

Does Agricultural Trade Liberalization Help the Poor in Tunisia? A Dynamic General Equilibrium Approach

Nadia Belhaj Hassine¹ Bernard Décaluwé²

Abstract

Computable General Equilibrium (CGE) models have gained continuously in popularity as an empirical tool for assessing the impact of trade liberalization on growth, poverty and equity. In recent years, there have been attempts to extend the scope of CGE trade models to the analysis of the interaction of agricultural growth, poverty and income distribution. Conventional models ignore however the channels linking technical change in agriculture, trade openness and poverty. This study seeks to incorporate econometric evidence of these linkages into a dynamic sequential CGE model, to estimate the impact of alternative trade liberalization scenarios on welfare, poverty and equity.

The analysis uses the latent class stochastic frontier model in investigating the influence of international trade on agricultural technological change and productivity. The estimated productivity gains induced from a more opened trade regime are combined with a general equilibrium analysis of trade liberalization to evaluate the direct welfare benefits of poor farmers and the indirect income and prices outcomes. These effects are then used to infer the impact on poverty using the traditional top-down approach and the Tunisian household survey.

Key words: *Openness, Agriculture, Productivity, Poverty, Latent class model, CGE modelling.*

JEL classification: C24, C33, D24, F43, I32, Q17.

¹ Associate Professor, University of Nabeul, Tunisia; PEP; LEGI-EPT; LEAD. Tel: +216 22 200757, fax: +216 913155, Courriel: nadia@hbhgts.com.

² Professor, University Laval, Quebec Canada; PEP ; CEPIL, CIRPEE. Tel :+ 1 418 6565561, fax: +1 418 6567798 Courriel: bdec@ecn.ulaval.ca.

1. Introduction

The gradual opening of agricultural markets during the recent wave of globalization focused political and economic attention on the links between international trade, agricultural development and poverty. More liberalised trade regimes have been advocated worldwide for their growth and welfare enhancing effects, as they are assumed to facilitate the transfer of new technology and to boost productivity (Winters, 2002; Cline, 2004; Nissanke and Thorbecke, 2006). Beyond its direct benefit to rural livelihoods, growth in agricultural productivity stimulates linkages to the non-farm rural economy, causing economic growth and rapid poverty reduction (Hwa, 1988; Datt and Ravallion, 1998; Irz *et al.*, 2001, Thirtle *et al.*, 2003; Bravo-Ortega and Lederman, 2005; Christiaensen *et al.*, 2006; Ravallion and Chen, 2007; Self and Grabowski, 2007).

The growing interest on the economics of trade reforms has generated a corresponding increase in the number of empirical approaches investigating the impact of trade policy on inequality and poverty. Applied General Equilibrium (AGE) models are widely used because of their ability to produce disaggregated results at the microeconomic level, within a consistent macroeconomic framework. Even though most of the simulations show welfare gains from the removal of trade barriers, the estimated benefits greatly diverge across the studies (Bouët, 2006). The difficulty of assessing the true poverty impacts of trade reforms is in part explained by the complexity of the dynamic implications of external trade liberalization. In most studies the long-run productivity mechanisms tend to be treated in rather ad hoc ways. CGE frameworks generally deal poorly with the productivity effects of international technology spillovers. While these dynamic responses to international openness are gradually being incorporated in some CGE applications, the most influential CGE frameworks in the policy debate are at quite some distance from fully integrating these forces (Vos, 2007).

This study attempts to make a contribution to the existing literature in filling that gap. The analysis tempts to explore the short and long run effects of alternative trade liberalization scenarios on agricultural and economic growth and to synthesize poverty and inequality implications. The method used here is based on two links, one connecting trade openness to farming performance, and another connecting agricultural productivity to economic growth,

poverty and equity. Our approach first seeks to investigate the key parameters that can serve as a basis for estimating dynamic agricultural productivity gains from increased trade, and then incorporate econometric evidence of the productivity linkages into a dynamic sequential CGE model, to arrive at a comprehensive calculation of alternative trade liberalization scenarios on commodity and factor prices, as a basis for then calculating the corresponding impact on poverty and inequality. This methodology will be applied to explore the potential income and distributional implications of agricultural trade liberalization in the Tunisian country.

