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THE SOURCES OF THE TOTAL FACTOR PRODUCTIVITY GROWTH IN LITHUANIAN FAMILY FARMS: A FÄRE-PRIMONT INDEX APPROACH

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Abstract:
The Lithuanian agricultural sector still features the processes of land reform, farm structure development, and modernisation. Accordingly, there is a need to utilise the benchmarking techniques in order to fathom the underlying trends and sources of efficiency and productivity. This paper therefore aims at analysing the productive efficiency and the total factor productivity in the Lithuanian family farms. The research is based on the Farm Accountancy Network Data covering the period of 2004–2009. The Färe-Primont Indices were employed to estimate and decompose the total factor productivity changes. Furthermore, the stochastic kernels were applied to analyse the distributions of the efficiency scores along with the econometric analysis which aimed at revealing the relationships of the environmental variables and the efficiency scores. The results do indicate that the technical efficiency was a decisive factor causing decrease in TFP efficiency for crop and mixed farms. Meanwhile, the scale efficiency constituted a serious problem for mixed farms. Indeed, these farms were the smallest ones if compared to the remaining farming types. Finally, the mix efficiency was low for all farming types indicating the need for implementation of certain farming practices allowing for optimisation of the input-mix.

Keywords: total factor productivity, data envelopment analysis, Färe-Primont indices, family farms.
JEL Classification: C610, D240, Q120

1. Introduction

Being the primary economic sector, the agricultural sector rewards analysis of the productive efficiency therein. Indeed, increase in efficiency and productivity there leads to release of the production factors, which can thus be employed in other economic activities rendering higher value added (Nauges *et al.*, 2011; Samarajeewa *et al.*, 2012). In addition, the public support allocated to farmers, training programmes *etc.* induce the need for assessment of changes in agricultural efficiency. Besides efficiency, the total factor productivity is an important measure describing farm ability to transform the inputs into certain outputs and thus the overall shifts in the production frontier (Fulginiti and Perrin, 1997; Coelli and Rao, 2005).

One of the most elaborated measures for efficiency is data envelopment analysis (DEA), see, for instance, studies by Murillo-Zamorano (2004), Knežević *et al.* (2011), Borůvková and Kuncová (2012), Votápková and Žák (2013), Zelenyuk (2012).

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Accordingly, various studies employed DEA for efficiency and productivity analysis in agriculture (Alvares, Arias, 2004; Gorton, Davidova, 2004; Douarin, Latruffe, 2011; Bojnec, Latruffe, 2011). However, efficiency estimates are not enough to identify the underlying trends of productivity. Therefore, the productivity indices are employed to measure changes in the total factor productivity (Mahlberg *et al.,* 2011; Sufian, 2011). Furthermore, the DEA is suitable for providing distance function estimates which are the essential components of the productivity indices. Among the well-established indices of Malmquist, Luenberger, Hicks-Moorsteen, the Färe-Primont Index offers some new features for the production analysis. Recently, O'Donnell (2011b) developed the package DPIN which facilitates the computations of the latter indices. Rahman and Salim (2013) employed the Färe-Primont Index for analysis of the agricultural productivity and efficiency.

The Lithuanian agricultural sector, like other ones operating in the transitional economies, still features the processes of land reform, farm structure development, and modernisation. Accordingly, there is a need to utilise the benchmarking techniques in order to fathom the underlying trends and sources of efficiency and productivity. This paper therefore aims at analysing the productive efficiency and the total factor productivity in the Lithuanian family farms. The research is based on the Farm Accountancy Network Data covering the period of 2004–2009. The package DPIN was employed to implement the Färe-Primont Indices. Furthermore, the stochastic kernels were applied to analyse the distributions of the efficiency scores along with the econometric analysis which aimed at revealing the relationships of the environmental variables and the efficiency scores.

The paper is organised in the following manner: Sections 2–4 discuss the preliminaries to the Färe-Primont Indices based on DEA. Section 5 presents the data used. Results of the empirical analysis are presented in Section 6.

2. The Measures of Productivity and Efficiency

Productivity is generally defined as a ratio of output over input (Färe *et al.*, 2008). However, this principle becomes a more complex one in the presence of multi-input and/or multi-output technology. Let there are K decision making units (DMUs) observed during T time periods with each using inputs $\mathbf{x}_k^t = \left(x_{1k}^t, x_{2k}^t, \ldots, x_{mk}^t\right)'$ and producing outputs $\mathbf{y}_k^t = \left(y_{1k}^t, y_{2k}^t, \ldots, y_{nk}^t\right)'$, where $k = 1, 2, ..., K$ is a DMU Index, $t = 1, 2, ..., T$ denotes a respective time period, and m and n are the numbers of inputs and outputs, respectively. As O'Donnell (2008, 2012) put it, the total factor productivity (TFP)[1] of a DMU is then defined as $TFP_{kt} = Y_{kt} / X_{kt}$, where $Y_{kt} \equiv Y(\mathbf{y}_k^t)$ is an aggregate output, $X_{kt} \equiv X(\mathbf{x}_k^t)$ is an aggregate input, and $Y(\cdot)$ and $Y(\cdot)$ are non-negative non-decreasing linearly-homogeneous aggregator functions, respectively. One can further compute the index comparing the TFP of DMU k in period t with the TFP of DMU l in period s:

$$TFP_{ls,kt} = \frac{TFP_{kt}}{TFP_{ls}} = \frac{Y_{kt} / X_{kt}}{Y_{ls} / X_{ls}} = \frac{Y_{kt} / Y_{ls}}{X_{kt} / X_{ls}} = \frac{Y_{ls,kt}}{X_{ls,kt}}, \tag{1}$$

where $Y_{ls,kt} \equiv Y_{kt} / Y_{ls}$ and $X_{ls,kt} \equiv X_{kt} / X_{ls}$ are output and input quantity indices, respectively. Indeed, Equation 1 measures the growth in TFP as a measure of output growth divided by a measure of input growth (O'Donnell, 2011a).

1 Indeed, one can also use the term multi-factor productivity instead of TFP. This might be more relevant in the sense that an analysis might not cover *all* factors of production.

