Part-Time Farming and Scale Efficiency

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Abstract

While many studies have compared the technical efficiency of part-time and full-time farms, we add to the existing literature by extending this analysis to scale efficiency. Based on a sample of crop farms in Austria between 2010 and 2017, we find that part-time farms are more scale efficient when they are evaluated with respect to their production technology and the difference in scale efficiency between part-time and full-time farms increases over time. Although we do not find any significant difference in technical efficiency, full-time farms have a higher technological change. Furthermore, an analysis of the determinants of scale efficiency confirms that factors facilitating farm growth also increase scale efficiency.

Keywords

part-time farming; scale efficiency; stochastic frontier analysis; crop farms; Austria

1 Introduction

In most areas of the world, including the European Union (EU), farming is characterized as predominantly small family businesses with a significant share of farm managers and other family members working part-time on the farm while also participating in off-farm employment. Within the EU, combining part-time farming with other gainful activities has increased its prominence as an essential element of farmer's business strategy (EUROPEAN COMMISSION, 2013). Part-time farming is related to the size of the farm (GIOIA, 2017). Given a steady increase in labor productivity, farms need to increase their size to employ the same amount of annual working units (AWUs). In this setting, part-time farming has been identified as i) a long-term survival strategy (GASSON, 1986; KIMHI and BOLLMAN, 1999); ii) a stepping stone on the way out of the farm sector (e.g., for older farmers without a successor) (KIMHI, 2000; STIGLBAUER and WEISS, 2000; WEISS, 1999a); iii) a first step into farming by new entrants (GASSON, 1986;); iv) an expression of the bond with the occupation and continuation of an ongoing family farming tradition (e.g., a successor with a university degree in agricultural sciences could take over the full-time farm of the parents as a part-time farmer while also working off-farm as an extension specialist) (GLAUBEN et al., 2004); or v) a means of facilitating structural reform of the farm sector (PFEFFER, 1989; WEISS, 1999b), i.e., a necessity given increasing labor productivity and constraints in factor markets (SCHMITT, 1988). While capital constraints might be less of a problem in most Western European countries, land availability is a major constraint. Land sales markets are relatively thin in most EU countries (CIAIAN et al., 2016), which often makes land rental the only alternative to obtain additional land (CIAIAN et al., 2012).

Over the last five decades, farm subsidies, including the coupled and decoupled payments of the Common Agricultural Policy (CAP), have incentivized farms to stay in the sector part-time rather than exit (BREUSTEDT and GLAUBEN, 2007; GOETZ and DEBERTIN, 2001; RAGGI et al., 2013).[1] Additionally, through income and insurance effects, subsidies can change the working motivation of farmers, increase investments in new technologies, and change allocations of inputs and outputs, which could have impacts on the economic performance of farms (ZHU and LANSINK, 2010). Given the high share of part-time farms in the EU and other developed countries and the sizeable budget spent on agriculture, it seems pertinent to ask how part-time farms perform compared to full-time farms. There is a considerable amount of literature investigating the impact of off-farm labor participation on technical efficiency (AHMED and MELESSE, 2018; CHAVAS et al., 2005; COELLI et al., 2002; GOODWIN and MISHRA, 2004). While some

[1] As a reviewer correctly pointed out, subsidies are not the only incentives to continue unprofitable farming. The possibility of inheriting a farm or specific taxation laws are other examples. However, we cannot cover these other incentives due to a lack of data.

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studies find a negative impact (BRÜMMER, 2001; KILIC, et al., 2009; KELLERMANN et al. 2011; SABASI et al., 2019), others find a positive impact (BJØRNSEN and MISHRA, 2012; BOJNEC and FERTŐ, 2013; PFEIFFER et al., 2009), and some find no impact (BAGI, 1984; CHANG and WEN, 2011; LIEN et al., 2010). A few studies (CHAVAS et al., 2005; COELLI et al., 2002; SHITTU, 2014) investigate the impact of off-farm labor on allocative and production efficiency. Only a few studies compare the technical efficiency of part-time and full-time farms (BAGI, 1984; CHANG and WEN, 2011). To the best of our knowledge, CHAVAS et al. (2005) is the only study explicitly estimating scale efficiency for part-time farms. However, they do this in a very different context, namely for farm households in the Gambia, and do not compare the scale efficiency between part-time and full-time farms. Therefore, the aim of this study is to: i.) estimate and compare the scale and technical efficiency of part-time and full-time farms utilizing an unbalanced panel of 344 crop farms in Austria; and ii) investigate the impacts of farm manager characteristics (e.g., experience, education level), farm organizational and technological characteristics (e.g., owned land shares, capital intensity), and environmental factors (e.g., soil quality, altitude) on the scale efficiency of these farms.

