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The effect of land fragmentation on risk and technical efficiency of crop farms

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Abstract

Using a 2007–2014 panel of Austrian crop farms, we analyze the effect of multiple dimensions of land fragmentation on farms' production efficiency and risk performance. We use Data Envelopment Analysis (DEA), a non-parametric linear programming approach, to estimate efficiencies. Technical efficiency is decomposed into i) scale efficiency, ii) pure technical efficiency, and iii) input-mix efficiency. Risk efficiency, a concept borrowed from modern portfolio theory, measures the performance of a farm relative to a mean-variance frontier. A second-stage DEA analysis reveals that farms with fewer plots and a shorter average farmstead to plot distance tend to be more technically efficient. Larger plots allow for better exploitation of returns to scale. The scattering of plots has no statistically significant effect on technical efficiency but provides benefits in terms of higher risk efficiency. Land consolidation projects should carefully weigh the costs and benefits associated with different dimensions of land fragmentation.

Keywords: Land consolidation; Farmland fragmentation; Economies of scale; Agricultural productivity; Risk management; Data Envelopment Analysis

JEL codes: Q12, Q15, Q18

1 INTRODUCTION

Land fragmentation (LF) describes a land use pattern in which "a single farm consists of numerous discrete parcels, often scattered over a wide area" (Binns 1950). A rich and long-standing debate about the adverse effects of LF on agricultural productivity (e.g., Binns, 1950; Sargent, 1952; Nylon, 1959; Shaw, 1963) prompted governments to apply land reforms (Beringer, 1962; Oldenbuerg, 1990) and land consolidation programs (Gatty, 1956; Jacoby, 1959; Lambert, 1963; Jiang, et al. 2022) to overcome unfavorable farm structures that impede rationalization of agricultural resource use.

Especially, Western European countries have a long tradition of land consolidation dating back to the 19th century (Lambert, 1963) with an enormous increase in consolidation projects after World War II. In Austria, the total area where land consolidation and voluntary land exchange schemes were ever implemented amounts to more than 40% of the total agricultural area (BMLFUW, 2013). This might explain why the literature on the effects of LF on farm performance mainly focuses on developing and transition economies (e.g., Nguyen et al., 1996; Wan and Cheng, 2001; Tan et al., 2008; Lu et al., 2018; Rahman and Rahman, 2009; Monchuk et al., 2010; Hung et al., 2007; Ali et al., 2018; Larochelle and Alwang, 2013; Rao, 2019; Ciaian et al., 2018; Deininger et al., 2012; Hristov et al., 2009; Di Falco et al., 2010; Boliari ,2013; Zenka et al., 2016; Looga et al., 2018) and little is known about how LF effects the performance of Western European farms (exceptions are

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Latruffe and Piet, 2014 for France and Olsen et al., 2017 for Denmark, as well as the following studies focusing on dairy farms in Spain, Finland, and Ireland: Corral et al., 2011; Orea et al., 2015; Niskanen and Heikkilä, 2015; and Bradfield et al., 2020). As far as we know, no study assessing the productive implications of LF for Western European crop farms exists.[2]

We contribute to the literature by assessing the effect of LF on farms' technical and risk efficiency using a 2007–2014 panel of Austrian crop farms. This allows us to inform the ongoing debate about whether land consolidation as a partially publicly financed task will still be required in the future. While the number of land consolidation schemes and the area covered by land consolidation is decreasing in Austria (BMLFUW, 2023), Mansberger and Seher (2017) report that agricultural demand for land consolidation still exists in Austria's alpine valleys, lowlands, and hilly regions, which is where crop farming in the country is concentrated. For centuries, partible and impartible inheritance traditions existed side by side in these regions, resulting in a considerable variation in LF across farms (Gatterer et al., 2024). The different institutional and agro-ecological context in Western Europe, such as high wages, advanced levels of mechanization/automation, better off-farm employment opportunities, and better functioning factor markets, compared to developing countries makes Austria an interesting case study region.

While the private costs for farmers[3] associated with fragmented land are well understood, the potential benefits of LF in terms of risk reduction and crop scheduling (Bentley, 1987) have received much less attention in the agricultural economics literature (exceptions are Blarel, 1992 and Goland, 1993). A few relatively recent studies report beneficial effects of LF in terms of lower variability in yield or output (Kawasaki, 2010; Rao, 2019), reduction in farmers' exposure to weather variability (Veljanoska, 2018), and improvement in farm households' food security (Knippenberg et al., 2022). Against the background of increasing climate variability putting crop production at risk (Vogel et al., 2019; Beillouin et al., 2020), we contribute to this literature by not only assessing the effect of LF on farms' technical, but also risk efficiency.

The concept of risk efficiency originates from the literature on the performance evaluation of investment funds/portfolios (Markowitz, 1952). Risk efficiency measures the distance of a portfolio to a mean-variance frontier. Murthi et al. (1997) introduced the estimation of risk-return frontiers using Data Envelopment Analysis (DEA). We borrow the concept of Murty et al. (1997) for the performance assessment of mutual funds and provide an original application to the risk performance assessment of farms. We consider farms' mean and standard deviation (negative semi-deviation) of agricultural revenues over the 2007-2014 period as output and input variable in the DEA-models, respectively. Furthermore, we apply a recently introduced measure and decomposition of technical efficiency (Mendelová, 2022) that extend radial measures of technical efficiency to include slacks. This allows us to decompose technical efficiency into i) scale efficiency, ii) pure technical efficiency, and iii) input-mix efficiency shedding light on the channels through which the different dimensions of LF affect the technical efficiency of farms.

[2] While the productivity of livestock farms can be affected by LF via the production of animal feed stuff, manure application, and transfer of livestock to pastures, the effect of LF on crop farms can be considered to be more relevant (Kapfer, 2007) due to the foremost importance of land as a production factor.

[3] Besides private costs and benefits for farmers, public benefits of LF in terms of higher biodiversity (Clough et al., 2020) and public costs associated with higher pesticide and chemical fertilizer expenditure per hectare (Hou et al., 2020; Abay et al., 2022) are reported. LF may result in extra roadwork, road safety issues, and greenhouse gas emissions (Latruffe and Piet, 2014; Hiironen and Niukkanen, 2014) are reported.

LF is a complex phenomenon that encompasses multiple dimensions: i) small farm size, ii) high number of plots, iii) low plot size, iv) irregularly shaped plots, v) spatial distribution of plots and iv) size distribution of the fields (King and Burton, 1982). The size and the number of plots are probably the most frequently applied LF measures (Latruffe and Piet, 2014) but many studies fail to capture the spatial dimension of LF (e.g., Kawasaki, 2010; Deininger et al., 2012; Orea et al., 2015; Looga et al., 2018). To disentangle the potentially diverging effects of different dimensions of LF on farm performance, we simultaneously control for multiple dimensions of LF, including average distance among parcels and between farmstead and parcels, in our regression models.

The remainder of this paper is organized as follows: Section 2 provides background about the potential mechanisms behind the effects of LF on farm performance and a brief literature review; the methods, data, and results are described in Sections 3, 4, and 5, respectively; and Section 6 provides concluding remarks.

