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Productivity and efficiency in Czech agriculture: Does farm size matter?

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Abstract: This paper deals with the sources of total factor productivity (TFP), namely technical efficiency, scale efficiency, and technological change, considering the size of agricultural producers and using balanced panel data in the period 2014–2018 drawn from the Farm Accountancy Data Network (FADN) database for three sectors of Czech agriculture – cereals, milk, and beef. The investigation is based on the stochastic frontier (SF) modelling of an input distance function (IDF) with four error components (heterogeneity, statistical noise, persistent and transient inefficiency). The sector-specific models are estimated by a four-step estimating procedure with a system generalised method of moments (GMM) estimator to address the endogeneity problem. The results reveal inter- and intra-sectoral differences in productivity drivers. In particular, the smallest producers lag considerably behind the largest ones due to the scale effect (SEC). While large farms should focus on technological change, improvements in scale and technical efficiency have been identified as the main sources of coping with productivity losses for small farmers.

Keywords: Czech Republic; input-distance function; stochastic frontier analysis; technical efficiency; total factor productivity

Productivity and efficiency are often considered as indicators or measures of competitiveness over the long term (European Commission 2009). Competitiveness, as a multidimensional concept (Man et al. 2002), is characterised by long-term orientation, relativity, and dynamism and is defined as the capacity of the enterprise to amalgamate its resources and capabilities, seeking to create value-adding, hard-to-duplicate competencies (Barney 2001). Current policy trends focus research attention on the relationship between the size of agricultural holdings and their productivity and efficiency since small and large farms differ from each other in many respects, including access to financial resources and human capital, managerial styles, organizational structure, capacity to gather information, and their vulnerability to changing market conditions (Man et al. 2002). Economists have been trying to address the research question of whether small farms perform better or worse than large farms for decades. The origins go back to the 1960s, e.g. Sen (1962). More recently, Foster and Rosenzweig (2017) proposed a theoretical model that incorporates factor market imperfections and economies of size in mechanization. Their model presents a size-land productivity relationship with a U-shaped pattern, with the highest levels being achieved by the smallest and largest farms, which is in line with the assumption of greater self-exploitation of family labour (Griffin et al. 2002) as well

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as with the resource-based theory explaining competitive advantage based on the heterogeneous distribution of resources (Lafuente et al. 2020).

However, based on empirical analysis, Rada and Fuglie (2019) pointed out that the U-shaped pattern of the size-productivity relationship appears to evolve with the stage of economic development. According to their results, in high-income countries, the relationship between farm size and total factor productivity (TFP) is more straightforward. While the productivity of large farms is growing faster than others, small farms face a clear productivity disadvantage.

The lower productivity of small farms was also found by Key (2019), who analysed US agriculture, Keizer and Emvalomatis (2014), whose study investigated the Dutch dairy sector, and Alvarez and Arias (2004), who assessed Spanish dairy production. In the Czech Republic, the lagging behind of small farms was observed, for example, by Novotná and Volek (2015), who analysed the size-labour productivity relationship, and by Čechura (2014) and Rudinskaya et al. (2019), whose studies took into consideration the heterogeneity of farms with regard to their size in the evaluation of technical efficiency. Moreover, Bokusheva and Čechura (2017) provided evidence for the positive association between farm size and TFP in Czech cereal production.

According to these studies, the competitive weakness of small farms may be due to their lower likelihood of developing economies of scale, lower innovation potential, and higher technical inefficiency. Lafuente et al. (2020) found the reason for competitive weakness to be the inability of small farms to capitalise on competitiveness-enhancing investments. Key (2019) added that some recent technological advances (e.g. variation in new seeds, robotic feeding and milking systems, precision agricultural technologies) have raised the productivity of larger farms more than smaller ones. This could determine whether small farms can persist as viable economic units, since if technological progress will favour larger farms, the economies of a size that give large farms a competitive advantage will increase over time and will accelerate the loss of competitiveness of small farms, leading to the cessation of their activity or concentration into larger units – a trend that is observed in the Czech Republic as well as in the entire European Union (Eurostat 2018).

