Green productivity in agriculture:  
A critical synthesis  

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Executive summary

This report has been prepared for the OECD with a view towards the development of the green growth strategy for the agricultural sector. The purposes of this study are three-fold.

1) Review the literature for available approaches for measuring green productivity in agriculture, and provide a critical synthesis.
2) Propose an operational method for assessing green productivity in agriculture at cross-country level.
3) Illustrate the proposed method and the information it can provide with an empirical study.

Since the empirical literature on agricultural productivity is large, the literature review presented in this report aims to structure the literature by pointing out some relevant streams together with some key references. Our review starts with the discussion of alternative approaches to constructing total factor productivity (TFP) indices, keeping in mind the environmental effects that do not typically have observable market prices. Therefore, we pay particular attention to the frontier approaches to TFP measurement, where the aggregation of inputs and outputs is conducted by applying shadow prices rather than market prices. We briefly review parametric, nonparametric, and semi-nonparametric approaches as methodological alternatives to frontier estimation. We then discuss specific methodological issues related to agriculture. These include the modelling of damage control inputs, the material balance accounting and its interpretation, and the modelling of production risk. We then turn attention to environmental issues specific to agriculture, recognizing the nutrient emissions and the green-house gas emissions as potential indicators for which comparable data are available.

In the empirical part of the paper, we examine a panel of 13 OECD countries over the time period 1990 – 2004. The countries, time horizon, and the environmental variables have been chosen based on data availability. We use the net production value obtained from the FAOSTAT as the output variable. As for the input variables, we compare three alternative model specifications:

i) The economic model (ECON) that includes the conventional production factors: labour, capital stock, and the land area.

ii) The environmental model (ENV) that includes the agricultural green-house gas emissions, the nitrogen stock, the phosphorus stock, and the land area as the environmental resources.

iii) The mixed model (MIX) that includes all input variables of both the ECON and ENV models described above.

These three models are estimated using three alternative econometric methods:

a) Stochastic Frontier Analysis (SFA), which is a stochastic, parametric approach to frontier estimation, widely used in the applied econometrics literature.

b) Data Envelopment Analysis (DEA), which is a deterministic, nonparametric approach, used in particular in the operational research literature.

c) Stochastic semi-Nonparametric Envelopment of Data (StoNED), which is a recently developed approach that combines the DEA-style nonparametric frontier with a SFA-style probabilistic treatment of inefficiency and noise.

The empirical application indicates large differences across countries in both the level of TFP and its growth rate. Further, the results differ considerably depending on the specification of the set of input variables and the choice of the estimation method.

Interestingly, the ENV model yields a better empirical fit than the ECON model: the environmental indicators explain a larger proportion of variance in the net production value than the conventional primary inputs. As a result, the results of the ENV and MIX models are more similar to each other, while the results of the ECON model deviate considerably from the other two model specifications.
The results also depend on the choice of the frontier estimation method. The results of the SFA and StoNED methods are relatively similar, particularly in the ENV and MIX models. The DEA results differ notably from those obtained with the other two methods. These findings suggest that the results are relatively robust to the assumptions regarding the functional form of the frontier, and that explicit modelling of stochastic noise is a more critical factor in this application.
List of acronyms

CO2 - Carbon Dioxide
CRS - Constant returns to scale
DEA - Data Envelopment Analysis
DI - Input distance function
ECON - Model specification where only economic production factors are used as inputs.
EE - Environmental efficiency (index)
EFF - ‘Efficiency change’: the sub-component of the Malmquist TFP index that represents the movement of the country towards the frontier (catching up) or away from the frontier (falling behind)
ENV - Model specification where only environmental indicators are used as inputs.
EU - The European Union
FAOSTAT - Statistical database of the Food and Agriculture Organization of the United Nations
GHG - Green-House Gas
LA - Land area: the total utilized agricultural area (in ha)
MIX - Model specification that includes both economic and environmental inputs.
ML - Maximum likelihood
OECD - Organization for Economic Cooperation and Development
OLS - Ordinary Least Squares
SFA - Stochastic Frontier Analysis
StoNED - Stochastic semi-Nonparametric Envelopment of Data
TECH - ‘Technical change’: the sub-component of the Malmquist TFP index that represents the shift of the frontier over time
TFP - Total Factor Productivity
UNFCCC - United Nations Framework Convention on Climate Change
VA - Value added
1. Introduction

OECD has developed a **Green Growth Strategy** since 2009, together with partners across government and civil society. The purpose of this strategy is to help countries achieve economic growth and development while at the same time combating climate change and preventing costly environmental degradation and the inefficient use of natural resources. The first proposal of green growth indicators was published in the report OECD (2011a), where production is taken as the starting point, and thus the proposed indicators can be viewed as measures of environmental or resource productivity. The strategy for green growth in food and agriculture is outlined in OECD (2011b), based on studies by Asche (2011), Blandford (2011), Burrell (2011), Hall and Dorai (2010), and Stevens (2011).

Agriculture is one of the key sectors for green growth. Agriculture causes or contributes to several of the most serious global environmental problems, such as deforestation, water stress, eutrophication of surface and underground water systems, discharge of toxic waste from pesticides, and green-house gas (GHG) emissions (e.g. methane from manure). Accounting for the environmental externalities in the agricultural productivity analysis presents major challenges, both methodologically and empirically.

The objectives of this study are threefold. Our first objective is to survey the available approaches for measuring green productivity in agriculture, and provide a critical synthesis. Based on the critical survey, our second objective is to propose a systematic method for assessing green productivity in agriculture at cross-country level. Thirdly, we illustrate the proposed method and the information it can provide with an empirical study to 13 countries in years 1990 – 2004, using three environmental variables: GHG emissions from agriculture, and the stocks of nitrogen and phosphorus accumulated in agricultural land. The countries, time horizon, and the environmental variables have been chosen based on data availability. While the empirical application is limited in terms of the number of countries, years, and environmental variables, we believe the empirical comparisons presented below will provide useful methodological insights.

Regarding the literature review, we must emphasize that the literature related to this theme is very large and scattered over several disciplines such as agricultural economics, agronomy, ecological and environmental economics, econometrics, production economics, and operations research, among others. The empirical literature can be classified according to the scope as farm and sector level studies (e.g., Reinhard et al., 1999, 2000; Brümmer et al., 2002), aggregate level country specific studies (e.g., the USA in Cox and Chavas, 1990, Jorgenson and Gollop, 1992, Ball, Hallahan, and Nehring, 2004; the UK in Thirtle and Bottomley, 1992; China in Kalirajan et al., 1996; Fan and Zhang, 2002), and international cross country comparisons (e.g., Bureau et al., 1995; Lusigi and Thirtle, 1997; Ball et al., 2001; Coelli and Prasada Rao, 2005). The common methodological approaches in this literature include the growth accounting (e.g., Jorgenson and Gollop, 1992), index number approaches (e.g., Kuosmanen et al., 2004; Kuosmanen and Sipiläinen, 2009; O’Donnell, 2010), and frontier approaches such as the data envelopment analysis (DEA) (e.g., Bureau et al., 1995) and stochastic frontier analysis (SFA) (e.g., Coelli and Prasada Rao, 2005). Recently, many empirical TFP studies in the agricultural sector try to take at least some environmental considerations into account (e.g., Reinhard et al., 1999, 2000; Reinhard and Thijsse, 2000; Ball, Lovell, Nehring, and Luu, 2004; Coelli et al., 2007). Given a large amount of literature, our objective is not to identify and cite every study that is relevant in this theme, but rather, try to provide some structure to the enormous literature, and pinpoint some important streams of literature that deserve to be considered.

The rest of the report is organized as follows. Section 2 introduces some standard approaches to productivity measures and discusses the choice of the appropriate index number in the present context. Section 3 examines how environmental indicators could be incorporated to productivity and efficiency analysis. Section 4 discusses some alternative approaches to the estimation of technology distance.
functions, which can provide shadow prices for the environmental factors and other inputs and outputs that are not traded in competitive markets. Section 5 reviews some issues related to the econometric model specification, which are relevant in the context of agriculture. Section 6 discusses environmental issues related to agriculture, and introduces the three environmental factors considered in the empirical application. Section 7 presents an empirical analysis of 13 OECD countries in years 1990 – 2004. The empirical comparison considers three alternative orientations to productivity measurement as well as three alternative frontier estimation techniques. Finally, Section 8 provides concluding remarks and the methodological recommendations.

2. Productivity indices

Productivity is generally understood as the ratio of output to input (e.g., OECD, 2001). In the case of a single input \( x \) and a single good output \( y \), the level of productivity is simply

\[
\text{Prod} = \frac{y}{x}.
\]

The productivity change from period \( t \) to \( t+1 \) is measured by the index

\[
\Delta \text{Prod} = 100 \cdot \frac{y^{t+1} / x^{t+1}}{y^t / x^t}.
\]

The distinction between the level and the change of productivity is worth emphasizing, as the two get often confused in casual conversation. When economists talk about productivity, they usually refer to the productivity indices that measure the productivity change. However, the level of productivity is also of interest in the present context. The term catching up refers to the fact that countries with low level of productivity initially can exhibit much high productivity growth rates than countries that have already achieved a high level of productivity (see, e.g., Ball, Hallahan, and Nehring, 2004, for further discussion).

The main difficulty in productivity measurement concerns the aggregation of multiple inputs and multiple outputs to input and output indices. Agriculture is a prime example of a sector where joint production of multiple outputs using multiple resources is common. Agricultural production process can be modelled as transformation of multiple inputs denoted by vector \( x \) (e.g., land, capital, labour, feed, fertilizers, etc.) to multiple outputs denoted by vector \( y \) (e.g., crops, milk, meat, eggs, vegetables etc.). The input vector \( x \) may contain both economic inputs such as labour and capital, and environmental or natural resources such as GHG emissions or energy consumption. Without a loss of generality, we can partition the input vector as \( x = (x_{\text{ECON}}, x_{\text{ENV}}) \), where \( x_{\text{ECON}} \) is the vector of economic resources and \( x_{\text{ENV}} \) is the vector of environmental resources. In a similar fashion, the output vector \( y \) contains economic outputs (goods and services) as well as environmental services (e.g., landscape management). In this report we assume all outputs \( y \) are desirable (i.e., goods), and the use of all inputs is costly.

At the aggregate level, it is not always obvious whether an environmental indicator should be treated as an input or an output. For example, GHG emissions are obviously an output from the perspective of production, but from the perspective of the society, the GHG emissions can be seen as a burden to the nature’s absorptive capacity, which is an input. By this argument, the conventional approach in the environmental economics literature is to model undesirable outputs as inputs (e.g., Cropper and Oates, 1992; Hailu and Veeman, 2001). Recently, the appropriate modelling of environmental bads as inputs or outputs has attracted critical debate (see, e.g., Färe and Grosskopf, 2003; Kuosmanen and Podinovski, 2009, for discussion and further references). One important study worth noting is Korhonen and Luptacik (2004), where it is shown that in the DEA method the specification of environmental factors (e.g., the GHG emissions) as inputs or outputs does not affect the efficient frontier. However, the specification can affect the scaling properties of the technology (e.g., the returns to scale, scale elasticity and scale
efficiency) and the measurement of efficiency as a distance to the frontier. At the aggregate level, however, it is usual to assume the benchmark technology exhibits constant returns to scale (CRS) (see, e.g., Färe et al., 1994; or Kuosmanen and Sipiläinen, 2009). For convenience, in this report we assign all undesirable factors (whether inputs or outputs to production) to vector $x$, and we attribute all desirable factors (whether inputs or outputs) to vector $y$.

Introduction of environmental factors to vectors $x$ and $y$ increases the dimensionality of these vectors, but the fundamental challenge remains: to measure productivity, we need to aggregate the elements of $x$ and $y$, in one way or another, to obtain an input quantity index and an output quantity index. There are several ways to approach this challenge.

Partial productivity measures consider the ratio of a single output (or some aggregate measure such as the revenue) to a chosen input of interest. For example, labour productivity could be measured in physical units as crop yield per hour of labour, or in monetary terms as agricultural revenue per wage expenses. In a similar vein, the commonly used eco-efficiency indicators are typically constructed as a ratio of good output to bad output ($y/b$), where the nominator and the denominator are chosen arbitrarily from the elements of vectors $y$ and $b$, or using some aggregated quantity (e.g., the average of the elements of vector $b$ subject to some kind of prior normalization). While the partial productivity and eco-efficiency rations can be simple and intuitive, their interpretation can be difficult as it is often unclear what the optimal or appropriate level of labour productivity (or eco-efficiency) should be. The optimal level would likely depend on a number of factors such as the relative prices of other resources such as land and capital. Maximizing labour productivity or eco-efficiency is not the (usual) objective of the firm. While partial productivity indices can be useful proxy indicators in some context, the exact information content of these simple indicators is questionable. Further, trying to compare multiple partial productivity indicators can confuse the overall picture, and even lead to a misleading assessment of the overall productivity performance.

The measurement of total factor productivity (TFP) requires a more systematic aggregation of inputs and outputs to an input index and an output index (respectively), in one way or another. The index theory provides several quantity index formulae, which could be used for aggregation. The classic Laspeyres, Paasche, and Fisher ideal indices apply the observed prices of inputs and outputs as index weights.\footnote{The Laspeyres index uses the prices of the base period as index weights, whereas the Paasche index uses the prices of the target period. The Fisher ideal index is the geometric mean of the two.} The Fisher (1922) ideal index is known to satisfy a number of axiomatic tests (e.g., Diewert, 1992; Diewert and Nakamura, 2003). The widely used Törnkvist index is a weighted geometric mean, where the weights are defined as cost shares for inputs and revenue shares for outputs.

The Malmquist index and its variants (e.g. Malmquist-Bjurek and Malmquist-Luenberger productivity indices noted below) resolve the aggregation problem by using marginal rates of substitution or transformation, also referred to as shadow prices. In the spirit of the revealed preference theory, the shadow prices can reveal the underlying preferences of a manager or a decision maker responsible for the production decisions. At the aggregate level of a sector, however, the observed production outcomes are not controlled by any single decision maker, but are a result of a combination of private production decisions by individual firm managers, who operate subject to policy interventions and regulation by the government. The shadow prices are not purely private, but they do not necessarily reflect the values of the society either. The general rationale of the shadow prices approach in the present context is to evaluate TFP of the agricultural sector of a country in the most favourable light in the sense that the prices of inputs and outputs are chosen to maximize the TFP level of the evaluated sector. Cherchey et al. (2007) refer to this principle as the ‘benefit of the doubt’ weighting.
In competitive markets, rational profit maximizing firms use inputs such that the marginal rates of substitution are equal to the relative prices of inputs in the market. Hence, the shadow prices are equal to the market prices. Therefore, in a competitive market environment, the Malmquist index can be shown to be equivalent to the Fisher and the Törnkvist indices under certain conditions (see, e.g., Caves et al., 1982; Färe and Grosskopf, 1992; Balk, 1993; 1998). Even though the conditions for the exact equivalence are rather restrictive, the conventional Fisher and Törnkvist indices can provide reasonable approximations of the Malmquist index for firms that operate in a competitive market environment.