Tunisia has taken steps towards greater integration in the global economy as it is 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. Agriculture is an economically and socially important sector in Tunisia, although highly distorted due to trade barriers and protective policies. As this country 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. The adoption of new technologies and the subsequent increase in agricultural productivity are reasonably expected to offer a route out of poverty through generating employment opportunities and increasing wages rates in the rural areas. There is a concern that technological progress may be biased in favour of skilled and educated labour and tends to be labour saving. Hence, technical change may exasperate wage inequality slowing the pace of poverty reduction. Furthermore, if the poor are mostly in unskilled small farmers and are not sufficiently equipped to take advantage of the advances, poverty will be unaffected, or maybe even worsened (Winters, 2004; Winters *et al.*, 2004). In an attempt to shed some light on these issues, this paper examines the role of international trade in promoting technology transfer and stimulating farming productivity growth and investigates the influence of agricultural productivity on livelihoods of the poor, asking whether technological development is pro-poor.

The paper starts by sketching a conceptual framework for exploring the effects of international trade on agricultural productivity in Tunisia and its main trading partners in the Mediterranean. For this purpose we measure technical efficiency (TE) and Total Factor Productivity (TFP) indexes using the latent class stochastic frontier model to account for cross-country heterogeneity in production technologies. Then we present an empirical

framework in which international trade and technology transfer provide two potential sources of productivity growth for countries behind the technological frontier.

The analytical framework for the analysis of the poverty and inequality implications of the trade induced productivity gains consists of a dynamic CGE model. The model structures and assumptions are discussed in section 3. Section 4 reviews the data, while section 5 reports some empirical results and draws some conclusions.

2. Econometric model

2.1 Productivity Measurement: Panel Data Specification of a Latent Class Stochastic Frontier Model

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. 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).

The parametric stochastic frontier models have the advantage of controlling for such random events and of distinguishing the statistical noise effects from technical inefficiency. Based on the econometric estimation of the production frontier, the efficiency of each producer is measured as the deviation from the best practice technology. Evenly productivity change is computed as the variation over time of the producer's distance from the frontier and is decomposed into technical change, scale economies, and changes in technical efficiency (Sena 2003; Kumbhakar 2004).

Estimation of these models hinges, however, on the restraining belief that all producers use a common technology. It is nevertheless unlikely that units in different countries or regions operate under the same technology. Comparisons of inter-country production functions raise then the issue of accommodating the technological differences in the stochastic frontier models, given that the effects of unmeasured heterogeneity might be misguidedly labeled as

inefficiency (Green 2003; Kumbhakar and Tsionas 2003; Moutinho *et al.* 2003; Corral and Alvarez 2004; Kumbhakar 2004; Orea and Kumbhakar, 2004).

In an attempt to overcome this drawback, two approaches have been proposed in the recent analyses. One method is to split the sample of observations into several groups according to some exogenous sample separation information. Alternatively, a cluster analysis may be applied to the dependent variable, and then a technological reference is estimated for each group (Kolari and Zardkoohi 1995; Grifell and Lovell 1997; Mester 1997). This two stage procedure fails, however, to exploit the inter-group information in estimating the separate stochastic frontiers.

The latent class stochastic frontier models have been recently designed as better suited to modeling technological heterogeneity. These models combine the stochastic frontier approach with a latent sorting of individuals into discrete groups and enable to control for heterogeneity through the simultaneous estimation of the probability of class membership and a mixture of several technologies. This single stage approach is proved to outperform the two stage procedure that precludes the efficient utilization of information regarding one particular class to estimate the other class frontiers (Green 2001b, 2002, 2003; Caudill 2003; Kumbhakar 2004; Orea and Kumbhakar 2004).

We use a panel data specification of the latent class stochastic frontier approach to study inter-country agricultural productivity performance in the Mediterranean region and to investigate the factors driving productivity growth. Comparisons of cross-country productivity provide useful insights on the relative position of each country in terms of potential agricultural production, and on the factors explaining the inter-country diversity of performance.