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If input and output prices are known, the aggregate quantities can be computed by employing Paasche, Laspeyres, Fisher, Tornqvist Indices. Otherwise, Malmquist, and Hicks-Moorsteen Indices relying on distance functions can be employed. However, all of these fail the transitivity test and thus cannot be used for multi-temporal and multi-lateral comparisons (O'Donnell, 2011a). Meanwhile, Lowe, Färe-Primont, and geometric Young Indices are suitable for such comparisons. Färe-Primont Index relies on distance functions and does not require price information. Indeed, it relies on non-linear weighting functions and normalised shadow (or support) prices (O'Donnell, 2011a).

The change in TFP defined in Equation 1 can be further analysed by decomposing it into certain terms describing efficiency and productivity changes. It was O'Donnell (2008) who argued that a TFP Index can be decomposed into the two terms describing TFP efficiency (TFPE) change and technology change (TC). Specifically, the TFPE measures the difference between an observed TFP and maximal TFP related to the underlying technology. In case of DMU k in period t we have:

$$TFPE_{kt} = TFP_{kt} / TFP_t^*, \tag{2}$$

where $TFP_t^* = \max_k TFP_{kt}$ denotes the maximal TFP possible for period t. Similarly, the following equation holds for DMU l in period s:

$$TFPE_{is} = TFP_{ls} / TFP_s^*. \tag{3}$$

Thus, the change in TFPE catches the change in DMU's performance (efficiency change – EC), whereas the TC accounts for change in the maximal TFP. The TFP change (*cf.* Equation 1) then decomposes as:

$$TFP_{ls,kt} = \frac{TFP_{kt}}{TFP_{ls}} = \underbrace{\left(\frac{TFP_t^*}{TFP_s^*}\right)}_{TC}\underbrace{\left(\frac{TFPE_{kt}}{TFPE_{ls}}\right)}_{EC}. \tag{4}$$

The EC term in Equation 4 can be further decomposed into measures of scale efficiency change (SEC) and mix efficiency change (MEC). The concept of the mix efficiency was introduced by O'Donnell (2008). Whereas scale efficiency is related to economies of scale, mix efficiency is related to economies of scope. The difference between allocative efficiency and mix efficiency lies in the fact that the former is a value concept (*i.e.* cost, revenue, profit), and the latter one is a productivity (quantity) concept. All in all, mix efficiency indicates possible improvement in productivity due to changes in input structure.

The following Figure 1 depicts the concept of the mix efficiency in the input space (in the presence of two inputs). The curve passing through points B, R, and U is an input isoquant, *i.e.* an efficient frontier. An isocost is based on input prices, whereas the dashed lines going through points A, B, R, and U are iso-aggregate-input lines. Specifically, they were established by the virtue of the simple linear aggregation function $X_{kt} = \alpha_1 x^t_{1\ k} + \alpha_2 x^t_{2\ k}$, where $\alpha_1 \geq 0$ and $\alpha_2 \geq 0$. The slope of an iso-aggregate-input line thus becomes $-\alpha_1 / \alpha_2$ and intercept varies depending on the aggregate input quantity in between X_{kt} / α_2 and $\hat{X}_{kt} / \alpha_2$. The DMU operating at point A could move towards point B in case it managed to reduce its input consumption securing the same level of output and holding input structure constant; as a result the aggregate input would fall from X_{kt} down to $\bar{X}_{kt}$. Minimisation

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of costs without any restrictions on input mix results in a movement from B to R and subsequent decrease in aggregate input from $\bar{X}_{kt}$ to $\breve{X}_{kt}$. Minimisation of the aggregate input without constraints on the input mix entails a movement from B to U and a decrease in aggregate input from $\bar{X}_{kt}$ to $\hat{X}_{kt}$. The following measures of efficiency can be defined in terms of Figure 1:

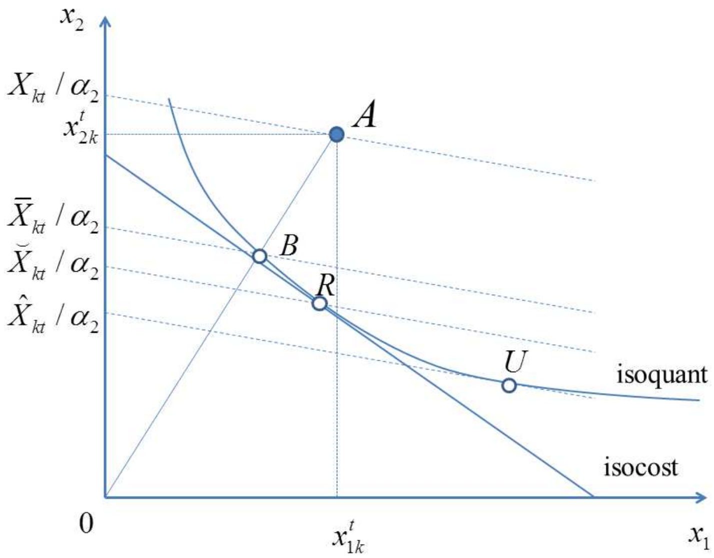
$$ITE_{kt} = \bar{X}_{kt} / X_{kt}, \tag{5}$$

$$AE_{kt} = \breve{X}_{kt} / \bar{X}_{kt}, \tag{6}$$

$$IME_{kt} = \hat{X}_{kt} / \bar{X}_{kt}. \tag{7}$$

Indeed, Equation 5 defines an input-oriented measure of the technical efficiency (Farrell, 1957), Equation 6 stands for a measure of the allocative efficiency (Färe, Grosskopf, 1990; Thanassoulis *et al.*, 2008), and Equation 7 defines an input-oriented measure of the mix efficiency (O'Donnell, 2008).

