-0.065*		0.25**	0.087**		0.312*	0.728**		-0.182*	0.076
Fertilizers		0.09**	0.111**	-0.08*	-0.06**	-0.068*			-0.032*	0.136**		0.03**	0.07*		0.031*	0.027*		0.03	0.002
Machinery		-0.027*	-0.318*	-0.96**	-0.152*	-0.118**			0.928**	0.225**		-0.88**	-0.87**		-0.41**	0.686*		-0.012*	-0.057
HDI		0.127*	-0.07	0.046*	-0.075*	-0.055**			-0.047*	0.46**		-	-		-0.025*	-0.356*		-0.025*	-0.356*
Land GINI		-0.27**	-0.05*	-0.747*	-0.041*	-0.78*			-0.419*	-0.21**		0.156**	0.263**		0.275*	-0.38**		0.123**	0.046**
Land quality		-	-	-	-	-			-	-		0.387**	0.259**		0.398**	0.762**		0.273**	0.039**
Intercept		7.12*	6.87*	-1.16*	1.824*	1.77*			2.34*	9.92*		-1.3*	-3.77*		-2.58*	-1.12*		-2.57*	-3.91*
Log-likelih.		154.74			69.716				688.573			327.306			297.54			125.55	
N. of Obs.		224			224				224			224			224			224	

*,** significant at the 1% and 10% levels respectively

Table B4: Efficiency Indexes by Class

	OVERALL SAMPLE			CLASS 1			CLASS 2			CLASS3			CLASS4		
	Mean	**St.dev**	**Nb.**	**Mean**	**St.dev**	**Nb.**	**Mean**	**St.dev**	**Nb.**	**Mean**	**St.dev**	**Nb.**	**Mean**	**St.dev**	**Nb.**
Fruits	0.527	0.249	224	0.492	0.326	93	0.631	0.265	87	0.606	0.276	45			
Citrus	0.707	0.178	224	0.691	0.073	16	0.548	0.231	68	0.737	0.116	60	0.825	0.221	80
Shell	0.692	0.218	224	0.603	0.283	112	0.741	0.177	64	0.761	0.129	48			
Vegetables	0.558	0.212	224	0.733	0.161	35	0.486	0.282	146	0.589	0.274	43			
Cereals	0.526	0.291	224	0.427	0.116	101	0.556	0.228	43	0.665	0.171	80			
Leguminous	0.623	0.128	224	0.747	0.177	56	0.546	0.271	136	0.82	0.105	32			
Total pool	0.786	0.129	1344	0.649	0.309	68	0.729	0.134	418	0.783	0.167	296	0.876	0.143	562

Table B5: Efficiency Scores and TFP Growth

	FRUITS		CITRUS		SHELL		VEGETABLES		CEREALS		PULSES		POOL	
	TE[a]	**TFPG**[b]	**TE**	**TFPG**	**TE**	**TFPG**	**TE**	**TFPG**	**TE**	**TFPG**	**TE**	**TFPG**	**TE**	**TFPG**
ALGERIA	0.471	4.77	0.375	4.82	0.613	-1.52	0.403	-0.43	0.452	3.98	0.521	-0.79	0.648	1.77
EGYPT	0.545	9.28	0.718	4.89	0.595	1.71	0.352	5.82	0.529	5.07	0.624	4.89	0.705	5.25
FRANCE	0.733	6.45	0.691	-1.89	0.858	1.13	0.592	7.48	0.902	6.57	0.953	6.4	0.973	4.3
GREECE	0.508	3.78	0.787	1.42	0.524	-2.01	0.413	-0.48	0.636	4.16	0.611	0.97	0.798	1.28
ISRAEL	0.521	3.85	0.741	2.79	0.743	2.59	0.607	3.83	0.397	-1.24	0.629	4.02	0.702	2.62
ITALY	0.633	8.77	0.777	5.89	0.696	4.28	0.511	6.45	0.656	6.26	0.709	1.11	0.918	5.44
JORDAN	0.368	4.38	0.565	3.05	0.582	3.63	0.689	3.08	0.283	-1.65	0.743	3.47	0.624	2.64
LEBANON	0.702	9.1	0.675	2.96	0.754	7.91	0.865	9.88	0.508	7.88	0.847	-1.59	0.829	4.92
MOROCCO	0.379	-0.71	0.712	4.7	0.707	2.47	0.428	6.29	0.481	1.49	0.561	4.56	0.697	3.11
PORTUGAL	0.497	0.76	0.716	0.28	0.809	5.85	0.743	-0.22	0.509	1.6	0.493	-0.92	0.738	1.2
SPAIN	0.615	6.19	0.882	5.02	0.646	-1.96	0.539	6.26	0.641	9.48	0.537	6.1	0.906	5.12
SYRIA	0.362	2.96	0.739	5.75	0.825	5.85	0.616	5.16	0.619	3.49	0.669	1.27	0.726	4.33
TUNISIA	0.479	1.82	0.559	3.25	0.708	2.55	0.566	3.37	0.527	1.23	0.557	2.41	0.723	2.44
TURKEY	0.587	9.42	0.942	9.63	0.941	8.77	0.642	7.91	0.771	5.92	0.737	8.27	0.912	8.31

a: Technical efficiency score, b: TFP growth.