The latent class stochastic frontier framework posits that there is a latent sorting of the producers into J discrete unobserved groups, each using a different production technology. The model appears as a finite mixture of stochastic frontier models, where the technology for the j^{th} group is specified as:

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

subscript i indexes producers (or countries) ($i: 1 \dots N$), t ($t: 1 \dots T$) indicates time and j ($j: 1, \dots, J$) 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 $u_{it|j}$.

In order to estimate (1) by the maximum likelihood method we assume the noise term $v_{it|j}$ to follow a normal distribution $N(0, \sigma_{v_j}^2)$ and the inefficiency term $u_{it|j}$ to be 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.

Following these authors, we adopt the scaled specification for $u_{it|j}$ by writing it as³:

$$u_{it|j} = \exp(\ln(z_{it})\delta_j)\omega_{it|j} \quad (2)$$

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:

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

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. The salient feature of the latent class model is that the class

³ See Wang and Schmidt, (2002) and Alvarez *et al.*, (2006) for the discussion of the practical advantages of models with the scaling property.

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. To constrain these probabilities to sum to unity, we parameterize P_{ij} as a multinomial logit model:

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

Where, q_i is a vector of 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:

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

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). Using the parameters estimates and Bayes' theorem, we compute the conditional posterior class probabilities from:

$$P_{j|i} = \frac{LF_{ij} P_{ij}}{\sum_j LF_{ij} P_{ij}} \quad (6)$$

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 i.e., country i is classified into group k ($:1...J$) if $P_{k|i} = \max_j P_{j|i}$. Furthermore, the estimated posterior probabilities help to compute the

efficiency scores. Given that there are J groups, the latent class model estimates J different frontiers from which the inefficiencies of the producers can be computed by two methods. 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:

$$\ln TE_{it} = \sum_{j=1}^J P_{j|i} \ln TE_{it|j} \quad (7)$$

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 criteria are expressed as:

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

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

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*.

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. TFP growth is defined as the difference between the rate of growth of output and the rate of growth in input use and can be computed from⁴:

$$\dot{TFP} = TC + \dot{TE} + Scale \quad (9)$$

where $TC = \frac{\partial \ln f}{\partial t}$, $\dot{TE} = \frac{-\partial u_{it|j}}{\partial t}$, and $Scale = \frac{(\varepsilon_j - 1)}{\varepsilon_j} \sum_k \varepsilon_{kj} \dot{x}_k$. ε_j is the sum of all the input elasticities⁵ ε_{kj} .

⁴ See Kumbhakar and Lovell (2000) for the tri-partite decomposition of productivity growth.

⁵ Since input elasticities vary across groups, productivity change estimates from equation (9) are group-specific. Unconditional productivity measures can be obtained as a weighted sum of these estimates.

Equation (9) decomposes TFP growth into a scale component, which measures a scale effect when inputs expand over time; a technical change component, which measures the rate of outward shift of the conditional best-practice frontier; and efficiency improvement.

2.2. International trade and agricultural productivity growth

From the estimated latent class model we obtain TE and TFP measures for each country. We turn then to examining the role of international trade in promoting technology transfer, as well as in facilitating productivity growth and catch up with the frontier technology.

Studies by Griffith *et al.* (2004) and by Cameron *et al.* (2005) emphasize the importance of technology transfer, international trade and human capital for productivity growth in countries behind the technological frontier. In these models technology gap is used to capture the potential for technology transfer, and is included as both a level and an interaction term to capture an effect on the speed of technology transfer. Following these authors we derive an equation for agricultural productivity growth as:

$$GTFP_{it} = \alpha_i + \alpha_1 H_{it-1} + \alpha_2 IT_{it-1} + \theta_1 GAP_{it-1} + \theta_2 H_{it-1} GAP_{it-1} + \theta_3 IT_{it-1} GAP_{it-1} + \mu' X_{it-1} + v_{it} \quad (10)$$

where $GTFP_{it}$ is the growth rate of agricultural TFP of country i at time t , H is the human capital level of the country, IT is a measure of international trade, GAP is the technology gap, and X is vector of control variables including institutional factors⁶. α_i is a country-specific constant and v_{it} is an error term.

