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PARTIAL FACTOR PRODUCTIVITY IN LITHUANIAN FAMILY FARMS: THE MULTIPLIER DATA ENVELOPMENT ANALYSIS APPROACH

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The two measures of productivity prevail in the economic researches, namely total factor productivity and partial productivity (single factor productivity). This paper aimed at analysing the partial factor productivity in the Lithuanian family farms and identifying the associated policy implications. Specifically, the partial productivities of labour, land, intermediate consumption, and assets were considered. The multiplier data envelopment analysis (DEA) model was employed for the analysis. The research covered the period of 2004–2009 and relied on the data from 200 family farms. The aggregate inputs were treated as the dimensionless measures of the partial productivity identifying strengths and weaknesses of the productive technology associated with respective factors (inputs). Decomposition of the aggregate inputs showed that the crop and mixed farming were the most labour intensive activities, i. e. labour shares in the aggregate inputs were lower than those for the livestock farms. Land and intermediate consumption, on the other hand, were found out to be the two relatively more productive factors specific with generally increasing shares in the aggregate input during 2004–2009.

Key words: partial productivity, family farms, Lithuania, data envelopment analysis.
JEL codes: C440, C610, Q100, Q130.

Introduction

The productivity of certain production factors is an important feature of the productive technology, for it enables to fathom the underlying trends in both factor markets (Petrick, 2012) and decision making units (firms). As for the agricultural sector, the intervention into the factor markets is facilitated in the form of the public support. Therefore, it is worthwhile to analyse the patterns of productivity in the agricultural sector and thus draw reasonable policy implications.

The two measures of productivity prevail in the economic researches, namely total factor productivity (TFP) and partial productivity (single factor productivity). The TFP measures the overall productivity as a ratio of the aggregate output over the aggregate input (Fried, 2008). The Malmquist, Luenberger, Hicks-Moorsteen, Färe–Primont etc. productivity indices are employed to estimate the changes in TFP. The partial productivity can be analysed by the means of the frontier methods, either parametric or non-parametric ones. Whereas the parametric methods (e. g. stochastic frontier analysis) require assuming a certain form of the production function, the non-parametric methods (e. g. data envelopment analysis) define an empirical production frontier without any assumptions on the functional form thereof.

The partial factor productivity in the Lithuanian agricultural sector has not been explicitly analysed yet. I. Kriščiukaitienė et al. (2010) employed the ordinary least squares (OLS) regression to construct the production frontier and thus derive output elasticities. The latter study, though, did not analyse the dynamics of the elasticities. Furthermore, the deterministic OLS production frontier was based on the deviances from average rather than observations featuring the best practice. The performance of the Lithuanian agricultural sector was also analysed by the means of the frontier methods (Vinciūnienė, 2009; Baležentis, 2012a), however most of the researches were based on the aggregate data. The TFP dynamics was analysed on a basis of the farm-level data (Baležentis, 2012b). The partial productivity yet remained an issue for the future analyses.

This paper, therefore, aims at analysing the partial factor productivity in the Lithuanian family farms and identifying the associated policy implications. The multiplier data envelopment analysis (DEA) model is employed for the latter purpose (Charnes, 1978). The research covers the period of 2004–2009 and relies on the data from 200 family farms. The paper is organised in the following manner: Section 1 presents the preliminaries for data envelopment analysis. Section 2 describes the data set and the research methodology. Finally, results of the analysis are discussed in Section 3.

1. DEA as a partial productivity measure

DEA is a nonparametric method of measuring the efficiency of a decision-making unit (DMU) such as a firm or a public–sector agency. The very term of efficiency was initially defined by G. Debreu (1951) and then by T. C. Koopmans (1951). G. Debreu discussed the question of resource utilization at the aggregate level, whereas T. C. Koopmans offered the following definition of an efficient DMU: *A DMU is fully efficient if and only if it is not possible to improve any input or output without worsening some other input or output*. Due to similarity to the definition of Pareto efficiency, the former is called Pareto-Koopmans Efficiency. Finally, M. J. Farrell (1957) summarized works of Debreu and Koopmans thus offering frontier analysis of efficiency and describing two types of *economic efficiency*, namely *technical efficiency* and *allocative efficiency* (indeed, a different terminology was used at that time). The concept of technical efficiency is defined as the capacity and willingness to produce the maximum possible output from a given bundle of inputs and technology, whereas the allocative efficiency reflects the ability of a DMU to use the inputs in optimal proportions, considering respective marginal costs. However, Farrell did not succeed in handling Pareto-Koopmans Efficiency with proper mathematical framework.

