Explaining differences in farms efficiencies in Polish agriculture

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ABSTRACT

This paper deals with the estimation of a random coefficient model. The virtue of this approach is that it considers firm heterogeneity, which conventional SFA models do not. When the model is applied to Polish farms, the results indicate that the conventional random and fixed effect models overestimate the potential production increases due to the reduction of inefficiency. Additionally, our findings provide evidence of the importance of input quality for efficiency analysis. Moreover, the results indicate that farm heterogeneity is a significant determinant of agricultural production. We found that differences in productivity between the farms can partly be attributed to farm size, degree of integration in the product markets and incurred transaction costs.

Keywords: SFA, random component model, Poland, agriculture, firm heterogeneity

JEL classification: Q12, C23, D24, L23

1 INTRODUCTION

There are numerous technical and economic efficiency analyses of agriculture in central and eastern European countries (CEECs). Further, nonparametric but deterministic approaches (DEA), as well as stochastic but parametric approaches (SFA) have been widely applied (e.g. Backus et al., 2006; Brümmer et al., 2002; Munroe, et al, 2001; Latruffe et al, 2004). One of the basic assumptions of DEA and SFA is that inputs and outputs are homogeneous among farms. This implies that the farms' inputs can be changed to a common level or structure and all farms will have identical output. However, in principle, the productivity of the individual farm inputs differ with regard to the specialisation of farms, climate conditions and factor qualities such as soil fertility, human capital (including management skills) and capital structures and vintages. These factors cause the input aggregates provided in the statistics to be non-homogeneous but rather heterogeneous, which in turn limits the comparability of input use among farms. Unfortunately, the available statistical information does not permit the correction of this heterogeneity bias. The consequences of the non-consideration of the heterogeneity farm input are (1) that efficiency is overestimated since variation in input heterogeneity is transferred into the inefficiency scores; (2) that the efficiency scores are biased, which implies that no consistent policy recommendation can be derived; and (3) that the production elasticities are biased as well, which causes an inaccurate description of the production structures and their adjustment in response to policy and price changes.

In this paper, a two-stage econometric approach accounting for the heterogeneity bias will be applied. First, following Alvarez et al., (2003, 2004) we will estimate a random coefficient specification of production technology. At this stage, farm heterogeneity will be determined endogenously within the analysis of a production function. In the second step we will identify the determinants of this estimated variable. The empirical application deals with Polish agriculture. Due to length restrictions, we limit the results discussion to problem (1) and (2).

2 THEORETICAL BACKGROUND

The theoretical framework is developed within a panel data framework, with i = 1,…,N firms and t = 1,..,T observations per firm. We follow the input augmentation approach and assume a production technology in which output ($\mathbf{y}_{it}$) is produced with effective input ($\mathbf{x}^e{}_{it}$). The effective inputs are given by:

(1) $$\mathbf{x}^e{}_{it} = \mathbf{x}_{it} e^{\boldsymbol{\tau}_{xt} t} e^{\boldsymbol{\theta} \mathbf{q}_{it}} e^{\boldsymbol{\mu} m_i}.$$

Here, $\mathbf{x}_{it}$ represent observable inputs and outputs, t accounts for productivity change over time, $\mathbf{q}$ is the quality of the input and m_i represents a non-observable firm-specific factor. We specify technology as a translog production function ($f(\mathbf{x}^e{}_{it})$). Rearranging terms provides:

(2) $$\begin{aligned} \ln f\left(\mathbf{x}^e{}_{it}\right) &= \alpha_0 + \alpha_m m_i + \frac{1}{2}\alpha_{mm} m_i^2 + \left(\alpha_t + \alpha_{tm} m_i\right)t + \frac{1}{2}\alpha_{tt} t^2 \\ &+ \left(\boldsymbol{\alpha}_{\mathbf{x}} + \boldsymbol{\alpha}_{\mathbf{x}t} t + \boldsymbol{\alpha}_{\mathbf{x}m} m_i\right)' \ln \mathbf{x}_{it} + \ + \left(\boldsymbol{\alpha}_q + \boldsymbol{\alpha}_{qt} t + \boldsymbol{\alpha}_{qm} m_i\right)' \ln \mathbf{x}_{it} \\ &+ \frac{1}{2}\ln \mathbf{x}_{it}' \mathbf{A}_{\mathbf{xx}} \ln \mathbf{x}_{it} + \frac{1}{2}\ln q_{it}' \mathbf{A}_{qq} \ln q_{it} + \ln \mathbf{x}_{it}' \mathbf{A}_{\mathbf{x}q} \ln \mathbf{q}_{it} \end{aligned}.$$