Since the objective of this study is to measure productivity in the context of agriculture, taking into account the environmental resources and undesirable outputs, the use of prices as index weights will present at least the following challenges:

1) There are no markets for most environmental resources and bad outputs (such as nutrient emissions to water systems). Therefore, market prices for the environmental variables are unobservable, even in principle.

2) Many economic inputs and outputs do not have market prices either. Most notably, it is difficult to determine price for the farm labour, as this often consists of work conducted by the farmer and his/her family. Ideally, the price of labour input should represent the opportunity cost of labour. The average wage rate paid for the temporary hired labour can be observed, but it is hardly a good proxy for the opportunity cost of farmer’s own wage. Other economic inputs and outputs that are not traded in the market include the intermediate inputs such as feedstuff produced at the farm for animals, and the consumption of outputs at the farm.

3) Even if prices are observed, the markets for agricultural inputs and outputs are subject to market distortions such as quotas, subsidies, and other regulation. Thus, the observed input prices do not necessarily represent the opportunity cost of resources. For example, the EU has recently decoupled the subsidies from outputs. However, the subsidies are paid based on the land area and the number of livestock units. This will obviously influence the prices of agricultural land and livestock. Further, investment subsidies for farm capital influence the opportunity cost of capital inputs. On the output side, there are quotas for production of outputs such as milk, which influence the output prices. There are also subsidies for exporting agricultural outputs to other countries (or outside the EU). Due to the complicated agricultural policy, it is difficult to estimate the opportunity costs of inputs and outputs based on the observed price information available from agricultural markets.

4) Even if reliable information of opportunity costs of inputs and outputs could be obtained, the theoretical requirements for using the price-based aggregation would likely fail. Although the assumptions of rational profit maximization (Caves et al., 1982) can be relaxed, the interpretation of TFP as a welfare measure requires that the firms have chosen input vectors \( x \) and output vectors \( y \) that are allocatively efficient from the social point of view. Given the heavy regulation of the agricultural markets, assuming allocative efficiency may be unrealistic in this sector.

The economic valuation of environmental damages or services is an important theme in environmental economics. In general, the valuation could be based on the stated or revealed preferences. Contingent valuation is a well-known example of the stated preference methods (see, e.g., Hausman, 2012, for a critical review). In the revealed preference approaches, such as the travel cost method, the economic prices of environmental goods and services are inferred indirectly based on the observed behaviour or choices of economic agents. Given the problems concerning not only the environmental effects, but also the economic prices of productive inputs and outputs, a conventional valuation study using either stated or revealed preferences would be extremely costly to conduct.
3. Environmental productivity and efficiency

In production economics, the usual approach to avoid the problems 1) - 4) is to resort to the Malmquist index or its variants, which were briefly mentioned above. The Malmquist productivity index, introduced by Caves et al. (1982), is defined in terms of the technology distance functions by Shephard (1953, 1970).\(^2\) In general, we can characterize the production technology by means of the production possibility set
\[ T' = \{ (x, y) \mid \text{inputs } x \text{ can produce outputs } y \text{ in period } t \} , \]
which takes the bad outputs explicitly into account. The Shephard input distance function (DI) can be rephrased as
\[ DI'(x, y) = \sup \{ \lambda \mid \frac{x}{\lambda}, y \in T \} . \]
The rationale of the input distance function is the following (see, e.g., Fried et al., 2008, Section 1, for a more detailed presentation). Given the input vector \( x \) and the output vector \( y \), we scale down all inputs proportionately by factor \( 1/\lambda \) until we reach the boundary of the production possibility set \( T \). The maximum value of \( \lambda \) (‘sup’ refers to the supremum operator) indicates how far the evaluated unit is from the frontier of \( T \). If \( \lambda = 1 \), then the evaluated unit is on the boundary of \( T \) and it is considered to be technically efficient. Values \( \lambda > 1 \) indicate that the same outputs could be produced with a smaller amount of input resources, and hence the evaluated unit is inefficient. Farrell (1957) applies the reciprocal \( 1/\lambda \) as the measure of efficiency (or efficiency index). Note that values \( \lambda < 1 \) are also possible: this means that the evaluated unit is located outside the production possibility set. This can occur in the inter-temporal context where we evaluate an observed input-output vector from period \( t \) relative to the production possibility set of period \( t-1 \). Observed units may also lie outside the production possibility set due to data errors or omitted factors.

Assume for a moment that the production set \( T \) is known. We discuss the estimation of \( T \) (or DI) from data in more detail in Sections 4 and 5.

The Malmquist TFP index can be defined in terms of DI as
\[ M(t, t+1) = \left( \frac{DI'(x', y')}{{DI'(x''', y''')}^{1/2}} \right)^{1/2} \]
Nishimizu and Page (1982) showed that the Malmquist index can be decomposed as
\[ M(t, t+1) = TECH(t, t+1) \cdot EFF(t, t+1) \]
\[ TECH(t, t+1) = \left( \frac{DI'(x''', y''')}{{DI'(x''', y''')}^{1/2}} \right)^{1/2} \]
\[ EFF(t, t+1) = \frac{DI'(x', y')}{{DI'(x''', y''')}^{1/2}} \]
where TECH and EFF represent the contributions of technical change (if the sign of TECH is positive, there is technical progress) and efficiency change (if the sign of EFF is positive, efficiency has improved). Färe et al. (1994) introduced the additional component of scale efficiency change. Ray and Desli (1997) started the critical debate concerning the appropriate decomposition and its interpretation, which continues today (see, e.g., Lovell, 2001, for further discussion and references). Bjurek (1996) has proposed a variant of the Malmquist index, which has the separate output index and the input index, similar to the conventional Fisher and Törnqvist indices. Recently, the more general Malmquist-Luenberger indices that

\(^2\) The Shephard output distance function is the reciprocal of the radial Farrell (1957) efficiency measure. Debreu’s (1951) coefficient of resource utilization is sometimes suggested as a dual of the input distance function. However, Debreu uses the net inputs (which include the outputs with the negative sign). Hence, Debreu’s coefficient is actually the dual of McFadden’s (1978) gauge function.
are defined using the directional distance function (rather than the radial distance) have gained popularity, particularly in applications involving environmental bads.

The previous definition of the Malmquist index in terms of the input distance function is compatible with environmental factors included in vectors $x$ and $y$: it is possible to apply the conventional Malmquist TFP index to strictly economic inputs and outputs, environmental inputs and outputs, or a mixture of both economic inputs and outputs. Another possibility is to replace the input distance function (which assumes radial equiproportionate scaling of all inputs $x$, keeping outputs $y$ at constant level) with a more general directional distance function (Chambers et al., 1996; 1998), which allows one to scale each input and output by different amounts. In this approach, a researcher must specify direction vectors $g^x$ and $g^y$, which define the projection of evaluated input-output vectors (e.g., data points) to the boundary of the production possibility set $T$. The TFP index constructed using the directional distance function is referred to as the Malmquist-Luenberger index (e.g., Chung et al., 1997).

The generality of the directional distance function does not come for free. In particular, the choice of the direction vectors $g^x$ and $g^y$ will generally influence the levels of the TFP index and its components. In other words, the results depend on the choice of the direction.

Another potential problem worth noting (depending on the specification of the inputs and outputs, and the chosen direction vector) concerns the physical dependence of outputs on inputs. This issue is closely related to the possible violations of the material balance principle, to be discussed in more detail in Section 5.2. For example, consider a coal fired power plant which generates carbon dioxide ($CO_2$) as an undesirable side product. Suppose in the chemical reaction of the combustion process the output of $CO_2$ is directly proportional to the fuel input. Then, denoting the fuel input as $x$ and the $CO_2$ output as $y$, the ratio $y/x$ is a constant, which is the same across all countries and all time periods. Since the material and energy contained in the inputs $x$ must exit the production system in outputs $y$, simultaneous increase of good output $y$ and reduction of resources $x$ is infeasible in this example. However, this does not necessarily mean that production is organized or run efficiently. Since in the previous example the fuel input and $CO_2$ were assumed to be perfectly correlated, one of them could be excluded from the model as redundant without any loss of information, in order to break the direct physical link from an input to an output. Moreover, even if the undesirable output is not perfectly correlated with the input, a high positive correlation between the two may cause problems with multicollinearity.

A general problem with the environmentally sensitive TFP measures is that the measured TFP growth can be driven entirely by improved labour productivity or capital productivity. In other words, even though the environmental resources $x_{ENV}^i$ are included in the input vector $x$, there is no guarantee that they have actually any impact on the TFP index. This is because the environmentally sensitive TFP measures typically allow the shadow prices of inputs to be zero. For example, suppose a country employs a dirty technology that emits large amounts of pollution per unit of economic output, but requires only a minimal amount of capital input. Thanks to its high capital productivity (output per capital), such a country would appear very efficient according to the conventional distance functions.

A potential solution to the previous challenges is to resort to the notion of environmental productivity (also referred to as eco-efficiency or environmental performance). Departing from the simple eco-efficiency indicators defined as the ratio of the economic output to environmental pressure, Kuosmanen and Kortelainen (2005) propose to use the following ratio of aggregates,

$$EE_i = \left( \frac{VA_i}{g(Q^i_{x_{ENV}})} \right)$$

where $VA$ is the value added of the firm, industry, or economy $i$ (i.e., the gross output minus intermediate inputs), $Q$ is a transformation matrix, the elements of which represent the contribution of each bad output
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(material substances or energy) to specific environmental problem (e.g., climate change, eutrophication, toxic waste), and $g$ is a function that aggregates the environmental pressures in each theme to a single index of environmental pressure. Function $g$ could be interpreted as a damage function. Without a loss of generality, we can normalize the unknown function $g$ such that

$$\max \frac{VA_h}{g(Qx^{ENV})} = 1.$$ 

Using this normalization, $EE$ is a measure of relative efficiency that is constrained between 0 and 1.

Note that the value added $VA$ in the nominator takes into account the outputs $y$ (valued at the market prices) and inputs $x$, except for the primary inputs labour and capital. The elements of $Q$ can take into account the existing information about harmfulness of individual substances. If no information is available, $Q$ could be simply an identity matrix $I$. The damage function $g$ can be estimated by nonparametric methods. Kuosmanen and Kortelainen (2005) apply the duality theory to show that it is possible to estimate the shadow prices and measure relative environmental performance using an input distance function defined with respect to the augmented production set that uses $VA$ as the output indicator.

The measure $EE$ has a natural interpretation as an extension of the simple eco-efficiency ratios to the multivariate case. Alternatively, one can interpret it as a generalized decoupling measure. In this approach, at least some environmental pressures must have a strictly positive shadow cost. The practical benefit of the approach is that we do not need data for the primary inputs such as labour and capital. Further, aggregation of good outputs and intermediate inputs to value added at the aggregate level, and the aggregation of individual bad outputs (e.g., different greenhouse gases) to environmental pressures helps to decrease the number of input-output variables, which is particularly useful for nonparametric estimation (to alleviate the curse of dimensionality).

Kortelainen (2008) has further extended the approach to the inter-temporal context, suggesting that the Malmquist index and its decomposition to TECH and EFF components can be applied to the environmental performance measure $EE$. However, one should be careful with the interpretation of the TECH and EFF component in this context. When the conventional economic inputs are excluded, the TECH component may capture such effects as input substitution or more efficient utilization of economies of scale or scope. Similarly, the EFF can increase, for example, through investments to new technology. Parallel arguments can be made in the case of conventional production models, too, but the risk for misleading interpretation seems particularly high in the environmental performance approach that departs from the production theory. The problem concerns mainly the labelling and interpretation. Technically, TECH represents the shift of the empirical frontier over time, and EFF represents the movements toward or away from the frontier. While the interpretation of the frontier shift as technical progress can be questionable and potentially misleading, inventing some new labels to replace the established TECH and EFF would not solve the problem of interpretation, but it would make the report more difficult to read for those who are familiar with the established decomposition of the Malmquist index. Therefore, having alerted the reader of possible caveats in the interpretation, this report uses the established terminology and abbreviations.

In conclusion, while the price-based aggregation of inputs and outputs has its merits, due to the problems discussed above, we would recommend the Malmquist index or its variants as the preferred approach in the present context of green agricultural productivity analysis. The environmental factors can be included in the definition of the production set to obtain environmentally sensitive TFP measures, in contrast to the purely economic TFP measures that ignore the environment. Alternatively, it is possible to apply environmental productivity measures that take the trade-off between the economic value added and the environmental quality explicitly into account.

In practice, the shadow price approach implies that we need to estimate the production set $T$ or the distance
function(s) $D_I$ from empirical data in one way or another. We will examine some alternative approaches to estimation in the next section.

4. Estimation of technology distance functions

4.1 Brief literature review

The estimation of distance functions for the Malmquist-style productivity indices (or just for their own sake) falls to the domain of productivity and efficiency analysis (see, e.g., Fried et al., 2008). This multidisciplinary field intersects such disciplines as economics, operations research, management science, statistics, and public administration. This field covers such areas as production theory, index theory (productivity and efficiency indices), microeconomic theory of the firm, econometric estimation of production, cost, profit, and distance functions, mathematical programming approaches to frontier estimation, among others. There are thousands of empirical applications of productivity and efficiency analysis in such fields as agriculture, banks and financial institutions, education, health care, energy, transportation, and utilities, among many others.

Traditionally, the field is dominated by the two approaches: the axiomatic, nonparametric data envelopment analysis (DEA; Charnes et al., 1978) and the probabilistic, parametric stochastic frontier analysis (SFA: Aigner et al., 1977; Meesuen and Vanden Broeck, 1977). The main advantages and disadvantages of these approaches are the following (we abstract from technical details in this report; see, e.g., Fried et al., 2008, for a more detailed presentation of these methods.)

The main appeal of DEA lies in its axiomatic, nonparametric treatment of the frontier, which does not assume a particular functional form but relies on the general regularity properties such as free disposability, convexity, and assumptions concerning the returns to scale. However, the conventional DEA approach attributes all deviations from the frontier to inefficiency, and ignores any stochastic noise in the data.

The key advantage of SFA is its stochastic treatment of these deviations, which are decomposed into a non-negative inefficiency term and a random disturbance term that accounts for measurement errors and other random noise. However, SFA builds on the parametric regression techniques, which require an ex ante specification of the functional form. Since the economic theory rarely justifies a particular functional form, the flexible functional forms, such as the translog are frequently used. In contrast to DEA, the flexible functional forms often violate the monotonicity, concavity/convexity and homogeneity conditions. Further, imposing these conditions can cost the flexibility.