2 BACKGROUND

2.1 Land fragmentation and productivity

Low plot size or a high number of plots increase organizing and monitoring costs of production processes (Di Falco et al., 2010) and impede mechanization and exploitation of economics of scale (Latruffe and Piet, 2014). Smaller and shorter plots increase turning maneuvers on the field and increase working time, fuel consumption, and variable machinery cost (Neubauer, 2012). Smaller average plot size, congruent with a higher number of plots for a fixed farm area, is associated with a larger share of area dedicated to field boundaries and headlands per hectare. Numerous studies stress the lower yield potential at plot peripheries (e.g., Kapfer, 2007): More frequent turning maneuvers at head lands accelerate soil compaction with the latter harming yields (Shaheb, 2021). Lower yields at field boundaries can be caused by higher weed pressure, shading from trees and hedgerows, and patchy application of seed, pesticide, and fertilizer. However, yield may be higher near the edge of the field if boundaries provide helpful ecosystem services (Duelli and Obrist, 2003), such as pollination services from bees (Garibaldi et al., 2011) or wind protection from tree lines (de Jong and Kowalchuk, 1995). Seed, pesticide, and fertilizer consumption is likely to be higher at field peripheries because it is unavoidable to cross these areas multiple times with certain equipment (Kapfer, 2007; Klare et al., 2005). Evidence that smaller plots are associated with higher pesticide and chemical fertilizer expenditure per hectare is shown in Hou et al. (2020) and Abay et al. (2022). The amount of time dedicated to setting-up machinery increases with the number of plots (Neubauer, 2012). The literature suggests smaller and irregularly shaped plots can hinder adoption of innovations and appliance of modern technologies and soil investments (Nguyen et al., 1996; Niroula and Thapa, 2005; Hung et al., 2007; Tan et al., 2008; Rahman and Rahman, 2008). The discussion suggests that a high number of plots or low average plot size tends to increase input requirements per hectare and reduce yields. We hypothesize a negative effect of both measures on the production efficiency of crop farms.

Large distances, both between farmstead and plots and among plots, increase the time, fuel, and variable machinery cost for transporting inputs (seeds, fertilizer, and pesticides), outputs (harvest), workers, and equipment (Latruffe and Piet, 2014). Larger distances can incur higher costs for agricultural infrastructure development, such as irrigation/drainage canals and farm roads (Niroula and Thapa, 2005) or even prevent such investments. Not only do the costs of water transportation increase with distance, but also maintenance and monitoring costs of irrigation systems and perhaps water leakage. Tang et al. (2015) find that LF decreases allocative efficiency of irrigation water use in China's Guanzhong plain and Penov (2004) shows that LF has contributed to the

Table 1
Potential effects of different dimensions of land fragmentation on farm performance

Land fragmentation dimension	Description of mechanism	Effect on technical efficiency	Effect on production and price risk
High number of plots/ Low plot size	High number of turning maneuvers increases working time, fuel consumption, and variable machinery cost	−	
	Larger area of field boundaries and headlands increases harvest loss and pesticide and fertilizer consumption	−	
	Increased set-up time for machinery	−	
	Limited uptake of investment and innovation (e.g., machinery, drainage, and irrigation)	−	
	Easier detection of diseases, pests, and water stress		−
Large farmstead-plot distance	Increases travel time, fuel consumption, and variable machinery cost for transportation of inputs, workers, outputs, and equipment	−	
	Difficult water management	−	+
	Delayed detection of diseases, pests, and water stress	−	+
Large distances between plots	Increases travel time, fuel consumption, and variable machinery costs for transportation of inputs, workers, outputs, and equipment	−	
	Difficult water management	−	+
	Heterogeneous agro-ecological conditions facilitate risk spreading, crop diversification, and labor synchronization	±	−
	Reduced production risk from adverse growing conditions, such as diseases, pests, hail, storm, frost, drought, and flooding		−

Source: Based on Hung et al. (2007), Neubauer (2012), Latruffe and Piet (2014), and Olsen et al. (2017).

abandonment and decline of Bulgaria's irrigation system. If large distances between plots translate into diverse microclimates across plots (e.g., due to variety in soil type, wind, insulation, moisture, slope, and altitude) this might encourage farmers to diversify their crop portfolio. Multiple studies find that crop diversification enhances yields, productivity, and technical efficiency (cf. Di Falco, 2012 and Bareille and Lagier, 2023), while others find a negative effect (Mzyece and Ng'ombe, 2020). Crop diversification and cultivation of the same crop in diverse microclimates can reduce production risk, avoid household labor bottlenecks, and minimize the use of hired labor (Bentley, 1987).

Research on the effects of LF on agricultural productivity in developing and transition economies abounds. Most of these studies find that LF, most frequently measured as the number of plots and average plot size, is associated with lower agricultural output, higher costs, or reduced productivity/efficiency in settings as diverse as rural China (Nguyen et al., 1996; Wan and Cheng, 2001; Tan et al., 2008; Lu et al., 2018), India (Jha et al., 2005; Manjunatha et al., 2013, Deininger et al., 2016), Bangladesh (Rahman and Rahman, 2009), Vietnam (Hung et al., 2007), Rwanda (Ali et al., 2018), and Bolivia (Larochelle and Alwang, 2013). Others, like Rao (2019) in the case of Tanzania or Ciaian et al. (2018) and Deininger et al. (2012) for Albania, find that LF is positively associated with technical efficiency.[4] This suggests that agro-ecological and institutional context matters. How LF is measured and if multiple dimensions of LF are considered also play a role: Monchuk et al. (2010) find that the number of plots have a negative impact on productivity of Indian farms, but spatial separation of plots and variability in plot size do not significantly impact productivity when controlling for the number of plots.

Regarding Europe, most studies on the effects of LF on farm performance focus either on transition economies (for Macedonian vegetable farms see Hristov et al., 2009; for Bulgaria Di Falco et al., 2010 and Boliari, 2013; for Czechia Zenka et al., 2016; and for Estonia Looga et al., 2018) or dairy farms (for Spain see del Corral et al., 2011 and Orea et al., 2015; for Finland Niskanen and Heikkilä, 2015; and for Ireland Bradfield et al., 2021). There are two exceptions – one study focusing on the French region Brittany (Latruffe and Piet, 2014)[5] and the other on Denmark (Olsen et al., 2017) – although these studies pool farms with very different production specializations and report average effects across all farm types.

2.2 Land fragmentation and risk

The spatial dispersion of plots, i.e., scattered plots or large distances between plots, can reduce production risk for farmers from adverse weather conditions, such as hail, flooding, frost, and storms, and from crop pests and diseases spread. Veljanoska (2018) finds for farms in Uganda that higher fragmentation decreases loss of crop yield when households experience rainfall anomalies, but that fragmentation remains harmful for farms not experiencing such a shock. Knippenberg et al. (2020) report that LF in Ethiopia mitigates the adverse effect of low rainfall on food security because households with diverse plot characteristics grow a greater variety of crop types. Similarly, Rao (2019) finds that LF being "concurrent with crop diversification" allowed farmers in Tanzania to mitigate production risk by diversifying production among separate land plots with heterogeneous agronomic conditions. For a sample of Bulgarian farms, Di Falco et al. (2010) find

[4] Cholo et al. (2019) and Knippenberg et al. (2020) focus on food security as an outcome variable and find that LF reduces food insecurity in Ethiopia.

[5] Due to data limitations, Latruffe and Piet (2014) relate measures of farm performance to land fragmentation indices measured at the municipality-level.

that LF fosters crop diversification and reduces profitability, but they do not study the effect of LF on risk. Ciaian et al. (2018) document that LF is an important driver of production diversification in rural Albania. The risk reducing effect of crop diversification is documented in multiple studies (cf. Di Falco and Perrings, 2005; Chavas and Di Falco, 2012; Bangwayo-Skeete et al., 2012; Bozzola and Smale, 2020; Antonelli et al., 2022).