Human capital and international trade enter in equation (10) both separately and in interaction with the technology gap. The trade interaction captures the effect of international integration on productivity growth through the speed of technology transfer, while the human capital interaction reflects a country's capacity to adopt advanced technology. We expect the countries that lie further behind the frontier to experience higher rates of productivity growth. Technology gap indicates the deviation of country frontiers from the best practice technology labeled as metafrontier (Battese *et al.*, 2004). We estimate the metafrontier by taking the outer envelop of the group specific frontiers, $f(x_{it}, \beta^*) = \max_j f(x_{it}, \beta_j)$. Then we measure the

⁶ $\dot{TFP}$ in equation (7) can be considered as the empirical counterpart of $GTFP$.

technology gap as the ratio of the output for the frontier production function for group j relative to the potential output defined by the metafrontier, $GAP_{it} = \frac{f(x_{it}, \beta_j)}{f(x_{it}, \beta^*)}$.

3. Poverty implications of trade liberalization: a dynamic CGE model

The effects of trade liberalization and agricultural productivity change on poverty are assessed using a dynamic sequential general equilibrium approach including product differentiation. The basic features of the model are inspired from the prototype model of Van der Mensbrugghe (2005), Rattsø and Stokke (2005), Diao et al. (2005) and from Chemingui and Dessus (1999), Decaluwé et al. (1999), Bchir et al. (2002), Annabi et al. (2005) and Chemingui and Thabet (2006).

The model is calibrated to data from a Tunisian social accounting matrix for 2001. It distinguishes 38 production sectors, including 25 agricultural and food activities with 13 urban industries and services. Factors of production are classified as capital, land, labor and natural resources. Land is further differentiated according to the perennial features of the crops, the irrigation intensity and the varieties grown. Labor is classified by the level of qualification (skilled and unskilled). Institutions include households, companies, government and foreign trading partners. The household bloc is desegregated into rural and urban households. The trading partners are decomposed into European Union countries and rest of the world.

3.1. The model structure

a. Production structure

The model's production functions are of the nested structure. Perfect complementarity is assumed between value added and the intermediate consumptions in each sector. Value added is a Cobb Douglas (CD) function of labor, land, capital and natural resources. Labor is a CES bundle of skilled and unskilled labor. Land is also decomposed by type in a CES nest. Land is agriculture specific and labor is assumed to be fully mobile. Capital and natural resources are assumed to be sector specific. The model incorporates product differentiation by variety and quality.

b. Demand structure

In the demand side, the preferences across sectors are represented by the LES (Linear Expenditure System) function to account for the evolution of the demand structure with the changes in income level.

The consumption choices within each sector are a nesting of CES functions. The subutility specifications are an augmented version of the Dixit-Stiglitz structure of preferences designed to capture the particular status of domestic goods, together with product differentiation according to geographical origin as well as horizontal and vertical differentiation. Quality enters as a utility shifter with the horizontal differentiation between varieties.

Total demand is made up of final consumption, intermediate consumption and capital goods. Sectoral demand of these three compounds follows the same pattern as final consumption.

c. Overview of the model

Ignoring the difference between foreign and domestic goods, we assume that consumer's utility depends on consumption of the output of several industries (i) each of which contains a large number of differentiated varieties (ω) produced by heterogeneous firms. We assume that the upper tier of utility determining consumption of the different goods is LES and that the lower tier of utility determining consumption of varieties takes the CES form,

$$U = \prod_i (C_i - C_{\min i})^{\alpha_i} \quad (11)$$

C_i is a consumption index defined over consumption of individual varieties, $q_i(\omega)$, with dual price index, P_i , defined over prices of varieties, $p_i(\omega)$,

$$C_i = \left[\int_{\omega \in \Omega_i} (\theta_i(\omega) q_i(\omega))^\rho d\omega \right]^{\frac{1}{\rho}}, \quad P_i = \left[\int_{\omega \in \Omega_i} \left(\frac{p_i(\omega)}{\theta_i(\omega)} \right)^{1-\sigma} d\omega \right]^{\frac{1}{1-\sigma}} \quad (12)$$

with $\rho = \frac{\sigma-1}{\sigma}$, σ the elasticity of substitution between any two goods and $\theta(\omega)$ the quality of variety (ω). Let $Q_I \equiv C_i$ and $P_I \equiv P_i$ the aggregate industry good and price respectively.