The emerging literature on stochastic semi-parametric or semi-nonparametric frontier estimation has mainly departed from the SFA side, replacing the parametric frontier function by a nonparametric specification that can be estimated by kernel regression or local maximum likelihood (ML) techniques. Fan et al. (1996) and Kneip and Simar (1996) were among the first to apply kernel regression to frontier estimation in the cross-sectional and panel data contexts, respectively. Fan et al. (1996) proposed a two-step method where the shape of the frontier is first estimated by kernel regression, and the conditional expected inefficiency is subsequently estimated based on the residuals, imposing the same distributional assumptions as in standard SFA. Kneip and Simar (1996) similarly use kernel regression for estimating the frontier, but they make use of panel data to avoid the distributional assumptions. Other recent semi-parametric approaches include Park et al. (1998) and Kumbhakar et al. (2007).

In economics, two important predecessors of DEA include Farrell (1957) and Afriat (1972).
Departing from DEA, Banker and Maindiratta (1992) were the first to consider maximum likelihood estimation of the stochastic frontier model subject to the global free disposability and convexity axioms adopted from the DEA literature. More recently, Kuosmanen (2008) developed a finite-dimensional representation for the infinite dimensional nonparametric least squares problem to find the best fitting curve from the class of monotonic increasing and concave functions. The representation theorem by Kuosmanen (2008) allows one to formulate and solve the infinite dimensional least squares problem using quadratic programming. Building on this result, Kuosmanen and Kortelainen (2012) developed a more general semi-nonparametric frontier model that encompasses the traditional data envelopment analysis (DEA) and stochastic frontier analysis (SFA) as its restricted special cases (see also Kuosmanen and Johnson, 2010). Kuosmanen and Kortelainen (2012) coined the name StoNED (stochastic semi-nonparametric envelopment of data) for the new approach.

The StoNED approach has solid methodological foundations through its quadruple roots in the SFA literature in econometrics, the DEA literature in operations research, the concave regression literature in statistics, and the revealed preference theory in microeconomics. Although the method was introduced very recently, there are already several empirical applications as well as methodological extensions to StoNED. Most notably, Johnson and Kuosmanen (2011, 2012) extended the StoNED approach to include contextual variables that represent the operational conditions or practices. In other words, the contextual variables can be used for modelling observed heterogeneity of firms and their operating environments. Regarding empirical works, Kuosmanen and Kuosmanen (2009) apply StoNED to a sample of Finnish dairy farms in the first published empirical application of the method. Another noteworthy application of StoNED has been in the regulation of electricity distribution networks in Finland (Kuosmanen, 2012), which has had major economic impacts on the sector.

A more detailed description of the assumptions and properties of the DEA, SFA, and StoNED methods is presented in Appendix 1.

4.2 Generic econometric model

Typically, the agricultural sector of a country produces hundreds of different food products, which form the output vector $y$. In practice, it is necessary to aggregate at least some of the products to broader product categories. Since the number of possible product categories is also large, in the following we will use the total value added of the agricultural sector as the aggregate output variable, and denote it by $y$. As noted in Section 2, both economic and environmental resources are included in the input vector $x$.

We characterize the maximum value added obtainable by given input resources in period $t$ by the aggregate production function $f'(x)$. Assuming $f$ exhibits constant returns to scale, we can write the input distance function for country $i$ in period $t$ as

$$DI'(x_i, y_i) = \sup \{ \lambda \mid y_i = f'(x_i / \lambda) \} = f'(x_i) / y_i$$

Taking natural logarithms of the both sides of the previous equation, and denoting $u_i = \ln DI'(x, y)$ we can reorganize the equation to obtain

$$\ln y_i = \ln f'(x_i) - u_i$$

This is an econometric representation of a deterministic production model where all deviations from the frontier are attributed to inefficiency. If the functional form of $f$ is unknown, but we are willing to assume that $f$ is a monotonic increasing and concave function, we can apply DEA to estimate $f$ and $u$. However, random data errors and omitted variables will be wrongly attributed to inefficiency, and the DEA estimator of the frontier is inconsistent. Introducing a stochastic noise term $v$ (akin to the idiosyncratic disturbance term in regression analysis), the generic stochastic frontier model can be stated as

$$\ln y_i = \ln f'(x_i) - u_i + v_i$$
This model can be estimated by standard SFA techniques, but the functional form of \( f \) needs to be assumed beforehand; usually log-linear functions such as the Cobb-Douglas or translog are used. However, the advantage of SFA over the nonparametric DEA is that it takes the stochastic noise term explicitly into account, and applies the probability theory to distinguish inefficiency from noise. The StoNED model encompasses the previous DEA and SFA models: the functional form of \( f \) is not restricted beforehand (\( f \) is assumed to be monotonic increasing and concave as in DEA), but the composite error term \( e_i = y_i - u_i \) is used similar to SFA. For a more detailed discussion about the estimation, we refer to Kuosmanen and Kortelainen (2012).

Section 7 applies the semi-nonparametric StoNED method to the panel data of agricultural production in 13 OECD countries. For comparison, the corresponding results obtained using the panel data SFA and DEA methods are also reported. However, before proceeding to the empirical application, we first discuss some methodological and specification issues specific to agriculture.

5. Model specification and some methodological issues specific to agriculture

5.1 Damage control inputs

Damage control inputs such as chemical pesticides or insect resistant crops do not directly increase yield, but rather, increase the share of potential output that is realized by reducing damage. Thus, productivity assessment of these inputs is not as straightforward as that of direct (yield increasing) inputs. Lichtenberg and Zilberman (1986) were the first to discuss the special nature of damage control inputs and to account for this characteristic using a built-in damage control function. Subsequently, there has been some debate about the appropriate way to model the damage control inputs in agriculture (see, e.g., Carpentier and Weaver, 1997; Kuosmanen et al., 2006; for discussion and references).

The econometric treatment of damage control inputs suggested by Lichtenberg and Zilberman (1986) is similar to the modelling of so-called “environmental” variables (i.e., measured characteristics of the operating environment), exogenous factors, contextual variables, non-discretionary inputs or facilitating inputs in the literature of SFA (see, e.g., Kumbhakar et al., 1991; Battese and Coelli, 1995; Alvarez et al., 2006) and DEA (e.g., Johnson and Kuosmanen, 2011, 2012). In general, denote these variables by vector \( z \).

Some studies assume that the \( z \)-variables are uncorrelated with inputs \( x \) (thus the term exogenous factors), but in the case of damage control inputs it is necessary to allow for possible correlations between the elements of \( z \) and \( x \).

The damage control and other facilitating inputs could be taken into account in the econometric specification as follows. Assuming that \( z \) do not enter the damage function directly, but rather influence efficiency of production, we can write the generic econometric model as

\[
\ln y_i = \ln f'(x_i) - u_i + v_i
\]

In the SFA literature, the inefficiency term \( u \) is modelled as a random variable. The \( z \)-variables can influence the mean and the variance of its distribution. In the DEA literature, a common approach is to resort to a two-stage estimation strategy where the impacts of \( z \)-variables are estimated from the DEA efficiency estimates (e.g. Kuosmanen et al., 2006). Recently, Johnson and Kuosmanen (2012) show that joint estimation of the effects of \( x \) and \( z \) (in a single stage) is possible.

5.2 Material balance

The material balance approach (Ayres and Kneese, 1969; Georgescu-Roegen, 1986) has recently attracted interest in environmental economics (e.g., Daly, 1997; Baumgärter 2004; Pethig, 2006; Ebert and Welsch,
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2007; and Førsund, 2009; among others). In the context of agriculture, the nutrient balance method is used in a number of productivity studies (e.g., Reinhard et al., 1999, 2000; Reinhard and Thijsse, 2000; Coelli et al., 2007; Lauwers, 2009; Meensela et al., 2010; Hoang and Coelli, 2011).

Several papers in this stream of literature criticize the conventional models of bad outputs for being incompatible with the law of mass conservation and the fundamental laws of physics. Following the seminal article by Ayres and Kneese (1969), the conventional material balance equation is usually presented in the linear form as the difference between the total quantity of substance $s$ in the inputs and the total quantity of $s$ in the outputs, formally:

$$s = a^Tx - b^Ty,$$

where $s$ is a flow variable that represents the surplus (or deficit) of substance $s$, $a$ and $b$ are non-negative vectors that represent the content of substance in the inputs and outputs. If the production process is governed by the material balance equations stated above, it may be physically impossible to increase the production of good outputs $y$ and reduce the bad outputs $b$ and inputs $x$, as we already noted in Section 3. This can be problematic for the environmentally sensitive TFP measures.

Abstracting from the material balance context, our interpretation of the previous material balance argument is the following. Suppose the production model takes explicitly into account all factors that influence production, including such aspects as skill and motivation. In the theoretical case where all aspects that affect production are explicitly taken into account, the set of input factors will explain the observed outputs perfectly (in regression terminology, we have a perfect fit with the coefficient of determination equal to 1). Hence, there is no inefficiency or unexplained residuals. This implies that all firms or countries are equally productive, and we cannot draw a distinction between inefficient or efficient producers.

The efficiency indices that are constructed from the unexplained residuals ultimately depend on the omitted variables: the variables that are excluded from the analysis. In the worst case, efficiency differences capture unobserved random variation, and thus the efficiency analysis produces nothing but random noise. If the objective of the analysis is to assess green productivity, we may make a deliberate choice to exclude some of the input or output variables from the analysis. This is exactly the reasoning behind the environmental performance approach by Kuosmanen and Kortelainen (2005). By using value added as an aggregate measure of inputs and outputs, they deliberately depart from the conventional production models by excluding labour and capital inputs from the analysis. If the focus is on environmental performance, it can be argued that efficient use of labour is not a valid excuse to pollute.

Another issue worth noting concerns the dynamics of the material balance. In practice, the material balance equation can be used for estimating the quantities of pollutants that are not directly observable or difficult to measure. In agriculture, it is standard to use the nutrient balance method to estimate the surplus of nitrogen and phosphorus. OECD applies this method for calculating nitrogen and phosphorus balances at country level (see OECD, 2007a,b), and subsequently uses the nutrient balances to construct indicators of environmental performance (OECD, 2008). However, it is important to note that these surplus measures are flow variables that ignore the nutrient flows in the previous periods and the accumulation of nutrients to the soil. The cycle of nutrients in the soil is a very slow process, particularly in the case of phosphorus.

The recent study by Kuosmanen and Kuosmanen (2012) suggests it would be more appropriate to consider the stocks of nutrients rather than the flows. They propose a simple dynamic model of material balance, which takes the time and the accumulation of nutrients explicitly into account. Specifically, stock of nutrient ($Z$) in country $i$ in period $t$ can stated as

$$Z_{it} = (1 - \delta_i)Z_{i,t-1} + s_{it} = (1 - \delta_i)Z_{i,t-1} + a^T x_{it} - b^T y_{it},$$

where $\delta_i$ is the decay rate of nutrient in country $i$. In practice, the nutrient stocks could be constructed from the available data of nutrient flows in a similar manner to the capital stocks constructed from
investments: the nutrient surplus is analogous to capital investment. In the measurement and analysis of productivity, it is standard to use the capital stock (or a flow of services from the stock) rather than the investment flow. By the same argument, it would be appropriate to use in environmental performance analysis or environmentally sensitive TFP measurement the stocks of nutrients or the flow of nutrients from the stock to water, air, and soil. For practical purposes, the flow of nutrients from the stock (i.e., the decay of the nutrient stock) is usually assumed to be proportionate to the stock, and hence the choice to use stock or flow variables does not matter.

Whether one is interested in flow or stock variables, explicit modelling of the nutrient stock is in our view important both from the conceptual and practical point of view. From the conceptual point of view, taking the past nutrient inputs and the accumulation of nutrients in the long term explicitly into account provides a better proxy of the environmental pressure from nutrients than the nutrient surplus or deficit during a single period. Note that the nutrient balance can be positive (surplus) or negative (deficit). Nutrient deficit can be good or bad for the society, depending on the current stock of nutrients. In general, the socially optimal level of nutrient balance depends on the current level of the nutrient stock.

From a practical point of view, the nutrient deficit is problematic in the assessment of green productivity. Nutrient deficit can sometimes occur at the country level (see, e.g., OECD, 2011a; Section 1.4), but it is very common at the farm level. Consider, for example, a simple ratio of agricultural value added to the nitrogen balance as a partial productivity indicator (the same issue concerns TFP indices as well). If a country has nitrogen deficit, this ratio becomes negative. To avoid the problem of negative productivity indices, a common practice is to add a sufficiently large number (say $M$) to the nutrient balance figures such that all data points become positive. But in this case, what is the meaning of the value added divided by the nitrogen balance plus $M$? Technically, the problem with the rescaled nutrient balance figures is that they are defined on the interval scale, and hence mathematical operations such as multiplication and division are not meaningful. The nutrient stock effectively resolves the problems caused by temporary nutrient deficit: the nutrient stock is always positive, and so is the nutrient flow from the stock (i.e., the decay of stock).

5.3 Production risk

Agricultural productivity tends to fluctuate over time due to random variations in temperature, rainfall, and other weather conditions. Farmers can take different measures to manage the production risk. For example, they can diversify their activities over various production lines (e.g., joint production of crops and dairy products) and use the land for cultivating different crops. The damage control inputs discussed above are a way to reduce the risk of pest damages. The input use (e.g., capital intensity) can also influence the production risk.

Taking production risk into account in productivity and efficiency analysis is a challenge that goes beyond the data and measurement problems. For example, consider rainfall as a random variable that is beyond the control of the farmer. Even though farmers cannot control the rain, they can affect their risk exposure through their input choices (consider, e.g., capital investment to an irrigation system). A farmer makes his production decisions based on some expected amount of rainfall. Even if the input choices were perfectly rational in light of the ex ante expectations, if the realized amount of rainfall differs from the expected value, then the farmer’s input choices may appear to be inefficient in light of the ex post evaluation.

Just and Pope (1978) were the first to take the production risk explicitly into account as a part of the production model. Kumbhakar (1993, 2002) has adapted the production risk model to the SFA setting. Technically, the treatment of production risk resembles the standard econometric approaches to heteroscedasticity (e.g., Greene, 2011). In practice, we can make the variance of the inefficiency term $\mu$, the noise term $v$, or possibly both, depend on inputs $\mathbf{x}$ and potentially some other factors (e.g., weather
variables) to take the production risk explicitly into account. If the inefficiency term \( u \) is heteroscedastic, then this needs to be taken into account in the efficiency analysis or performance measurement as well.

The conventional Just and Pope model of production risk assumes some specific continuous probability distribution for the output loss due to the risk factors. In contrast, Chambers and Quiggin (1998, 2000) model the risk by assuming a discrete set of states that occur with certain probabilities. They apply the state-contingent approach to analyse principal-agent problems and the pollution control, among other applications. Recently, O’Donnell et al. (2010) examine how the state-contingent approach could be applied in productive efficiency analysis to take into account the production risk.

5.4 Critical synthesis

The previous sub-sections review some econometric modelling issues that are particularly relevant to agricultural productivity analysis. Most of the previous studies known in the literature tend to focus on dealing with one of these issues in isolation, ignoring the other issues noted above. Ideally, it would be important to consider the damage control inputs, material balance, and production risk simultaneously, provided that necessary data are available. Further methodological research is clearly needed to achieve a better synthesis of these issues.