To gain further insights into the long-term farm structure in the Czech Republic, this study aims to evaluate the differences in productivity and efficiency among the farm size groups and the sources of productivity growth in these size groups in three sectors of Czech agriculture, namely cereals, milk, and beef production. In particular, the authors aim to address the following research questions. The first question relates to the identification of intra-sectoral differences in TFP with respect to farm size. The second question deals with the drivers of productivity dynamics, and whether these drivers differ both inter- and intra-sectorally, and with respect to farm size. This paper contributes to the current state of knowledge through the empirical application of the most advanced techniques to estimate unbiased and consistent technological parameters and provide a robust estimate of technical efficiency, decomposed into transient and persistent parts, and by comparing five size groups of agricultural producers in three production specializations. This study fills the gap in efficiency and productivity research in the Czech Republic, as most previous studies investigated only one part of overall technical efficiency, especially time-varying, and did not evaluate the relationship between farm size and productivity in inter-sectoral comparisons.

MATERIAL AND METHODS

We employ an estimation procedure that provides consistent estimates of technology parameters, the two components of technical efficiency and heterogeneity effect. Moreover, since the endogeneity problem usually frustrates researchers in productivity and efficiency analysis and leads to inconsistent estimates (Ullah et al. 2018), we use a method, which controls for the potential endogeneity of regressors to obtain consistent estimates of technology, as well as productivity and efficiency measures.

The first attempt to control for potential endogeneity bias in the productivity and efficiency analysis goes back to Farsi et al. (2005) who proposed the true random effect model with the Mundlak (1978) extension:

$$y_{it} = \alpha_0 + \beta' x_{it} + \phi' \overline{x}_i + \alpha_i + v_{it} - u_{it} \tag{1}$$

where: y_{it} – output of i^{th} firm in period t; x_{it} – vector of production inputs; β – vector of parameters to be estimated; $\overline{x}_i$ – vector of the firm means; ϕ – corresponding vector of parameters; α_i – random time-invariant firm effects, independent and identically distributed (i.i.d.) $N\left(0, \sigma_\alpha^2\right)$; α_0 – constant; v_{it} – stochastic noise; u_{it} – time-varying technical inefficiency.

We assume that v_{it} and u_{it} are independent and identically distributed (i.i.d.) following $N\left(0, \sigma_{v_{it}}^2\right)$,

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$N^{+}\left(0, \sigma^2_{u_{it}}\right)$, and are distributed independently of each other and of regressors.

Specification [Equation (1)] controls for the heterogeneity, however, it does not distinguish between the firm unobserved heterogeneity and the time-invariant technical efficiency term. Thus, Tsionas and Kumbhakar (2012) introduced the stochastic frontier analysis (SFA) model [an extension of the true random effects model by Greene (2005)] that overcame this limitation. Their model contains four components of the error term: firm-specific heterogeneity, the time-invarian–persistent–component of technical efficiency, the time-varying–transient–component of technical efficiency, and the stochastic error term:

$$y_{it} = \alpha_0 + \beta' x_{it} + \chi_i + v_{it} - \eta_i - u_{it} \tag{2}$$

where: v_{it}, u_{it}, χ_i, η_i – independent and identically distributed (i.i.d.) variables following $N\left(0, \sigma^2_v\right)$, $N^{+}\left(0, \sigma^2_u\right)$, $N\left(0, \sigma^2_\chi\right)$ and $N^{+}\left(0, \sigma^2_\eta\right)$.

All components of the error term are again assumed to be independently distributed of each other and of the regressors.

The four components model avoids the following specification problems. The model is specified incorrectly and the results are biased if the model misses one or more of these components. Specifically, the model produces an upward bias inefficiency estimate if we do not distinguish between firm effects (latent heterogeneity) and efficiency. Conversely, the model provides a downward bias estimate of overall efficiency, if the firm effects and persistent inefficiency are not treated separately (Kumbhakar et al. 2015).

In this study, we follow Bokusheva and Čechura (2017) and apply the four-step procedure to get feasible and consistent estimates of technology and components of the error term. This procedure is an extension of the heteroskedastic four-component stochastic frontier (SF) model formulation Tsionas and Kumbhakar (2012), which captures all necessary error-term components but does not address the endogeneity problem. Bokusheva and Čechura (2017) extend the Tsionas and Kumbhakar approach and use the two-step system generalised method of moments (GMM) estimator to get an unbiased parameters estimate.