Figure 1 | The Concept of Mix Efficiency (O'Donnell, 2011a)



The measures of TFP and efficiency can be further depicted in an input-output space (Figure 2). The points A, R, and U come from Figure 1 and denote the observed production plan, technically efficient production plan with mix restrictions, and technically efficient production plan without mix restrictions, respectively. The curve passing through points B and D is a mix-restricted frontier, whereas that passing through points E and U is an unrestricted frontier. The rays passing through each point are associated with respective TFP levels. The Farrel (1957) input-oriented measure of efficiency can thus be described in terms of the TFP change: $ITE_{kt} = TFP_A / TFP_B \equiv TFP_{BA}$. Similarly, the mix efficiency measure defined by O'Donnell (2008) can be given as $IME_{kt} = TFP_B / TFP_U \equiv TFP_{UB}$. The input-oriented scale efficiency measure, ISE, compares TFP at the efficient point B to the highest one under the same input-mix at point D:

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$$ISE_{kt} = \frac{Y_{kt} / \bar{X}_{kt}}{\tilde{Y}_{kt} / \tilde{X}_{kt}}. \tag{8}$$

The residual mix efficiency, RME, measures the difference between the maximal TFP for the unrestricted frontier (point E) and TFP at the scale-efficient point D:

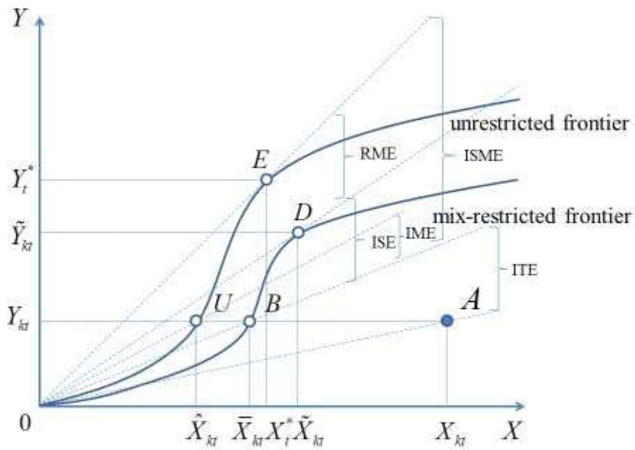
$$RME_{kt} = \frac{\tilde{Y}_{kt} / \tilde{X}_{kt}}{TFP_t^*}. \tag{9}$$

The input-oriented scale-mix efficiency, ISME, encompasses ISE and RME and thus compares the maximal TFP at point E to that at the scale-efficient point D:

$$ISME_{kt} = \frac{Y_{kt} / \bar{X}_{kt}}{TFP_t^*}. \tag{10}$$

Further details on these measures can be found in O'Donnell (2008).

Figure 2 | The Input-Oriented Measures of Technical, Scale and Mix Efficiency (O'Donnell, 2011a)



The TFP efficiency, TFPE, can therefore be decomposed into several terms: $TFPE_{kt} = ITE_{kt} \times ISME_{kt} = ITE_{kt} \times ISE_{kt} \times RME_{kt}$. In an input-oriented framework, the TFP index given by Equations 1 and 4 can also be decomposed in the following way:

$$TFP_{ls,kt} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{ITE_{kt}}{ITE_{ls}}\right)\left(\frac{ISME_{kt}}{ISME_{ls}}\right) = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{ITE_{kt}}{ITE_{ls}}\right)\left(\frac{ISE_{kt}}{ISE_{ls}}\right)\left(\frac{RME_{kt}}{RME_{ls}}\right). \tag{11}$$

An analogous decomposition is available for the output orientation (O'Donnell, 2011a). The components defined in Equation 11 can be estimated by employing linear programming models.

3. Estimation of the TFP Indices and their Components via DEA

As Figures 1–2 suggest, estimation of the TFP indices involves estimation of the underlying production frontiers. These can be established by the virtue of linear programming

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models. These models are non-parametric ones and therefore require neither assumptions on the functional form of the production frontier nor on distributions of the error terms. The estimated is locally linear in the neighbourhood of the efficient point, ($\mathbf{x}_k^t$, $\mathbf{y}_k^t$) and takes the following form: $\left(\mathbf{y}_k^t\right)'\boldsymbol{\alpha} = \left(\mathbf{x}_k^t\right)'\boldsymbol{\beta} + \gamma$, where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are non-negative $n \times 1$ and $m \times 1$ vectors of intensity variables, respectively. As O'Donnell (2011a) argues, the underlying technology can be represented by the input and output distance functions. The output distance function for the technology available in period t is defined as:

$$D_O\left(\mathbf{x}_k^t, \mathbf{y}_k^t, t\right) = \left(\left(\mathbf{y}_k^t\right)'\boldsymbol{\alpha}\right) / \left(\left(\mathbf{x}_k^t\right)'\boldsymbol{\beta} + \gamma\right), \tag{12}$$

with variable γ describing the assumptions on returns to scale. Specifically, $\gamma = 0$ ensures constant returns to scale (CRS) technology. In order to entail a unique solution, the aggregate output is constrained by setting $(\mathbf{y}_k^t)'\boldsymbol{\alpha} = 1$. The following linear programming problem then estimates the output distance function under variable returns to scale (VRS):

$$\begin{aligned} & D_O\left(\mathbf{x}_k^t, \mathbf{y}_k^t, t\right)^{-1} = OTE_{kt}^{-1} = \min_{\boldsymbol{\alpha},\boldsymbol{\beta},\gamma} \left(\mathbf{x}_k^t\right)'\boldsymbol{\beta} + \gamma \\ & \text{s. t.} \\ & \gamma\mathbf{1} + \mathbf{X}'\boldsymbol{\beta} \geq \mathbf{Y}'\boldsymbol{\alpha} \\ & \left(\mathbf{y}_k^t\right)'\boldsymbol{\alpha} = 1 \\ & \boldsymbol{\alpha} \geq \mathbf{0}, \boldsymbol{\beta} \geq \mathbf{0} \end{aligned} \quad , \tag{13}$$

where $\mathbf{1}$ is a $K^t \times 1$ vector of ones, $\mathbf{X}$ is an $m \times K^t$ matrix of observed inputs, $\mathbf{Y}$ is an $n \times K^t$ matrix of observed outputs, and $\mathbf{0}$ is a vector of zeros of the appropriate length. Here K^t denotes the number of DMUs operating in the period t[2].

