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DECOMPOSITION OF THE TOTAL FACTOR PRODUCTIVITY IN LITHUANIAN FAMILY FARMS BY THE MEANS OF THE HICKS-MOORSTEEN INDEX

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This study employs the Hicks-Moorsteen total factor productivity index and data envelopment analysis to measure total factor productivity changes in Lithuanian family farms. Furthermore, these changes are decomposed into separate effects. The aim of the paper is to identify the prospective guidelines for a reasonable agricultural policy and scientific research aimed at increasing productivity of the Lithuanian family farms. The paper discusses the peculiarities of the distance functions, presents the concept of the Hicks-Moorsteen TFP index, and assesses the TFP changes in Lithuanian family farms by the means of the Hicks-Moorsteen TFP index. The research covers the period of 2004–2009 and is based on micro data. The mean increase of TFP reached some 20% in the analyzed sample of the Lithuanian family farms throughout 2004–2009. It turned out that the crop farms experienced the highest TFP decrease in terms of efficiency effect. Therefore the latter farms should implement certain technological measures. The livestock farms exhibited rather high values of efficiency and technical effects, albeit activity effect was relatively low.

Key words: total factor productivity, efficiency, Hicks-Moorsteen index, data envelopment analysis, family farms.
JEL codes: C430, C440, C610, Q100, Q120.

Introduction

It is the total factor productivity (TFP) indices that can help to fathom the dynamics of productivity in a certain economic sector. Unlike the partial productivity indicators and indices, TFP indices focus on multiple production factors which are considered as inputs and products (outputs). Furthermore, these indices can be decomposed into specific terms identifying technical effect (shifts in production frontier), efficiency effect (catch-up), scale effect etc. Accordingly one can define the sources of productivity grow and thus streamline private or public strategic management policies.

The agricultural sector is subject to even more extensive researches in efficiency and productivity thanks to public support and regulations. As O'Donnell (2012) pointed out, a proper decomposition of the TFP indices can provide the policy-makers with valuable information on the underlying causes of changes in productivity. For instance, large scale R&D projects as well as market development can result in effects of sector–wide technical progress, whereas implementation of state–of–the–art technologies in supported farms might affect technical efficiency change. Similarly, fiscal measures might alter the relative prices and thus the input– or output–mix. All of these phenomena can be quantified by the means of TFP indices.

The three types of TFP indices are usually employed, namely (i) Malmquist index, (ii) Luenberger index, and (iii) Hicks-Moorsteen index (Färe, 2008). They can be utilized in either parametric or nonparametric way. Although Lithuanian agricultural sector has been analyzed by the means of nonparametric frontier methods, viz. Data Envelopment Analysis (DEA) and Free Disposable Hull, the TFP indices were not employed (Vinciūnienė, 2009; Rimkuvienė, 2010; Baležentis, 2012a, 2012b). This study, therefore, utilizes the Hicks-Moorsteen TFP index (Bjurek, 1994; Lovell, 2003; Epure, 2007) and DEA to measure TFP changes in Lithuanian family farms and decompose these changes into separate effects.

The aim of the paper is to identify the prospective guidelines for a reasonable agricultural policy and scientific research aimed at increasing productivity of the Lithuanian family farms. The followings tasks were thus set: (i) to discuss the peculiarities of the distance functions; (ii) to present the concept of the Hicks-Moorsteen TFP index, and (iii) to assess the TFP changes in Lithuanian family farms by the means of the Hicks-Moorsteen TFP index. The research covers the period of 2004–2009. The sample consists of 200 farms reporting to the Farm Accountancy Data Network (FADN).

The paper is organized in the following manner. Section 2 discusses the basics of production analysis by the means of frontier techniques. Section 3 treats the Hicks-Moorsteen TFP index and its estimation via DEA. Finally, Section 4 presents the data used and results of the analysis.

1. Preliminaries of the productive technology

In order to relate the Debreu–Farrel measures to the Koopmans definition of efficiency, and to relate both to the structure of production technology, it is useful to introduce some notation and terminology (Fried et al., 2008). Let producers use inputs $x = (x_1, x_2, ..., x_m) \in \Re_+^m$ to produce outputs $y = (y_1, y_2, ..., y_n) \in \Re_+^n$. Production technology then can be defined in terms of the production set:

$$T = \{(x, y) | x \text{ can produce } y\}. \quad (1)$$

Thus, Koopmans efficiency holds for an input-output bundle $(x, y) \in T$ if, and only if, $(x', y') \notin T$ for $(-x', y') \geq (-x, y)$.