In our analysis, we assume that the transformation process can be well approximated by the translog multiple inputs and outputs input distance function (IDF). Then, the four-step estimating procedure in the four components model can be introduced as in Equation (3).

Estimation procedure. In the first step, we use the two-step system GMM estimator, which controls for potential endogeneity in Equation (3) using the system of equations – the first equation in differences and the second equation in levels – with the two types of inner instruments: lagged IDF variables in levels for the equation in differences and lagged IDF variables in differences for the equation in levels; together with the set of additional variables in levels (outer instruments). The validity of instruments is tested by the Hansen *J*-test (Hansen 1982), controlling the orthogonality of all instruments, and by the Arellano-Bond test of autocorrelation [$AR(2)$], controlling the validity of lagged instruments (Arellano and Bond 1991).

The second step uses the residuals from the first step to estimate the random effects model using the generalised least squares method to get theoretical values of:

$$\alpha_i = \mu_i - \left(\eta_i - E\left(\eta_i\right)\right) \text{ and} \tag{4}$$

$$\varepsilon_{it} = v_{it} - \left(u_{it} - E\left(u_{it}\right)\right) \tag{5}$$

In the third step, ε_{it} is used to estimate transient technical inefficiency by employing the standard SFA technique [i.e. the method of maximum likelihood and Jondrow et al. (1982) procedure assuming that: $v_{it} \sim N\left(0, \sigma^2_v\right)$, $u_{it} \sim N^{+}\left(0, \sigma^2_u\right)$].

Finally, the persistent technical inefficiency is estimated in the fourth step using theoretical values of α_i

$$\begin{aligned} -\ln X_{1it} = {} & \alpha_0^{*} + \sum_{m=1}^{M}\beta_m \ln Y_{m,it} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N}\beta_{mn}\ln Y_{m,it}\ln Y_{n,it} + \sum_{m=1}^{M}\sum_{j=2}^{J}\delta_{mj}\ln Y_{m,it}\ln \tilde{X}_{j,it} + \sum_{j=2}^{J}\beta_j \ln \tilde{X}_{j,it} + \\ & + \frac{1}{2}\sum_{j=2}^{J}\sum_{k=2}^{K}\beta_{jk}\ln \tilde{X}_{j,it}\ln \tilde{X}_{k,it} + \alpha_t t + \frac{1}{2}\alpha_{tt}t^2 + \sum_{m=1}^{M}\alpha_{mt}\ln Y_{m,it}t + \sum_{j=2}^{J}\alpha_{jt}\ln \tilde{X}_{j,it}t + \alpha_i + \varepsilon_{it} \end{aligned} \tag{3}$$

where: X_1 – input that is used for normalisation to achieve homogeneity of degree 1 in inputs; $\tilde{X}_j = X_j / X_1$ – normalised j^{th} input; $\tilde{X}_k$ = normalised k^{th} input; Y_m – m^{th} output; Y_n – n^{th} output; t – time trend; α, β, δ – parameters, $\alpha_0^{*} = \alpha_0 - E\left(\eta_i\right) - E\left(u_{it}\right)$, $\alpha_i = \mu_i - \left(\eta_i - E\left(\eta_i\right)\right)$; ε_{it} – composite error term, $\varepsilon_{it} = v_{it} - \left(u_{it} - E\left(u_{it}\right)\right)$.

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and the Jondrow et. al. (1982) procedure with the following assumptions: $\mu_i \sim N\left(0, \sigma_\mu^2\right)$, $\eta_i \sim N^+\left(0, \sigma_\eta^2\right)$. The overall technical efficiency is then quantified according to Kumbhakar et al. (2015):

$$OTE_{it} = \exp\left(-\hat{u}_{i0}\right) \times \exp\left(-\hat{u}_{it}\right) \tag{6}$$

TFP is calculated using the Törnqvist-Theil index (TTI) (Diewert (1976) in the form of Caves et al. (1982). TTI exactly determines the changes in production if a production model has the translog form. The index is constructed as deviations from the sample means. Moreover, TFP can be decomposed into a scale effect (SEC), technical efficiency effect (TEC), and technological change effect (TC).