In the input-oriented case, the input distance function is used to describe the technology prevailing in the period t:

$$D_I\left(\mathbf{x}_k^t, \mathbf{y}_k^t, t\right) = \left(\left(\mathbf{x}_k^t\right)'\boldsymbol{\eta}\right) / \left(\left(\mathbf{y}_k^t\right)'\boldsymbol{\varsigma} - \delta\right), \tag{14}$$

where $\boldsymbol{\varsigma}$ and $\boldsymbol{\eta}$ are non-negative $n \times 1$ and $m \times 1$ vectors of intensity variables, respectively; and δ is a convexity constraint. In this case the aggregate input is restricted by imposing $(\mathbf{x}_k^t)'\boldsymbol{\eta} = 1$. The associated linear programming problem is then given by

$$\begin{aligned} & D_I\left(\mathbf{x}_k^t, \mathbf{y}_k^t, t\right)^{-1} = ITE_{kt} = \max_{\boldsymbol{\eta},\boldsymbol{\varsigma},\delta} \left(\mathbf{y}_k^t\right)'\boldsymbol{\varsigma} - \delta \\ & \text{s. t.} \\ & \mathbf{X}'\boldsymbol{\eta} \geq \mathbf{Y}'\boldsymbol{\varsigma} - \delta\mathbf{1} \\ & \left(\mathbf{x}_k^t\right)'\boldsymbol{\eta} = 1 \\ & \boldsymbol{\eta} \geq \mathbf{0}, \boldsymbol{\varsigma} \geq \mathbf{0} \end{aligned} \quad . \tag{15}$$

Note that the input- or output-oriented measures of efficiency can be also estimated by the means of dual DEA models (envelopment models). In case of the input-oriented efficiency measurement, the following problem is solved:

2 In our case we employed a balanced panel and thus had $K^t = 200$ for all t.

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$$
\begin{aligned}
& D_I\left(\mathbf{x}_k^t, \mathbf{y}_k^t, t\right)^{-1} = ITE_{kt} = \min_{\boldsymbol{\theta},\rho} \rho \\
& \text{s. t.} \\
& \mathbf{X}\boldsymbol{\theta} \leq \mathbf{x}_k^t \rho \\
& \mathbf{Y}\boldsymbol{\theta} \geq \mathbf{y}_k^t \\
& \boldsymbol{\theta}'\mathbf{1} = 1 \\
& \boldsymbol{\theta} \geq \mathbf{0}
\end{aligned} \tag{16}
$$

where $\boldsymbol{\theta}$ is a $K^t \times 1$ vector of peer weights. The model given by Equation 15 involves a convexity constraint, $\boldsymbol{\theta}'\mathbf{1} = 1$, which renders variable returns to scale (VRS) estimates of efficiency. An analogous model is available for the output orientation. The CRS estimates are obtained via the following problem:

$$
\begin{aligned}
& D_I^{CRS}\left(\mathbf{x}_k^t, \mathbf{y}_k^t, t\right)^{-1} = ITE_{kt}^{CRS} = \min_{\boldsymbol{\theta},\rho} \rho \\
& \text{s. t.} \\
& \mathbf{X}\boldsymbol{\theta} \leq \mathbf{x}_k^t \rho \\
& \mathbf{Y}\boldsymbol{\theta} \geq \mathbf{y}_k^t \\
& \boldsymbol{\theta} \geq \mathbf{0}
\end{aligned} \tag{17}
$$

Computations of $D_O^{CRS}\left(\mathbf{x}_k^t, \mathbf{y}_k^t, t\right)$ is a straightforward generalisation. The scale efficiency can be obtained by $ISE_{kt} = ITE_{kt}^{CRS} / ITE_{kt}$ for an input orientation and $OSE_{kt} = OTE_{kt}^{CRS} / OTE_{kt}$ for an output orientation.

The discussed DEA models will enable to estimate aggregate quantities, levels of efficiency, and TFP.

4. Estimation of Aggregate Inputs and Outputs

If prices are not available, one cannot employ the well-established indices for aggregation. However, it is Malmquist, Hicks-Moorsteen, and Färe-Primont Indices that can be employed without explicit price data. Indeed, the shadow prices are used instead to construct the aggregate indices.

Let $\mathbf{x}_0$, $\mathbf{y}_0$, and t_0 denote the representative input quantities, output quantities, and time period, respectively. The representative technology is defined by choosing the reference production plans[3]. The DEA models given by Equations 13 and 15 are then solved for the representative quantities, *i.e.* $D_O(\mathbf{x}_0, \mathbf{y}_0, t_0)$ and $D_I(\mathbf{x}_0, \mathbf{y}_0, t_0)$ are estimated. The latter two problems thus yield certain values which solve them for the reference quantities. Specifically, $\boldsymbol{\alpha}_0$ and $\boldsymbol{\beta}_0$ and γ_0 solve Equation 13 with respect to the representative quantities, whereas $\boldsymbol{\varsigma}_0$, $\boldsymbol{\eta}_0$ and δ_0 solve Equation 15 with respect to the same quantities. The calculated optimal values can then be inserted into Equations 12 and 14, respectively. The first-order derivatives (gradients) of $D_O(\mathbf{x}_0, \mathbf{y}_0, t_0)$ and $D_I(\mathbf{x}_0, \mathbf{y}_0, t_0)$ can be treated as

3 For instance, O'Donnell (2011b) uses the sample means to construct the two representative vectors for the DPIN program and sets M^t equal to the sample size. Therefore, the representative technology is defined by considering all observations.