The main purpose of this section was to recognize importance of these issues in the present context. We must emphasize that the empirical study reported in Section 7 does not take all of the methodological issues discussed in this section explicitly into account. We do apply the material balance accounting to construct the nutrient stocks, which are used as environmental inputs, and we try to capture random idiosyncratic risks implicitly by assuming a stochastic noise term in the model. We recognize that more thorough investigation of the role of damage control inputs and production risk would be worthwhile. In practice, one of the major constraints concerns the data availability, which will be discussed next.

6. Environmental issues specific to agriculture

In this section we examine the main environmental questions related to agriculture. Our discussion is focused on the current situation in the OECD countries. Globally, agriculture is closely related to environmental problems such as deforestation or water stress, particularly in developing countries. In the OECD countries, clearing of forests for agricultural lands is a less important problem, and the current environmental discussion is focused more on the undesirable emissions from agricultural activities to air, water and soil.

In the context of high income countries, commonly used indicators for the environmental pressures caused by agriculture include the following:
- Nitrogen emissions to air, soil, and water
- Phosphorus emissions to air, soil, and water
- GHG emissions (particularly CO2)
- Consumption of fossil fuels
- The use of toxic pesticides
- Land use diversity

We will next briefly discuss the above environmental issues, commenting the measurement problems and data availability.

The nitrogen and phosphorus balances can be calculated using the nutrient balance method (OECD, 2007a,b). The data for nitrogen and phosphorus surpluses (or deficits) are available. However, it is not
directly obvious how these variables should enter productivity analysis. One problem with the nutrient balance measures concerns the negative values (deficits). The nutrient balance is defined on the interval scale, whereas the productivity ratios and more sophisticated TFP measures would require the ratio scale. One possibility to avoid this problem is to apply the stocks of nutrients as suggested by Kuosmanen and Kuosmanen (2012). Alternatively, we could utilize the nutrient stocks to estimate the emissions of nutrients to air, soil, and water separately.

The main sources of GHG emissions from agriculture include the methane from manure and the use of fossil fuels for energy. Different GHGs could be aggregated to CO2 equivalents by using the coefficient representing the global warming potential, used and published by the United Nations Framework Convention on Climate Change (UNFCCC). Precise estimation of the GHG emissions from agriculture is challenging, but proxy indicators could be calculated based on available data on energy use and the livestock.

Pesticides are both an environmental and health concern. However, the measurement of the damage caused by pesticides is challenging. Even if we ignore the social welfare considerations, the problem with pesticides is that there exists a very large number of different pesticides products, with different toxic properties. In practice, we would have to aggregate the pesticide products to some pesticides index in one way or another. However, it would be misleading to just add up the quantities of pesticides, or use some cost based aggregate. For example, it is possible that less expensive pesticides are also more harmful to the environment. If we are interested in the environmental pressure, the aggregation of different pesticides products should somehow reflect the relative harmfulness of different pesticides products. While it would be interesting and important to take the pesticides use explicitly into account, we leave this issue for future research due to data problems.

In contrast to monoculture, diversity of land use is beneficial both for biodiversity and for recreational uses. Land use diversity could be measured, for example, by the standard Shannon-Weaver diversity index. While land use diversity could be easily incorporated to the productivity analysis at the farm level, it is not necessarily appropriate to apply the same approach at the country level. More specifically, the Shannon-Weaver diversity indices calculated at the country level cannot be disaggregated to the farm level, or vice versa. It would seem necessary to calculate the diversity indices first at disaggregate level (e.g., farm level), and then use the country average or median. However, this would be both tedious and costly.

7. Empirical application

7.1 Data and model specification

In this application we compare three alternative orientations to productivity measurement: purely economic (ECON), purely environmental (ENV), and the mixed economic and environmental (MIX). The total factor productivity (TFP) index used in the application is the conventional Malmquist index, consisting of the technical change (TECH) and efficiency change (EFF) components. The frontier is estimated by the panel data version of stochastic semi-nonparametric envelopment of data (StoNED: Kuosmanen and Kortelainen, 2012) assuming monotonicity, convexity, and constant returns to scale. Technical change is captured by a parametric, linear time trend. For comparison, we will also consider the conventional SFA and DEA approaches. In Section 7.3 we estimate the conventional Cobb-Douglas production function by SFA, specifying the most productive country as the benchmark as in Schmidt and Sickles (1984), and capturing the technical change by a linear trend. In Section 7.4 we apply the panel data version of DEA suggested by Ruggiero (2004), which is capable to assimilate stochastic noise.

The empirical analysis has been conducted using the following software packages. The StoNED model was
estimated using the GAMS (General Algebraic Modeling System) software and its MINOS solver (see http://homepre.net/index.php/computations for further details). The SFA model was estimated using the Stata software (see http://www.stata.com/). The DEA model using the EMS software (Efficiency Measurement System: see http://www.holger-scheel.de/ems/). See Appendix 1 for a more detailed description of the assumptions and properties of the DEA, SFA, and StoNED methods.

Comparable sector level data on economic inputs and outputs as well as environmental variables are not available for all OECD countries. Based on data availability, we have included in the cross country comparison 13 OECD countries: AUT, DEN, FIN, FRA, GER, GRE, ITA, NED, NOR, POR, SPA, SWE, and UK. The time span of the study is 15 years, from 1990 to 2004. Unfortunately, more recent data were unavailable for many key variables. In future research, it would be interesting to extend the present study to cover a larger set of countries (including non-European countries) and more recent years, provided that comparable data are available.

As the output variable, one could use the gross output or the value added; see OECD (2001) for a detailed discussion of these two approaches. In the present context, it is convenient to resort to the value added approach where the use of intermediate inputs is subtracted from the gross output. It is somewhat challenging to obtain comparable data of the use of intermediate inputs at the sectoral level. Further, a large number of input variables can cause problems for estimation, in particular, possible multicollinearity in the parametric approaches, and the so-called ‘curse of dimensionality’ in the non-parametric approaches. Therefore, in this study we use the net production value (constant 2004-2006 prices, 1 000 Int. $) reported by FAOSTAT as the output variable \( y \) in all three alternative models. Based on the description provided by FAOSTAT, it seems that this output variable excludes the intermediate inputs (seed and feed are explicitly mentioned in the description), which are included in the gross production value reported by FAOSTAT.

The three model specifications differ in terms of the specification of the inputs.

The ECON model includes the following inputs:
- Capital K (gross capital stock, constant 2005 prices, FAOSTAT),
- Labour L (primary agriculture employment, number employed, OECD)
- Land LA (total agricultural land area, hectares, OECD)

The ENV model includes the following variables (treated as input factors):
- Agricultural total GHGs (Tonnes CO2 equivalent, OECD)
- Nitrogen stock N (own calculations, based on the nitrogen surplus reported by OECD)
- Phosphorus stock P (own calculations, based on the phosphorus surplus reported by OECD)
- Land LA (total agricultural land area, hectares, OECD)

The model MIX contains all six input variables of both the ECON and ENV models.

The inputs of the ECON model are rather standard. Note that the land capital could be modelled as a part of the capital stock. Based on the description of FAOSTAT, the gross capital stock reported by FAOSTAT only includes the physical assets in use. Therefore, we model the land area as a separate input variable. Further, it is common to express all input and output variables proportional to the land area (e.g., output per hectare). In fact, dividing all input variables and the output by one of the input variables effectively imposes the CRS assumption; we will utilize this property in Section 7.3.

The ENV model includes all environmental variables for which comparable data are available. The GHG emissions take into account the use of fossil fuels for energy, but also methane emissions from livestock. Based on the discussion in Section 5.2, we prefer to use the stocks of nitrogen and phosphorus as indicators of environmental pressure from nutrients use. Finally, the ENV model also includes the land area, which
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can be considered as a part of the natural capital. A practical reason for including the land area is that we can impose CRS consistently across all models by dividing all input variables and the output by the same input variable, the land area. In other words, we can express all variables on a per hectare basis.

The MIX model combines the economic and environmental perspectives, allowing us to model trade-offs and substitution possibilities between economic inputs and environmental resources explicitly. Note that both the ECON and ENV models are nested within the more general MIX model. The ECON model is obtained from the MIX model by restricting the shadow prices of the environmental variables as equal to zero. Similarly, the ENV model is obtained from the MIX model by setting the shadow prices of the economic inputs equal to zero. As a result, the empirical fit of the MIX model (measured, e.g., by the coefficient of determination $R^2$) is always better than that of the ECON model or that of the ENV model. A limitation of the MIX model is that does not distinguish whether high TFP level or TFP growth is due to good performance in economic or environmental criteria. Therefore, it is useful to consider and compare the results of all three approaches.

To gain intuition to the levels and changes in productivity in this sample of countries during the time period, we first examine partial productivity measures, the average labour and capital productivity, presented in Tables 1 and 2.

**Table 1: Labour productivity ($y/L$) in the sample countries; averages of 1990 – 2004**

<table>
<thead>
<tr>
<th>Country</th>
<th>Mean $y/L$</th>
<th>Efficiency</th>
<th>rank</th>
<th>$\Delta y/L$</th>
<th>rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>18.82</td>
<td>41 %</td>
<td>7</td>
<td>4.48 %</td>
<td>5</td>
</tr>
<tr>
<td>DEN</td>
<td>46.28</td>
<td>100 %</td>
<td>1</td>
<td>4.55 %</td>
<td>4</td>
</tr>
<tr>
<td>FIN</td>
<td>11.82</td>
<td>26 %</td>
<td>10</td>
<td>3.63 %</td>
<td>7</td>
</tr>
<tr>
<td>FRA</td>
<td>39.40</td>
<td>85 %</td>
<td>3</td>
<td>4.69 %</td>
<td>3</td>
</tr>
<tr>
<td>GER</td>
<td>26.52</td>
<td>57 %</td>
<td>5</td>
<td>4.30 %</td>
<td>6</td>
</tr>
<tr>
<td>GRE</td>
<td>9.82</td>
<td>21 %</td>
<td>12</td>
<td>3.41 %</td>
<td>8</td>
</tr>
<tr>
<td>ITA</td>
<td>20.03</td>
<td>43 %</td>
<td>6</td>
<td>5.76 %</td>
<td>1</td>
</tr>
<tr>
<td>NED</td>
<td>45.22</td>
<td>98 %</td>
<td>2</td>
<td>2.33 %</td>
<td>11</td>
</tr>
<tr>
<td>NOR</td>
<td>11.27</td>
<td>24 %</td>
<td>11</td>
<td>1.82 %</td>
<td>12</td>
</tr>
<tr>
<td>POR</td>
<td>5.68</td>
<td>12 %</td>
<td>13</td>
<td>3.37 %</td>
<td>9</td>
</tr>
<tr>
<td>SPA</td>
<td>18.77</td>
<td>41 %</td>
<td>8</td>
<td>5.39 %</td>
<td>2</td>
</tr>
<tr>
<td>SWE</td>
<td>17.24</td>
<td>37 %</td>
<td>9</td>
<td>2.72 %</td>
<td>10</td>
</tr>
<tr>
<td>UK</td>
<td>30.61</td>
<td>66 %</td>
<td>4</td>
<td>0.94 %</td>
<td>13</td>
</tr>
</tbody>
</table>

**Notes:** The unit of measurement for labour productivity $y/L$ is $1,000 per worker. Efficiency is calculated as the ratio of mean labour productivity $y/L$ of country and the mean labour productivity of Denmark, which has the highest $y/L$ ratio in the sample. $\Delta y/L$ is the geometric mean of the annual changes in labour productivity $y/L$.

Countries are sorted in alphabetical order in Table 1: the first column indicates the country abbreviation. The second column indicates the average labour productivity in $1,000 per worker. The third column indicates the relative labour efficiency, calculated as the ratio of country’s average labour productivity and that of Denmark, the country with the highest labour productivity in this sample. To help a reader to quickly recognize the most productive and least productive countries, the fourth column indicates the relative rank of a country in terms of labour productivity. Observe the large differences in the level of labour productivity across countries. For example, Greece and Portugal achieve on the average only 21% and 12% of the labour productivity of Denmark during this time period. The large differences in labour productivity across countries are not surprising given the intensive use of capital intensive production technologies in some countries in contrast to more traditional labour intensive agriculture in others.
Column $\Delta y/L$ in Table 1 indicates the change in labour productivity, calculated as the geometric mean of the annual changes of $y/L$. The last column indicates the relative rank of a country in terms of labour productivity growth. All countries achieved positive labour productivity growth during this period. The highest growth occurred in Italy, followed by Spain and France.

Table 2 presents the analogous statistics for capital productivity $y/K$. Observe the large differences in the level of capital productivity across countries. No other country in the sample comes even close to the capital productivity of the Netherlands. We should add that the measurement of the capital stock is a challenging task, and the data of capital stocks reported by FAOSTAT might not be fully comparable across countries, but in this study, we assume the FAOSTAT data are correct. As for the changes, the growth of capital productivity $\Delta y/K$ is rather modest compared to the labour productivity growth. For Norway, Sweden, and the United Kingdom, capital productivity declined during this time period. The comparison of Tables 1 and 2 reveals a rather different picture both in terms of the levels of productivity and the productivity growth. This highlights the need to resort to TFP measures that can accommodate multiple input factors, including environmental factors.

**Table 2: Capital productivity ($y/K$) in the sample countries; average of 1990 – 2004**

<table>
<thead>
<tr>
<th>Country</th>
<th>Mean $y/K$</th>
<th>Efficiency rank</th>
<th>$\Delta y/K$ rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>244.6</td>
<td>26 %</td>
<td>10</td>
</tr>
<tr>
<td>DEN</td>
<td>410.1</td>
<td>44 %</td>
<td>2</td>
</tr>
<tr>
<td>FIN</td>
<td>136.9</td>
<td>15 %</td>
<td>12</td>
</tr>
<tr>
<td>FRA</td>
<td>387.9</td>
<td>42 %</td>
<td>4</td>
</tr>
<tr>
<td>GER</td>
<td>304.5</td>
<td>33 %</td>
<td>8</td>
</tr>
<tr>
<td>GRE</td>
<td>399.7</td>
<td>43 %</td>
<td>3</td>
</tr>
<tr>
<td>ITA</td>
<td>365.2</td>
<td>39 %</td>
<td>5</td>
</tr>
<tr>
<td>NED</td>
<td>925.5</td>
<td>100 %</td>
<td>1</td>
</tr>
<tr>
<td>NOR</td>
<td>132.4</td>
<td>14 %</td>
<td>13</td>
</tr>
<tr>
<td>POR</td>
<td>248.2</td>
<td>27 %</td>
<td>9</td>
</tr>
<tr>
<td>SPA</td>
<td>346.1</td>
<td>37 %</td>
<td>6</td>
</tr>
<tr>
<td>SWE</td>
<td>187.9</td>
<td>20 %</td>
<td>11</td>
</tr>
<tr>
<td>UK</td>
<td>338.2</td>
<td>37 %</td>
<td>7</td>
</tr>
</tbody>
</table>

**Notes:** Efficiency is calculated as the ratio of mean capital productivity $y/K$ of country and the mean capital productivity of the Netherlands, which has the highest $y/K$ ratio in the sample. $\Delta y/K$ is the geometric mean of the annual changes in capital productivity $y/K$.