The various parameters associated with t and m_i are functions of the original parameters $\boldsymbol{\alpha}_{\mathbf{x}}, \mathbf{A}_{\mathbf{xx}}$, as well as the productivity terms $\boldsymbol{\tau}, \boldsymbol{\theta}, \boldsymbol{\mu}$. Technical efficiency can be introduced by assuming that the actual m_i is not necessarily at its optimal level (m_i^*). Accordingly, we define technical efficiency as:

(3) $$\ln TE_{it} = \ln f\left(\mathbf{x}^e{}_{it}\right) - \ln f\left(\mathbf{x}^e{}_{it}\right)_{|m_i = m_i^*} \leq 0.$$

The last inequality results from the fact that the production function with optimal firm-specific effects (m_i^*) is assumed to be efficient. Since neither m_i nor m_i* are observable, (3) cannot be estimated directly. Alvarez et al., (2003, 2004) develop an estimable model. From (2) and (3) it follows:

(4) $$y_{it} = \ln f\left(\mathbf{x}^e{}_{it}\right)_{|m_i = m_i*} + \ln TE_{it} \;;$$

(4') $$y_{it} = \ln f\left(\mathbf{x}^e{}_{it}\right)_{|m_i = m_i*} - u_{it} \quad with \;\; u_{it} = -\ln TE_{it} \;.$$

Equation (4) can be estimated by maximum simulated likelihood with the following distributional assumptions: $\ln TE_{it} \sim N^{+}(0, \sigma_u)$, and $m_i* \sim \bullet(0,1)$. The symbol $\bullet$ indicates that m_i* might possess any distribution with zero mean and unit variance. In addition, random effects are considered in the variable $v_{it} \sim N(0, \sigma_v)$.

3 EMPIRICAL IMPLEMENTATION AND ESTIMATION RESULTS

We utilised an unbalanced data set consisting of eight years of observations, from 1994 to 2001, on 580 Polish agricultural farms; the total number of observations was 4,455[1]. The respective accountancy information was provided by the Polish Institute of Agricultural and Food Economics - National Research Institute (IERiGZ-PIB). Output was approximated by gross agricultural production. This indicator is, in our view, an appropriate measure of output since it includes sales, home consumption and stock changes.

We distinguished between four inputs (land, labour, capital and intermediate inputs). Land input was approximated by the sum of arable land and grassland in use. Unused land was excluded in order to provide a more accurate indicator of land used in production. Labour was measured by the hours of work allocated to agriculture by family members and hired labour. As an indicator of capital input, an aggregate of depreciation of farm assets (buildings, machinery, and equipment) and expenditure on services was constructed. We argue that this is a more comprehensive measure of capital input than is the endowment with fixed assets since farms may lease capital services instead of purchasing the corresponding equipment. Intermediate inputs were approximated by total variable costs minus the abovementioned index of capital input. A correction was conducted in order to avoid double counting.

Since the data on production, capital and intermediate inputs were in current values, we deflated the series by the corresponding price indices provided by the Statistical Office in Poland (GUS var. issues, a, b). The deflators were the price index of purchased goods and

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[1] Thus, on average there are about 7.7 observations per farm.

services in agriculture, the price index for investment, and a price index for variable inputs, respectively.

Quality of land is measured by a corresponding soil quality index. Labour quality was approximated by the attained education level of the farm head, which ranges from 1 (no agricultural education) to 6 (university degree). Capital quality is represented by the vintage of equipment; the choice of this variable results from our assumptions that capital quality increases as the ratio between investments and capital stock increases. Quality of intermediate inputs was approximated by the share of purchased seed and feed on total seed and feed use.