Irrigation can be considered as a tool to reduce production risk, especially the risk of drought. If large distances limit the adoption of irrigation, the variability of yields can be expected to increase. Foudi and Erdlenbruch (2012) show that irrigation technology serves as a form of self-insurance for French farmers and that irrigating farmers have higher means and lower variance of profits than non-irrigating farmers. Early detection of pests and diseases can significantly increase crop yield. Farmers might monitor remote plots less frequently for pests and diseases, suggesting an increased production risk for farms with larger farmstead-plot distances. Large sized plots might hamper the visual detection of pests and diseases because part of the fields may not be easily reached by humans (Kiraga et al., 2022).

Only a few studies assess the effect of LF on the risk of farms (Blarel, 1992; Goland, 1993; Kawasaki, 2010; Rao, 2019). Most use the Simpson index as a measure of LF (Blarel, 1992 for Rwanda; Kawasaki, 2010 for Japan; Rao, 2019 for Tanzania), an indicator which ignores the spatial aspects of LF. Furthermore, the Simpson index combines multiple fragmentation dimensions, which does not allow one to disentangle the potentially contrary effects of various dimensions of LF on farm performance. All of these previous studies find that an increase in LF in terms of the Simpson index is associated with a decline in output (per hectare) variability. Kawasaki (2010) finds that yield variability of rice farms in Japan declines as the number of parcels increases and Goland (1993) proves the effectiveness of field scattering as a risk buffering activity for Cuyo Cuyo farmers in Peruvian highlands.

3 METHODS

3.1 Measuring land fragmentation

In this subsection, we describe how LF is measured. Each farm i consists of K_{it} $(k=1,...,K_{it})$ plots in year t. The area of plot k and of farm i are denoted as a_k and A_{it}, respectively. The first LF measure informs the number of plots on the farm – the more plots the higher the degree of fragmentation:

$$nplots_{it} = K_{it} . \tag{1}$$

The above measure is likely the most frequently applied LF measure (Latruffe and Piet, 2014).[6] However, it fails to capture the spatial dimension of LF (Bentley, 1987). Therefore, and similar to Latruffe and Piet (2014), we apply two distance-based measures of LF. The first describes the average distance between the farmstead and the plots in kilometers, namely:

[6] The Simpson index (SI) is another common measure of LF. A higher value of the Simpson index (SI) is usually associated with a higher degree of fragmentation. However, the SI is an increasing function in the number of plots and a decreasing function in plot size variability (Monchuk and Deininger, 2010; Knippenberg et al., 2020). An increase in plot size variability is considered to reflect an increase in LF rather than a decrease (King and Burton, 1982). In addition, the SI is a decreasing function in average plot size (Knippenberg et al., 2020).

$$avfpd_{it} = \frac{1}{A_{it}} \sum_{k=1}^{K_{it}} a_k \sqrt{(w_k - \overline{w}_i)^2 + (z_k - \overline{z}_i)^2}\ , \tag{2}$$

where $\sqrt{(w_k - \overline{w}_i)^2 + (z_k - \overline{z}_i)^2}$ is the Euclidean distance between the farmstead of farm i and its k-th plot and (w_k, z_k) and ($\overline{w}_i$, $\overline{z}_i$) are the coordinates of the k-th plot and the farmstead, respectively. We weigh each farmstead-plot distance with the area of the plot to give more weight to distances travelled to larger plots and calculate an average by dividing by farm area.

The second distance-based measure relates to the scattering of plots across the farm or the distance between plots. We calculate the average nearest neighbor distance as follows:

$$avnnd_{it} = \frac{1}{K_{it}} \sum_{k=1}^{K_{it}} \arg\min_{l \neq k}^{K_{it}} \left(\sqrt{(w_k - w_l)^2 + (z_k - z_l)^2} \right), \tag{3}$$

where $\arg\min_{l \neq k}^{K_{it}} \left(\sqrt{(w_k - w_l)^2 + (z_k - z_l)^2} \right)$ is the distance of plot k to its next closest (neighboring) plot in kilometers and (w_k, z_k) and (w_l, z_l) are the coordinates of plot k and of plot $l \neq k$, respectively. Summing up the nearest neighbor distances for each plot and dividing by the number of plots, K_{it}, provides an average of the nearest neighbor distance across all plots on farm i.

3.2 Measuring and decomposing technical efficiency

Consider n farms each using m inputs to produce s outputs. For each farm i, $i \in \{1,...,n\}$ input and output vectors in period t, $t \in (1,...,T)$ are denoted as $\mathbf{x}_{it} = \left(x_{1it},...,x_{mit}\right)' \in \mathbb{R}$ and $\mathbf{y}_{it} = \left(y_{1it},...,y_{sit}\right)' \in \mathbb{R}$, respectively. The matrix $\mathbf{X}_t = (\mathbf{x}_{1t},...,\mathbf{x}_{nt}) \in \mathbb{R}$ denotes the matrix of inputs in period t and the matrix $\mathbf{Y}_t = (\mathbf{y}_{1t},...,\mathbf{y}_{nt}) \in \mathbb{R}$ denotes the matrix of outputs. The radial technical efficiency of farm i in period t is obtained by solving the following linear program (LP), which is the first phase of the well-known input-oriented CCR model (Charnes et al., 1978). We chose an input-orientation because agricultural inputs are more controllable by farmers than outputs.

$$\begin{aligned} &[\mathrm{CCR-I}] \quad \min_{\theta_{it},\boldsymbol{\lambda}_t} \ \theta_{it}^{CCR} \quad \text{subject to} \\ &\qquad \mathbf{s}_{it}^{-} = \theta_{it}^{CCR}\mathbf{x}_{it} - \mathbf{X}_t\boldsymbol{\lambda}_{it} \\ &\qquad \mathbf{s}_{it}^{+} = Y_t\boldsymbol{\lambda}_{it} - \mathbf{y}_{it} \\ &\qquad \boldsymbol{\lambda}_{it} \geq 0,\ \mathbf{s}^{-} \geq 0,\ \mathbf{s}^{+} \geq 0 \end{aligned}, \tag{4}$$

where $\boldsymbol{\lambda}_{it} \in \mathbb{R}$ is the intensity vector and $\mathbf{s}_{it}^{-}$ and $\mathbf{s}_{it}^{+}$ are the vectors of input slacks (input excesses) and output slacks (output shortfalls), respectively. The optimal vectors of slacks, $\mathbf{s}_{it}^{-*} = (s_{1it}^{-*},...,s_{mit}^{-*})$ and $\mathbf{s}_{it}^{+*} = (s_{1it}^{+*},...,s_{sit}^{+*})$, are obtained in the second phase, where we maximize the objective function

$\mathbf{es}_{it}^{-} + \mathbf{es}_{it}^{+}$ subject to the constraints in Eq. (4) with θ_{it}^{CCR} fixed at its optimum found in the first phase, i.e., $\theta_{it}^{CCR*} \in (0,1]$. θ_{it}^{CCR*} indicates the maximal radial reduction potential of all inputs that is feasible under the given constant returns to scale (CRS) technology in period t. We allow for technological change by estimating a separate production frontier for each year. Farms for which θ_{it}^{CCR*} is equal to one are Farrell-efficient (Farrell, 1957).