The modern version of DEA originated in studies by A. Charnes, W. W. Cooper and E. Rhodes. Hence, these DEA models are called CCR models. Initially, the fractional form of DEA was offered. However, this model was transformed into input and output-oriented multiplier models, which could be solved by means of the linear programming (LP). In addition, the dual CCR model (i. e. envelopment program) can be described for each of the primal programs.

Productivity means ratio of output to input. In case we have many firms ($k = 1, 2, ..., K$) each of them producing outputs ($j = 1, 2, \ldots, n$) by employing multiple inputs ($i = 1, 2, \ldots, m$), we can describe the activity of each of the observed firms by considering the input–output bundles (x_i^k, y_j^k). The productivity of the *k*–th firm can be expressed as the ratio of virtual output aggregate to the virtual input aggregate:

$$P_k = \frac{\sum_{j=1}^{n} v_j y_j^k}{\sum_{i=1}^{m} u_i x_i^k}, \forall k, \tag{1}$$

where $u_i \geq 0$ and $v_j \geq 0$ are input and output weights, respectively.

Efficiency means the ratio of the observed productivity to the yardstick productivity. By bounding efficiencies of the firms under considerations to the values of 0 and 1, we can define the following fractional programming problem for the *t*–th firm ($t = 1, 2 \ldots, K$):

$$\begin{aligned} & \max E_t = \frac{\sum_{j=1}^{n} v_j^t y_j^t}{\sum_{i=1}^{m} u_i^t x_i^t} \\ & \text{s. t.} \\ & 0 \leq \frac{\sum_{j=1}^{n} v_j^t y_j^k}{\sum_{i=1}^{m} u_i^t x_i^k} \leq 1, k = 1, 2, ..., K \\ & u_i^t, v_j^t \geq 0, i = 1, 2, .., m, j = 1, 2, ..., n \end{aligned} \quad . \tag{2}$$

By fixing the denominator and equating it to unity, we have an input oriented (output maximising) measure of efficiency—multiplier Data Envelopment Analysis (DEA) model—which, indeed, is a linear programming problem (Charnes, 1978):

$$\begin{aligned} & \max \phi_t = \sum_{j=1}^{n} v_j^t y_j^t \\ & \text{s. t.} \\ & \sum_{i=1}^{m} u_i^t x_i^t = 1 \\ & \sum_{j=1}^{n} v_j^t y_j^k - \sum_{i=1}^{m} u_i^t x_i^k \leq 0, k = 1, 2, ..., K \\ & u_i^t, v_j^t \geq 0, i = 1, 2, .., m, j = 1, 2, ..., n \end{aligned} \quad . \tag{3}$$

This model attributes the highest weights to those outputs which provide the highest advantage for the firm in the production process.

By applying the aforementioned operations for the numerator, we would arrive at the input minimization multiplier DEA model. Similarly, the highest weights in this case are attributed to those inputs which cause the emergence of strengths in the production process.

The DEA model in Eq. 3 assumes constant returns to scale (CRS). The variable returns to scale (VRS) technology can be assumed by considering the following problem (Cooper, 2007):

$$
\begin{aligned}
&\max \phi_t = \sum\nolimits_{j=1}^{n} v_j^t y_j^t - v_0 \\
&\text{s. t.} \\
&\sum\nolimits_{i=1}^{m} u_i^t x_i^t = 1 \\
&\sum\nolimits_{j=1}^{n} v_j^t y_j^k - \sum\nolimits_{i=1}^{m} u_i^t x_i^k - v_0 \le 0, k = 1, 2, ..., K \\
&u_i^t, v_j^t \ge 0, i = 1, 2, .., m, j = 1, 2, ..., n \\
&v_0 \text{ unrestricted}
\end{aligned}
, \tag{3}
$$

where $v_0 < 0$ is associated with increasing returns to scale and $v_0 > 0$ is associated with decreasing returns to scale.