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the revenue- and cost-deflated output and input shadow prices, $\mathbf{p}_0$ and $\mathbf{w}_0$, respectively (Färe, Grosskopf, 1990):

$$\mathbf{p}_0 \equiv \partial D_O\left(\mathbf{x}_0, \mathbf{y}_0, t_0\right) / \partial \mathbf{y}_0 = \boldsymbol{\alpha}_0 / \left(\left(\mathbf{x}_0\right)' \boldsymbol{\beta}_0 + \gamma_0\right), \tag{18}$$

$$\mathbf{w}_0 \equiv \partial D_I\left(\mathbf{x}_0, \mathbf{y}_0, t_0\right) / \partial \mathbf{x}_0 = \boldsymbol{\eta}_0 / \left(\left(\mathbf{y}_0\right)' \boldsymbol{\varsigma}_0 - \delta_0\right). \tag{19}$$

The shadow prices given by Equations 18–19 can be used to compute the aggregate inputs and outputs, respectively:

$$X_{kt} = (\mathbf{x}_k^t)' \mathbf{w}_0, \tag{20}$$

$$Y_{kt} = (\mathbf{y}_k^t)' \mathbf{p}_0. \tag{21}$$

The aggregate input index defined by Equation 20 might then be utilised to estimate the minimum aggregate input, $\hat{X}_{kt}$, capable of producing $\mathbf{x}_k^t$ without restrictions on the input-mix structure. O'Donnell (2011a) showed that Equation 16 can be transformed into a problem which seeks minimum of the ratio of the optimal aggregate input, $X(\mathbf{x})$, to the observed aggregate output, $X(\mathbf{x}_k^t)$ with an additional constraint, $\mathbf{x} = \rho \mathbf{x}_k^t$, ensuring that the input-mix is being held fixed. After deleting the latter constraint, the following linear programming problem yields the optimal aggregate input quantity under unrestricted input-mix:

$$\begin{aligned} &\hat{X}_{kt} = \min_{\boldsymbol{\theta}, \mathbf{x}} X(\mathbf{x}) \\ &\text{s. t.} \\ &\mathbf{X}\boldsymbol{\theta} \le \mathbf{x} \\ &\mathbf{Y}\boldsymbol{\theta} \ge \mathbf{y}_k^t \\ &\boldsymbol{\theta}'\mathbf{1} = 1 \\ &\boldsymbol{\theta} \ge \mathbf{0} \end{aligned} \tag{22}$$

where $X(\mathbf{x})$ is the Färe-Primont input aggregator function (*cf.* Equation 20). The output-oriented problem corresponding to Equation 22 is

$$\begin{aligned} &\hat{Y}_{kt} = \max_{\boldsymbol{\theta}, \mathbf{y}} Y(\mathbf{y}) \\ &\text{s. t.} \\ &\mathbf{X}\boldsymbol{\theta} \le \mathbf{x}_k^t \\ &\mathbf{Y}\boldsymbol{\theta} \ge \mathbf{y} \\ &\boldsymbol{\theta}'\mathbf{1} = 1 \\ &\boldsymbol{\theta} \ge \mathbf{0} \end{aligned}, \tag{23}$$

where $Y(\mathbf{y})$ is the Färe-Primont output aggregator function (*cf.* Equation 21).

The aggregator functions given by Equations 20 and 21 can be employed to estimate the maximal TFP in period t: $TFP_t^* = \max_k TFP_{kt} = \max_k \left\{Y_{kt} / X_{kt}\right\}$. The remaining measures of efficiency defined in Section 2 are then computed residually: $TFPE_{kt} = TFP_{kt} / TFP_t^*$, $OSME_{kt} = TFPE_{kt} / OTE_{kt}$, $ISME_{kt} = TFPE_{kt} / ITE_{kt}$, and $RME_{kt} = OSME_{kt} / OSE_{kt}$.

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5. Data Used

The data for 200 farms selected from the Farm Accountancy Data Network (FADN) sample cover the period of 2004–2009[4]. Thus a balanced panel of 1,200 observations was employed for analysis. However, the four observations were later omitted due to infeasibility. The technical efficiency was assessed in terms of the input and output indicators commonly employed for agricultural productivity analyses. More specifically, the utilized agricultural area (UAA) in hectares was chosen as land input variable, annual work units (AWU) – as labour input variable, intermediate consumption in Litas, and total assets in Litas as a capital factor. The last two variables were deflated by respective real price indices provided by Eurostat. On the other hand, the three output indicators represent crop, livestock, and other outputs in Litas (Lt), respectively. The aforementioned three output indicators were deflated by respective real price indices.

The analysed sample covers relatively large farms (mean UAA – 244 ha). As for labour force, the average was 3.6 AWU. In order to quantify the differences in efficiency across certain farming types, the farms were classified into the three groups in terms of their specialization. Specifically, farms with crop output larger than 2/3 of the total output were considered as specialized crop farms, whereas those specific with livestock output larger than 2/3 of the total output were classified as specialized livestock farms. The remaining farms fell into a residual category called mixed farming. Table 1 summarizes the input and output variables.

Table 1 | The Means for Inputs and Outputs

Farming type	AWU	UAA, ha	Intermediate consumption, Lt	Assets, Lt	Output, Lt		
					Crop	Livestock	Other
Crop	3.6	285	323,980	944,691	494,956	9,599	6,633
Livestock	4.1	130	224,338	1,031,422	85,738	365,520	6,196
Mixed	3.1	122	142,240	521,821	106,183	128,782	2,883
Arithmetic average	3.6	244	286,277	893,458	391,845	67,609	6,040
Harmonic mean	3.6	155	205,838	760,562	129,861	26,159	4,552

The last row in Table 1 also reports the harmonic means of the farming type-specific averages to account for different numbers of farms under each farming type.

6. Results

The TFP measures and indices were estimated by the virtue of the Färe-Primont TFP Indices. Specifically, the levels of TFP measures and indices represent the time-specific performance of the Lithuanian family farms under a transitive multilateral framework,

4 In Lithuania, the whole FADN sample comprises some 1,300 farms.

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whereas the changes in TFP measures and indices account for dynamics thereof measured against the arbitrarily chosen reference farm.

The following Table 2 reports the mean values of the TFP measures for different farming types. Given the Färe-Primont Index is a transitive one, all the comparisons were made with reference to year 2004 as a base period. In order to ensure the time reversal capability, the rates of TFP change were logged. As a result, the crop farms exhibited the growth of TFP of 16.5% during 2004–2009, whereas livestock and mixed farms featured TFP growth of 24.3% and 39.1%, respectively. Note that years 2006 and 2009 were those of the declining TFP for all farming types. The mean TFP levels for crop, livestock, and mixed farming were 0.21, 0.28, and 0.16, respectively. The annual logged growth rates ranged in between 3.3% and 7.8% p. a.