Data. The analysis is based on the balance panel dataset of microeconomic data (physical as well as financial data) of Czech agricultural producers. The dataset, drawn from the Farm Accountancy Data Network (FADN) database provided by the Institute of Agricultural Economics and Information, covers the period from 2014 to 2018 (FADN 2021). The sample of farms consists of specialised cereals, field crops, mixed crops, and mixed crops and livestock farms according to the FADN farm typology. As this study focuses on cereals, milk, and beef production, only agricultural producers with at least a 10% share of cereal/milk/beef production in total production are included in the corresponding samples [10% production limit is a compromise between the importance of particular output (cereal, milk and beef) in total farm output (expressing a certain level of specialisation in respective output) and a sufficient number of observations]. Moreover, the same percentage production limit is used for all productions for purposes of comparative analysis.). That is, the cereals sector is represented by 2 190 observations, the milk sector by 1 365 observations, and the beef sector by 640 observations, respectively.

The technology of each sector is modelled by the IDF with the following vectors of outputs (y) and inputs (x):

– Cereals: Cereals output (yC) is defined as the value of cereals production; the output of other crops ($yAOC$) is measured as the difference between the value of total crop output minus cereals output; other farm output ($yAOO$) is calculated as the difference between the value of total farm output and the value of total crop output.
– Milk: Milk output (yC) is defined as the value of milk production; other livestock production ($yAOC$) is measured as the difference between the value of livestock output minus milk output; other farm output ($yAOO$) is calculated as the difference between the value of total farm output and the value of total livestock output.
– Beef: Beef output (yC) is defined as the value of beef production; other livestock production ($yAOC$) is measured as the difference between the value of livestock output minus beef output; other farm output ($yAOO$) is calculated in the same way as for milk.

The vectors of inputs consist of land (xL) [expressed in hectares of farm utilised agricultural area (UAA)], labour (xW) [measured in annual working unit (AWU)], capital (xK) (represented by the sum of contract work and capital depreciation), and materials (xM) [defined as total intermediate consumption (the sum of total crops and livestock-production-specific costs and total farming overheads without contract work)]. Material is used to normalise the three other input variables.

Outputs, as well as inputs in monetary values, are deflated using the price indices (output- and input-specific) from the Eurostat database (2010 = 100) (Eurostat 2021a–d). Moreover, these indices together with characteristics of producers (e.g. share of rented land, share of energy crops area, material use intensity, milk yield, total subsidies per hectare, environmental subsidy share) are used in the GMM estimation as instrumental variables along with the lagged values of IDF variables (for additional information about instrumental variables see Roodman 2009). The sample descriptive statistics of the output and input variables are provided in Table S1 in electronic supplementary material (ESM; for the ESM see the electronic version).

RESULTS AND DISCUSSION

Technology. The parameter estimates of the IDFs for cereals, milk, and beef production are provided in Tables S1–S3 in ESM (for the ESM see the electronic version). The signs of the first-order parameters evince the consistency of the estimates with economic theory. In particular, the IDF parameter estimates are non-increasing in outputs and non-decreasing in inputs. In addition, the condition of concavity in inputs is met in all models. The estimates also show good statistical qualities. The majority of the first-order parameters are significant at the 5% significance level. The Wald test (α = 0.05) rejects the null hypotheses of the zero value for the second-order parameters. Hansen's J-test statistics and the $AR(2)$ test confirm the validity of the GMM estimates.

The translog IDFs are estimated with all variables in logarithm normalised by their sample means. In this

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way, the first-order parameters can be interpreted as output elasticity and input cost shares, evaluated on the sample mean. Table 1 summarises these cost shares, which capture the relative importance of that input in the production process. In line with this definition, the estimated cost shares reveal that the agricultural production in all analysed sectors is highly material-intensive since material inputs play a dominant role in the cost structure. The importance of other inputs is sector-specific. The beef sector indicates higher labour intensity, while the cereals sector is more land-intensive. The cost share of capital is the lowest in all sectors.

The absolute value of the sum of output elasticities is lower than 1 in all the analysed sectors: 0.93, 0.95, and 0.90 in the cereals, milk, and beef sector, respectively. Figure 1 presents the violin plot (a modified box plot, which adds the estimated kernel density) of the dual measure – returns to scale (RTS). The estimated values indicate the sub-optimal scale of operations in all sectors since the majority of farms can be characterised by increasing RTS. In particular, evaluated on size group means, constant RTS (representing the optimal scale of operations) are not rejected (t-test: $t = -1.471$, $\Pr(|T| > |t|) = 0.165$) only in the group of the largest producers in the beef sector. In other words, agricultural producers, except for large farms in the beef sector, could considerably improve their productivity by increasing their scale of operations. However, if we take into account the dynamics of the economies of scale, we may observe the opposite pattern in the group of small farms. In particular, smaller farms moved away from the optimal scale during the analysed period.