The optimal consumption and expenditure decisions are given by⁷:

$$q_i(\omega) = (\theta_i(\omega))^{\sigma-1} \left(\frac{p_i(\omega)}{P_I} \right)^{-\sigma} Q_I, \quad r_i(\omega) = (\theta_i(\omega))^{\sigma-1} \left(\frac{p_i(\omega)}{P_I} \right)^{1-\sigma} R_I \quad (13)$$

⁷ See Melitz (2001) and Bernard *et al.* (2006) for a similar formulation.

with $p_i(\omega)q_i(\omega) = r_i(\omega)$ and $R_I = P_I Q_I$

The production side of the model follows Melitz (2003) and Bernard *et al.* (2006) in that production involves a fixed and variable cost every period, and only variable costs move systematically with firm productivity. Production requires multiple factors of production whose intensity of use varies across industries. We assume that the cost function takes the following Cobb Douglas form:

$$CT_i = F_i + \left(\frac{q_i}{A_i} \right) \prod_k w_k^{\beta_i^k} \quad (14)$$

with $F_i(\omega)$ the fixed cost, A_i the total factor productivity (TFP), w_{ki} the factor prices, including skilled and unskilled wages, and β_i^k the factors shares in marginal cost.

As shown in equation (13) demand for a product variety depends upon the own variety price, the price index for the product and the price indices for all other products. We assume that firms are small enough relative to the industry that they have no power to influence the industry price index. The price of firm's variety in one product market only influences the demand for its varieties in other product markets through the price indices. Therefore, the firm's inability to influence the price indices implies that its profit maximization problem reduces to choosing the price of each product variety separately to maximize the profits derived from that product variety (Bernard et al., 2006).

Factors demand may be expressed as:

$$x_{ki} = \beta_i^k (A)^{-1} (w_k)^{\beta_i^k - 1} \prod_h w_h^{\beta_i^h} \quad (15)$$

d. Productivity dynamics

Productivity growth is generated through technology adoption and own innovations. Technology adoption is assumed to combine the gap to the technological leader, defining the learning potential through imitation; human capital, indicating the ability to exploit foreign technology; and the level of foreign trade which represents the channel transmitting the new technology to domestic producers. The equation for productivity growth can be specified in the following form:

$$\hat{A} = \alpha_1 H + \alpha_2 Trade + \alpha_3 GAP + \alpha_4 H * GAP + \alpha_5 Trade * GAP \quad (16)$$

where $\hat{A}$ is the proportional change in productivity, H is the education level, $Trade$ total trade, and GAP is the technology gap.

As increased openness may lead to skill biased productivity growth, we investigate this effect through the following CES specification of aggregate labor demand. Following Rattsø and Stokke (2005) aggregate labor demand is specified as:

$$L_i = \left[\gamma_{1,i} A^{\rho_l - 1/2\beta} UL^{\rho_l} + \gamma_{2,i} A^{\rho_l + 1/2\beta} SL^{\rho_l} \right]^{\frac{1}{\rho_l}} \quad (17)$$

The direction and degree of technological bias is introduced through the parameter β , which gives the elasticity of the marginal productivity of skilled relative to unskilled labor with respect to labor augmenting technical progress. For β equal to zero, technical change is neutral and does not affect the relative efficiency of the three labor types. With a positive value of β technical change favors skilled workers, while negative values imply that improvements in technology are biased towards unskilled labor.