Table 2 | Dynamics of the TFP across Different Farming Types, 2004–2009

Farming type	2004	2005	2006	2007	2008	2009	Mean over 2004–2009
TFP levels							
Crop	0.196	0.194	0.151	0.226	0.251	0.231	0.208
Livestock	0.235	0.259	0.242	0.306	0.347	0.300	0.281
Mixed	0.123	0.154	0.129	0.183	0.187	0.181	0.159
TFP***	0.468	0.522	0.522	0.522	0.559	0.559	0.525
TFP indices (base year 2004)							
Crop	1.000	0.993	0.771	1.155	1.284	1.179	
Livestock	1.000	1.100	1.031	1.300	1.476	1.275	
Mixed	1.000	1.256	1.049	1.494	1.527	1.479	
TFP*	1.000	1.116	1.116	1.116	1.194	1.194	
Logged TFP changes (%)							
Crop	0.0	-0.7	-26.0	14.4	25.0	16.5	3.3
Livestock	0.0	9.5	3.0	26.2	38.9	24.3	4.9
Mixed	0.0	22.8	4.8	40.2	42.3	39.1	7.8
TFP*	0.0	11.0	11.0	11.0	17.7	17.7	2.9

Note: TFP^* denotes the level of maximal *TFP*. The means of *TFP* levels are averages, whereas the means of *TFP* changes are given as ln(*TFP*2009 / *TFP*2004) / 5.

The TFP efficiency was decomposed into the four terms, namely TFP^*, ITE, ISE, and RME. The maximal TFP (TFP^*) increased throughout the research period due to assumption of no negative technical change: the value of 0.468 was observed for year 2004, 0.5223 for 2005–2007, and 0.559 for 2008–2009. Therefore, the best performing farms managed to increase their TFP even further. Specifically, the technical change of

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some 17.7% had occurred during 2004–2009 (2.9% p. a.). Figure 3 exhibits the kernel densities of the remaining efficiency measures for the three farming types. Indeed, these plots depict variation of the respective TFP measures for the whole period of 2004–2009 The Gaussian kernels (Silverman, 1986) were used to approximate the underlying empirical distributions.

The upper left plot of Figure 3 depicts the densities of the TFP efficiency (TFPE) scores. TFPE indicates the extent to which a certain farm is deviated from the point of maximal productivity: The lower TFPE, the lower the ratio of the observed TFP to the maximal TFP. These computations can be interpreted as a movement from point A towards point E in Figure 2. Note that the point of maximal productivity, E, is located on the mix-unrestricted frontier. It was the livestock farms that exhibited the highest mean efficiency (0.53). The latter farming also exhibited the highest standard deviation (SD) of 0.19 associated with TFPE. The coefficient of variation (CV), however, was the lowest one (0.37) if compared to the remaining farming types. The crop farming featured the mean TFPE of 0.4 and SD of 0.16. Accordingly, the CV approached the value of 0.41. Finally, the mixed farming was peculiar with rather low mean TFPE of 0.30, whereas SD remained at 0.17 and CV increased up to 0.55. As the upper left plot in Figure 3 suggests, the underlying density for the mixed farms was a bi-modal one. Therefore, at least two clusters of the mixed farms can be considered. The latter implies that in spite of the diversification, the mixed farms did not manage to maintain a substantial level of the TFPE as well as its variation.

The densities for input-oriented technical efficiency (ITE) are depicted in the upper right plot of Figure 3. ITE compares the observed TFP to that related to the technically efficient production plan. The latter levels of TFP are associated with, respectively, points A and B in Figure 2. The ITE scores, thus can be interpreted as factors of the input contraction needed (holding the structure of the input-mix fixed) to ensure the technical efficiency. It is evident that the crop and mixed farms concentrated around the two values of the ITE with one of these values falling in between 0.4 and 0.6, and another approaching unity (*i.e.* technically efficient region). Indeed, the crop farming featured the lowest mean ITE, namely 0.69. Furthermore, the SD of 0.19 resulted in the CV of 0.27, which was the highest value if compared to other farming types. The mixed farming was associated with more favourable ITE indicators: mean ITE was 0.73, SD – 0.15, and CV – 0.20. On the other hand, it was the livestock farms that were specific with the highest ITE. Particularly, the mode of the underlying density was located near the value of unity and the mean ITE was 0.85. In addition, the variation in the efficiency was also a low one (SD – 0.14 and CV – 0.16).