Analogous to labour and capital productivity, environmental partial productivity measures could be calculated using the environmental indicators noted above. Since such environmental partial productivity indicators have been reported elsewhere (see, e.g., OECD, 2008, 2011a), we turn our focus on the TFP measures.

7.2 Stochastic semi-nonparametric envelopment of data
We first estimate the following log-transformed production models by convex nonparametric least squares (CNLS: Kuosmanen, 2008; Kuosmanen and Kortelainen, 2012)

ECON: $\ln y_{it} = \ln f(K_{it}, L_{it}, LA_{it}) + Trend \cdot t + \varepsilon_{it}$

ENV: $\ln y_{it} = \ln g(GHG_{it}, N_{it}, P_{it}, LA_{it}) + Trend \cdot t + \varepsilon_{it}$

MIX: $\ln y_{it} = \ln h(K_{it}, L_{it}, LA_{it}, GHG_{it}, N_{it}, P_{it}) + Trend \cdot t + \varepsilon_{it}$
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where \( f, g, \) and \( h \) are unknown monotonic increasing and concave functions that exhibits constant returns to scale, \( \text{Trend} \) is a parameter that represents Hicks neutral technical change, and \( \varepsilon_i \) is the disturbance term that captures both inefficiency and noise. Note that in the panel data setting the idiosyncratic errors cancel out over time. Thus, we follow Schmidt and Sickles (1984) and use the average of the residuals of the most efficient country as the benchmark level to define the frontier. The country specific efficiency levels are estimated as the geometric mean of the residuals of country \( i \) divided by the geometric mean of the residuals in the most efficient country

\[
\text{Eff}_i = \frac{\prod_{t=1}^{T} \exp(\varepsilon_{it})}{\max_h \prod_{t=1}^{T} \exp(\varepsilon_{ht})}.
\]

The nonparametric estimator of the production function \( f \) is a piece-wise linear function that is characterized by supporting hyper-planes. The coefficients of the supporting hyper-planes can be interpreted as marginal products of inputs. Table 3 reports summary statistics of the estimated marginal products in the ECON, ENV, and MIX models. Note that the marginal products vary across countries and years.

**Table 3: Marginal products of inputs in ECON, ENV, and MIX models: summary statistics of the CNLS estimates (prices of 2004 – 2006)**

<table>
<thead>
<tr>
<th></th>
<th>ECON</th>
<th>ENV</th>
<th>MIX</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>K</strong></td>
<td>Mean</td>
<td>St. Dev.</td>
<td>Min</td>
</tr>
<tr>
<td>L ($/pers.)</td>
<td>0.1045</td>
<td>0.1429</td>
<td>0</td>
</tr>
<tr>
<td>LA ($/ha)</td>
<td>394.48</td>
<td>312.12</td>
<td>0</td>
</tr>
<tr>
<td>R²</td>
<td>0.855</td>
<td>0.942</td>
<td>0.948</td>
</tr>
<tr>
<td>GHG ($/ton)</td>
<td>194.54</td>
<td>167.39</td>
<td>0</td>
</tr>
<tr>
<td>N ($/ton)</td>
<td>1785.50</td>
<td>135.04</td>
<td>0</td>
</tr>
<tr>
<td>P ($/ton)</td>
<td>1785.50</td>
<td>135.04</td>
<td>0</td>
</tr>
<tr>
<td>LA ($/ha)</td>
<td>249.08</td>
<td>101.91</td>
<td>0</td>
</tr>
<tr>
<td>R²</td>
<td>0.855</td>
<td>0.942</td>
<td>0.948</td>
</tr>
</tbody>
</table>

In the ECON model, the average marginal product of capital is 0.10, which means that capital investment pays back in 10 years on average in the sample of countries considered. For some countries (e.g., Greece, Portugal) the payback period is very short, less than 4 years. For others (e.g., Norway, Finland, Sweden) the marginal product of capital is zero, which suggest these countries have overinvested in capital goods.
The marginal product of labour is on average 7,540 dollars per person per year. The maximum value is 34,546 dollars per person per year (France 2004). Austria, Denmark, Finland, France, Germany, Norway, and Sweden achieve consistently labour productivity of more than 10,000 dollars per person. The marginal product of labour is lowest in Portugal, Greece, and Spain. The marginal product of agricultural land is on average 394 dollars per hectare. The maximum is 2,249 dollars per hectare (the Netherlands 1991). In general, the marginal products of land and labour have a high positive correlation across countries: countries that have a high marginal productivity of labour tend to have also high marginal productivity of land. In this respect, land might be modelled as a part of the capital stock.

Interestingly, the empirical fit of the ENV model is better than that of the ECON model (the R² statistics are 0.942 in the ENV model and 0.855 in the ECON model, respectively), even though the labour and capital inputs are excluded. The R² increases only marginally when the labour and capital are restored in the MIX model. Note that the estimated average marginal product of capital is very small in the MIX model, and those of labour and land are also considerably smaller in the MIX model than in the ECON model. The estimated marginal products of GHG and the nitrogen stock also decrease when moving from the ENV model to the MIX model, but not dramatically. The estimated marginal product of the phosphorus stock is on average larger in the MIX model than in the ENV model. Considering both the empirical fit and the estimated marginal products, these finding suggests that the environmental resources (GHG, N, and P) can explain empirically the observed variations across countries and years better than the labour and capital inputs used in the conventional production models.

Table 4 reports the parameter estimates of the time trend. The parametric trend is estimated simultaneously together with the nonparametric production function f (see Johnson and Kuosmanen, 2011; 2012, for details). The time trend is positive and statistically significant at 5% significance level. Interpreting the time trend as global frontier shift, the annual rate of technical progress is TECH = \exp(0.016) = 1.01618, which indicates 1.618 % technical progress per year, assumed constant across all countries and years.

Table 4: Parameter estimates of the time trend; semi-nonparametric StoNED model

<table>
<thead>
<tr>
<th>Model</th>
<th>Coefficient</th>
<th>St. error</th>
<th>t stat</th>
<th>p-value</th>
<th>lower 95%</th>
<th>upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECON</td>
<td>0.0160</td>
<td>0.0070</td>
<td>2.2871</td>
<td>0.0233</td>
<td>0.0022</td>
<td>0.0299</td>
</tr>
<tr>
<td>ENV</td>
<td>0.0119</td>
<td>0.0044</td>
<td>2.6828</td>
<td>0.0079</td>
<td>0.0032</td>
<td>0.0206</td>
</tr>
<tr>
<td>MIX</td>
<td>0.0162</td>
<td>0.0042</td>
<td>3.8614</td>
<td>0.0002</td>
<td>0.0079</td>
<td>0.0244</td>
</tr>
</tbody>
</table>

Consider next the country specific efficiency estimates obtained with the ECON, ENV, and MIX models. Both the level and change of efficiency and TFP are of interest, as well as the relative performance rankings of countries.

We start with the results of the ECON model, presented in Table 5. The 13 countries considered are listed in alphabetical order, as in Tables 1 and 2 above. The first column indicates the efficiency level, calculated as the geometric mean of the annual efficiency estimates in years 1990 – 2004. Recall that 100% efficiency represents the average efficiency of the best performing country in the sample. To help a reader to identify the best performing countries as well as the worst performers, the second column of Table 5 indicates the relative ranking of country in terms of the efficiency level. However, the ranking of countries is not the main focus of this exercise. The third column indicates the average annual percentage change in efficiency, calculated as the geometric mean of the annual changes in the efficiency levels. The next column indicates the relative rank of the country in terms of the efficiency change. The rightmost column indicates the average TFP change, calculated as the product of the efficiency change and the technical change components. For the sake of interpretation, we express the average TFP change as percentage per year, calculated using the geometric mean of the TFP change between immediately adjacent years. Since the
technical change is assumed to be constant across all countries and years, the relative ranking of TFP changes is exactly the same as the efficiency change ranking.

**Table 5: Efficiency levels, efficiency change, and TFP change according to the ECON model; Seminonparametric StoNED estimates**

<table>
<thead>
<tr>
<th>Country</th>
<th>EFF level</th>
<th>Rank</th>
<th>EFF change</th>
<th>Rank</th>
<th>TFP change</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>31 %</td>
<td>9</td>
<td>1.060 %</td>
<td>1</td>
<td>2.695 %</td>
</tr>
<tr>
<td>DEN</td>
<td>64 %</td>
<td>2</td>
<td>0.852 %</td>
<td>3</td>
<td>2.484 %</td>
</tr>
<tr>
<td>FIN</td>
<td>20 %</td>
<td>13</td>
<td>0.396 %</td>
<td>6</td>
<td>2.021 %</td>
</tr>
<tr>
<td>FRA</td>
<td>45 %</td>
<td>3</td>
<td>0.440 %</td>
<td>5</td>
<td>2.065 %</td>
</tr>
<tr>
<td>GER</td>
<td>44 %</td>
<td>4</td>
<td>0.674 %</td>
<td>4</td>
<td>2.302 %</td>
</tr>
<tr>
<td>GRE</td>
<td>42 %</td>
<td>5</td>
<td>-1.279 %</td>
<td>12</td>
<td>0.318 %</td>
</tr>
<tr>
<td>ITA</td>
<td>41 %</td>
<td>6</td>
<td>0.915 %</td>
<td>2</td>
<td>2.548 %</td>
</tr>
<tr>
<td>NED</td>
<td>100 %</td>
<td>1</td>
<td>-0.138 %</td>
<td>7</td>
<td>1.477 %</td>
</tr>
<tr>
<td>NOR</td>
<td>23 %</td>
<td>12</td>
<td>-0.733 %</td>
<td>10</td>
<td>0.873 %</td>
</tr>
<tr>
<td>POR</td>
<td>26 %</td>
<td>10</td>
<td>-0.460 %</td>
<td>9</td>
<td>1.150 %</td>
</tr>
<tr>
<td>SPA</td>
<td>36 %</td>
<td>8</td>
<td>-0.927 %</td>
<td>11</td>
<td>0.676 %</td>
</tr>
<tr>
<td>SWE</td>
<td>25 %</td>
<td>11</td>
<td>-0.340 %</td>
<td>8</td>
<td>1.272 %</td>
</tr>
<tr>
<td>UK</td>
<td>37 %</td>
<td>7</td>
<td>-1.391 %</td>
<td>13</td>
<td>0.204 %</td>
</tr>
</tbody>
</table>

**Note:** Global technical change (TECH) is estimated as 1.618 % for all countries and years.

In the ECON model, the Netherlands is by a large margin the most efficient country in transforming economic inputs to agricultural value added in the sample of countries considered (compare with Table 2). The efficiency levels are scaled relative to the average performance of the Netherlands. Denmark distinguishes itself as the second most efficient agricultural producer after the Netherlands (recall that Denmark had the highest labour productivity in Table 1). The other Nordic countries, Finland, Norway, and Sweden, are the least efficient countries in the sample.

The global technical progress is estimated as 1.618 % across all countries and years. All countries achieve positive TFP growth according to the ECON model. The largest growth (catching up) is achieved in Austria, Italy, and Denmark. Efficiency change is negative (falling behind) in the United Kingdom, Greece, Spain, Norway, Portugal, Sweden, and the Netherlands. This group includes both the most efficient producer (NED), but also some of the least efficient producers (NOR, SWE). There are some signs of catching up the lead of the Netherlands, most notably in Austria, Italy, and Denmark, but also in Germany, France, and Finland. The country specific TFP trajectories are presented in Appendix 2, to be discussed in more detail in Section 7.5.

Table 6 presents the analogous results for the ENV model. In this case, the subset of environmental inputs is included in the model, and the economic inputs (labour, capital) are excluded. Recall from Table 3 that the empirical fit of the ENV model is better than that of the ECON model.

In terms of the levels, Italy is the most environmentally efficient producer according to the ENV model in this sample, followed by the Netherlands. The differences in the levels of environmental efficiency remain large, but not as dramatic as in the ECON model. Sweden, Finland and Norway are among the least efficient countries also in terms of the ENV model.

Regarding the changes, Italy also shows the highest average rate of efficiency improvement, while Norway has relatively large efficiency decline. The high positive correlation between the levels and changes in environmental efficiency suggests that countries diverge rather catch up in terms of their environmental
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performance. However, when we take the technical progress (on average 1.2% per year) into account, the environmental TFP growth is positive in all countries, except for Norway. For most countries, the average environmental TFP growth falls below the economic TFP growth.

Table 6: Efficiency levels, efficiency change, and TFP change according to the ENV model; Semi-nonparametric StoNED estimates

<table>
<thead>
<tr>
<th>Country</th>
<th>EFF level</th>
<th>Rank</th>
<th>EFF change</th>
<th>Rank</th>
<th>TFP change</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>72 %</td>
<td>4</td>
<td>0.750 %</td>
<td>4</td>
<td>1.955 %</td>
</tr>
<tr>
<td>DEN</td>
<td>70 %</td>
<td>5</td>
<td>1.130 %</td>
<td>2</td>
<td>2.341 %</td>
</tr>
<tr>
<td>FIN</td>
<td>43 %</td>
<td>12</td>
<td>0.637 %</td>
<td>6</td>
<td>1.841 %</td>
</tr>
<tr>
<td>FRA</td>
<td>64 %</td>
<td>7</td>
<td>0.787 %</td>
<td>3</td>
<td>1.994 %</td>
</tr>
<tr>
<td>GER</td>
<td>64 %</td>
<td>6</td>
<td>0.016 %</td>
<td>7</td>
<td>1.213 %</td>
</tr>
<tr>
<td>GRE</td>
<td>75 %</td>
<td>3</td>
<td>0.638 %</td>
<td>5</td>
<td>1.842 %</td>
</tr>
<tr>
<td>ITA</td>
<td>100 %</td>
<td>1</td>
<td>1.511 %</td>
<td>1</td>
<td>2.726 %</td>
</tr>
<tr>
<td>NED</td>
<td>88 %</td>
<td>2</td>
<td>-0.139 %</td>
<td>8</td>
<td>1.056 %</td>
</tr>
<tr>
<td>NOR</td>
<td>41 %</td>
<td>13</td>
<td>-1.676 %</td>
<td>13</td>
<td>-0.499 %</td>
</tr>
<tr>
<td>POR</td>
<td>61 %</td>
<td>9</td>
<td>-1.108 %</td>
<td>12</td>
<td>0.075 %</td>
</tr>
<tr>
<td>SPA</td>
<td>62 %</td>
<td>8</td>
<td>-0.668 %</td>
<td>11</td>
<td>0.521 %</td>
</tr>
<tr>
<td>SWE</td>
<td>50 %</td>
<td>10</td>
<td>-0.402 %</td>
<td>9</td>
<td>0.790 %</td>
</tr>
<tr>
<td>UK</td>
<td>45 %</td>
<td>11</td>
<td>-0.632 %</td>
<td>10</td>
<td>0.558 %</td>
</tr>
</tbody>
</table>