It is due to J. K. Sengupta (1995) that the variables or multipliers u_i and v_j used to weight the multiple inputs and outputs, respectively, can be interpreted in a number of ways. First, these can be treated as shadow prices of respective inputs (outputs). Second, the multipliers can be considered as weights for index numbers. Third, the multipliers can be interpreted as parameters of the underlying production frontier. Indeed, input and output weights cannot be considered as the direct measures of the partial productivity, for they are related to the efficiency score (ratio) rather than output levels. Anyway, for an efficient DMU, the following equation holds (under CRS):

$$\sum\nolimits_{j=1}^{n} v_j^* y_j^k = \sum\nolimits_{i=1}^{m} u_i^* x_i^k , \tag{4}$$

with u_i^* and v_j^* being the optimal weights. Therefore, the higher values of the products $u_i^* x_i^k$ are associated with higher partial productivities of particular inputs.

The values of the weights depend on the range of the input and output quantities. Therefore, either the initial data should be scaled down (normalisation) or the DEA weights should be multiplied by respective input (output) quantities in order to arrive at comparable weights.

2. Data and methodology

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 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 price indices and aggregated into a single one.

The analysed sample covers relatively large farms (mean UAA – 244 ha). As for labour force, the average was 3.6 AWU. One can note that crop farms were specific with the highest variation of the variables under analysis save 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.

The input oriented DEA model (cf. Eq. 3) entails the virtual input equal to unity; therefore one can easily estimate the contribution of each input to the efficiency score. The output oriented DEA model, though, minimises the virtual input, which then becomes greater or equal to unity. In the latter case the following normalisation procedure was carried out for each input share specific for the *t*-th DMU:

$$\left(u_i^t x_i^t\right)^* = u_i^t x_i^t \, / \sum\nolimits_{i=1}^{m} u_i^t x_i^t \, . \qquad (5)$$

The latter normalization procedure implicitly distributes the slack of the objective function, v_0, proportionally across the inputs. However, the further studies could attempt to employ the more sophisticated techniques (Hougaard, 2004).

3. Results

The resulting average input shares are presented in Figs. 1–2. As one can note, the crop farms exhibited the largest shares of the aggregate input related to labour quantity both under VRS and CRS. The labour share accounted for some 40% under VRS in the inpu-oriented DEA model, whereas it fluctuated around 18% in other models. The lowest labour shares in the aggregate inputs, and, hence, the lowest labour productivity, were observed for the livestock farms. The latter finding is not surprising given animal farming usually requires more labour input. Especially, the labour-intensive technology is a prevailing one in the dairying sector. Noteworthy, labour share in the aggregate input was the most volatile one across CRS and VRS technologies. Therefore, the labour productivity was highly dependent on the assumed technology's curvature and farm size. Specifically, labour was the most productive in extremely small and large farms.

The labour shares in the aggregate inputs tended to decrease within all farming types under VRS assumption during 2004–2009. However, they slightly increased for the livestock and mixed farms under CRS technology.