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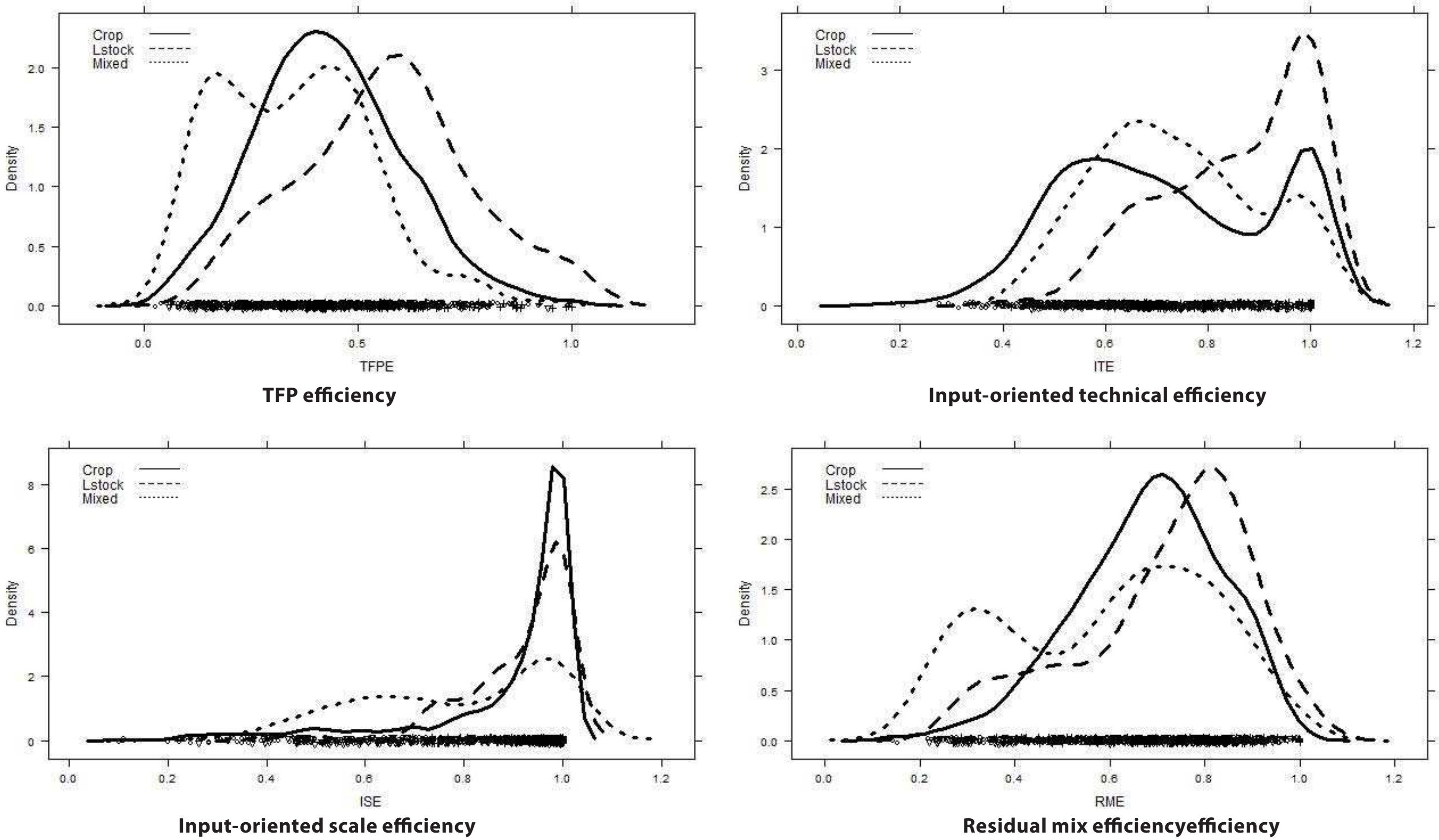
Figure 3 | Densities of the Efficiency Scores for Different Farming Types



Note: Bold, dashed, and dotted lines represent densities for crop, livestock, and mixed farms, respectively

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The densities of the input-oriented scale efficiency (ISE) scores are given in the lower right plot of Figure 3. ISE compares the TFP at technically efficient point to that prevailing at the point of mix-invariant optimal scale. Thus, holding input-mix fixed we further move from point B towards point D in terms of Figure 2. As one can note, these densities are rather compact ones with means located around the point of efficiency. Therefore, it is likely that the underlying technology is a CRS one. However, this paper does not focus on the issue[5]. The livestock farming was associated with the highest mean ISE, 0.91, as well as the lowest variation thereof (SD – 0.10, CV – 0.11). The crop farms were specific with the mean ISE of 0.86 and a higher level of variation in these scores (SD – 0.17, CV – 0.20). Finally, the mixed farms diverged from the optimal scale to the highest degree: The mean ISE was 0.76, SD – 0.19, and CV – 0.26.

The lower left plot of Figure 3 presents the densities of the residual mix efficiency (RME) scores across the three farming types. RME measures the TFP gains possible due to changes in the input-mix. Specifically, the TFP at mix-invariant optimal scale is compared to the TFP associated with optimal scale of the unrestricted frontier. Therefore, we look at points D and E in Figure 2. The livestock farms featured the highest mean RME (0.69), albeit its variation was the second lowest one (SD – 0.17, CV – 0.25). The crop farming exhibited similar mean RSE (0.67) as well as the lowest variation thereof (SD – 0.13, CV – 0.20). The mixed farming was associated with the lowest mean RSE (0.55) and the highest variation thereof (SD – 0.20, CV – 0.37). Given the density depicted in Figure 3, the mixed farms were grouped around RME levels of 0.2–0.4 and 0.6–0.8. Therefore, certain sub-types of the mixed farms did not manage to achieve the substantial level of RSE.

The results do indicate that the ITE was a decisive factor causing decrease in TFPE for crop and mixed farms. Meanwhile, the ISE constituted a serious problem for mixed farms. Indeed, these farms were the smallest ones if compared to the remaining farming types (*cf.* Table 1). Finally, the mix efficiency was low for all farming types indicating the need for implementation of certain farming practices allowing for optimisation of the input-mix.

The econometric models were further employed to analyse the underlying drivers of the TFP growth. The TFPE, ITE, ISE, and RME were regressed over the selected environmental variables describing farm specifics. The following factors were chosen as regressors. The utilised agricultural area (*UAA*) identified the scale size and was considered a proxy for farm size. Indeed, the question of the optimal farm size has always been a salient issue for policy makers and scientists (Alvarez, Arias 2004; Gorton, Davidova 2004; van Zyl *et al.* 1996). The ratio of crop output over the total output (*CropShare*) captures the possible difference in farming efficiency across crop and livestock farms. Similarly, the dummy variable for organic farms (*Organic*) was used to quantify the difference between organic and conventional farming. It is due to Offermann (2003) that Lithuanian organic farms exhibit 60–80% lower crop yields depending on crop species if compared to same values for conventional farming. The demographic variable, namely age of farmer (*Age*) was introduced to ascertain whether young–farmers–oriented policy measures can influence the structural efficiency. Finally, the effect of production subsidies on efficiency was estimated by considering ratios of production subsidies to output (*SubsShare*).