Technology set can also be represented by input requirement and output correspondence sets, respectively:

$$I(y) = \{x | (x, y) \in T\}, \quad (2)$$

$$O(x) = \{y | (x, y) \in T\}. \quad (3)$$

The isoquants or efficient boundaries of the sections of T can be defined in radial terms as follows (Farrel, 1957). Every $y \in \Re_+^n$ has an input isoquant:

$$isoI(y) = \{x | x \in I(y), \lambda x \notin I(y), \lambda < 1\}. \quad (4)$$

Similarly, every $x \in \Re_+^m$ has an output isoquant:

$$isoO(x) = \{y | y \in O(x), \lambda x \notin O(x), \lambda > 1\}. \quad (5)$$

In addition, DMUs might be operating on the efficiency frontier defined by Eqs. 4–5, albeit still use more inputs to produce the same output if compared to another efficient DMU. In this case the former DMU experiences a slack in inputs. The following subsets of the boundaries $I(y)$ and $O(x)$ describe Pareto-Koopmans efficient firms:

$$effI(y) = \{x | x \in I(y), x' \notin I(y), \forall x' \leq x, x' \neq x\}, \tag{6}$$

$$effO(x) = \{y | y \in O(x), y' \notin O(x), \forall y' \geq y, y' \neq y\}. \tag{7}$$

Note that $effI(y) \subseteq isoI(y) \subseteq I(y)$ and $effO(x) \subseteq isoO(x) \subseteq O(x)$.

There are two types of efficiency measures, namely Shepard distance function, and Farrel distance function. These functions yield the distance between an observation and the efficiency frontier. Shepard (1953) defined the following input distance function:

$$D_I(x, y) = \max\{\lambda | (x/\lambda, y) \in I(y)\}. \tag{8}$$

Here $D_I(x, y) \geq 1$ for all $x \in I(y)$, and $D_I(x, y) = 1$ for $x \in isoI(y)$. The Farrel input-oriented measure of efficiency can be expressed as:

$$E_I(x, y) = \min\{\theta | (\theta x, y) \in I(y)\}. \tag{9}$$

Comparing Eqs. 8 and 9 we arrive at the following relation:

$$E_I(x, y) = 1/D_I(x, y), \tag{10}$$

with $E_I(x, y) \leq 1$ for $x \in I(y)$, and $E_I(x, y) = 1$ for $x \in isoI(y)$.

Similarly, the following equations hold for the output-oriented measure:

$$D_O(x, y) = \min\{\lambda | (x, y/\lambda) \in O(x)\}, \tag{11}$$

$$E_O(x, y) = \max\{\phi | (x, \phi y) \in O(x)\}, \tag{12}$$

$$E_O(x, y) = 1/D_O(x, y), \tag{13}$$

where $E_O(x, y) \geq 1$ for $y \in O(x)$, and $E_O(x, y) = 1$ for $y \in isoO(x)$.

Note that the Farrel measures, E_I and E_O, are homogeneous of degree –1 in inputs and outputs, respectively; whereas the Shepard measures, D_I and E_O, are homogeneous of degree +1 in inputs and outputs, respectively.

2. Hicks-Moorsteen productivity index

A Hicks-Moorsteen (or Malmquist TFP) productivity index for the base period *t* is defined as the ratio of a Malmquist output quantity index at the base period *t* and a Malmquist input quantity index at the base period *t* (Kerstens, 2010):

$$HM_{T(t)}\left((x^t, y^t), (x^{t+1}, y^{t+1})\right) = \frac{E^O_{T(t)}(x^t, y^t) / E^O_{T(t)}(x^t, y^{t+1})}{E^I_{T(t)}(x^t, y^t) / E^I_{T(t)}(x^{t+1}, y^t)}, \tag{14}$$

where $E^O_{T(t)}$ and $E^I_{T(t)}$ are, respectively, output- and input- oriented Farrel measures of efficiency (cf. Eqs. 9 and 12). Obviously, $y^t < y^{t+1}$ entails $E^O_{T(t)}(x^t, y^t) > E^O_{T(t)}(x^t, y^{t+1})$ and thus the numerator in Eq. 14 becomes greater than unity. Similarly, $x^{t+1} < x^t$ makes $E^I_{T(t)}(x^t, y^t) > E^I_{T(t)}(x^{t+1}, y^t)$ and thus the denominator in Eq. 14 becomes lesser than unity. Therefore Hicks-Moorsteen index exceeding (less than) unity indicates productivity gain (loss).