The reduced form specification of technological bias is assumed to be an increasing and convex function of adoption relative to innovation:

$$\beta = \left(\left(\frac{\alpha_4 + \alpha_5}{\alpha_1 + \alpha_2} \right)^2 - 1 \right) \quad (18)$$

The proportional change in factor demand is affected by productivity variation in the following way:

$$\hat{x}_{ki} = \hat{q}_i + (\beta_i^k - 1) \hat{w}_{ki} + \sum_{h \neq k} \beta_h \hat{w}_{hi} - \sum_h \beta_i^h \hat{A}_{hi} \quad (19)$$

3.2. Parameters estimation

The previous model forms the theoretical basis of our empirical analysis. Different types of parameters are required to allow the empirical implementation of the model. We will estimate the model's behavioral parameters econometrically.

The effect of trade openness on agricultural productivity is captured through the estimation of equation (10).

To investigate whether trade opening induces skill-biased technical change and whether it affects wage inequality we need to estimate the parameters in equation (17). Assuming competitive labor markets, and using the CD specification for value added and the CES form for labor demand; the relative wages may be written as a function of the relative productivity and the relative labor supply as follows:

$$\ln\left(\frac{w_s}{w_u}\right) = \delta_i + \alpha\left(\left(\frac{TRADE}{I}\right)^2 - 1\right)\ln A_L + (\rho_i - 1)\ln\left(\frac{SL}{UL}\right) \quad (20)$$

where w_s and w_u are the skilled and unskilled wages respectively. Equation (20) will be estimated using the non linear least square approach.

3.3. Income distribution and poverty

This section discusses incomes distribution and attempt to provide a brief overview on the methodology used to analyze the external choc effects on poverty.

The common poverty measures can be formally characterized in terms of per capita income and relative income distribution as follows:

$$P = P(Y, L(p)) \quad (21)$$

where Y is per capita income and $L(p)$ is the Lorenz curve. P denotes the poverty measure which we assume to belong to the Foster-Greer-Thorbecke class (1984):

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

We follow Decaluwé et al.(1999), by adopting specific intra-group income distributions in order that conform to the different socio-economic characteristics of the groups, and by endogenizing the poverty line and the resulting poverty incidence among the different socioeconomic household groups.

The analysis of the poverty impacts of agricultural trade liberalization and productivity growth is based on simulations of the model described earlier using the SAM for 2001 as

base. The model calibration is based on the SAM and the econometric results obtained from the previous section.

Since adapting to a trade policy shock is neither immediate nor costless, setting a dynamic analysis is useful in studying the different adjustment periods, i.e. the short- and medium-run impacts. The analysis is conducted using a sequential dynamic set-up, where capital stock is updated endogenously with a capital accumulation equation, whereas technological change is updated exogenously between periods.

The model is designed of such way to capture the direct and indirect effects of agricultural trade liberalization on commodity and factor prices as a basis for then calculating the corresponding impact on poverty. The model incorporates econometric evidence of the trade-productivity linkages. The poverty implications of alternatives trade liberalization scenarios are inferred using the traditional “top-down” approach.

We first simulate the CGE model to generate full vector of commodity and factor prices owing to policy experiment. These are then fed into a microsimulation framework to conduct a detailed analysis of income distribution and poverty at the household level using the Tunisian household survey of 1995.

4. Data

Our study requires an important database:

4.1. The econometric analysis

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, international trade, human capital, agricultural research effort, land distribution, land quality, climatic conditions, institutional factors, per capita income, and income inequality. 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); and the productivity change equation in (10). The data are the FAO (FAOSTAT), World Bank (WDI), AOAD, Eurostat, CEPII, AMAD, ASTI, UN-WIDER, 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 to estimate the stochastic production frontier consist of thirty six agricultural commodities belonging to six product categories (fruits, shell-fruits, citrus fruits, vegetables, cereals, and pulses) and five inputs (cropland, irrigation water, fertilizers, labor and machines)⁸. The agricultural product categories include the main produced and traded commodities in the Mediterranean region. Substantial protection measures exist in the form of entry prices, customs tariffs, quotas, and safeguard clauses. These measures aim at restricting the exchange of commodities considered as a potential source of strong competition in the Mediterranean basin, and for which greater openness may have serious domestic economic and social consequences. 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. All the input and output variables are measured in quantity.