A well-known shortcoming of such radial measures of efficiency is that they ignore non-radial input reduction potentials given by $\mathbf{s}_{it}^{-*}$ and $\mathbf{s}_{it}^{+*}$. In the case of nonzero slacks, a Farrell-efficient farm is not Pareto-Koopmans efficient (Koopmans, 1951). While Farrell technical efficiency can be achieved without altering the input-mix (the proportions in which inputs are used), additional reduction potentials in some inputs – indicated by nonzero input-slacks – can only be attained by changing the input proportions. Hence, the inefficiency associated with any nonzero input-slacks in the above two-phase procedure is referred to as input-mix inefficiency.

Non-radial measures of efficiency (e.g., Färe and Lovell, 1978; Tone, 2001) provide one solution among others (Portela and Thanassoulis, 2006) to the problem of nonzero slacks DEA. Tone (1998) and Asbullah and Jaafar (2010) introduce non-radial measures of technical efficiency that can be separated into Farrell (radial) and mix efficiency. Using a simple numerical example, Mendelová (2022) shows that both approaches, for different reasons, may overestimate mix inefficiency and suggests a new measure and decomposition of technical efficiency that overcomes these shortcomings.

Following Mendelová (2022), we apply the following comprehensive measure of technical efficiency (TE_{it}) that can be divided into radial efficiency and input-mix efficiency (IME_{it}):

$$TE_{it} = \frac{1}{m}\sum_{r=1}^{m}\frac{\theta_{it}^{CCR*}x_{rit} - s_{rit}^{-*}}{x_{rit}} = \theta_{it}^{CCR*} - \frac{1}{m}\sum_{r=1}^{m}\frac{s_{rit}^{-*}}{x_{rit}}. \tag{5}$$

The ratio $\frac{\theta_{it}^{CCR*}x_{rit} - s_{rit}^{-*}}{x_{rit}}$ provides a measure of the efficient use of input r. Hence, TE_{it} indicates the mean maximal reduction potential over all inputs or the mean input efficiency. We observe that $TE_{it} \le \theta_{it}^{CCR*}$ and $TE_{it} = \theta_{it}^{CCR*}$ if and only if all input slacks are zero, i.e., there is no input-mix inefficiency. The input-mix efficiency measure $IME_{it} \in (0,1]$ is calculated as the ratio of TE_{it} over θ_{it}^{CCR*}, i.e., $IME_{it} = \frac{TE_{it}}{\theta_{it}^{CCR*}}$, which leads to the following separation of technical efficiency into the Farrell (radial) efficiency and input-mix efficiency: $TE_{it} = \theta_{it}^{CCR*} \times \frac{TE_{it}}{\theta_{it}^{CCR*}} = \theta_{it}^{CCR*} \times IME_{it}$.

Following Banker et al. (1984), we further divide the Farrell-type technical efficiency, i.e., θ_{it}^{CCR*}, into scale (SE_{it}) and pure technical efficiency (PTE_{it}). Pure technical efficiency evaluates the efficiency of a farm net of any impact of scale size. Estimating PTE_{it} requires solving Eq. (4)

by adding the convexity constraint $\mathbf{e}\boldsymbol{\lambda}_{it} = 1$, which allows for variable returns to scale (VRS) of the production technology (Afriat, 1972). The scale efficiency of farm i in period t is calculated at its observed constant mix of inputs and outputs as the ratio of the Farrell-type technical efficiency (CRS) over the pure technical efficiency (VRS), i.e., $SE_{it} = \frac{\theta_{it}^{CCR*}}{PTE_{it}} \in (0,1]$, which leads us to the following final equation of overall technical efficiency:

$$TE_{it} = \theta_{it}^{CCR*} \times IME_{it} = \frac{\theta_{it}^{CCR*}}{PTE_{it}} \times PTE_{it} \times IME_{it} = SE_{it} \times PTE_{it} \times IME_{it} \, . \tag{6}$$

Scale efficiency can be interpreted as a measure of how far the scale size of a farm is away from its socially optimal size (Sickles and Zelenyuk, 2019). The (observed) socially optimal scale size (or most productive scale size) is achieved when the average product (i.e., the output to input ratio) reaches its maximum. In other words, the amount of inputs required to produce one unit of output is minimized. The average product is maximized if farms operate under constant returns to scale (i.e., farms that are on the CRS production frontier have a scale efficiency score of one). Farms operating under decreasing returns to scale (DRS) or increasing returns to scale (IRS) can increase the average product by decreasing or increasing the size of operation, respectively.

3.3 Measuring (downside) risk efficiency

Now, we consider the primal (i.e., the multiplier model) of the LP shown in Eq. (4) (i.e., the envelopment model). Next, we substitute the output vector $\mathbf{y}_{it}$ and the input vector $\mathbf{x}_{it}$, as well as the corresponding matrices $\mathbf{Y}_t$ and $\mathbf{X}_t$, with the mean ($\mu_{i,b-c}$) and standard deviation ($\sigma_{i,b-c}$) of aggregate farm output over the period b to c, respectively:

$$\begin{aligned} [MYP] \qquad & \max_{v,u} \; RE_i = \frac{u\mu_{i,b-c}}{v\sigma_{i,b-c}} \qquad \textit{subject to} \\ & \frac{u\mu_{i,b-c}}{v\sigma_{i,b-c}} \le 1 \qquad (\forall\, i = 1,\ldots,N) \; . \\ & u \ge 0, v \ge 0 \end{aligned} \tag{7}$$

The fractional program in Eq. (7) resembles the DEA-model for the assessment of portfolio performance in Murthi et al. (1997).[7] In a similar vein, Tiedemann and Latacz-Lohmann (2011) apply this concept in the context of farm performance assessment. They integrate the standard deviation of aggregate farm output into DEA-models together with conventional inputs (i.e., land,

[7] They consider the risk-free return of a portfolio as the output and a measure of risk (i.e., the standard deviation of the portfolio returns) and transactions costs as inputs. The idea of such a DEA-model is to construct a portfolio frontier or a mean-variance efficient frontier in the spirit of Markowitz (1952). This frontier is spanned by efficient combinations of expected portfolio returns and portfolio risk, i.e., risk-return combinations that minimize the risk of a portfolio for a given level of expected return (or maximize the expected return for a given level of risk).

labor, and capital deprecation) and output and derive a measure of risk-adjusted (technical) efficiency.[8]

Since Eq. (7) represents a DEA-model with one input (standard deviation), one output (mean), and CRS, we do not need to solve this fractional program and can simplify the measurement of risk efficiency as follows:

$$RE_i = \frac{\mu_{i,b-c} / \sigma_{i,b-c}}{\max\limits_{i \in (1,..,N)} \left\{ \mu_{i,b-c} / \sigma_{i,b-c} \right\}} = \frac{(CV_{i,b-c})^{-1}}{\max\limits_{i \in (1,..,N)} \left\{ (CV_{i,b-c})^{-1} \right\}} \tag{8}$$

Risk efficiency, RE_i, is the ratio of the inverse of the coefficient of variation of aggregate farm output, denoted as $CV_{i,b-c}^{-1}$ ($= \mu_{i,b-c} / \sigma_{i,b-c}$), over the maximal observed $CV_{i,b-c}^{-1}$ across the sample. The coefficient of variation measures the dispersion of farm output around its mean (relative dispersion) and is considered as a measure of (relative) risk (Miller and Karson, 1977; Mahmoudvand and Oliveira, 2018) in the finance literature. El Benni et al. (2012) use the coefficient of variation of gross farm revenues and total household income to study revenue and income risk in Swiss agriculture. A farm is risk efficient ($RE_i = 1$) if it has the lowest coefficient of variation of farm output in the sample. Risk efficiency decreases with increasing (relative) dispersion of farm output and takes on values between zero and one, i.e., $RE_i \in (0,1]$. To put it differently, RE_i measures the distance between the i-th farm's (relative) output dispersion and the lowest (relative) output dispersion observed in the sample.