The estimate of technological change is statistically significant ($\alpha = 0.05$) and negative in all analysed sectors (Tables S2–S4 in ESM; for the ESM see the electronic version). That is, evaluated at the sample mean, cereals, milk, and beef producers experienced technological regress in the period 2014–2018; however, the technological regress decelerates over time. As there are various reasons for technological regress, such as the obsolescence of equipment and the deterioration of worker qualifications (Latruffe 2010), both financial and human resources are required to overcome the decline. Although small farms usually face greater constraints on access to resources than large farms (Lafuente et al. 2020), our results show (Figure S1 in ESM; for the ESM see the electronic version) that the technological change turned out to be positive in the second half of the analysed period in the groups of small farms (up to 100 ha), and even in the case of the smallest cereal farms, minor technological progress can be observed

Table 1. Cost shares (%)

	Cereals	Milk	Beef
Land	16.13	11.28	13.89
Labour	15.44	14.13	23.19
Capital	12.25	9.28	8.79
Material	56.18	65.31	54.16

Source: Authors' own calculation based on FADN (2021)

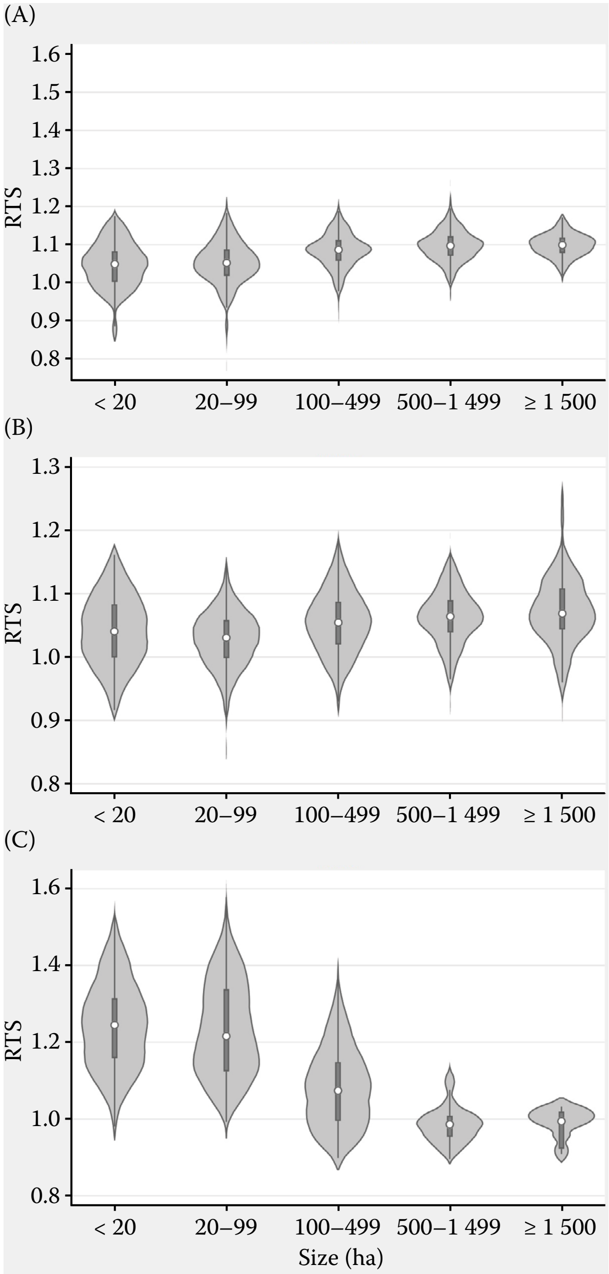

Figure 1. Returns to scale (RTS): (A) cereals, (B) milk, and (C) beef

Source: Authors' own calculation based on FADN (2021)

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Table 2. Technological change