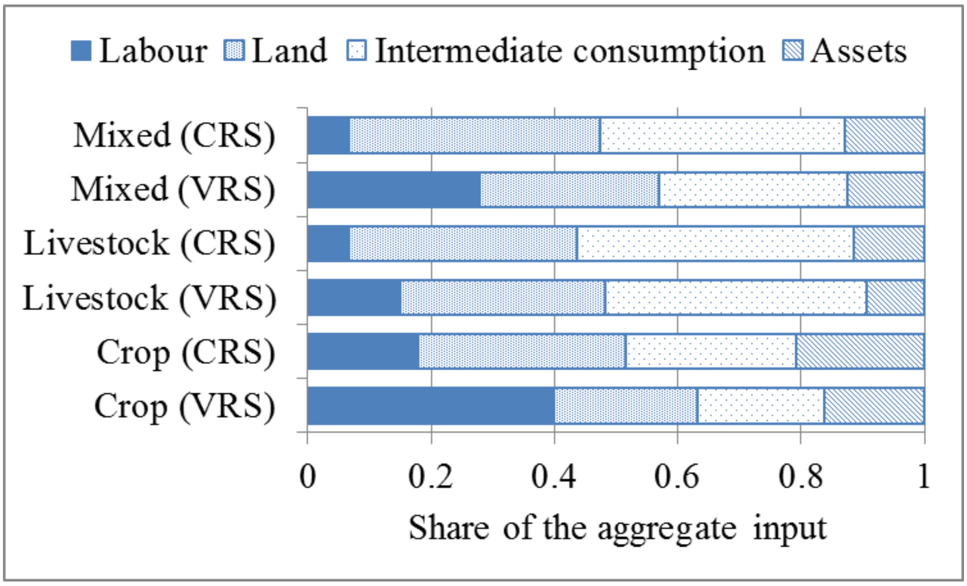

Fig. 1. The average input shares across farming types (input-oriented DEA)

Land share in the aggregate input varied in between 23% and 40% depending on the farming type, returns to scale, and orientation of a DEA model. Generally, it was the livestock and mixed farms that exhibited the higher input shares associated with land and thus higher land productivity. Contrary to the labour share, the land share in the aggregate input tended to be lower under VRS rather than CRS technology. The latter finding implies that the highest land productivity was observed in the medium sized farms. The latter difference featured its highest magnitude in the mixed farm group. All in all, land was one of the most productive factors for the livestock and mixed farms, possibly due to higher value-added generated in animal farming. Anyway, land remained the most productive factor of the crop farming under CRS assumption with the aggregate input share of 33–34% depending on the DEA model orientation.

The land productivity generally increased during 2004–2009. The decrease was observed for the mixed farms under the CRS technology. Therefore, the medium–sized mixed farms might exhibit a further decrease in land productivity. However, the latter farming type was specific with the highest land share in the aggregate input.

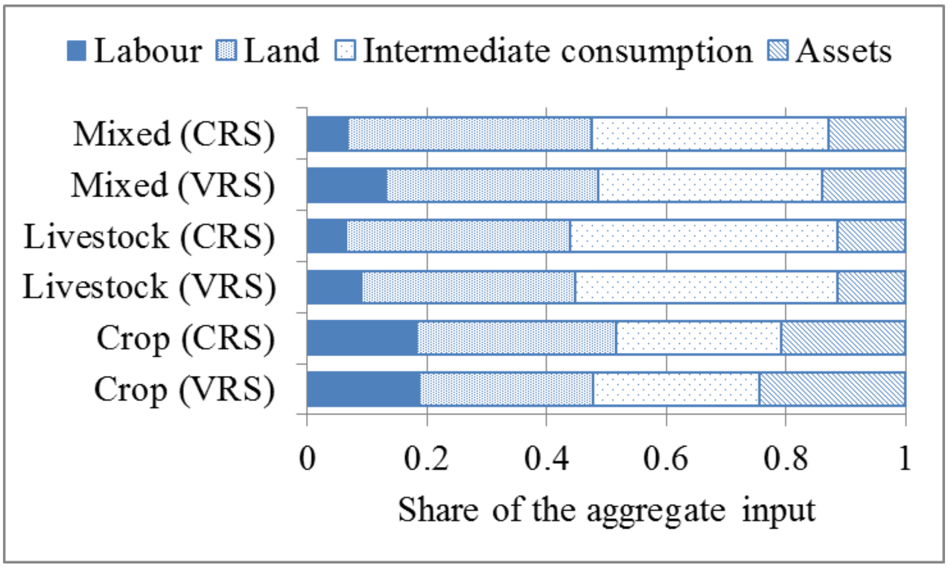

Fig. 2. The average input shares across farming types (output-oriented DEA)

The livestock farms exhibited the highest shares (42–45%) of intermediate consumption in the aggregate inputs. Meanwhile, the mixed farms were specific with the respective shares accounting for some 31–40% of the aggregate input. Finally, the crop farms featured the values of 21–28%. The livestock farms, thus, can be considered as those facilitating the most productive practice of intermediate consumption. At the other end of spectrum, the crop farms should improve their technologies in terms of intermediate consumption.