The inefficiency effect model and the productivity growth equation incorporate an array of control variables representing openness to trade, human capital, land holdings, agricultural research effort, land quality, and institutional quality. Three different measures are used to proxy the degree of openness of each country, the ratio of agricultural exports plus imports to agricultural value added (AGVA), agricultural trade barriers, and the share of agricultural machinery and equipment imports in AGVA. Agricultural commodities are currently protected with a complex system of ad-valorem tariffs, specific tariffs, tariff quotas, and are subject to preferential agreements. The determination of the appropriate level of protection is a fairly complex task. The MacMaps database constructed by the CEPII provides ad-valorem tariffs, and estimates of ad-valorem equivalent of applied agricultural protection, taking into account trade arrangements (Bouët *et al.* 2004). Our data on agricultural trade barriers are drawn from this database.

⁸ We construct aggregate output and input indices for each product category using the Tornqvist and EKS indexes. For each country i and in each product category k , we compute tornqvist output and input indexes, taking alternatively all the countries j ($j \neq i$) as numeraire, using the following formula:

$$T_{ij}^k = \prod_{h \in k} \left(\frac{y_{hi}}{y_{hj}} \right)^{\frac{(\omega_{hi} + \omega_{hj})}{2}} \quad \text{where } y_{hi} \text{ and } y_{hj} \text{ are outputs (or inputs) of } h\text{-th agricultural commodity in countries } i \text{ and } j \text{ respectively, and } \omega_{hi} \text{ and } \omega_{hj} \text{ are the } h\text{-th output (input) shares. We use the Eltető-Köves-Szulc (EKS) procedure which defines the quantity index for product } k \text{ and country } i \text{ as the geometric weighted average of these indices: } Q_i^k = \prod_{j=1}^I (T_{ij}^k)^{a_j} \text{ where } a_j \text{ is the share of country } j \text{ in the total production of the } k\text{-th commodity (including countries } 1, \dots, I \text{ only). See Hallak (2003) and Rao } et al. (2004) \text{ for a similar procedure.}$$

The use of the share of agricultural machinery and equipment imports as a measure of international trade is explained by the fact that foreign technology diffuses mainly through capital goods, the productivity effects of openness might then be suitably captured by this variable. Human capital is measured by average years of schooling in the population over age 25 and is included to capture the labor quality and the ability to absorb advanced technology. Land quality, land fragmentation and the distribution of agricultural holdings are often cited as sources of inefficiency in agriculture (Vollrath, 2007). The inefficiency model includes land quality, which is measured by the percent of land under irrigation; land fragmentation, which is controlled for by the percent of holdings under five hectares; and inequality in operational holdings measured by the land Gini coefficient to capture these effects. Agricultural research effort is measured by public and private R&D expenditures. Institutional quality includes various institutional variables considered as indicators of a country's governance, namely, political stability, government effectiveness, and control of corruption. These variables reflect the ability of the government to provide sound macroeconomic policies and impartial authority which protects property rights and enforces contracts.

Regarding the determinants of the latent class probabilities, we consider country averages of five separating variables related to natural and modern input endowments as well as to climatic conditions. The variables included in the class probabilities are total number of wheel and crawler tractors, total applied fertilizers, total agricultural land, average farm size, and rainfall levels. Tractors and fertilizers help to identify countries endowed with modern production factors. Average farm size captures the differences in the scale of agricultural holdings across countries and distinguishes countries with important small farms (Vollrath, 2007). Total agricultural land and rainfall levels capture the influence of resources endowments and climatic conditions on class membership.

4.2. The CGE analysis

The construction of the Social Accounting Matrix requires very detailed observations at the sectoral level. An important desegregation of the agricultural sector is needed for the analysis purposes. The required data concerns sectoral outputs, value added, intermediate inputs, consumption, investment, import, export, taxation and factorial income distribution. Other data could prove to be necessary with the progression of the study. Data are taken from various sources: I.N.S. the national statistical agency of Tunisia, the different reports of the Ministry of Finance and Planning and of the Ministry of agriculture.