One can easily fathom the underlying computations of the Hicks-Moorsteen index by considering the single input and single output example (Fig. 1). For this case variables x^{τ} and y^{τ} will represent scalars rather than vectors with $\tau = \{t, t+1\}$. Here, one can assess the productivity change with respect to the efficiency frontier of the period *t*. The net change in output (i. e. numerator in Eq. 14) is captured by the vertical difference between (x^t, y^t) and (x^t, y^{t+1}). Meanwhile, the net change in input is measured by considering the horizontal difference between (y^t, x^t) and (y^t, x^{t+1}). Note that the Farrel input and output distance functions are homogeneous of degree –1 in inputs and outputs, respectively. Thus, Eq. 14 gets the following form:

$$HM_{T(t)}\left((x^t, y^t),(x^{t+1}, y^{t+1})\right) = \frac{(y^t)^{-1} E^O_{T(t)}(x^t,1) \big/ (y^{t+1})^{-1} E^O_{T(t)}(x^t,1)}{(x^t)^{-1} E^I_{T(t)}(1,y^t) \big/ (x^{t+1})^{-1} E^I_{T(t)}(1,y^t)} = \frac{(1/y^t)/(1/y^{t+1})}{(1/x^t)/(1/x^{t+1})} = \frac{y^{t+1}/y^t}{x^{t+1}/x^t} = \frac{y^{t+1}/x^{t+1}}{y^t/x^t}; \qquad (15)$$

meaning that the Hicks-Moorsteen index is a ratio of the two average products for different periods.

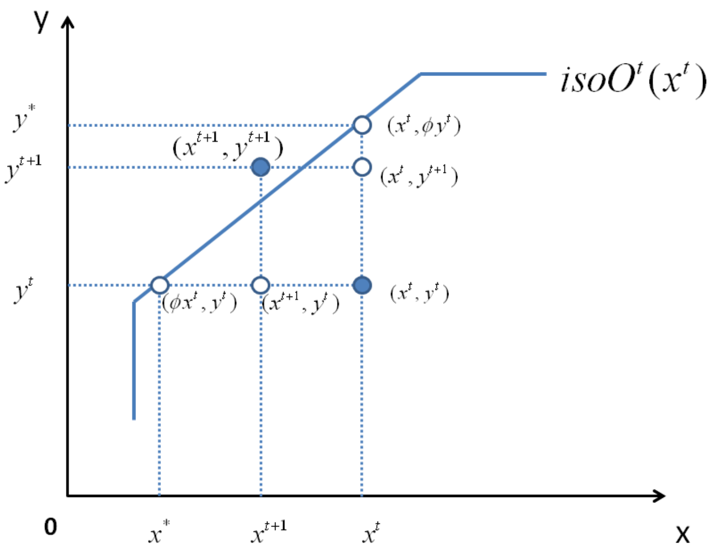

Fig. 1. The Hicks-Moorsteen TFP index based on the Farrel measures.

One can define a Hicks-Moorsteen productivity index at the base period *t*+1 in the following way:

$$HM_{T(t+1)}\left((x^t, y^t),(x^{t+1}, y^{t+1})\right) = \frac{E^O_{T(t+1)}(x^{t+1}, y^t) \big/ E^O_{T(t+1)}(x^{t+1}, y^{t+1})}{E^I_{T(t+1)}(x^t, y^{t+1}) \big/ E^I_{T(t+1)}(x^{t+1}, y^{t+1})}. \qquad (16)$$

Note it has the same interpretation as the previously defined index. A geometric mean of these two Hicks-Moorsteen productivity indices yields:

$$HM_{T(t),T(t+1)}\left((x^t, y^t),(x^{t+1}, y^{t+1})\right) = \Big(HM_{T(t)}\left((x^t, y^t),(x^{t+1}, y^{t+1})\right) \cdot HM_{T(t+1)}\left((x^t, y^t),(x^{t+1}, y^{t+1})\right)\Big)^{1/2}. \qquad (17)$$

The latter index can be interpreted in the same manner as the previously discussed ones.