Note: Global technical change (TECH) is estimated as 1.197 % for all countries and years

Table 7: Efficiency levels, efficiency change, and TFP change according to the MIX model; Semi-nonparametric StoNED estimates

<table>
<thead>
<tr>
<th>Country</th>
<th>EFF level</th>
<th>Rank</th>
<th>EFF change</th>
<th>Rank</th>
<th>TFP change</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>73 %</td>
<td>4</td>
<td>1.080 %</td>
<td>3</td>
<td>2.727 %</td>
</tr>
<tr>
<td>DEN</td>
<td>78 %</td>
<td>3</td>
<td>1.367 %</td>
<td>2</td>
<td>3.018 %</td>
</tr>
<tr>
<td>FIN</td>
<td>46 %</td>
<td>12</td>
<td>0.536 %</td>
<td>6</td>
<td>2.174 %</td>
</tr>
<tr>
<td>FRA</td>
<td>71 %</td>
<td>6</td>
<td>0.752 %</td>
<td>4</td>
<td>2.394 %</td>
</tr>
<tr>
<td>GER</td>
<td>68 %</td>
<td>7</td>
<td>0.134 %</td>
<td>7</td>
<td>1.765 %</td>
</tr>
<tr>
<td>GRE</td>
<td>72 %</td>
<td>5</td>
<td>0.635 %</td>
<td>5</td>
<td>2.274 %</td>
</tr>
<tr>
<td>ITA</td>
<td>100 %</td>
<td>1</td>
<td>1.475 %</td>
<td>1</td>
<td>3.129 %</td>
</tr>
<tr>
<td>NED</td>
<td>90 %</td>
<td>2</td>
<td>-0.369 %</td>
<td>9</td>
<td>1.255 %</td>
</tr>
<tr>
<td>NOR</td>
<td>41 %</td>
<td>13</td>
<td>-1.890 %</td>
<td>13</td>
<td>-0.291 %</td>
</tr>
<tr>
<td>POR</td>
<td>58 %</td>
<td>9</td>
<td>-1.457 %</td>
<td>12</td>
<td>0.148 %</td>
</tr>
<tr>
<td>SPA</td>
<td>65 %</td>
<td>8</td>
<td>-0.616 %</td>
<td>10</td>
<td>1.003 %</td>
</tr>
<tr>
<td>SWE</td>
<td>54 %</td>
<td>11</td>
<td>-0.141 %</td>
<td>8</td>
<td>1.486 %</td>
</tr>
<tr>
<td>UK</td>
<td>54 %</td>
<td>10</td>
<td>-0.943 %</td>
<td>11</td>
<td>0.671 %</td>
</tr>
</tbody>
</table>

Note: Global technical change (TECH) is estimated as 1.629 % for all countries and years

Finally, consider the mixed economic and environmental (MIX) model. The efficiency levels and changes and the overall TFP changes are reported in Table 7. Overall, the results are rather similar to those of Table 6. This is not surprising keeping in mind the fact that the empirical fit does not increase much when we move from the ECON model to the MIX model. Italy and the Netherlands are again the most efficient countries, and Finland and Norway are the least efficient ones. The average rates of changes in TFP are higher in the MIX model than in the ENV model for all countries, and the levels of efficiency are also higher in the MIX model for all countries except for Greece and Portugal. This is expected since the MIX
model includes a larger number of input variables, and hence it must have a better empirical fit than the ENV model.

In conclusion, the ECON and ENV models show performance of some countries in rather different light: consider, for example, Italy and the Netherlands. The results of the MIX model lean towards the ENV model. We find that all three orientations work reasonably well in the context of semi-nonparametric StoNED estimation, providing results that are in line with the partial productivity measures reported above and the results of the SFA and DEA estimators to be discussed next. The MIX model can provide a reasonable combination of the ECON and ENV models. However, it could be argued that the orientation of the MIX model can blur the interpretation of the ECON and ENV models. In this application, the MIX model seems to provide little additional value to the purely environmental ENV model.

7.3 Parametric SFA

For comparison, we repeat the previous analysis, imposing the Cobb-Douglas functional form for the frontier. Thus, the model can be estimated by standard least squares techniques. Specifically, we follow the panel data approach to SFA by Schmidt and Sickles (1984). The CRS assumption is imposed by dividing all input variables by the agricultural land area (thus all variables are expressed per hectare). The ECON model can be stated in the log-linear form as

ECON: \( \ln(y_{it} / LA_{it}) = \beta_0 + \beta_K \ln(K_{it} / LA_{it}) + \beta_L \ln(L_{it} / LA_{it}) + \text{Trend} \cdot t + \epsilon_{it} \)

ENV: \( \ln(y_{it} / LA_{it}) = \beta_0 + \beta_{GHG} \ln(GHG_{it} / LA_{it}) + \beta_N \ln(N_{it} / LA_{it}) + \beta_P \ln(P_{it} / LA_{it}) + \text{Trend} \cdot t + \epsilon_{it} \)

MIX: \( \ln(y_{it} / LA_{it}) = \beta_0 + \beta_K \ln(K_{it} / LA_{it}) + \beta_L \ln(L_{it} / LA_{it}) + \beta_{GHG} \ln(GHG_{it} / LA_{it}) + \beta_N \ln(N_{it} / LA_{it}) + \beta_P \ln(P_{it} / LA_{it}) + \text{Trend} \cdot t + \epsilon_{it} \)

In the ECON model, the output elasticity of land can be obtained as \( 1 - (\beta_K + \beta_L) \). The time trend represents the technical change of the global frontier, which is constant across all countries and time periods. The coefficients estimated by OLS and the standard errors and other supporting statistics are reported in Table 8.

In the ECON model, the coefficients of K and L are positive and statistically significant at 5% significance level. The output elasticity of land is 0.321. The time trend is positive and of the expected magnitude (TECH = 1.0122, implying 1.22% technical progress per annum), but it is statistically insignificant. The empirical fit of the ECON model is rather poor, the coefficient of determination is only 0.214. The model as a whole is still highly significant in the F-test.

The ENV model achieves a much better empirical fit: the coefficient of determination is 0.665. All coefficients are positive, and the coefficients of GHG and N stock are significant, while the coefficient of the P stock is insignificant. The output elasticity of land is 0.188. The time trend is positive and significant: TECH = 1.0156, implying 1.56% technical progress per year.

The MIX model must obviously have a better empirical fit than the ENV model. However, the coefficient of determination increases only marginally to 0.689. The increase is not statistically significant. Further, the MIX model provides somewhat counterintuitive results. The coefficient of capital K becomes negative, but insignificant, whereas in the ECON model it was positive and highly significant. The coefficients of GHG and N do not change dramatically compared to the ENV model. The time trend is positive and statistically significant in the MIX model.
In conclusion, the ENV model achieves much better empirical fit than the ECON model. The MIX model does not add significantly to the explanatory power of the ENV model, and the coefficient of capital $K$ becomes negative in the MIX model. This illustrates problems associated with the MIX model. In our view, separate modelling of ECON and ENV models is preferred, whereas the MIX approach tends to obscure the interpretation and lead to counterintuitive results.

Consider next the country specific efficiency estimates obtained with the ECON, ENV, and MIX models. Both the level and change of efficiency and TFP are of interest, as well as the relative performance rankings of countries.

We start with the results of the ECON model, presented in Table 9, prepared analogous to Tables 5 – 7 presented above.

In the ECON model, the Netherlands is by a large margin the most efficient country, similar to the StoNED results presented and discussed above. The efficiency levels are scaled relative to the average performance of the Netherlands. In this comparison, no other country can achieve even 50% of the performance level of the Netherlands. The least efficient countries are Finland, Norway, and Sweden. We note that the SFA estimates of both the levels of efficiency and the relative country rankings are almost perfectly correlated with the StoNED estimates (the correlation coefficient of efficiency levels is 0.979). Although the empirical fit of the parametric SFA model is considerably lower than that of the semi-nonparametric StoNED, the efficiency estimates are almost identical.
Table 9: Efficiency levels, efficiency change, and TFP change according to the ECON model; Cobb-Douglas production function estimated by OLS

<table>
<thead>
<tr>
<th>Country</th>
<th>EFF level</th>
<th>Rank</th>
<th>EFF change</th>
<th>Rank</th>
<th>TFP change</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>25 %</td>
<td>9</td>
<td>0.388 %</td>
<td>5</td>
<td>1.617 %</td>
</tr>
<tr>
<td>DEN</td>
<td>46 %</td>
<td>2</td>
<td>0.663 %</td>
<td>3</td>
<td>1.895 %</td>
</tr>
<tr>
<td>FIN</td>
<td>16 %</td>
<td>13</td>
<td>-0.064 %</td>
<td>8</td>
<td>1.160 %</td>
</tr>
<tr>
<td>FRA</td>
<td>38 %</td>
<td>3</td>
<td>0.149 %</td>
<td>6</td>
<td>1.375 %</td>
</tr>
<tr>
<td>GER</td>
<td>34 %</td>
<td>5</td>
<td>0.708 %</td>
<td>1</td>
<td>1.941 %</td>
</tr>
<tr>
<td>GRE</td>
<td>28 %</td>
<td>7</td>
<td>-0.109 %</td>
<td>9</td>
<td>1.115 %</td>
</tr>
<tr>
<td>ITA</td>
<td>37 %</td>
<td>4</td>
<td>0.663 %</td>
<td>2</td>
<td>1.896 %</td>
</tr>
<tr>
<td>NED</td>
<td>100 %</td>
<td>1</td>
<td>-0.317 %</td>
<td>10</td>
<td>0.904 %</td>
</tr>
<tr>
<td>NOR</td>
<td>17 %</td>
<td>12</td>
<td>-1.268 %</td>
<td>13</td>
<td>-0.059 %</td>
</tr>
<tr>
<td>POR</td>
<td>20 %</td>
<td>10</td>
<td>0.131 %</td>
<td>7</td>
<td>1.357 %</td>
</tr>
<tr>
<td>SPA</td>
<td>28 %</td>
<td>8</td>
<td>0.493 %</td>
<td>4</td>
<td>1.724 %</td>
</tr>
<tr>
<td>SWE</td>
<td>20 %</td>
<td>11</td>
<td>-0.937 %</td>
<td>11</td>
<td>0.276 %</td>
</tr>
<tr>
<td>UK</td>
<td>31 %</td>
<td>6</td>
<td>-1.143 %</td>
<td>12</td>
<td>0.068 %</td>
</tr>
</tbody>
</table>

Note: Global technical change (TECH) is estimated as 1.225 % for all countries and years

The global technical progress is estimated as 1.225 % across all countries and years. The largest growth (catching up) is achieved in Germany, Italy, and Denmark. Efficiency change is negative (falling behind) in Norway, UK, Sweden, Netherlands, Greece, and Finland. This group includes both the most efficient producer (NED), but also the two least efficient producers (FIN, NOR). The SFA estimates of efficiency change are also almost perfectly correlated with the StoNED estimates (the correlation coefficient of annual country-specific efficiency changes is as high as 0.974), but the average rates of efficiency change and the relative rankings are not exactly identical. The differences in the overall TFP estimates are mainly due to the time trend, where the SFA estimate (1.225% per year) is notably lower than the StoNED estimate (1.618% per year).

Table 10: Efficiency levels, efficiency change, and TFP change according to the ENV model; Cobb-Douglas production function estimated by OLS

<table>
<thead>
<tr>
<th>Country</th>
<th>EFF level</th>
<th>Rank</th>
<th>EFF change</th>
<th>Rank</th>
<th>TFP change</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>71 %</td>
<td>3</td>
<td>0.532 %</td>
<td>5</td>
<td>2.098 %</td>
</tr>
<tr>
<td>DEN</td>
<td>67 %</td>
<td>5</td>
<td>1.236 %</td>
<td>3</td>
<td>2.813 %</td>
</tr>
<tr>
<td>FIN</td>
<td>42 %</td>
<td>11</td>
<td>0.265 %</td>
<td>7</td>
<td>1.826 %</td>
</tr>
<tr>
<td>FRA</td>
<td>62 %</td>
<td>6</td>
<td>0.317 %</td>
<td>6</td>
<td>1.880 %</td>
</tr>
<tr>
<td>GER</td>
<td>60 %</td>
<td>7</td>
<td>0.535 %</td>
<td>4</td>
<td>2.101 %</td>
</tr>
<tr>
<td>GRE</td>
<td>69 %</td>
<td>4</td>
<td>1.486 %</td>
<td>2</td>
<td>3.067 %</td>
</tr>
<tr>
<td>ITA</td>
<td>100 %</td>
<td>1</td>
<td>1.755 %</td>
<td>1</td>
<td>3.340 %</td>
</tr>
<tr>
<td>NED</td>
<td>80 %</td>
<td>2</td>
<td>-0.270 %</td>
<td>8</td>
<td>1.284 %</td>
</tr>
<tr>
<td>NOR</td>
<td>36 %</td>
<td>12</td>
<td>-2.121 %</td>
<td>13</td>
<td>-0.597 %</td>
</tr>
<tr>
<td>POR</td>
<td>52 %</td>
<td>8</td>
<td>-0.633 %</td>
<td>9</td>
<td>0.915 %</td>
</tr>
<tr>
<td>SPA</td>
<td>50 %</td>
<td>9</td>
<td>-0.890 %</td>
<td>12</td>
<td>0.654 %</td>
</tr>
<tr>
<td>SWE</td>
<td>49 %</td>
<td>10</td>
<td>-0.838 %</td>
<td>11</td>
<td>0.707 %</td>
</tr>
<tr>
<td>UK</td>
<td>34 %</td>
<td>13</td>
<td>-0.813 %</td>
<td>10</td>
<td>0.732 %</td>
</tr>
</tbody>
</table>

Note: Global technical change (TECH) is estimated as 1.558 % for all countries and years

The SFA estimates of the ENV model are presented in Table 10. As in the StoNED model, Italy is the most
Green productivity in agriculture: a critical synthesis

efficient country with a clear margin to the Netherlands. Italy is also improving its environmental performance over time faster than any other country in the sample. The total environmental performance change is positive to all countries, except for Norway, thanks to the relatively large technical progress component (1.558% per year, which is constant across all countries and years). The SFA model supports our earlier conclusion that countries appear to diverge in their environmentally performance over time, as the inefficient countries are lagging behind. Indeed, the SFA estimates of the ENV model are highly correlated with the corresponding StoNED estimates: the correlation coefficient of the efficiency levels is 0.916, and the correlation of the annual country-specific efficiency changes is 0.919. In the ENV model, the SFA estimate of the technical change (1.558% per year) is higher than the corresponding StoNED estimate (1.197% per year). This explains the high average rates of the TFP change in the SFA model.