Table 1: Variable definitions and descriptive statistics

Variable	Description	Symbol	Mean	Standard deviation	Minimum	Maximum
Output	gross agricultural production, deflated (in 1000 ZL)	O	127.38	149.19	1.72	2384.79
Labour	hours of work (family and hired labour); hours per year	A	3823.20	1734.06	247.00	16790.00
Land	arable land and grassland in use (Hectare)	L	15.93	15.19	1.17	191.26
Capital	depreciation of farm assets plus expenditure on services, deflated (in 1000 ZL)	C	928.71	589.41	34.13	5181.82
Intermediate inputs	total variable costs minus depreciation, deflated (in 1000 ZL)	V	154.30	136.20	8.97	1748.67
Labour quality	agricultural education of farm head (education level)	QA	2.44	1.35	1.00	6.00
Land quality	land quality index	QL	0.84	0.29	0.16	1.75
Capital quality	investment in relation to capital stock	QC	0.12	0.10	0.00	1.64
Intermediate input quality	share of purchased seed & feed of total seed & feed used	QV	0.30	0.186	0.00	1.00

Source: IERiGZ-PIB, own calculations.

Estimation results are presented in Table 2. First, regarding the impact of technical change, the estimation suggests that this is a relevant phenomenon in Polish agriculture. Indeed, its impact was positive and increasing over the entire period under investigation ($\alpha_T > 0$ and $\alpha_{TT} > 0$). In addition, we estimated factors using technological change similar in size for three inputs except capital ($\alpha_{hT} > 0$, for h = A, L, and V).

Table 2: Parameter estimates for the random coefficient model with unobservable factors

Means random processes		Biased technical change		Second order cross effects	
Constant	0.058***				
T	0.030***				
A	0.210***	A·T	0.006***	A·L	-0.001
L	0.232***	L·T	0.008***	A·C	0.043***
C	0.098***	C·T	-0.008***	A·V	-0.124***
V	0.5694***	V·T	0.002	AQ·A	-0.007
QA	0.1422***	QA·T	-0.008**	AQ·L	0.014***
QL	0.0087***	QL·T	0.001	AQ·C	0.113*
QC	0.1382***	QC·T	-0.038***	AQ·V	0.085***
QV	0.170***	QV·T	-0.003	L·C	0.083***
Unobservable factor		**Second order own effects**		L·V	-0.051***
0·M (Const.)	0.125***			L·QA	0.092***
T·M	0.005***	T·T	0.002***	L·QL	-0.006*
A·M	0.008	A·A	0.117***	L·QC	0.133**
L·M	0.013**	L·L	-0.046**	L·QV	-0.089***
C·M	0.047***	C·C	0.056***	C·V	-0.115***
V·M	-0.075***	V·V	0.214***	C·QA	-0.023
QA·M	-0.015*	QA·QA	0.171***	C·QL	-0.007*
QL·M	0.006***	QL·QL	0.001	C·QC	-0.053
QC·M	0.047*	QC·QC	-0.242*	C·QV	0.102***
QV·M	0.093***	QV·QV	-0.404***	V·QA	-0.074***
M·M	0.007**			V·QL	0.006
Efficiency indicators				V·QC	-0.094
Sigma	0.143***			V·QV	-0.015
Lambda	1.023***			QA·QL	0.021***
				QA·QC	-0.027
Note: *, **,*** denote significance at a =0.1, .05 and 0.01 level, respectively. Number of observations: 4,455.				QA·QV	0.104**
Source: Own estimates.				QL·QC	-0.029*
				QL·QV	-0.014
				QC·QV	0.087

Theoretical consistency requires that the production function is increasing and quasi-concave in inputs. Since all $\alpha_h \geq 0$ for h = A, L, C, V, the monotonicity requirement is fulfilled at the approximation point. With regard to the curvature conditions, we restricted the testing to the necessary condition of quasi-concavity. Thus, we checked whether the law of decreasing returns holds for individual inputs. This law finds its expression in the following inequality:

$\alpha_{hh} + \alpha_h^2 - \alpha_h < 0$. The calculations provide that the inequality holds for all h inputs, with h = A, L, C, V.

Moreover, the means of the random parameter estimates are consistent with empirical observations. Variable costs accounted for about 60% of total production costs. Summing up the values of α_h , with h = A, L, C, V, provides that the elasticity of scale is approximately 1.09. Slightly increasing returns to scale are also found in other studies of Polish agriculture (Latruffe, et al., 2005). The parameters related to the quality of the inputs are significant and have the expected sign ($\alpha_{Qh} \geq 0$, for h = A, L, C, V). Thus, the findings provide evidence that the higher the quality of an input is, the higher is the productivity of that input.