5 The bootstrapping-based tests can be employed to test the hypotheses of returns to scale (Simar, Wilson, 2002).

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Given the analysis relied on the panel data, the F-test was employed to check whether the data do exhibit farm- and time-specific effects. The null hypothesis of insignificant effects was rejected at the significance level of 1%. Furthermore, the Hausman test rejected the random-effects model at the significance level of 1%. Accordingly, the two-way fixed-effects models were estimated for TFPE, ITE, ISE, and RME:

$$y_k^t = \boldsymbol{\beta}(\mathbf{z}_k^t)' + u_k + u_t + \varepsilon_k^t, \tag{24}$$

where y is the component of TFP ($y = \{TFPE, ITE, ISE, RME\}$), $\boldsymbol{\beta}$ is the vector of coefficients, $\mathbf{z}^t_k$ is the vector of the environmental variables, u_k is farm-specific effect, and u_t is time-specific effect. The elasticities can then be computed as follows:

$$\mathbf{e}_k^t = \boldsymbol{\beta}\mathbf{z}_k^t / y_k^t, \tag{25}$$

where $\mathbf{e}_k^t = \boldsymbol{\beta}\mathbf{z}_k^t / y_k^t$ is a vector of elasticities of the same dimension as $\boldsymbol{\beta}$ and $\mathbf{z}'_k$.

The estimated models are given in Table 3. The ITE and RME were poorly explained by the selected variables (R^2 were 0.05 and 0.10, respectively). The results showed that the farm size had a positive effect on TFP, ISE, and RME. Therefore, the larger farms are more likely to increase their TFPE by operating at the optimal scale and adjusting their input-mixes. However, the ITE remained unaffected by the farm size. The crop share had a negative effect on TFPE, ITE, and RME. The latter finding implies that crop and mixed farms experienced lower technical and mix-efficiency as well as TFP levels. Nevertheless, these farms did not deviate from the optimal size of scale to a significant extent. The ratio of subsidies to the total output had a negative impact on TFPE, ITE, and ISE. Therefore, the increasing subsidy rate negatively affected the TFP as well as technical efficiency. Given the relation to the mix-efficiency measure (RME) was not significant, it can be concluded that the subsidies do accelerate farm growth but do not distort the input-mix. Farmer age had no significant impact on the analysed efficiency and TFP measures save that of RME: It turned out that older farmers manage to achieve higher mix-efficiency. The latter finding might be explained by the fact that more experienced farmers ensure the proper input-mix structure. Accordingly, the educational programmes for the younger farmers remain important in the light of results of the analysis. Finally, the organic farming was not associated with any significant effects on TFP and efficiency.

Table 3 | Coefficients of the Fixed-Effects Model

	TFPE	ITE	ISE	RME
UAA	0.00021***	0.00003	0.00014 *	0.00012 *
CropShare	-0.36191***	-0.29410 ***	-0.05598	-0.17346 ***
SubsShare	-0.13163***	-0.09888 ***	-0.15401 ***	-0.01435
Age	0.00105	0.00028	0.00011	0.00154 .
Organic	0.01029	-0.02610	0.03664	-0.01305
Adj.	0.13	0.05	0.10	0.02
F-statistic	29.877***	11.4348***	28.6***	5.87311***

Note: Significance codes for respective p-values: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1.

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Given the environmental variables were expressed in different dimensions, the efficiency elasticities were computed in terms of Equation 25. The results are given in Table 4. Farm size in hectares (*UAA*) was the least important factor in terms of its contribution to the efficiency and TFP levels. Farmer age played an important role in the context of RME. Meanwhile, the negative effect of crop share outweighed those of subsidy rate and farm size. One can further note that organic farming practice was not associated with significant changes in TFP and its components.

Table 4 | Efficiency Elasticities (E) across Different Models

		UAA	CropShare	SubsShare	Age	Organic
TFPE	Mean E	**0.127**	**-0.870**	**-0.201**	0.151	0.002
	E at mean	**0.120**	**-0.670**	**-0.100**	0.113	0.001
ITE	Mean E	0.018	**-0.705**	**-0.150**	0.037	-0.006
	E at mean	0.017	**-0.543**	**-0.074**	0.028	-0.003
ISE	Mean E	**0.081**	-0.135	**-0.235**	0.017	0.009
	E at mean	**0.076**	-0.104	**-0.117**	0.012	0.004
RME	Mean E	**0.073**	**-0.417**	-0.022	**0.222**	-0.003
	E at mean	**0.069**	**-0.321**	-0.011	**0.167**	-0.001

Note: Bold figures are those associated with significant regression coefficients.

The technical change of some 19.4% throughout 2004–2009 (3.6% *p.a.*) identified by the means of the Färe-Primont Index was higher than that previously obtained by the Malmquist Index (Balezentis *et al.*, 2013) because the maximal TFP is not estimated by the Malmquist Index. In addition, different aggregator functions are involved in computations of these two productivity indices. Anyway, crop and mixed farms exhibited the highest mean TFP gains as it was the case with Malmquist Index.

All in all, the TFP efficiency of the Lithuania family farms was mainly determined by the technical and mix-efficiency during 2004–2009. These measures, in turn, were better for livestock farming if compared to mixed and crop farming. Specifically, the increase of crop share in the total output of 1% caused decrease in the TFPE of 0.87% on average. An increase in subsidy rate of the same margin resulted in decrease in TFPE of 0.2% on average.

7. Conclusions

The Färe-Primont Index enabled to estimate the dynamics of the TFP in the Lithuanian family farms. Furthermore, the TFP was decomposed into measures describing not only the conventional efficiency and technology changes but also mix-efficiency. Therefore, the technical scale, and scope efficiencies were considered.

The The Färe-Primont Index indicated the technical change of some 17.7% during 2004–2009 (2.9% *p.a.*). The latter estimate is higher than that obtained by the Malmquist

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Index in the previous studies. However, both of these indices showed the same differences among farming types. The results do indicate that the technical efficiency was a decisive factor causing decrease in TFP efficiency for crop and mixed farms. Meanwhile, the scale efficiency constituted a serious problem for mixed farms. Indeed, these farms were the smallest ones if compared to the remaining farming types. Finally, the mix efficiency was low for all farming types indicating the need for implementation of certain farming practices allowing for optimisation of the input-mix.

The econometric analysis implied that farm size in hectares was the least important factor in terms of its contribution to the efficiency and TFP levels. Farmer age played an important role in the context of the residual mix efficiency. Meanwhile, the negative effect of crop share outweighed those of subsidy rate and farm size. One can further note that organic farming practice was not associated with significant changes in TFP and its components.

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