Finally, the results of the MIX model are presented in Table 11. Similar to the ENV model, Italy is the most efficient country in the MIX model, with largest efficiency improvement. Somewhat surprisingly, the Netherlands (the 1st in the ECON model and the 2nd in the ENV model) falls now to the fourth position after Austria and Denmark. However, the efficiency level of the Netherlands does not change dramatically compared to the ENV model. The least efficient countries are again Norway, the United Kingdom, and Finland. Overall, the country specific efficiency results of the MIX model are rather similar to those of the ENV model. Moreover, the SFA estimates of the MIX model are highly correlated with the corresponding StoNED estimates: the correlation coefficient of the efficiency levels is 0.934, and the correlation of annual country-specific efficiency changes is 0.981. However, the SFA estimate of technical change (2.067% per year) is considerably larger than the corresponding StoNED estimate (1.629). This shows in the large estimates of the overall TFP change reported in Table 11.

Table 11: Efficiency levels, efficiency change, and TFP change according to the MIX model; Cobb-Douglas production function estimated by OLS

<table>
<thead>
<tr>
<th>EFF level</th>
<th>Rank</th>
<th>EFF change</th>
<th>Rank</th>
<th>TFP change</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT 77 %</td>
<td>2</td>
<td>0.634 %</td>
<td>4</td>
<td>2.715 %</td>
</tr>
<tr>
<td>DEN 76 %</td>
<td>3</td>
<td>1.296 %</td>
<td>3</td>
<td>3.390 %</td>
</tr>
<tr>
<td>FIN 45 %</td>
<td>11</td>
<td>0.278 %</td>
<td>7</td>
<td>2.351 %</td>
</tr>
<tr>
<td>FRA 72 %</td>
<td>5</td>
<td>0.516 %</td>
<td>6</td>
<td>2.594 %</td>
</tr>
<tr>
<td>GER 64 %</td>
<td>6</td>
<td>0.559 %</td>
<td>5</td>
<td>2.638 %</td>
</tr>
<tr>
<td>GRE 64 %</td>
<td>7</td>
<td>1.435 %</td>
<td>2</td>
<td>3.532 %</td>
</tr>
<tr>
<td>ITA 100 %</td>
<td>1</td>
<td>1.962 %</td>
<td>1</td>
<td>4.069 %</td>
</tr>
<tr>
<td>NED 76 %</td>
<td>4</td>
<td>-0.452 %</td>
<td>8</td>
<td>1.606 %</td>
</tr>
<tr>
<td>NOR 37 %</td>
<td>13</td>
<td>-2.166 %</td>
<td>13</td>
<td>-0.144 %</td>
</tr>
<tr>
<td>POR 46 %</td>
<td>10</td>
<td>-0.760 %</td>
<td>9</td>
<td>1.292 %</td>
</tr>
<tr>
<td>SPA 50 %</td>
<td>9</td>
<td>-0.791 %</td>
<td>10</td>
<td>1.260 %</td>
</tr>
<tr>
<td>SWE 55 %</td>
<td>8</td>
<td>-0.806 %</td>
<td>11</td>
<td>1.244 %</td>
</tr>
<tr>
<td>UK 40 %</td>
<td>12</td>
<td>-1.141 %</td>
<td>12</td>
<td>0.902 %</td>
</tr>
</tbody>
</table>

Note: Global technical change (TECH) is estimated as 2.067 % for all countries and years

In conclusion, the SFA and StoNED estimates provide a very similar picture of both the levels and changes of efficiency. However, the estimates of technical change (TECH) component reveal larger differences. Somewhat surprisingly, the parametric trend function proves more sensitive to the functional form assumption (i.e., the Cobb-Douglas specification) than the regression residuals and their country-specific averages in this particular application. It is possible that the linear trend function, which assumes Hicks neutral technical change, is a too restrictive specification of technical progress. More flexible specifications of technical change might be preferable in this case, but exploring this issue further falls beyond the scope of the present study.
7.4 Stochastic DEA

The conventional approach to applying DEA in the context of the Malmquist index is to treat the panel of countries as yearly cross sections that are completely independent of each other. This approach ignores the inter-temporal nature of the panel data. Ruggiero (2004) has proposed an alternative approach to applying DEA to panel data, which is more consistent with the StoNED and SFA approaches considered above. More specifically, Ruggiero first computes country-specific averages of inputs and outputs over the time periods included in the panel. He then proposes to apply DEA to thus obtained country averages. In this way, random variations from one year to another get averaged out from the input-output data. Hence, Ruggiero’s approach is less sensitive to idiosyncratic noise than the conventional DEA. Ruggiero refers to his method as “stochastic DEA”, and presents some simulation evidence in support of the method. The present study forms one of the first empirical applications of this method.

Since the performance of countries is measured relative to the fixed-base inter-temporal frontier spanned by the country-specific average values, we cannot distinguish between the efficiency change and technical change components in this method. However, we can measure TFP changes in terms of the change of the distance function (or efficiency index) over time.

Table 12 reports the DEA estimates of efficiency levels and the TFP changes in the ECON model. The Netherlands and Denmark are ranked as efficient countries in the DEA assessment. The efficiency differences across countries are large: Finland and Norway achieve only 26% and 25% efficiency levels, respectively, compared to the most efficient countries. The DEA efficiency estimates are positively correlated with the StoNED and SFA estimates (the correlation coefficients: DEA and StoNED 0.850, DEA and SFA 0.784).

**Table 12: Efficiency levels and TFP change according to the ECON model; inter-temporal production function estimated by stochastic DEA**

<table>
<thead>
<tr>
<th></th>
<th>EFF level</th>
<th>Rank</th>
<th>TFP change</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT</td>
<td>41 %</td>
<td>8</td>
<td>4.48 %</td>
<td>3</td>
</tr>
<tr>
<td>DEN</td>
<td>100 %</td>
<td>1</td>
<td>4.55 %</td>
<td>2</td>
</tr>
<tr>
<td>FIN</td>
<td>26 %</td>
<td>12</td>
<td>3.63 %</td>
<td>7</td>
</tr>
<tr>
<td>FRA</td>
<td>85 %</td>
<td>3</td>
<td>4.69 %</td>
<td>1</td>
</tr>
<tr>
<td>GER</td>
<td>57 %</td>
<td>5</td>
<td>4.30 %</td>
<td>4</td>
</tr>
<tr>
<td>GRE</td>
<td>43 %</td>
<td>6</td>
<td>0.31 %</td>
<td>13</td>
</tr>
<tr>
<td>ITA</td>
<td>43 %</td>
<td>7</td>
<td>4.04 %</td>
<td>5</td>
</tr>
<tr>
<td>NED</td>
<td>100 %</td>
<td>1</td>
<td>1.29 %</td>
<td>10</td>
</tr>
<tr>
<td>NOR</td>
<td>25 %</td>
<td>13</td>
<td>1.82 %</td>
<td>9</td>
</tr>
<tr>
<td>POR</td>
<td>27 %</td>
<td>11</td>
<td>1.15 %</td>
<td>11</td>
</tr>
<tr>
<td>SPA</td>
<td>40 %</td>
<td>9</td>
<td>3.73 %</td>
<td>6</td>
</tr>
<tr>
<td>SWE</td>
<td>38 %</td>
<td>10</td>
<td>2.72 %</td>
<td>8</td>
</tr>
<tr>
<td>UK</td>
<td>68 %</td>
<td>4</td>
<td>0.94 %</td>
<td>12</td>
</tr>
</tbody>
</table>

**Note:** Ruggiero’s (2004) inter-temporal panel data DEA approach does not allow us to separate TFP change to efficiency change and technical change components.

In general, the DEA estimates of TFP change reported in Table 12 are notably higher than the corresponding StoNED or SFA estimates. At this point, it is worth to emphasize that the average TFP growth rates reported for StoNED and SFA in Sections 7.2 and 7.3 were calculated using the chain index method where the value of any given period is compared to the value of its immediately preceding period. In contrast, the DEA estimates have been calculated relative to a fixed base period, since the DEA frontier
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is estimated using the average input-output data. Unfortunately, the Malmquist TFP index does not satisfy the circularity test (e.g., Pastor and Lovell, 2007). This means that individual indices cannot be consistently chained together by multiplying consecutive indices to convert them to some desired reference period: multiplying a chain of Malmquist TFP indices between the base period 0 and all consecutive periods until period $t$ will generally yield a different result than the direct comparison between periods $t$ and 0. This property of the Malmquist index can partly explain why the DEA estimates of the TFP change reported in Table 12 are higher than those reported for StoNED and SFA above.

The evolution of the comparable fixed base period TFP indices is presented graphically in Appendix 2 (to be discussed in more detail in Section 7.5). The general impression from these figures is that DEA tends to indicate higher TFP growth rates than the corresponding StoNED and SFA estimates. It appears that the DEA estimates are mainly driven by labour productivity growth (compare with Table 1), whereas the slower growth of capital productivity (Table 2) is given less weight in the DEA assessment. Recall that the main principle of DEA is to look at performance of countries in the most favourable light.

Consider next the DEA estimates of the ENV model reported in Table 13. In this model, it is clear that DEA suffers from low discriminating power: five countries are classified as 100% efficient (AUT, GRE, ITA, NED, and SPA). In particular, efficiency of Greece is a surprising result since Greece ranks relatively low in all other tables presented above. Only Finland and Norway are assigned similar (low) efficiency scores as in StoNED and SFA, all other countries are given the ‘benefit of the doubt’.

Table 13: Efficiency levels and TFP change according to the ENV model; inter-temporal production function estimated by stochastic DEA

<table>
<thead>
<tr>
<th>EFF level</th>
<th>Rank</th>
<th>TFP change</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT 100 %</td>
<td>1</td>
<td>2.36 %</td>
<td>4</td>
</tr>
<tr>
<td>DEN 82 %</td>
<td>6</td>
<td>2.60 %</td>
<td>3</td>
</tr>
<tr>
<td>FIN 44 %</td>
<td>13</td>
<td>2.13 %</td>
<td>6</td>
</tr>
<tr>
<td>FRA 74 %</td>
<td>7</td>
<td>2.33 %</td>
<td>5</td>
</tr>
<tr>
<td>GER 70 %</td>
<td>8</td>
<td>1.83 %</td>
<td>7</td>
</tr>
<tr>
<td>GRE 100 %</td>
<td>1</td>
<td>2.69 %</td>
<td>2</td>
</tr>
<tr>
<td>ITA 100 %</td>
<td>1</td>
<td>3.00 %</td>
<td>1</td>
</tr>
<tr>
<td>NED 100 %</td>
<td>1</td>
<td>1.00 %</td>
<td>9</td>
</tr>
<tr>
<td>NOR 45 %</td>
<td>12</td>
<td>-0.08 %</td>
<td>11</td>
</tr>
<tr>
<td>POR 65 %</td>
<td>10</td>
<td>-0.12 %</td>
<td>12</td>
</tr>
<tr>
<td>SPA 100 %</td>
<td>1</td>
<td>-0.44 %</td>
<td>13</td>
</tr>
<tr>
<td>SWE 65 %</td>
<td>9</td>
<td>1.52 %</td>
<td>8</td>
</tr>
<tr>
<td>UK 49 %</td>
<td>11</td>
<td>0.33 %</td>
<td>10</td>
</tr>
</tbody>
</table>

Note: Ruggiero’s (2004) inter-temporal panel data DEA approach does not allow us to separate TFP change to efficiency change and technical change components

The DEA estimates of the TFP change in the ENV model are reasonably well in line with the StoNED and SFA estimates. However, it worth to note the trade-off between the explanatory power (i.e., empirical fit) and the discriminating power of DEA. While the discriminatory power of DEA proved low in terms of the levels of efficiency, the empirical fit of the ENV model is much better than that of the ECON model, which explains why the estimates of TFP change are more consistent with the StoNED and SFA estimates.

Finally, the DEA estimates of the MIX model are reported in Table 14. This table highlights the difficulty of DEA to discriminate between countries as the number of input-output variables increases. Seven countries (more than half of the sample) are classified as 100% efficient. Similar to the ENV model, the
low discriminating power implies good empirical fit, which in turn results as estimates of TFP change that are reasonably well in line with the corresponding StoNED and SFA estimates.

**Table 14: Efficiency levels and TFP change according to the MIX model; inter-temporal production function estimated by stochastic DEA**

<table>
<thead>
<tr>
<th>EFF level</th>
<th>Rank</th>
<th>TFP change</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUT 100 %</td>
<td>1</td>
<td>2.63 %</td>
<td>7</td>
</tr>
<tr>
<td>DEN 100 %</td>
<td>1</td>
<td>3.96 %</td>
<td>1</td>
</tr>
<tr>
<td>FIN 51 %</td>
<td>12</td>
<td>3.04 %</td>
<td>4</td>
</tr>
<tr>
<td>FRA 100 %</td>
<td>1</td>
<td>3.07 %</td>
<td>3</td>
</tr>
<tr>
<td>GER 81 %</td>
<td>8</td>
<td>3.00 %</td>
<td>5</td>
</tr>
<tr>
<td>GRE 100 %</td>
<td>1</td>
<td>2.68 %</td>
<td>6</td>
</tr>
<tr>
<td>ITA 100 %</td>
<td>1</td>
<td>3.28 %</td>
<td>2</td>
</tr>
<tr>
<td>NED 100 %</td>
<td>1</td>
<td>1.29 %</td>
<td>9</td>
</tr>
<tr>
<td>NOR 45 %</td>
<td>13</td>
<td>-0.08 %</td>
<td>13</td>
</tr>
<tr>
<td>POR 66 %</td>
<td>11</td>
<td>0.20 %</td>
<td>12</td>
</tr>
<tr>
<td>SPA 100 %</td>
<td>1</td>
<td>0.37 %</td>
<td>11</td>
</tr>
<tr>
<td>SWE 72 %</td>
<td>9</td>
<td>1.94 %</td>
<td>8</td>
</tr>
<tr>
<td>UK 68 %</td>
<td>10</td>
<td>0.94 %</td>
<td>10</td>
</tr>
</tbody>
</table>

*Note: Ruggiero’s (2004) inter-temporal panel data DEA approach does not allow us to separate TFP change to efficiency change and technical change components.*

In conclusion, the above results highlight the trade-off between explanatory power and discriminatory power of DEA. In the ECON model the discriminatory power of efficiency estimates was reasonably good, but then the DEA frontier is spanned by two observations only. This results as poor empirical fit, and the estimates of TFP change are much higher than those obtained with other methods. In the ENV and MIX models, however, the discriminating power of DEA proves poor, but the estimates of TFP change are more reasonable.

Regarding the choice of the method, we find that results of the StoNED, SFA, and DEA differ notably. It can be objectively shown that the models are nested in the sense that both DEA and SFA can be obtained as restricted special cases of the more general StoNED model (Kuosmanen and Johnson, 2010; Kuosmanen and Kortelainen, 2012). The general principle in statistical testing of restrictions is that if two nested models do not exhibit significant differences, then then the assumptions of the restricted model can be maintained, whereas if the two models exhibit significant differences, the assumptions of the restricted model are rejected and the more general model is chosen. Unfortunately, statistical testing of models that have been estimated using nonparametric methods is not straightforward, as the degrees of freedom are not well defined. One might apply the bootstrap method, but to our knowledge, the statistical consistency of the bootstrap method for this particular purpose has not be established. Therefore, we conclude that the differences between methods appear to be economically significant, but we leave the statistical significance tests for future research.