The coefficient estimates of the unobservable factor m_i* are highly significant. Consistent with theory, the results show that the higher m_i* is, the higher is the output ($\alpha_{0M} > 0$, $\alpha_{MM} > 0$). Furthermore, the estimates indicate that technological change has improved the productivity of the unobserved factor ($\alpha_{TM} > 0$). In addition, the unobserved component leads to an increase of production elasticities and partial factor productivities of land and capital ($\alpha_{LM} > 0$, $\alpha_{CM} > 0$), while it has a negative impact on intermediate inputs ($\alpha_{VM} < 0$) and no significant impact on labour. A basically similar structure was estimated for the impact of m* on input quality.

Again, the significant findings can be interpreted as evidence in favour of the random parameter model with respect to the conventional SFE. At the same time, the results underscore our assumption that farm heterogeneity (m*) is an important determinant of agricultural production. If analyses fail to take this heterogeneity into account, then marked distortions of the production structures emerge. As a result, conventional productivity and efficiency analyses clearly overestimate the efficiency potential and thus do not produce any consistent conclusions relating to agricultural and economic policy. However, the question remains as to what factors determine m*.

4 EXPLANATION OF THE UNOBSERVED FIXED INPUT M*

The above results indicate the existence of an additional significant, unobservable production factor (m*) besides land, capital, labour and intermediate inputs and the respective inputs' qualities. Álvarez et al., (2004) consider this input to be managerial ability, which influences technical efficiency directly (as a latent farm-specific input) and indirectly (as a function) since it influences the use of other observable inputs. However, we argue that m* only partly absorbs the managerial issues, and hence should be considered more generally as a farm-specific factor. Following this view, we conduct further analysis in order to explain the 'components' of m*.

First we theoretically identified determinants that affect m*. In order to reduce the number of variables to a few important dimensions and to avoid multicolinearity problems, a factor analysis has been conducted. The analysis yielded a set of factors that allows the prior identification of possible determinants of m*. Since some observed variables significantly cross-loaded on more than one factor, the final decision regarding the allocation of the variables to a respective factor was supported by theoretical considerations.[2] Finally, three theoretical constructs (factors) representing i) Farm size, ii) Integration, and iii) Transaction costs could be identified. We assume that these three latent variables are exogenous variables influencing m* in the following way:

Farm size: We assumed that the larger a farm is, the higher is the effort associated with managing and operating said farm. In our model, this factor (theoretical construct) is related to three conventional variables: the agricultural gross output (Output) the holding size in hectare (Hectare), as well as the average plot size in hectare (Size of Plots). The theoretical variable "farm size" positively influences all the variables indicated here.[3] Basically, this hypothesis is related to the impact of economies of scale. The parameter estimates (Table 2) provide that increasing economies of scale could not be excluded. In this case, larger farms are more efficient, which corresponds with higher m*.

Integration: This factor can be represented by three observable variables indicating integration in product markets (Commercialisation, Specialisation) and labour markets (Diversification). From a theoretical point of view, it can be argued that the factor "Integration" encompasses a variety of attributes which influence farm behaviour internally and externally, and thus can lead to differences in performance (productivity) between farms. As an example, the more a farm is integrated in the market (Commercialisation[4]), and the higher the specialisation degree of agricultural production (Specialisation[5]), the more it is exposed to risks caused by changes in the institutional and economic environment. Governing

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2 We select variables with factor loadings higher than 0.5, which at the same time could be theoretically interpreted.

3 In this section, the reported observable variables and the estimated m* represent average values calculated over the investigated period, 1994-2001. Number of observations: 580.

4 Share of sold products on total agricultural production value.

5 Specialisation was calculated using Herfindahl-Index based on 28 agricultural products. See Jacquemin and Berry (1979) for the definition of the Herfindahl-Index.

market risks effectively (via contracts, price monitoring, etc.) is a challenging issue and hence requires more managerial efforts and higher managerial skills. Both variables are hypothesised to depend positively on the theoretical construct “Integration”. Furthermore, the descriptive statistics showed that farms with highly diversified agricultural production usually diversify their economic activities and are less integrated in the factor and product markets. Thus, we additionally introduce the variable “Diversification”[6] in this submodel, which is expected to depend negatively on the theoretical construct ‘Integration’. Based on the abovementioned considerations, we argue that the factor “Integration” has a positive influence on m*.

Transaction costs: The total costs incurred by a firm can be largely grouped into two components: production and transaction costs (Williamson 1989). Since the impact of transaction costs on production is negative, it can be assumed that the higher these costs are, the lower m* will be. The variable “transaction costs” is loaded by two components: transaction costs related to labour and transaction costs related to land.