The decomposition of the Hicks-Moorsteen index, however, is a rather complicated issue. Although Bjurek (1994, 1996) stated that the latter index can be decomposed in the similar way as the Malmquist index he did not present an explicit formulation of this procedure. Later on, Lovell (2003) described the general framework for decomposition of the Hicks-Moorsteen index and noted that is suffers from double accounting and a lack of economic interpretability. However, Lovell (2003) did offer the two ways to improve the decomposition by (i) partially orienting it or (ii) rearranging the terms of decomposition. Following the first approach one can decompose the Hicks-Moorsteen index with a base period *t* in the following way:

$$\begin{aligned} HM_{T(t)}\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \Delta TE_O\left(x^t, y^t, x^{t+1}, y^{t+1}\right) \cdot \Delta T_O\left(x^{t+1}, y^{t+1}\right) \cdot \\ \cdot \Delta S^t\left(x^t, y^t, \mu x^t, \nu x^t\right) \cdot \Delta OM^t\left(x^t, y^{t+1}, \nu y^t\right) \cdot , \\ \cdot \Delta IM^t\left(y^t, x^{t+1}, \mu x^t\right) \end{aligned} \tag{18}$$

where $HM_{T(t)}\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D^O_{T(t)}(x^t, y^{t+1}) / D^O_{T(t)}(x^t, y^t)}{D^I_{T(t)}(x^{t+1}, y^t) / D^I_{T(t)}(x^t, y^t)}$ is the total factor productivity index with $D^I_{T(\tau)}$ and $D^O_{T(\tau)}$ being the Shepard efficiency measures (cf. Eqs. 8 and 11, respectively) for $\tau = \{t, t+1\}$.

The two output-oriented terms ΔTE_O and ΔT_O in Eq. 18 measure efficiency change and technical change, respectively. They are obtained in the following way:

$$\Delta TE_O(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D^O_{T(t+1)}(x^{t+1}, y^{t+1})}{D^O_{T(t)}(x^t, y^t)}, \tag{19}$$

$$\Delta T_O(x^{t+1}, y^{t+1}) = \frac{D^O_{T(t+1)}(x^{t+1}, y^{t+1})}{D^O_{T(t)}(x^t, y^t)}. \tag{20}$$

The product of the remaining three terms, namely the scale effect (ΔS^t), the output mix effect (ΔOM^t), and input mix effect (ΔIM^t), constitutes the activity effect (Lovell, 2003). The latter three terms are computed in the following manner (Kerstens, 2010):

$$\Delta S^t(x^t, y^t, \mu x^t, \nu y^t) = \frac{D^O_{T(t)}(x^t, \nu y^t) / D^O_{T(t)}(x^{t+1}, y^{t+1})}{D^I_{T(t)}(\mu x^t, y^t) / D^I_{T(t)}(x^t, y^t)}, \tag{21}$$

$$\mu = \left[D^I_{T(t)}\left(x^t, y^{t+1} / D^I_{T(t)}\left(x^{t+1}, y^{t+1}\right)\right)\right]^{-1}, \tag{22}$$

$$\nu = \left[D^O_{T(t)}\left(x^{t+1} / D^O_{T(t)}\left(x^{t+1}, y^{t+1}\right), y^t\right)\right]^{-1}, \tag{23}$$

$$\Delta OM^t\left(x^t, y^{t+1}, \nu y^t\right) = \frac{D^O_{T(t)}(x^t, y^{t+1})}{D^O_{T(t)}(x^t, \nu y^t)}, \tag{24}$$

$$\Delta IM^t\left(x^{t+1}, \mu x^t, y^t\right) = \frac{D^I_{T(t)}(\mu x^t, y^t)}{D^I_{T(t)}(x^{t+1}, y^t)}. \tag{25}$$

The distance functions for Eqs. 18–25 can be obtained by employing the non–parametric method viz. Data Envelopment Analysis (DEA). For the following two equations the period notations *t* and *t*+1 are relaxed for sake of convenience. Say there are $k = 1,2,...,K$ decision making units (DMUs), each producing $j = 1,2,...,n$ outputs from $i = 1,2,...,m$ inputs. The input–oriented technical efficiency θ_t may be obtained by solving the following multiplier DEA program (Banker, 1984):

$$\left[D_{T(t)}^{I}(x^k, y^k)\right]^{-1} = \left\{ \min_{\theta_t, \lambda_k} \theta_t \left| \begin{array}{l} \sum_{k=1}^{K} \lambda_k x_i^k \le \theta_t x_i^t, \quad i = 1, 2, ..., m; \\ \sum_{k=1}^{K} \lambda_k y_j^k \ge y_j^t, \quad j = 1, 2, ..., n; \\ \sum_{k=1}^{K} \lambda_k = 1; \\ \lambda_k \ge 0, \quad k = 1, 2, ..., K; \\ \theta_t \text{ unrestricted} \end{array} \right. \right\}. \tag{26}$$