5. Estimation Results

This section summarizes the main results derived using the empirical application of the methodologies described in section 2.

5.1. 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 algorithm⁹. 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 agricultural TFP growth are investigated focusing on the role of trade openness in speeding the catch up process.

Table 1 presents the results of estimating the input elasticities of the production frontier.

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	

⁹ The estimation procedure was programmed in Stata 9.2.

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.

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 seem also 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.

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 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. International trade seems to exert a significant impact on improving efficiency in the Mediterranean farming sector. Educational attainment, land quality, agricultural research effort and institutional factors appear also to contribute to enhancing efficient input use. As expected, the unequal distribution of agricultural land and to a lesser extent land fragmentation have significant adverse effects on efficient resource use.

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

probabilities provide useful information in classifying the sample. We had no apriori expectation about the sign 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 decrease with an increase of the corresponding variables.

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.

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

Average efficiency scores and TFP changes are reported in Table 3. 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.

TABLE 3: 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.

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) and then estimate the model in equation (10) that links the TFP

growth rate to a host of variables, including trade openness, human capital, R&D, and institutional factors.

TABLE 4: IMPACT OF INTERNATIONAL TRADE ON AGRICULTURAL TFP GROWTH

	MACHINERY IMPORTS	TRADE VOLUMES	TRADE BARRIERS
Human capital	0.065**	0.014**	0.09**
International Trade	0.912***	0.232***	-0.424***
GAP	-0.146***	-0.175***	-0.186***
H*GAP	-0.085**	-0.247**	-0.157***
IT*GAP	-0.174***	-0.121**	0.163***
Land GINI	-0.026**	-0.02*	-0.058***
Land fragmentation	-0.046	-0.032*	-0.032*
Land quality	0.058*	0.052*	0.031*
R&D	0.003*	0.003*	0.011*
Cont. of Corruption	0.007*	0.033*	0.004*
Gov. effectiveness	0.03***	0.014**	0.016*
Political stability	0.004	0.004	0.002
N. of observations	1260	1260	1260
R ² adjusted	0.75	0.73	0.71

Notes: Dependant variable is GTFP. *H*Gap*: the product of human capital (*H*) and technology gap (*GAP*), *IT*GAP*: the product of international trade (*IT*) and technology gap. *H*, *IT*, *GAP* and the interaction terms are instrumented by their second lags. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels respectively.

These estimates provide interesting insights into the agricultural productivity dynamics. The results highlight the role of international trade in promoting technology transfer and point to the importance of education in facilitating the assimilation of foreign improvement of technology. The findings suggest that international trading opportunities would have larger benefits in countries with favourable internal factors relating to more equitable distributions of land, better land quality, significant R&D and positive institutional conditions.

5.2 CGE analysis

The existing SAMs for Tunisia are unlikely to adequately reflect the structural features of the national agricultural sector, we therefore compile a new SAM. Building a completely new SAM requires however gathering a huge amount of data; we use a top-down approach to carry

out the compilation of the new SAM. Our procedure follows two main steps. First, we construct a Macro SAM from national accounts. Second, we disaggregate the Macro SAM by activity and commodity to generate a Micro SAM. The disaggregation mainly relates to agriculture and agri-food processing commodities and is implemented using the national-accounts tables and different complementary sources such as the surveys conducted by the National Institute of Statistics (INS), the Ministry of agriculture... . This step is carried out in order to match with the commodity structure of the Tunisian household expenditures, and in a way that is consistent with the national accounts and coefficients from a prior SAM. As the data discrepancies in the micro matrix may cause unbalances, we apply the cross-entropy approach to generate a balanced SAM table.

We are currently running the model simulations.

6. SOME CONCLUSION

Proponents of globalization identify strong benefits from trade liberalisation 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 in Tunisia and a panel of its main trading partners. Agriculture is a vital sector in these 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 Tunisia 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 Tunisia 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 this country in the context of globalization.

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. 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.

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.

The work is still under progress; we are presently running the CGE model simulations to evaluate the impact of trade induced agricultural productivity growth on poverty and inequality.

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