Table B6: Growth and Inequality Elasticities

	HEADCOUNT				POVERTY GAP				SQUARED POVERTY GAP			
	PL1		PL2		PL1		PL2		PL1		PL2	
	GE[a]	IE[b]	GE	IE	GE	IE	GE	IE	GE	IE	GE	IE
ALGERIA	-4.2	2.13	-8.52	3.9	-2.74	3.42	-3.42	5.35	-1.55	19.78	-1.88	316.13
SPAIN	-4.6	2.25	-8.24	3.65	-2.96	3.55	-3.54	5.09	-1.67	24.65	-1.96	244.23
FRANCE	-6.08	2.69	-11.08	4.32	-3.68	4.05	-4.38	5.08	-2.06	54.77	-2.4	455
GREECE	-4.2	2.12	-7.87	3.76	-2.75	3.41	-3.39	5.2	-1.56	18.54	-1.87	259.39
ITALY	-4.42	2.21	-8.33	3.88	-2.92	3.52	-3.58	5.34	-1.65	14.29	-1.97	246.95
PORTUGAL	-3.56	1.92	-7.65	4.01	-2.41	3.18	-3.16	5.47	-1.37	12.51	-1.74	286.4
ISRAEL	-3.44	1.87	-6.77	3.71	-2.35	3.12	-3.03	5.15	-1.34	18.39	-1.67	214.1
JORDAN	-3.38	1.85	-7.42	3.94	-2.27	3.1	-3	5.39	-1.3	17.74	-1.65	315.08
LEBANON	-1.77	1.25	-2.98	2.95	-1.09	2.36	-1.51	4.33	-0.63	149.12	-0.84	884.11
MOROCCO	-3.17	1.77	-6.21	3.68	-2.17	3.01	-2.83	5.12	-1.24	18.16	-1.56	192.68
SYRIA	-2.59	1.56	-4.42	3.13	-1.75	2.75	-2.26	4.52	-1	40.51	-1.25	166.43
TUNISIA	-3.02	1.71	-6.02	3.6	-2.03	2.93	-2.66	5.03	-1.16	25.33	-1.47	251.81
TURKEY	-2.7	1.6	-5.71	3.62	-1.8	2.8	-2.43	5.04	-1.03	39.46	-1.34	330.83
EGYPT	-3.71	1.95	-6.04	3.3	-2.54	3.22	-3.08	4.71	-1.45	13.47	-1.71	114.51

a: Growth elasticity   b: Inequality elasticity
PL1 = Poverty line is 50% of mean GDP per capita income
PL2 = Poverty line is the mean income of the three first quintile shares

Table B7: Short and Long Run Elasticities of Poverty with Respect to Agricultural Productivity

	HEADCOUNT		POVERTY GAP		SQUARED POVERTY GAP	
	SHORT RUN	LONG RUN	SHORT RUN	LONG RUN	SHORT RUN	LONG RUN
ALGERIA	-0.171	-1.40	-0.329	-8.04	-2.310	-67.24
SPAIN	-0.185	-1.24	-0.345	-8.18	-2.899	-84.17
FRANCE	-0.236	-0.64	-0.404	-8.90	-6.543	-189.42
GREECE	-0.170	-1.36	-0.328	-7.99	-2.160	-62.87
ITALY	-0.181	-1.36	-0.341	-8.13	-1.646	-47.81
PORTUGAL	-0.147	-1.59	-0.301	-7.68	-1.431	-41.96
ISRAEL	-0.141	-1.58	-0.293	-7.56	-2.142	-62.66
JORDAN	-0.138	-1.60	-0.291	-7.60	-2.064	-60.44
LEBANON	-0.068	-1.83	-0.203	-6.71	-17.962	-522.94
MOROCCO	-0.129	-1.62	-0.280	-7.43	-2.115	-62.00
SYRIA	-0.104	-1.73	-0.249	-7.12	-4.819	-140.86
TUNISIA	-0.122	-1.63	-0.271	-7.35	-2.982	-87.30
TURKEY	-0.109	-1.71	-0.255	-7.23	-4.692	-137.13
EGYPT	-0.150	-1.47	-0.305	-7.63	-1.547	-45.22

Descriptive Statistics

GDPCAP: GDP per capita (2000 US $)

AGRVA: Agriculture value added (% of GDP)

GINI: GINI index

PHEAD1: Poverty headcount when poverty line is 50% of mean per capita GDP

PHEAD2: Poverty headcount when poverty line is the mean income of three first quintiles

QUAL: soil quality measured by the part of agricultural area incurring severe and very severe degradation in %

IRR: part of irrigated area in %

AGLAND: agricultural land (% of land area)

FERTCONS: Fertilizer consumption (100 grams per hectare of arable land)

AGMACH: Agricultural machinery, tractors per 100 hectares of arable land

RAIN: Average precipitations (1961-1990) in km^3/year.

LANDGINI: GINI coefficient for land holdings

AVHOLD: Average farm size

LFRAG: Part of holdings under 5ha

LITRACY: Literacy rate, adult total (% of people ages 15 and above)

TERTIARY: Labor force with tertiary education (% of total)

HDI: Human Development Index

MORT: Mortality rate, infant (per 1,000 live births)

R&D: agricultural R&D expenditures

FDI: Foreign direct investment, net inflows (% of GDP)

TRADE: Trade openness measured by agricultural export and import as % of agricultural value added

RLAW: Rule of law

CORR: Control of corruption

GVEFF: Government effectiveness

POLSTAB: Political stability

REGQUAL: Regularity quality

VOICE: Voice and accountability.