Size (ha)	Cereals		Milk		Beef	
	mean	SD	mean	SD	mean	SD
< 20	0.005	0.073	–0.012	0.074	–0.014	0.037
20–99	–0.010	0.073	–0.025	0.075	–0.014	0.034
100–499	–0.022	0.071	–0.037	0.073	–0.024	0.032
500–1 499	–0.021	0.072	–0.040	0.075	–0.030	0.031
≥ 1 500	–0.023	0.071	–0.045	0.074	–0.022	0.030

Source: Authors' own calculation based on FADN (2021)

(Table 2). These findings suggest that small farms may have taken advantage of agricultural support schemes like the Rural Development Programme, which is targeted at small and medium-sized farms.

The means of overall technical efficiency (93.8, 95.6 and 84.5% for the cereals, milk, and beef sector, respectively) indicate considerable space for technical efficiency improvements only in beef production. In other words, beef producers operating on the technological frontier have a considerable competitive advantage, as their costs are 15.5% lower compared to the sample average, while in the cereal and milk sectors, the differences in costs of an efficient farm compared to the sample average are only 6.2% and 4.4%, respectively.

According to Figure 2, which presents the violin plot of overall technical efficiency, small farms (< 20 ha) cope with higher technical inefficiencies than farms in other size groups. The lowest differences can be observed in the milk sector, where the average technical efficiency in the group of the smallest farms was 95.2%, whereas it was 95.7% in the group of the largest farms. On the contrary, the beef sector is characterised by the highest differences. The overall technical efficiency of the smallest size group was 83.2% on average, whereas it was 88.1% in the group of the largest farms. Since the main consequence of technical inefficiency is to raise production costs, the higher technical inefficiency of small farms makes them less competitive (Alvarez and Arias 2004).

The decomposition of overall technical efficiency into transient and persistent parts reveals that transient technical inefficiency, which is related to non-systematic management failures, shocks associated with new production technologies, and changes in human capital, contributes to a similar extent to overall technical inefficiency in all size classes and specialisations (Table 3). However, the standard deviations are smaller for larger producers, indicating that the groups of larger farms are more homogeneous in terms of the efficiency of input use. In other words, the technical efficiency of larger farms is close to the average technical efficiency

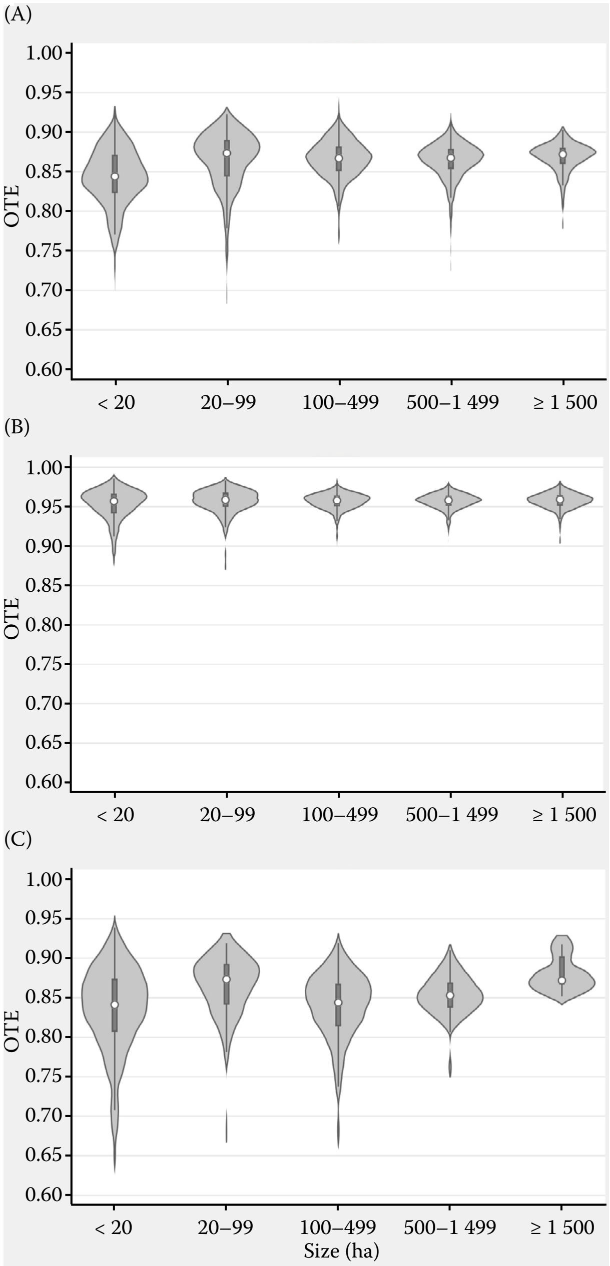

Figure 2. Overall technical efficiency (OTE): (A) cereals, (B) milk, and (C) beef