Meanwhile, the output–oriented technical efficiency ϕ_k may be obtained by solving the following multiplier DEA program:

$$\left[D_{T(t)}^{O}(x, y)\right]^{-1} = \left\{ \max_{\phi_t, \lambda_k} \phi_t \left| \begin{array}{l} \sum_{k=1}^{K} \lambda_k x_i^k \le x_i^t, \quad i = 1, 2, ..., m; \\ \sum_{k=1}^{K} \lambda_k y_j^k \ge \phi_t y_j^t, \quad j = 1, 2, ..., n; \\ \sum_{k=1}^{K} \lambda_k = 1; \\ \lambda_k \ge 0, \quad k = 1, 2, ..., K; \\ \phi_t \text{ unrestricted} \end{array} \right. \right\}_t. \tag{27}$$

3. Data and results

The technical and scale efficiency was assessed in terms of the input and output indicators commonly employed for agricultural productivity analyses (Bojnec, Latruffe 2008, 2011). 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. On the other hand, the three output indicators represent crop, livestock, and other outputs in Litas, respectively. Indeed, the three output indicators enable to tackle the heterogeneity of production technology across different farms.

The data for 200 farms selected from the FADN sample cover the period of 2004–2009. Thus a balanced panel of 1200 observations is employed for analysis. The analyzed sample covers relatively large farms (mean UAA – 244 ha). As for labour force, the average was 3.6 AWU.

In order to quantify the change in productivity across different farming types, the farms were classified into the three groups in terms of their specialization. Specifically, farms peculiar 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 the mixed farming category.

Changes in the total factor productivity (TFP) were estimated by employing Eqs. 18–25 which, in turn, required implementing DEA models as defined in Eqs. 26–27. Tables 1–4 present the dynamics of TFP change (HM) as well as its components, namely technical efficiency change effect (TE), technology change effect (T), and activity effect (AE). The activity effect was further decomposed into scale effect, input–mix effect, and output–mix effect.

As Table 1 reports, the mean increase of TFP reached some 20% in the analyzed sample of the Lithuanian family farms throughout 2004–2009. Note that the period of 2006–2008 was that of TFP growth, whereas the subsequent period of 2008–2009 was specific with decrease in TFP. Technology change (T) indicated that the production frontier moved inwards the origin point during 2004–2006 and 2008–2009. This finding implies that negative climatic impact as well as price fluctuations specific for the latter period resulted in an overall decrease in productivity of the agricultural sector. As a result the technology change decreased TFP growth by some 4.6%. Technical efficiency effect caused the decrease in TFP equal to 12.2%. Indeed, the latter effect was negative during the whole period of 2004–2009. The activity effect (AE) stimulated TFP growth and thus contributed to its increase by 52%. Decomposition of the activity effect revealed that it was the scale effect that caused these developments, whereas input– and output–mix effects caused decrease in TFP.

Table 1. Cumulative changes in TFP and its decomposition for the whole sample.

Year	HM	TE	T	AE
2005	0.959	0.944	0.952	1.068
2006	0.832	0.834	0.881	1.132
2007	1.301	0.892	1.198	1.218
2008	1.550	0.842	1.222	1.506
2009	1.199	0.828	0.954	1.519

In order to analyze the differences in TFP dynamics across different farming types, Tables 2–4 focus on crop, livestock, and mixed farms, respectively. The crop farms were specific with higher TFP decrease arising from efficiency change if compared to the mean for all farming types (21% and 17%, respectively). This difference, however, might be an outcome of measurements errors.

Table 2. Cumulative change in TFP and its decomposition for crop farms.