By using the standard deviation of output in Eq. (8), the risk efficiency measure takes into account positive and negative fluctuations around the mean. While positive deviations are acceptable by farmers, avoiding negative fluctuations of output might be more important to them. Therefore, we calculate downside risk efficiency (DRE_i) by substituting the standard deviation in Eq. (8) with the negative semi-deviation of output (Markowitz, 1959), a measure that only considers below-mean output fluctuations.

3.4 Explaining variations in technical efficiency and risk efficiency

In the 2nd-stage of our analysis, we explore how LF and other factors affect the various measures of efficiency. For this purpose, we consider the following two models:

$$E_{it} = \max\left\{1,\ \alpha + \beta \mathbf{Z}_{it} + \gamma \mathbf{F}_{it} + \delta \mathbf{D_t} + \nu_i + \varepsilon_{it}\right\} \qquad i = 1,...,n \quad t = 1,....,T \text{ ; and} \tag{9}$$

$$E_{i,b-c} = \max\left\{1,\ \phi + \eta \bar{\mathbf{W}}_{i,b-c} + \lambda \bar{\mathbf{F}}_{i,b-c} + \omega_{i,b-c}\right\} \qquad i = 1,...,n \quad b...base\ year \quad c...current\ year\ , \tag{10}$$

[8] Our model departs from the DEA-model in Tiedemann and Latacz-Lohmann (2011). While they derive a risk-adjusted measure of technical efficiency that also includes conventional inputs in the DEA-model, we want to assess (pure) risk efficiency of farms in the spirit of Modern Portfolio Theory or mean-variance analysis (Markowitz, 1952), and therefore exclude conventional inputs in the DEA-model. Another DEA-approach that incorporates risk into the measurement of technical efficiencies (of financial intermediaries in rural Taiwan) is that of Chang (1999). He considers some risk indicators as undesirable (weakly disposable) outputs in the DEA-model to derive risk-adjusted (technical) efficiency measures.

where E_{it} in Eq. (9) is either the technical, scale, pure technical, or input-mix efficiency index for the i-th farm in period t and $E_{i,b-c}$ in Eq. (10) is the (downside) risk efficiency index measured over the period b to c for the i-th farm. We calculate temporal means of variables for each farm over period b to c and collect them in vectors denoted with an overbar. $\mathbf{F}_{it}$ and $\bar{\mathbf{F}}_{i,b-c}$ are vectors of LF indices and vectors of time means of LF indices over the period b to c, respectively. γ and λ are the parameters of primary interest.

We investigate the following specification regarding $\mathbf{F}_{it}$ and $\bar{\mathbf{F}}_{i,b-c}$ for each efficiency index: $\mathbf{F}_{it} = [nplot_{it}, avfpd_{it}, avnnd_{it}]$ and $\bar{\mathbf{F}}_{i,b-c} = [\overline{nplot_{i,b-c}}, \overline{avfpd_{i,b-c}}, \overline{avnnd_{i,b-c}}]$.[9] Using multiple LF indices in one model allows us to disentangle the (potentially diverging) effects associated with different dimensions of LF.[10] No single indicator exists that could capture all of these dimensions (Bentley, 1987). $\mathbf{F}_{it}$ and $\bar{\mathbf{F}}_{i,b-c}$ cover the number of plots, the average farmstead-plot distance, and the average nearest distance between plots.

$\mathbf{Z}_{it}$ and $\bar{\mathbf{W}}_{i,b-c}$ are vectors of control variables and β and η are the corresponding parameters to be estimated. In all estimated specifications, $\mathbf{Z}_{it}$ and $\bar{\mathbf{W}}_{i,b-c}$ include a control for farm area measured as utilized agricultural area (UAA) in hectares. Regarding the *ceteris paribus* assumption in regression models, an increase in the number of plots while holding farm area constant would imply a decrease in average plot size. Hence, average plot size as one dimension of LF is not an explicit variable in our model. Instead, it is implicitly considered by simultaneously controlling for the number of plots and the UAA. In addition to farm size and based on findings in previous studies on the determinants of farm efficiency (cf. Latruffe, 2010; Latruffe and Piet, 2014) and risk (cf. El Benni et al., 2012; Rao, 2019), we decide to include in both $\mathbf{Z}_{it}$ and $\bar{\mathbf{W}}_{i,b-c}$ variables that control for farm specialization (Herfindahl index), off-farm income (proxied by the share of mangers' off-farm labor), and subsidies (subsidies per hectare). In addition, $\mathbf{Z}_{it}$ includes controls for the share of rented land, share of family labor, average soil quality, average slope of plots, farm mangers' age, gender, and education, as well as a dummy for organic farming. $\bar{\mathbf{W}}_{i,b-c}$ additionally controls for plot heterogeneity (CV of soil quality of plots and CV of the slope of plots), crop diversification (Shannon crop diversification index), and pesticide expenditures per hectare.

Eq. (9) accounts for unobserved common year-specific effects across farms by a set of $T-1$ time dummy variables collected in the vector $\mathbf{D_t}$ and for unobserved time-invariant farm-specific (random) effects v_i independent and identically distributed (i.i.d) $N(0,\sigma_v^2)$. ε_{it} is the idiosyncratic error term i.i.d. $N(0,\sigma_\varepsilon^2)$ independently of v_i. Given $E_{it} \leq 1$, Eq. (9) is a censored regression model

[9] We also estimate models i) where we substitute the number of plots with average plot size (results are available in Table C1 and Table C2 in the supplementary material) and ii) where we add quadratic terms of LF indices to investigate potential non-linear effects (results are available in Table D1 and Table D2 in the supplementary material).

[10] A correlation matrix for farm size (UAA in hectares) and LF indices (available in Table A1 in the supplementary material) and OLS-model diagnostics based on variance inflation factors (VIF) suggest that multicollinearity is of little concern in our specifications. All VIFs are below 3.63.

applied to panel data with random effects. Therefore, we apply the random-effects[11] Tobit model that accommodates censoring and within-cluster dependence of outcome variables (Greene 2018). We estimate Eq. (9) with maximum likelihood (ML) using the *xttobit* command in Stata 16, generating estimates of the parameters $(\alpha, \beta, \gamma, \delta, \sigma_v^2, \sigma_\varepsilon^2)$.[12] Regarding Eq. (10), $\omega_{i,b-c}$ is an idiosyncratic error term i.i.d. $N(0, \sigma_\omega^2)$. Since $E_{i,b-c} \leq 1$, we apply the Tobit model using the *tobit* command in Stata generating parameter estimates of $(\phi, \eta, \lambda, \sigma_\omega^2)$.

4 DATA

We use different sources to construct the dataset for our analysis: First, we apply plot-level data from the Austrian Integrated Administration and Control System (IACS) to construct LF indices. Second, for estimating technical and risk efficiencies, economic and physical data on inputs and outputs of farm production are extracted from the Austrian section of the Farm Accountancy Data Network (FADN). Control variables for the 2nd-stage DEA originate from both sources.