Polish agriculture is mainly organised into family farms. However, although family labour dominates, several farms employ a considerable amount of non-family hired labour. Pollak (1985) and Schmidt (1989) argue that the reasons for the dominance of family farms in Western agriculture are the transaction costs associated with the management of hired labour. These high transaction costs are the result of natural uncertainties and biological production processes, both of which prevent the conclusion of (almost) perfect or incentive-compatible contracts. This in turn implies high monitoring and control costs for hired labour. Thus, we assume that the variable “Hired labour”, defined as a proportion of total farm labour input, is positively correlated with the factor “Transaction costs”. The labour-related transaction costs (i.e., opportunism risk) may be reduced by substituting capital for labour. Thus, we assume the higher the mechanisation degree of a farm is, the lower are the overall transaction costs. We could control for this assumption by using man – land ratio calculated total labour hour per hectare of farmland. We assume that man - land ratio and transaction costs correlate positively.

Land-related transaction costs are captured by the variable ”Number of plots”. The descriptive statistics showed that the farms possess between one and 42 plots per farm. Consequently, we

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[6] Diversification represents the involvement of the family members in different economic activities (like off farm economic activity).The variable is defined as the share of non-agricultural labour hours on total family labour.

argue that governing fragmented farmland increases the farm-specific transaction costs (coordination, monitoring costs).[7]

In order to analyse the influence of those three theoretical constructs (factors) on the optimal management (m*, the farm heterogeneity), a structural equation model (SEM) has been applied using AMOS 7.0. Figure 2 shows the respective path diagram and directly provides information about the estimation results. For the purposes of transparency, only the direction of the influence (negative or positive) and the level of significance of the estimated parameters are presented. Observable variables are depicted in the path diagram by rectangles and the theoretical constructs (factors) by ellipses. The single-headed arrows leading from the latent to the observable variables provide information about how the identified constructs manifest themselves in practice. Principally, they represent partial regression coefficients, i.e., the arrow leading from size to management indicates that management (scores) depend partly on size. The error terms of the particular regressions (i.e., (m_1, t_i, s_i, i_i,) are enclosed in circles. The bi-directional arrows connecting the latent variables "Size" and "Integration" reflect the interactions between them, since respective tests provided evidence that accounting for this correlation improves the model fit. To solve the identification problem, we fixed the respective regression weights in the three submodels at unity (1). The same holds for the variance estimation of "errors". The thirteen 1s shown in the path diagram (Figure 2) indicate a satisfactory choice of identification constrains.

The findings displayed in Figure 2 show that all theoretical constructs (factors) have a highly significant influence on the observable variables. Furthermore, our hypotheses formulated for the impact of the three factors (size, integration, transaction costs) on the random variable m* are confirmed.

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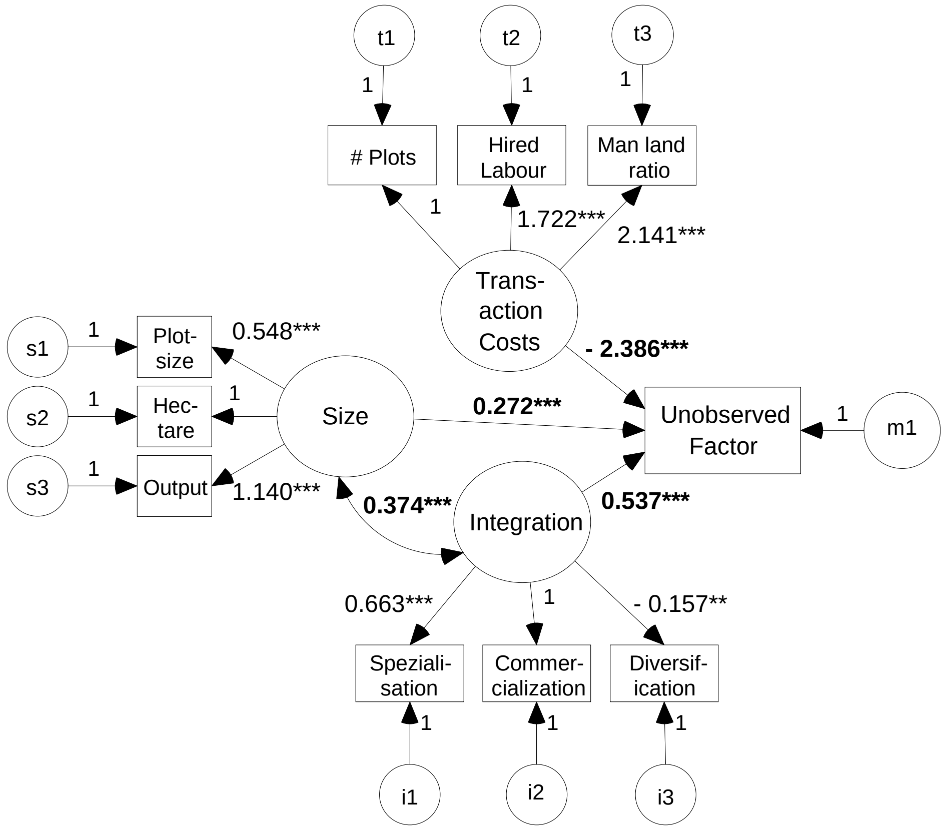
7 We do not provide descriptive statistics of the observable explanatory variable, since all variables have been standardised to take a value in the space $< -1; 1 >$.