Source: Authors' own calculation based on FADN (2021)

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Table 3. Decomposition of overall technical efficiency

Size (ha)	Cereals		Milk		Beef	
	mean	SD	mean	SD	mean	SD
Transient technical efficiency						
< 20	0.930	0.030	0.953	0.022	0.940	0.025
20–99	0.937	0.026	0.958	0.016	0.944	0.017
100–499	0.938	0.019	0.958	0.012	0.944	0.011
500–1 499	0.939	0.016	0.958	0.010	0.945	0.008
≥ 1 500	0.940	0.014	0.959	0.011	0.948	0.008
Persistent technical efficiency						
< 20	0.906	0.026	0.998	0.000	0.884	0.055
20–99	0.923	0.024	0.998	0.000	0.916	0.035
100–499	0.923	0.017	0.998	0.000	0.887	0.045
500–1 499	0.920	0.017	0.998	0.000	0.903	0.024
≥ 1 500	0.924	0.012	0.998	0.000	0.930	0.019

Source: Authors' own calculation based on FADN (2021)

of the size group. Furthermore, an increase in technical inefficiency in small size groups is observed during 2014–2018. This negative trend in technical efficiency is a common feature for all analysed sectors. Persistent technical inefficiency, indicating systematic failures in optimal resource use, was estimated only for cereals and beef producers. Milk producers do not indicate systematic failures in optimal resource use. In the cereal and beef sectors, persistent technical inefficiency dominates the overall technical inefficiency and is negatively associated with farm size. In particular, the group of the largest farms indicate considerably lower persistent inefficiencies as compared to the group of the smallest farms.

Finally, in all sectors, we can observe significant productivity improvements, after a decline in 2015, compared to the year 2014, evaluated at the sample mean. This productivity growth was driven by the group of larger farms, as shown in Table 4 and Figure S1 in ESM (for the ESM see the electronic version). While large farms (≥ 500 ha) experienced significant productivity growth over the period 2014–2018, smaller farms (< 100 ha) did not catch up, and the values of their Törnqvist-Theil TFP index generally remained negative. That is, small farms in all analysed sectors faced competitive losses, increasing the farms' vulnerability to market conditions (West and De Castro 2001), which is detrimental to economic efficiency. This result foreshadows structural changes in all investigated sectors, because if larger farms consistently experience faster productivity growth, then they are more competitive in the long run, which in turn encourages smaller farms to adapt by expanding their scale; alternatively, they are driven out of business and larger farms might acquire their assets (Keizer and Emvalomatis 2014).

Figure 3 presents the TFP components that help us to reveal the differences and drivers of TFP growth. The figures show a positive association between size and TFP. Moreover, it also holds in all sectors, that the main factor determining the productivity difference between small and large farms, is the scale-effect component. Moreover, the results suggest that the scale component was the main source of TFP growth.

Table 4. Total factor productivity (TFP) [Törnqvist-Theil index (TTI)]

Size (ha)	Cereals		Milk		Beef	
	mean	SD	mean	SD	mean	SD
< 20	–0.186	0.098	–0.199	0.111	–0.069	0.086
20–99	–0.123	0.092	–0.097	0.103	–0.051	0.068
100–499	–0.019	0.095	0.019	0.078	0.016	0.066
500–1 499	0.087	0.089	0.039	0.075	0.081	0.047
≥ 1 500	0.130	0.083	0.047	0.081	0.108	0.044

Source: Authors' own calculation based on FADN (2021)