Increases in the shares of the intermediate consumption were observed for all of the farming types irrespectively of the returns to scale during 2004–2009. The latter finding implies that Lithuanian farmers implement more and more resource-saving practices.

The low aggregate input shares associated with assets indicated that the Lithuanian family farms tend to accumulate the excessive amounts of equipment. The lowest asset productivity was observed for the livestock and mixed farms, where respective average input shares fluctuated around 9–14%. The highest asset productivity was observed for the crop farms with respective input shares of 16–24%. Furthermore, these shares followed a downward trend during 2004–2009.

Conclusions

1. The paper analysed the trends of the partial productivity of the four factors in the Lithuanian family farms. Specifically, these factors include labour, land, intermediate consumption, and assets. The multiplier data envelopment analysis model was implemented to obtain the aggregate input shares for the aforementioned factors.

2. The analysis showed that the crop and mixed farming were the most labour intensive activities, i. e. labour shares in the aggregate inputs were lower than those for the livestock farms. Therefore, these sectors should seek for labour-saving technologies. However, the equipment accumulation rates should be kept at a reasonable level, for asset productivity already appeared to be the lowest one if

compared to those of the remaining production factors. It might also be the commercial and institutional obstacles that prevented farm production from a steeper increase after increase in assets related to the public support under the means of the Common Agricultural Policy.

3. Land and intermediate consumption, on the other hand, were found out to be the two relatively more productive factors specific with generally increasing shares in the aggregate input during 2004–2009. The increase in land productivity might give a momentum for the expansion of the farms. These findings do also imply that the Lithuanian family farms are likely to be subject to some restrictions in current assets that would prevent from investments in land acquisition or reduce the volumes of intermediate consumption. The latter issues, though, constitute an issue for the further researches.

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DALINIS PRODUKTYVUMAS LIETUVOS ŪKININKŲ ŪKIUOSE: DAUGIKLIŲ DUOMENŲ APGAUBTIES ANALIZĖ

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Summary

Ekonominiuose tyrimuose dažniausiai nagrinėjamas dviejų rūšių produktyvumas: bendrasis ir dalinis produktyvumas. Šio straipsnio tikslas – įvertinti dalinį gamybos veiksnių produktyvumą Lietuvos ūkininkų ūkiuose ir jo reikšmę žemės ūkio politikos formavimui. Nagrinėjami gamybos veiksniai apėmė darbo, žemės, tarpinio vartojimo ir ilgalaikio turto apimtis (sąnaudas). Tyrimas remiasi Lietuvos ūkininkų ūkių, veikusių 2004–2009 m., imtimi. Tyrimui naudotas daugiklių duomenų apgaubties analizės modelis. Hipotetinių sąnaudų rodiklių, atspindinčių gamybos proceso stipriąsias ir silpnąsias puses, išskaidymas parodė, kad augalininkystės ir mišrūs ūkiai buvo imliausi darbui, t. y. darbo dalis hipotetiniuose sąnaudų rodikliuose buvo mažesnė už stebėtąją gyvulininkystės ūkiuose. Žemė ir tarpinis vartojimas buvo santykinai produktyviausi gamybos veiksniai visuose ūkininkavimo tipuose, jų produktyvumas augo visu tyrimo laikotarpiu.

Raktiniai žodžiai: dalinis produktyvumas, ūkininkų ūkiai, Lietuva, duomenų apgaubties analizė.
JEL kodai: C440, C610, Q100, Q130.