4.1 Sample selection

The period of investigation is 2009–2012 for the technical efficiency analysis because the necessary information for calculating the LF indices in Eq. (1)–Eq. (3) is only available for these years. The FADN is a rotating and stratified sample of Austrian farms consisting of about 2,200 farms per year or ~ 2% of all farms in Austria. We focus on crop farms whose revenues from crops account for more than 50% of total farm revenues net of subsidies each year. Farms are excluded if the difference between the UAA reported in the FADN and IACS is larger than 10%. We only consider farms for which we have information on location and geophysical characteristics for at least 85% of their plots. We also exclude farms that farm only one plot. We exclude farms whose total area declared by the famer in the IACS was 10% or more different from the area obtained by summing up the areas of each individual plot of the farm. Due to the potential sensitivity of DEA to outliers (Dyson et al., 2001), we apply the data cloud method (Bogetoft and Otto, 2011: pp. 149–153) and detect 11 outlying observations which are excluded from the sample. We also remove some observations due to missing information for some variables. The final sample is an unbalanced panel of 323 farms from 2009 to 2012 with 1,061 observations.

The risk efficiency analysis is based on a balanced panel of 181 farms – a subsample of the 323 farms considered in the technical efficiency analysis – for which we have data, except for LF indices, for all years from 2007 to 2014. Risk efficiency scores refer to the period 2007–2014 and are regressed on time means of LF indices calculated over the 2009–2012 period. Since LF is an almost time-invariant variable (slowly changing), we expect that including the years 2007–2008 and 2013–2014 for calculating the time mean of LF indices would not affect our results.

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[11] Since we are interested in the effects of slowly changing variables, i.e., LF indices, a fixed-effects estimator is inappropriate for short panels due to the high variance of the estimated parameters, i.e., inefficiency (Plümper and Troeger, 2007).

[12] The ML estimator of the parameter estimates in Eq. (9) is consistent and asymptotically unbiased (Banker and Natarajan, 2008). Another popular approach in the 2nd-stage DEA is to combine truncated regression with bootstrap methods (Simar and Wilson, 2007). Although Banker et al. (2019) show that "the effectiveness of the Simar-Wilson approach critically depends on the assumptions of the data generating process (DGP)."

4.2 Plot-level data from the Integrated Administration and Control System

The Austrian IACS contains plot-level information for all farms receiving direct payments under the Common Agricultural Policy of the EU. Land data in IACS are collected on two levels of aggregation: reference parcels (fields) and agricultural parcels (plots). Plots are pieces of land that are farmed with a single crop. Fields may contain several plots and thus different crop types. The average field of a crop farm consists of 1.17 plots. Hence, plot- and field-level are often identical.

IACS data provides plot-level information on area (plot size), planted crop, geophysical characteristics (slope gradient, altitude, and soil quality), and location allowing for the calculation of LF indices and control variables. Basic farm information, e.g., on the location of the farmstead, complements the dataset. To calculate the LF indices shown in Eq. (1)–Eq. (3), we only consider plots less than 7.49 km[13] away from the farmstead. Section B of Table 2 indicates that the average farm has 41 plots (with an average size of 1.50 ha), the mean average distance between the farmstead and the plots is 1.62 kilometers, and the mean average distance of a plot to the next closest plot is about 360 meters. Control variables derived from IACS plot-level data include average plot characteristics (i.e., average soil quality and average slope gradient of farm plots) and their relative dispersion measured by the coefficient of variation (descriptive statistics are available in Table B1 and Table B2 in the supplementary material).

4.3 Farm accountancy data

We measure farm output (gross output or revenues) as the sum of earnings from plant production, livestock, forestry, agricultural services, direct marketing, and other activities related to farming, net of subsidies. Labor is measured in annual working units (AWU) including family and hired workers, where one AWU is approximately 2,160 working hours per year. Land is measured by utilized agricultural area (UAA) in hectares and includes owned and rented land. Capital measures the average of a farm's capital stock at the beginning and end of the year, including farm buildings, machinery, equipment, standing timber, livestock, and assets from activities related to farming (e.g., agri-tourism, renting out machinery, and providing services to other farms). Materials cover expenditures for land use (e.g., seeds, fertilizer, and pesticides), livestock (e.g., fodder and veterinary), energy, and expenditures for other activities related to farming. Nominal gross output components, capital, and materials values are divided by appropriate price indices from the Austrian Statistical Office to derive implicit quantity values that are measured in constant (2009) Euros.

In the risk efficiency analysis, we are not interested in an implicit quantity index as a measure of farm output. Instead, we derive a measure of farm output that reflects both fluctuations in prices and quantities of farm output, i.e., we want to consider price and production risk in the analysis. Therefore, similar to Tiedemann and Latacz-Lohmann (2011) and El Benni et al. (2012), we deflate nominal revenues (net of subsidies) from farming activities with the Austrian consumer price index from Statistics Austria to make farm revenues comparable across years. Based on inflation-adjusted farm revenues, we calculate average revenues, the standard deviation, and negative semi-deviation of revenues over the period 2007 to 2014 for each farm.

[13] Nearly all (97.5%) of the plots of farms participating in the Austrian section of the Farm Accountancy Data Network are less than 7.49 km away from the farmstead. Larger farmstead-plot distances probably indicate that the corresponding plot is not accessed from the farm building for which we have the geo-coordinates. Such plots could be accessed from a secondary farm building or cultivated by a sub-contractor.

Table 2
Summary statistics of selected variables used in the two-stage Data Envelopment Analysis

	Arithmetic mean	Standard deviation	5th percentile	95th percentile
A: Variables used in 1st-stage DEA technical efficiency estimation (n = 1,061)				
Inputs				
Labor (AWU)	1.09	0.71	0.25	2.19
Capital (real, 2009 Euros)	179,169.22	137,003.14	35,607.09	438,750.50
Utilized agricultural area (hectare)	58.03	38.64	12.95	130.07
Material (real, 2009 Euros)	34,280.43	25,863.97	8,428.29	8,1510.24
Output				
Revenue (real, 2009 Euros)	58,736.86	46,926.97	10,702.30	149,433.15
B: Variables used in the 2nd-stage DEA for explaining variations in technical efficiency (n = 1,061)				
Land fragmentation				
Number of plots	41.45	30.85	13.00	90.00
Average farmstead-plot distance (kilometer)	1.62	0.85	0.38	3.02
Average nearest neighbor distance (kilometer)	0.36	0.20	0.14	0.76
C: Variables used in 1st-stage DEA risk efficiency estimation (n = 181)				
$\overline{\text{Revenue}_{07\text{-}14}}$ (2009 Euros)	80,467.63	62,280.40	19,023.25	175,152.79
$SD_{07\text{-}14}$ of revenue (2009 Euros)	18,121.92	13,303.86	3,860.62	45,824.80
Neg. semi-$dev_{07\text{-}14}$ of revenue (2009 Euros)	11,591.25	8,996.24	2,423.52	25,544.80

Note: Sections A and B show descriptive statistics for an unbalanced panel of 323 farms from 2009 to 2012 with 1,061 observations. Section C shows descriptive statistics for 181 farms, with farm-year averages reported with an overbar. The period over which farm-year averages, standard deviations, and semi-deviations of farm revenue are calculated is 2007 to 2014 as indicated by the subscript 07-14. AWU is agricultural working unit. Descriptive statistics on the full set of variables used in the 2nd-stage DEA to estimate Eq. (9) and Eq. (10) are available in Table B1 and Table B2 in the supplementary material, respectively.