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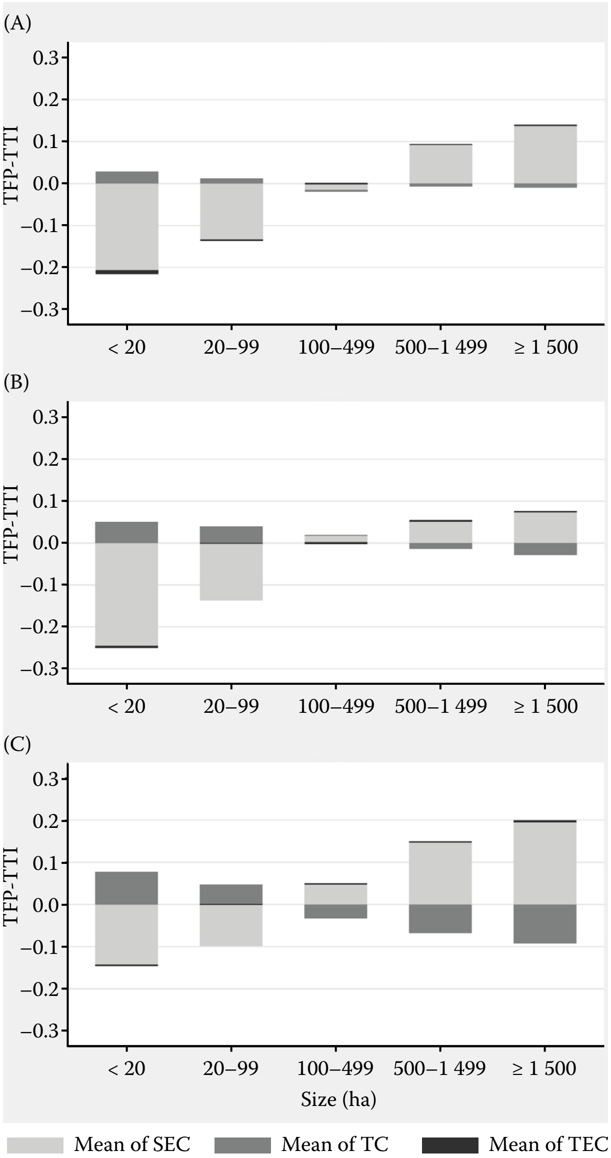

Figure 3. Törnqvist-Theil index of total factor productivity (TFP-TTI) decomposition

SEC – scale effect; TEC – technical efficiency effect; TC – technological change effect

Source: Authors' own calculation based on FADN (2021)

In particular, large farms have tended to adjust the scale of their operations to increase scale efficiency, while small farms were not able to approach the scale of production that minimises their costs. Technological change contributed positively to TFP growth in the groups of small farms and negatively in the groups of larger farms. Finally, the technical efficiency component did not contribute considerably to the TFP dynamics, except for the group of small farms, where the negative effect of the technical efficiency component was observed in all sectors.

CONCLUSION

This study examined the relationship between farm size and TFP in Czech cereals, milk, and beef production. The analysis was based on the use of the latest techniques of SFA to obtain robust estimates of production technology, efficiency, and TFP. Unlike previous studies, this study accounted for potential endogeneity and the existence of both transient and persistent technical efficiency.

The results revealed that the considerable productivity improvements observed in these sectors in 2014–2018 were driven by large farms. Small farms lagged behind large ones in both productivity and technical efficiency. In the future period, this competitive weakness can be expected to make small farms unable to face competitive pressure, which will be amplified by the efforts of large farms to acquire the resources available to small farms. This is particularly likely to be the case in the cereals sector, where the technology of larger farms exhibits increasing RTS. Thus, without policy interventions, the trend towards concentration will continue.

Moreover, these results have important policy implications. If the goal of policymakers is to slow down the continuing trend of concentration in agriculture (Šūmane et al. 2021), one approach is to design policies that will increase the productivity of smaller farms. The results showed that if this cannot be achieved by changing the scale of operations, it is necessary to increase the technical efficiency of small farms and to promote new cost-reducing practices such as sharing. According to Key (2019), such productivity-enhancing policies might include targeted subsidised loans or tax breaks for purchasing new capital goods, provision of expert advice, a networking platform, and the promotion of collaboration, overcoming limited access to resources such as finance, knowledge, and equipment. It is worth adding, however, that policy support for small farms faces a trade-off in aggregate productivity growth. Targeting support toward small farms leads to relatively small increases in aggregate productivity compared to targeting larger farms.

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