Year	HM	TE	T	AE
2005	0.918	0.920	0.938	1.063
2006	0.771	0.803	0.850	1.130
2007	1.308	0.876	1.243	1.202
2008	1.584	0.812	1.280	1.523
2009	1.200	0.793	0.995	1.521

The livestock farms exhibited higher increase in TFP, viz. 27% (Table 3), if compared to the mean increase of 20% for the whole sample. Indeed, it was only the livestock farms that managed to maintain TFP growth throughout the whole research period. It can therefore be assumed that livestock farms are more persistent to market shocks. Furthermore, livestock farms managed to sustain the growth of technical effect of 5.6% what does indicate that livestock farms benefited from the expanding production frontier. The latter process, though, was negatively affected by decreased livestock production prices in 2009. Noteworthy, livestock farms were specific with a lower activity effect if compared to the whole sample. Nevertheless, the decomposition of the activity effect revealed that the livestock farms faced the lowest TFP losses caused by output– and input–mix changes. Thus, livestock farms are likely to adjust the structure of both their inputs and production in a more reasonable way if compared to the other farming types. The scale effect, though, was rather meagre.

Table 3. Cumulative change in TFP and its decomposition for livestock farms.

Year	HM	TE	T	AE
2005	1.172	1.025	1.124	1.017
2006	1.238	0.955	1.178	1.100
2007	1.527	0.973	1.321	1.189
2008	1.557	0.950	1.309	1.253
2009	1.271	0.940	1.056	1.281

The mixed farming did also experience higher than average TFP growth rate of 27.1% with the single period of decreasing TFP in 2005–2006 (Table 4). The mixed farms were also specific with non-decreasing technical efficiency which is represented by a positive efficiency effect (TE) of 0.8%. On the other hand, these farms did not gain too much from the shifts in production frontier (i. e. sector–wide changes in prices, yields etc.): the technical effect resulted in TFP reduction of some 20%.

Table 4. Cumulative change in TFP and its decomposition for mixed farms.

Year	HM	TE	T	AE
2005	1.129	1.056	0.947	1.128
2006	0.982	0.957	0.879	1.168
2007	1.329	0.975	1.035	1.318
2008	1.604	0.997	1.016	1.583
2009	1.334	1.008	0.798	1.658

The variation of the productivity index and its terms can be assessed by analyzing respective coefficients of variation (ratio of the standard deviation to the mean). Specifically, Fig. 2 exhibits these coefficients across different farming types. As one can note, the highest variation in Hicks-Moorsteen TFP index was observed for crop farms, whereas the lowest for livestock farms. The mixed farms fell in between thus confirming their ability to diversify market risks.

As for the terms of the Hicks-Moorsteen TFP index, one can note that it was technical change that was specific with the highest variation and therefore the highest effect on the TFP index. Thus, the Lithuanian family farms were mostly impacted by external factors rather than internal ones (for instance, modernization), identified by efficiency change.

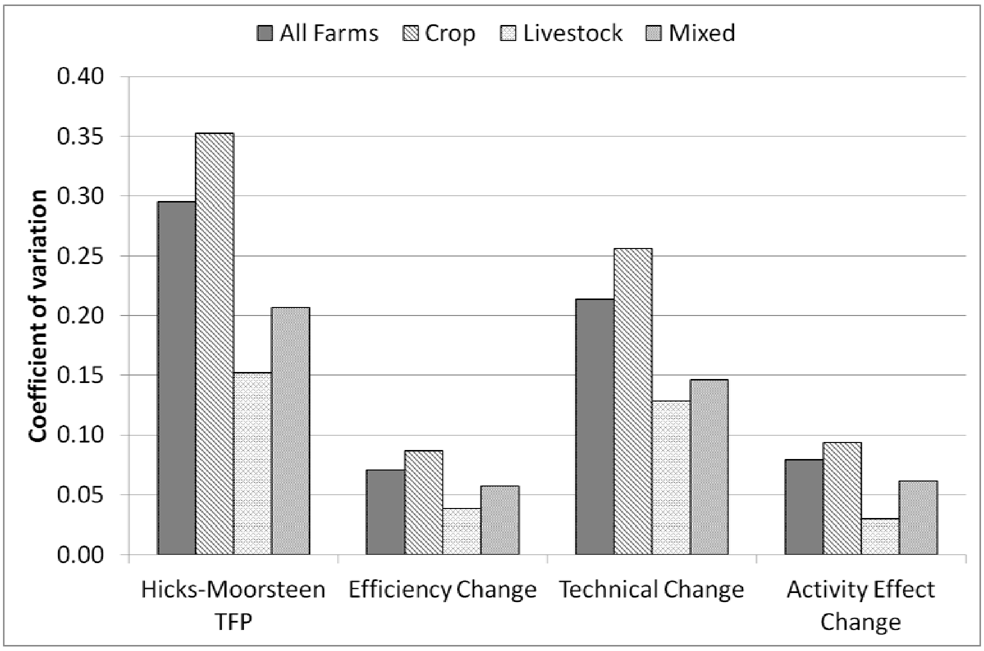

Fig. 2. Coefficient of variation of the Hicks-Moorsteen TFP index and its terms across different farming types, 2004–2009.