Sections A and C in Table 2 provide summary statistics on variables used to calculate efficiency scores. Mean gross output (in 2009 Euros) in the 2009–2012 panel is 58,736 Euros (net of subsidies). For 90% of farms, real revenue ranges between 10,702 Euros and 149,433 Euros. The average farm has an UAA of 58 hectares and the 5th and 95th percentile is 13 hectares and 130 hectares, respectively. Capital and labor vary considerably, with a mean value of 179,169 Euro and 1.09 AWU, respectively. Mean revenue, standard deviation, and negative semi-deviation (all in 2009 Euros) over the period 2007 to 2014 for the average farm is 80,467 Euros, 18,121 Euros, and 11,591 Euros, respectively. Summary statistics on the full set of variables used in the 2nd-stage DEA are available in Tables B1 and B2 in the supplementary material.

5 RESULTS

5.1 Efficiency scores

Table 3 provides information about the distribution of the efficiency scores. On average, technical efficiency (TE), scale efficiency (SE), pure technical efficiency (PTE), input-mix efficiency (IME), risk efficiency (RE), and down-side risk efficiency (DRE) is 0.52, 0.84, 0.67, 0.94, 0.45, and 0.39, respectively. This indicates that PTE is the main driver of TE, followed by SE. IME plays a minor role: 5%, 5%, 11%, and 36% of farm-year observations are technically, scale, pure technically, and input-mix efficient, respectively. The average RE and DRE is 0.45 and 0.39, respectively. The coefficient of correlation between the two scores is rather high, i.e., 0.94.

Table 3
Descriptive statistics of efficiency scores

	Geometric mean	Standard deviation	5th percentile	95th percentile	number of efficient observations
Technical efficiency and components (n = 1,061)					
Technical efficiency (TE)	0.52	0.20	0.26	1.00	55
= Scale efficiency (SE)	0.84	0.17	0.50	1.00	55
× Pure technical efficiency (PTE)	0.67	0.18	0.43	1.00	115
× Input-mix efficiency (IME)	0.94	0.07	0.80	1.00	380
Risk efficiency (n = 181)					
Risk efficiency (RE)	0.45	0.15	0.21	0.67	1
Down-side risk efficiency (DRE)	0.39	0.13	0.21	0.62	1

Note: RE and DRE scores refer to the period 2007–2014. TE, SE, PTE and IME refer to the period 2009-2012.

5.2 Effect of land fragmentation on technical efficiency

Table 4 provides the estimates of Eq. (9) regarding the determinants of TE and its components from random effects tobit models. The coefficient estimates and standard errors of LF indices and farm size are shown. Efficiency scores are multiplied by 100 and should be interpreted as percent. Full regression results are available in Table C1 of the supplementary material.

The panel-level variance (σ_{ν}^2) is high compared to the residual variance (σ_{ε}^2) throughout models (1) to (4), indicating that unobserved time-invariant farm specific effects are important. A likelihood-ratio test in the last row of Table 4 compares the pooled estimator with the panel estimator. We reject the null hypothesis that there are no panel-level effects at the 0.1% significance level. Pooled OLS estimates suggest a relatively good fit of the SE-model ($R^2 = 0.47$), but a large share of variability in PTE ($R^2 = 0.12$), the main driver of TE ($R^2 = 0.29$) remains unexplained.

Table 4 reports statistically significant and negative relationships between i) the number of plots as well as ii) the average farmstead-plot distance and farms' TE. The coefficient estimate for the average nearest neighbor distance is positive, but its high standard deviation does not allow the rejection of the null-hypothesis that the scattering of plots has no effect on TE. Our results are in line with the findings of Monchuk et al. (2010) for a sample of Indian farms: They report that the number of plots have a negative impact on productivity, but that the spatial separation of plots does not significantly impact productivity when controlling for the number of plots.

Model (1) in Table 4 shows that, everything else being equal, an increase in the *number of plots* by 10 decreases TE by 1.6 percentage points, on average. This effect is statistically significant at the 1% level. Holding farm area constant, increasing the number of plots coincides with decreasing average plot size. Hence, our estimates suggest a positive effect of average plot size on technical efficiency. Plot number (average plot size) has a statistically significant and negative (positive) effect on both SE (significant at the 10% level) and PTE (significant at the 5% level). Our results indicate that fewer or larger plots allow for a better exploitation of returns to scale. Farming multiple plots could affect PTE via increasing managerial effort (i.e., more time is devoted to organizing activities) and resource use per hectare, as well as decreasing yields.

Table 4
Determinants of technical efficiency and its components

	Dependent variable			
	(1)	(2)	(3)	(4)
	TE×100 (percent)	SE×100 (percent)	PTE×100 (percent)	IME×100 (percent)
Number of plots	-0.157***	-0.066*	-0.125**	0.023
	(0.046)	(0.035)	(0.053)	(0.022)
Average farmstead-plot distance (kilometer)	-2.992**	0.814	-4.658***	-0.106
	(1.172)	(0.882)	(1.349)	(0.569)
Average nearest neighbor distance (kilometer)	3.473	-0.903	7.812	3.227
	(3.883)	(2.773)	(5.430)	(2.023)
Farm Size, UAA (hectare)	0.144***	0.145***	0.063	-0.028
	(0.038)	(0.029)	(0.043)	(0.018)
σ_{ν}^{2}	13.572***	10.849***	16.426***	5.703***
	(0.682)	(0.530)	(0.802)	(0.354)
σ_{ε}^{2}	11.039***	7.375***	10.324***	6.311***
	(0.299)	(0.203)	(0.288)	(0.214)
Number of observations	1,061	1,061	1,061	1,061
Number of right-censored observations	55	55	115	380
Number of farms	323	323	323	323
p-value for H_0: no panel-level effects	0.000	0.000	0.000	0.000

Note: Dependent variables are efficiency scores multiplied by 100. TE, SE, PTE, and IME is technical efficiency, scale efficiency, pure technical efficiency, and input-mix efficiency, respectively. UAA is utilized agricultural area. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Coefficient estimates from random effects tobit models are reported with standard errors in parentheses. All models include a constant, time dummies, and controls for average soil quality of plots, average slope gradient of plots, and farm manager's age, gender, and education, as well as share of rented land, share of off-farm labor, share of family labor, subsidies per hectare, farm specialization (Herfindahl index), and organic farming. Full results are available in Table C1 in the supplementary material.

Increasing the *average farmstead-plot distance* by one kilometer reduces TE by ~3.0 percentage points, on average (significant at the 5% level). Longer average farmstead-plot distances have no significant effect on SE and IME, but affect TE through lowering PTE. Irrespective of farm size, the efficient use of resources becomes more difficult as average farmstead-plot distances increase. Longer distances increase transportation costs and aggravate water management. In addition, results might reflect wasting inputs due to leakage and evaporation during travel.

We find a positive but statistically insignificant relationship between the *average nearest neighbor distance* ($avnnd_{it}$) and TE. This relationship is driven by a positive coefficient estimate of $avnnd_{it}$ on PTE. The results are comparable to the findings in Latruffe and Piet (2014): They report a positive and statistically significant relationship between the normalized nearest neighbor distance and PTE, but no statistically significant effect on TE. Potential negative effects of longer distances between plots on TE could be compensated by higher yields through reduced production risk and cropping pattern optimization (cf. Latruffe and Piet, 2014).