### 7.5 Evolution of country specific TFP measures over time

Based on the average TFP levels and the average rates of TFP growth examined in the previous subsections, it may appear that the TFP estimates are sensitive to the specification of economic and environmental resources and to the choice of the estimation method. Indeed, the efficiency levels and the relative country rankings are highly dependent on the criteria used in the efficiency assessment, the weights assigned to the criteria, and the weighting method used.
Often the main focus of productivity analysis is on the development of TFP over time. Thus far, we have restricted attention the average growth rates of TFP, which can be conveniently summarized in tables. However, the evolution of country specific TFP trends is worth investigating in more detail. To this end, the fixed-base TFP indices (1990=100) according to the ECON, ENV, and MIX models, estimated by StoNED, SFA and DEA, are plotted for all countries included in this study in Appendix 2.

Appendix 2 contains $3 \times 13 = 39$ figures in total, so we cannot comment on each figure in detail. However, some empirical observations are worth noting.

The TFP indices of Austria and Denmark reveal relatively strong and consistent growth, irrespective of whether TFP is measured using economic or environmental criteria. The figures of France and Germany indicate temporary decline in productivity during the first half of the 1990’s, but since the mid-1990s the growth rates are relatively high. Similarly, Finland and Sweden exhibited relatively high TFP growth after their EU membership in 1995 (the EU membership apparently caused some temporary shocks, which appear earlier in the TFP figures of Sweden than in those of Finland). Interestingly, for Greece and Italy the environmentally oriented TFP indices show considerably higher TFP growth than the purely economic TFP measure. In contrast, for Norway and Spain the economic TFP index indicates higher growth than the environmental TFP measure. The Netherlands exhibits relatively stable but rather modest growth. For Portugal and the United Kingdom, the growth rate is close to zero, while in Norway the environmentally oriented TFP indices indicate productivity decline.

To conclude, two general remarks regarding the models and methods based on the figures presented in Appendix 2 are the following.

First, the TFP indices appear to be much more robust to the specification of the economic and environmental inputs (i.e., ECON, ENV, or MIX specification) than the estimated levels of TFP or efficiency. The ECON, ENV, and MIX models exhibit very similar inter-temporal patterns for all countries: similar growth trends and temporary shocks can be recognized in the TFP indices based on all three models. For many countries, however, the ECON model indicates higher TFP growth than the ENV or MIX models, particularly if one compares the DEA estimates.

Second, the TFP indices are also relatively robust to the choice of the estimation method. For many countries, the TFP indices computed based on the StoNED, SFA, and DEA distance functions are hardly distinguishable from the figure, particularly in the ENV and MIX models. The most notable differences due to the estimation method are found in the case of the ECON model, particularly for Austria, Denmark, Finland, France, Greece, and Spain. The large deviations particularly in the ECON model are explained by the fact that the ECON model yields lower empirical fit than the ENV and MIX models.

8. Concluding remarks and recommendations

This report addresses the following three issues. First, we presented a critical survey of literature considered relevant to the measurement and analysis of productivity and environmental efficiency in agriculture. Due to the limited scope of this study, we have certainly ignored many important studies worth citing, but we find that this limited survey nevertheless provides several valuable insights to this topic. Second, we examined the methodological options available, both some well-established and widely applied approaches and some new approaches that have been just recently introduced or are currently being introduced to the literature. Third, we conducted an empirical comparison of some of the methodological options suggested. The empirical comparison provided several valuable lessons, as discussed in the previous section.
Based on the insights and results obtained in this study, the following recommendations are proposed.

Firstly, we propose to draw a clear conceptual distinction between the environmentally oriented efficiency analysis (abbreviated as ENV above) where the economic resources are omitted, and the mixed economic and environmental orientation (abbreviated as MIX above) where both economic and environmental resources are considered. In particular, we find it somewhat misleading to call the latter approach “eco-efficiency” or “environmental efficiency”. In our view, if one is mainly interested in environmental or eco-efficiency, efficient use of labour or capital resources seems a poor excuse for weak performance in the environmental criteria. Following the usual notion of eco-efficiency, environmental efficiency concerns in our interpretation the trade-off between economic goods and environmental bads. From the welfare point of view, however, it is perfectly valid to combine the economic and environmental criteria in a common framework of productivity assessment. The mixed economic and environmental orientation can provide a useful overall measure of productivity from the welfare point of view, which can credit countries for advances in both economic and environmental efficiency.

Secondly, we discussed model specification issues related to agricultural production, including the damage control inputs, material balance, and production risk. All these issues are obviously relevant to environmental efficiency. In this report we paid particular attention on the material balance discussion, which is commonly used in the calculation of the nutrient emissions, most notably the nitrogen and phosphorus. We noted that if the production model consists solely of inputs and outputs governed by the material balance, then the production model reduces to the material balance equation and becomes redundant. To break the direct link between material input and output, we proposed to omit some of the variables that (almost) perfectly correlated with other variables. For example, the total energy input and the GHG tend to be so highly correlated that one could harmlessly omit one of them.

Another important issue related to the material balance concerns the use of nutrient surplus as an environmental indicator in productivity analysis. A problem with the conventional surplus measures is that the surplus is measured on the interval scale, and hence, it can yield negative values. However, productivity and efficiency measurement generally requires ratio scale variables in order to perform multiplication and division operations. To resolve this issue, we resorted to a dynamic model of material balance, in which the accumulation of nutrients is modelled similar to the usual perpetual inventory method for calculating the capital stock. It is standard to use the capital stock rather than investment (the corresponding flow variable) as an input in productivity measurement. Analogously, in the empirical study reported above we applied the stocks of nitrogen and phosphorus as environmental resources to production.

Thirdly, we considered a generic stochastic semi-nonparametric model of production that contains the conventional parametric-stochastic and nonparametric-deterministic models as its special case. We briefly reviewed the conventional frontier estimation techniques, DEA and SFA, and the recently introduced StoNED method. A more detailed description of the assumptions and properties of these methods is presented in Appendix 1. For comparison, all three approaches were applied in the empirical work reported above.

The comparison of the empirical results obtained in the three alternative model specifications – ECON, ENV, and MIX – obtained with three alternative frontier methods – StoNED, SFA, and DEA – reveals the following insights. The empirical fit of the ENV model proved better than that of the ECON model irrespective of the estimation method. The results of the MIX model followed relatively closely those of the ENV model in StoNED and SFA. The StoNED estimates of the marginal products, efficiency levels, and the efficiency and TFP changes appear reasonable in all three model specifications considered. The SFA estimates of the efficiency levels and changes were almost perfectly correlated with the corresponding StoNED estimates, but TFP changes differ to some extent due to the technical change component. The parameter estimates of the SFA models were reasonable in the ECON and ENV models, but in the MIX
model the capital input has the negative sign. Depending on the model specification, the DEA approach yields reasonable estimates of either the efficiency levels, or the TFP change, but not both. Based on these findings, we conclude there is a trade-off between the discriminatory power and the explanatory power of DEA.

While this report reviews and cites a large number of studies relevant to the theme, the relevant literature is so vast that a number of potentially important and relevant works have necessarily been omitted, as we recognized already in the introduction. We have considered a limited number of index numbers, estimation methods, model specification issues, and empirical issues considered relevant to the theme to be able to form a synthesis. This will necessarily mean that some important issues and results that do not directly fit into our synthesis have to be omitted. Extending the synthesis presented in this report provides fruitful avenues for further investigation.

In the similar vein, the empirical work reported in this study is necessarily limited by data availability and time constraints. The number of countries and time periods covered in the study could be extended in the future research. Further, the scope of environmental issues covered deserves to be extended. A number of important environmental issues were omitted from the application due to data availability, including the water stress and discharge of toxic pesticides. These observations highlight the need for future research on this topic.
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Appendix 1: Main features and assumptions of the different econometric methods applied in this study

Consider the standard production model:

\[ y_i = f(x_i) + \varepsilon_i \quad \forall i = 1, \ldots, n \]

where \( y_i \) denotes the output of firm \( i \), \( f \) is the production function, \( x_i \) is the input vector of firm \( i \), and \( \varepsilon_i \) is a random error term that represents the deviation of firm \( i \) from the production function. Different models of productive efficiency analysis can be classified according to how one specifies the production function \( f \) and the error \( \varepsilon \). Table A1 summarizes six alternative model variants together with some key references. We will discuss the criteria used in the classification in more detail below.

Table A1: Classification of frontier models

<table>
<thead>
<tr>
<th></th>
<th>Parametric</th>
<th>Nonparametric</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Deterministic:</strong></td>
<td>Corrected ordinary least squares (COLS)</td>
<td>Corrected convex non-parametric least squares (C2NLS)</td>
</tr>
<tr>
<td>2-stage estimation</td>
<td>Kuosmanen and Johnson (2010)</td>
<td></td>
</tr>
<tr>
<td><strong>Deterministic:</strong></td>
<td>Parametric programming</td>
<td>Data envelopment analysis (DEA)</td>
</tr>
<tr>
<td>Sign constraints</td>
<td>Farrell (1957), Charnes et al. (1978)</td>
<td>Farrell (1957), Charnes et al. (1978)</td>
</tr>
<tr>
<td><strong>Stochastic</strong></td>
<td>Stochastic frontier analysis (SFA)</td>
<td>Stochastic semi-nonparametric envelopment of data (StoNED)</td>
</tr>
</tbody>
</table>

Source: Adapted from Johnson and Kuosmanen (2010) and Keshvari and Kuosmanen (2013).

**Parametric vs. nonparametric:**

Frontier models are classified as parametric or nonparametric depending on the specification of the production function \( f \). Parametric models (the left column in Table A1) postulate a priori a specific functional form for \( f \) (e.g., Cobb-Douglas, translog, etc.) and subsequently estimate its unknown parameters. Nonparametric models (the right column in Table A1) assume that \( f \) satisfies certain regularity axioms (e.g., monotonicity and concavity), but no particular functional form is assumed.

The nonparametric approaches are generally considered to be more robust to the specification error. Another appealing feature of the nonparametric approaches is their axiomatic basis in the production theory, building on such axioms as free disposability, convexity, and constant returns to scale. However, the nonparametric approaches can be sensitive to the axioms that are imposed. Further, the nonparametric methods are subject to the curse of dimensionality: the nonparametric methods generally require a relatively large sample size and lose precision if the number of input variables increases. Finally, the conventional methods of statistical inferences do not readily apply to the nonparametric approaches.

**Deterministic vs. stochastic:**
Models are classified as deterministic or stochastic depending on the assumptions regarding the composite error term. In deterministic models (the top rows of Table A1), the error term $\epsilon$ represents inefficiency only. Therefore, the error term is constrained as $\epsilon_i \leq 0$ for all $i$. That is, it is impossible to produce more than the production function indicates. In practice, the sign-constraint can be imposed directly in the estimation (as in parametric programming or data envelopment analysis). Alternatively, one can first estimate an unconstrained model, and subsequently shift the frontier such that the sign constrained is satisfied (as in the corrected OLS and CNLS approaches).

The stochastic frontier models (the bottom row of Table A1) allow for the possibility that the observed output can exceed the production function due to measurement errors or omitted factors (e.g., exceptionally favourable weather conditions that are not controlled for in the model). In the stochastic frontier models, the error term is specified as $\epsilon_i = v_i - u_i$, where $v$ is a symmetric noise term (analogous to the usual disturbance term in regression analysis) and $u$ is an asymmetric, non-negative inefficiency term.

Virtually all empirical applications are subject to noise due to omitted factors (e.g., unobserved heterogeneity in the operational conditions or characteristics of the production units) and measurement errors. This is a powerful argument in favour of stochastic approaches. However, the stochastic frontier models do require some assumptions about the inefficiency and noise terms, which may seem restrictive to the proponents of the deterministic approaches. For example, the parametric distribution assumptions about the inefficiency term are somewhat arbitrary. However, making some restrictive assumptions about the noise may be a better option than overlooking the noise completely.

**DEA, SFA or StoNED?**

Until very recently, the practitioners of frontier estimation had to choose between the two main alternatives: parametric-stochastic SFA or the nonparametric-deterministic DEA. As a result, the field of productive efficiency analysis was divided between the proponents of these two main approaches and their variants.

The new StoNED method presents a third compelling option: a nonparametric-stochastic approach. In fact, the StoNED model is more general than the conventional alternatives in the sense that both DEA and SFA models can be obtained as constrained special cases of the StoNED model. While we cannot conclude that StoNED is objectively preferred to either DEA or SFA, it does have a greater range of applicability due to its less restrictive set of assumptions. Indeed, the general principle in statistical testing of restrictions is that if two models do not exhibit significant differences, then the assumptions of the restricted model can be maintained, whereas if the two models exhibit significant differences, the assumptions of the restricted model are rejected and the more general model is chosen.

The comparative advantages and disadvantages of competing estimators can be assessed in the controlled environment of Monte Carlo simulations. Simulated evidence on performance of DEA, SFA and StoNED can be found in the recent studies Kuosmanen and Kortelainen (2012), Johnson and Kuosmanen (2012), Kuosmanen et al. (2012), and Andor and Hesse (2013).
Appendix 2: Evolution of ECON, ENV, and MIX measures of TFP at the country level

This appendix provides graphical illustration of the country specific productivity developments, discussed in Section 7.4. The fixed-base TFP indices (1990=100) according to the ECON, ENV, and MIX models are plotted in separate figures for each country. For each country and each model, the TFP indices computed using StoNED (indicated by the thick black line), SFA (thick grey line), and DEA (thin black line) are presented in the same figure.

The fixed based period Malmquist indices have been calculated using the formula

\[
M(0,t) = \left( \frac{DI^0(x^0, y^0)}{DI^t(x^t, y^t)} \cdot \frac{DI^0(x^0, y^0)}{DI^t(x^t, y^t)} \right)^{1/2},
\]

where superscript 0 refers to the base year 1990 and t = 1991, ..., 2004. For the StoNED and SFA methods, the index number formula can stated as

\[
M(0,t) = \exp(\text{Trend} \cdot t + e_i - e_{i0}),
\]

where \(\text{Trend}\) is the estimated coefficient of the trend function and \(e_i\) is the regression residual of country \(i\) in period \(t\), estimated by StoNED or SFA.

For comparability, all figures are scaled to the interval [0, 200] such that the observed ranges of index numbers for each country fit within the interval.

Each page of this appendix portrays the TFP development in a single country by means of three figures (representing the ECON, ENV, and MIX models).
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AUT: ECON model

AUT: ENV model

AUT: MIX model
DEN: ECON model

DEN: ENV model

DEN: MIX model
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