What the carried out analysis of the TFP dynamics in Lithuanian family farms does suggest is that modernization of the agricultural practices is of high importance. The technical progress could be incentivized via the increased R&D expenditures as well as more reasonable distribution thereof, new education and training programmes. The activity effect is determined by scale changes as well as shifts in input– and output–mix. The ongoing expansion of large farms in Lithuania (Baležentis, 2012a) might result in positive effect on TFP (indeed, this effect was already present during the research period), whereas price policy can provide a momentum for adjustments in input– and output–mix.

The aforementioned issues require further analyses, especially those based on micro data. Specifically, bootstrapping techniques could be employed to tackle the statistical noise present in the data with second–stage analysis focused on identification of factors of TFP changes. One could also define separate production frontier for respective farming types. Finally, utilization of different TFP indices would allow approaching higher level of robustness.

Conclusions

Dynamics of the total factor productivity in the Lithuanian family farms was assessed on a basis of micro data covering 200 family farms and the period of 2004–2009. The Hicks-Moorsteen total factor productivity (TFP) index was employed to measure these changes. The distance functions were estimated on a basis of Data Envelopment Analysis models.

The mean increase of TFP reached some 20% in the analyzed sample of the Lithuanian family farms throughout 2004–2009. Indeed, the period of 2006–2008 was that of TFP growth, whereas the subsequent period of 2008–2009 was specific with decrease in TFP. Technology change indicated that the production frontier moved inwards the origin point during 2004–2006 and 2008–2009. This finding implies that negative climatic impact as well as price fluctuations specific for the latter period resulted in an overall decrease in productivity of the agricultural sector.

In order to arrive at reasonable policy implications, changes in TFP were assessed across farming types. It turned out that the crop farms experienced the highest TFP decrease in terms of efficiency effect. Therefore the latter farms should implement certain technological measures. These could be, for instance, adoption of state–of–the–art managerial practices, introduction of new crop species, and more efficient machinery utilization. The livestock farms exhibited rather high values of efficiency and technical effects, albeit activity effect was relatively low.

The further researches should attempt to identify specific factors determining the changes in TFP. This goal can be attained by employing other types of TFP indices for micro data analysis.

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LIETUVOS ŪKININKŲ ŪKIŲ BENDROJO PRODUKTYVUMO IŠSKAIDYMAS TAIKANT HIKSO–MORSTENO INDEKSĄ

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Straipsnyje nagrinėjamas Hikso-Morsteno bendrojo produktyvumo indekso ir duomenų apgaubties analizės taikymas matuojant bendrojo produktyvumo pokyčius Lietuvos ūkininkų ūkiuose. Šie pokyčiai taip pat yra išskaidomi į atskirus komponentus. Straipsnio tikslas – pasiūlyti efektyvias žemės ūkio politikos ir mokslinių tyrimų gaires, padėsiančias didinti Lietuvos ūkininkų ūkių produktyvumą. Straipsnyje aptariami nuotolio funkcijų bruožai, pristatoma Hikso-Morsteno produktyvumo indekso koncepcija, įvertinami bendrojo produktyvumo pokyčiai Lietuvos ūkininkų ūkiuose taikant pastarąjį indeksą. Tyrimo periodas – 2004–2009 m. Tyrimo rezultatai parodė, kad bendrasis produktyvumas Lietuvos ūkininkų ūkiuose tirtuoju laikotarpiu vidutiniškai padidėjo 20 proc. Specializuoti augalininkystės ūkiai pasižymėjo žemesniu efektyvumo lygiu ir dėl to mažesniu bendruoju produktyvumu. Specializuota gyvulininkystė pasiekė gana aukštus efektyvumo ir technologinius efektus, tačiau veiklos efektas (masto, sąnaudų ir produkcijos efektų vedinys) buvo žemesnis nei kitų ūkininkavimo tipų.

Raktiniai žodžiai: bendrasis produktyvumas, efektyvumas, Hikso-Morsteno indeksas, duomenų apgaubties analizė, ūkininkų ūkiai.
JEL kodai: C440, C610, Q100, Q130.