5.3 Effect of land fragmentation on risk efficiency

Table 5 provides estimation results of Eq. (10) with risk efficiency (RE) and downside risk efficiency (DRE), both multiplied by 100, as the dependent variable. Full regression results are available in Table C2 in the supplementary material. All coefficients of control variables have the expected sign (cf. El Benni et al., 2012; Rao, 2019), except for the CV of slope gradient of plots, farm size, and farm specialization (Herfindahl) index. The latter could be due to the high degree of specialization of farms in our sample and the low variability of this variable. OLS-estimates of models (1) and (2) in Table 5 indicate a R^2 of 0.17 and 0.15, respectively. Stochastic environmental factors seem to be responsible for a great part of variability in (D)RE.

Table 5
Determinants of (downside) risk efficiency

	Dependent variable	
	(1) RE×100 (percent)	(2) DRE×100 (percent)
$\overline{\text{Number of plots}_{09\text{-}12}}$	0.106**	0.120**
	(0.052)	(0.047)
$\overline{\text{Average farmstead-plot distance}_{09\text{-}12}}$ (kilometer)	-2.392	-2.526*
	(1.583)	(1.454)
$\overline{\text{Average nearest neighbor distance}_{09\text{-}12}}$ (kilometer)	17.056**	10.932*
	(6.953)	(6.380)
$\overline{\text{Farm\_size}_{07\text{-}14}}$, $\overline{\text{UAA}_{07\text{-}14}}$ (hectare)	-0.033	-0.039
	(0.041)	(0.037)
/		
σ_{ω}^{2}	179.56***	151.56***
	(18.968)	(16.014)
Number of observations	181	181
Number of right-censored observations	1	1

Note: Dependent variables are efficiency scores multiplied by 100. RE is risk efficiency and DRE is downside risk efficiency. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. Coefficient estimates from tobit models are reported with standard errors in parentheses. Variables with an overbar represent time averages. The period over which time averages are calculated is denoted by subscripts, i.e., 07-14 and 09-12 for the period 2007–2014 and 2009-2012, respectively. Risk efficiency scores refer to the period 2007–2014 and are regressed on time means of LF indices calculated over the 2009–2012 period. Time means of all other covariates refer to the period 2007–2014. All models include a constant and controls for pesticide expenditures per hectare, crop diversification (Shannon crop diversity index), the share of mangers' off-farm labor, subsidies per hectare, CV of soil quality of plots, CV of slope of plots, and farm specialization (Herfindahl index). Full results are available in Table C2 in the supplementary material.

Table 5 indicates a positive and statistically significant relationship between LF and risk efficiencies, except for the average farmstead-plot distance: On average, increasing the *number of plots* by 10 (which corresponds to a 22% increase for the average farm) lifts DRE and RE by 1.1 and 1.2 percentage points, respectively. An increase in the *average nearest neighbor distance* by 80 meters (a 22% increase for the average farm), suggests an improvement in RE by 1.4 percentage points, but a smaller effect on DRE. To put this in some perspective, an increase in pesticide expenditures per hectare by 15.20 Euros (a 22% increase for the average farm) tends to increase RE by 1.2 percentage points, on average. Increasing the *average farmstead-plot distance* by 361 meters (a 22% increase for the average farm) reduces RE by 0.9 percentage points**,** on average. An explanation could be that farmers visit more distant plots less frequently. This delays the detection of risks (e.g., pests, diseases, and water stress) and the implementation of countermeasures resulting in higher yield variability. Our results confirm the hypothesis that LF can reduce production and price risk and are in line with results in previous studies (Blarel, 1992; Goland, 1993; Kawasaki, 2010; Rao, 2019). We find a risk reducing effect from the number of and scattering of plots.

5.4 Summary of results

Table 6 shows the difference in the predicted TE and RE between the 95th and 5th percentile of each LF index. More plots are associated with lower TE, but provide benefits in terms of improved RE. Longer average distance between farmstead and plots is detrimental to both TE and RE. Larger distances between plots are associated with higher RE: the difference in predicted efficiency between the 95th and 5th percentile of the average nearest neighbor distance is 10.6 percentage points. The effect of this dimension of LF on TE is slightly positive, but statistically insignificant.

Table 6
Effect of land fragmentation on technical and risk efficiency measured as the difference in predicted efficiency between the 95th and 5th percentile of respective land fragmentation index

Land fragmentation index	Effect on TE×100 (percent)	Effect on RE×100 (percent)
Number of plots	-12.09	8.16
Average farmstead-plot distance (kilometer)	-7.90	-6.31
Average nearest neighbor distance (kilometer)	2.15	10.57
Farm size, UAA (hectare)	16.87	-3.86
Number of observations	1,061	181

Note: TE and RE is technical and risk efficiency, respectively. UAA is utilized agricultural area. Effects are reported in percentage points.

6 CONCLUSION

Using a panel dataset covering the years 2007–2014, we evaluate the effect of multiple dimensions of land fragmentation (LF) on the technical efficiency (TE) and risk efficiency (RE) of Austrian crop farms by Data Envelopment Analysis. TE is decomposed into i) scale efficiency, ii) pure technical efficiency, and iii) input-mix efficiency. RE, a concept borrowed from modern portfolio theory, measures the performance of a farm relative to a mean-variance frontier.

We find that farms with more plots and a larger average distance from farmstead to plots tend to be less technically efficient. The scattering of plots, having no statistically significant effect on TE, and a higher number of plots provide benefits in terms of lower agricultural output variability. When decreasing the number of plots (or increasing average plot size), farmers face a trade-off between higher TE and lower RE. Reducing the average farmstead-plot distance could provide a double dividend by raising both TE and RE.

In the Western European context, it is reasonable that from the farmers' perspective, the costs of LF (lower income/profits) outweigh its benefits (lower production and price risk): Labor costs are high in Austria, as well as costs for energy due to a high degree of mechanization. The EU's

Common Agricultural Policy provides a basic level of income to farmers in the form of direct payments based on area, where the EU average share of direct payments in agricultural factor income in the 2017–2021 period stood at 23%. Beyond direct payments, Western European farmers have access to a wider array of risk management tools than their peers in developing countries: e.g., access to storage, credit, pesticides, fertilizers, subsidized insurance schemes, off-farm employment opportunities, and automated pest and disease detection.

LF is an obstacle for resource-sparing crop production in Austria. Reducing the number of plots per farm and distances from the farmstead to plots can improve resource-efficiency and competitiveness of Austrian crop farms. These benefits might be realized by land consolidation schemes as a partially publicly financed task, but also by other voluntary land exchange arrangements between farmers. Increasing shares of rental land and ownership fragmentation may require reducing disincentives to landowners for participating in land consolidation schemes. Functioning land markets can support land consolidation. We suggest increasing land-mobility through providing incentives to landowners (tenants) for leasing out (renting in) and selling (buying) land.

Land consolidation schemes should not only consider the private costs and benefits to farmers, but also public costs and benefits associated with LF, such as increased biodiversity and resilience of the agricultural sector, but also higher levels of greenhouse gas emissions and potential road safety issues. Future research should quantify and compare the public costs and benefits of LF. Evaluating the effect of LF on ecological farm performance could be an interesting avenue of future research.

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