Figure 2: Path diagram of model explaining farm heterogeneity (variation of m*)



Source: Own calculations.

Note: Significance level **** = 1 %, *** = 5 %, **= 10 %, *= 15 %.,
Number of observations: 580.

The significant covariances show that two theoretical constructs (Size and Integration) are not stochastically independent, but that there is a mutual interaction between them. The positive correlation between those factors means that with farm growth it becomes increasingly difficult to govern integration in the value chains.

However, the model has a rather low explanatory power. Basically, all indicators were outside the desired regions[8]. Despite this, the model can be regarded as satisfactory for the approach outlined here, particularly as the results calculated for the relations between the variables were, on the whole, highly significant. A reason for the low explanatory content is the lack of available information. Additionally, some information was lost due to the averaging of m* and the respective explanatory variables at-times invariant variables.

[8] In detail, the absolute fit measures, i.e. Chi-Square divided by the degrees of freedom (CMIN/DF) and the root mean square error of approximation (RMSEA), are below the recommended thresholds indicating an adequate overall fit of the model (AMOS, 1995-2006).

5 CONCLUSIONS

Many studies deal with the efficiency and productivity of factor input in agriculture. Particularly for transition countries, this subject remains highly relevant, as the reallocation of farm resources has great potential in itself to improve overall productivity. However, farm heterogeneity has thus far been a neglected factor in productivity analyses.

In this paper we applied the approach of Alvarez et al., (2003, 2004) for taking account of farm heterogeneity while exploring the farms' (in)efficiency. The approach utilises a translog function and treats an unobserved farm-specific component as a random variable. The resulting econometric model is estimated as a stochastic production frontier with random coefficients (RPM). We extended the basic approach insofar as we explored the differences in the unobserved component.

The applied approach provides new insights into efficiency analysis in general, and efficiency problems faced by Polish farms in particular. Our analysis has some important implications. As expected, the unobserved component model provides lower efficiency scores than the alternative approaches, such as the random or the fixed-effect model. Since the statistical properties of the RPM favour this model, our assertion that standard SFA overestimates efficiency is confirmed. Additionally, our findings provide evidence of the importance of input quality for efficiency analysis. At the same time, the results indicate the existence of an additional significant, unobservable production factor besides land, capital, labour and intermediate inputs and the respective inputs' qualities. The identified farm-specific random parameter represents farm heterogeneity. The findings reveal that this factor might influence technical efficiency directly (as a farm-specific input) and indirectly (as a function) since it influences the use of other observable inputs.

To summarise, farm heterogeneity, defined as the capacity to deploy inputs efficiently, is a fundamental element of the production structures of Polish family farms. Moreover, it is possible to describe the determinants of farm heterogeneity in Polish agriculture in the form of a complex system of interdependencies (SEM). Important determinants are farm size and farm integration in supply chains, as well as the level of transaction costs. Thus, farm heterogeneity must not be equated with inefficiency, as happens in conventional efficiency analyses. On the contrary, it shows the maximum productivity – given the existing factor input – that a farm can achieve. Comparisons between farms only allow inferences to be made about the variation of the optimal form between farms, and thus cannot be used to draw conclusions about economic strategy. These can only be made when it is possible to identify to what extent and why an enterprise has not exploited all the potential at its disposal.

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