The remainder of this paper is organized as follows: Section 2 presents a short literature review and develops some hypotheses regarding the impact of different determinants on scale efficiency; Section 3 introduces the empirical model; Section 4 provides some information on part-time farming in the EU and Austria and describes our data; Section 5 presents the empirical results and discussions; and Section 6 provides concluding remarks.

2 Theoretical Background

2.1 Literature Review

Given the high share of part-time farms in the EU and other developed countries, several studies have investigated the effect of off-farm labor and part-time farming on at least three different dimensions of farm performance: i) farm exit and succession; ii) farm household income and welfare; and iii) farm efficiency. A frequently asked question is whether part-time farming is a steady-state phenomenon or the first step of the farm out of the agricultural sector (GASSON, 1986; PFEFFER, 1989). While BREUSTEDT and GLAUBEN (2007), KIMHI (2000), and KIMHI and BOLLMAN (1999) find that participation in off-farm labor decreases the probability of the farm to exit the sector, PAROISSIEN et al. (2021), STIGLBAUER and WEISS (2000), and WEISS (1999a, 1999b) find the opposite. Moreover, a lower likelihood of children to follow in the farm occupation is reported for part-time farms by ENGELHART et al. (2018), GASSON et al. (1988), LARCHER and VOGEL (2019), STIGLBAUER and WEISS (2000) and VOGEL (2006).

Regarding farm household income and welfare, KHANAL and MISHRA (2014) investigate agritourism and off-farm work participation decisions as alternative choices for income diversification. An important finding of their study is that small farms have higher household income if they choose both income diversification strategies rather than a single strategy. CHANG and MISHRA (2008) assess the impact of off-farm labor decisions by the operator and spouse on the farm household's food expenditures. They find that working off-farm affects food expenditures in different ways. The operator's off-farm work is positively related to food expenditures, while the spouse's decision is negatively associated with food expenditures. BABATUNDE and QAIM (2010) investigate the impact of off-farm income on different dimensions of food security and nutrition. They find that off-farm income has a positive effect. Moreover, off-farm income contributes to higher food production and farm income by easing capital constraints, thus improving household welfare in multiple ways.

Most related to our work are studies investigating the effect of off-farm labor participation and part-time farming on the efficiency of farms. GOODWIN and MISHRA (2004) define efficiency as gross cash income over total variable costs and report a statistically significant inverse relationship between off-farm work and efficiency among U.S. farms. Several studies use stochastic frontier analysis (SFA) or data envelopment analysis (DEA) to derive results regarding technical efficiency. Based on a farm household model, SABASI et al. (2019) show theoretically that an increase in farm household off-farm work decreases technical efficiency. They confirm this result empirically for U.S. dairy farms. For Slovenia, BRÜMMER (2001) finds that full-time farms are more technically efficient than part-time farms. COELLI et al. (2002) report a consistently negative impact of the share of off-farm labor on technical efficiency, allocative efficiency, and cost efficiency (i.e., the product of allocative and technical efficiency) among rice farmers in Bangladesh. KILIC et al. (2009) find for Albanian farm households that technical efficiency decrease with increasing non-farm income. Moreover, they show that households do not invest off-farm earnings in time-saving, efficiency-increasing technologies but instead use the earnings to ease out of crop production.

In contrast, several studies find a positive effect of off-farm labor on farm performance. BJØRNSEN and MISHRA (2012) apply the same measure of efficiency as GOODWIN and MISHRA (2004) but extent their work by also considering the labor decision of the farm operator's spouse. In contrast to GOODWIN and MISHRA (2004), they find that off-farm work positively affects the efficiency of Norwegian farms. PFEIFFER et al. (2009) examine the effects of off-farm income on agricultural production and technical efficiency of farms in Mexico. They find that although off-farm income negatively impacted agricultural output, a slight technical efficiency gain was observed among households with off-farm income. Likewise, BOJNEC and FERTŐ (2013) conclude that Slovenian farms with off-farm income attained slightly higher technical efficiency. Finally, AHMED and MELESSE (2018) find for maize farms in Ethiopia, that those who participate in off-farm activities have significantly higher technical efficiency compared to non-participants.

Furthermore, some studies do not find significant efficiency differences between part-time and full-time farms. For crop and mixed farms in the U.S., BAGI (1984) report little evidence that the technical efficiency of part-time farms is systematically lower than that of full-time farms. Among Norwegian farms, LIEN et al. (2010) find no evidence that off-farm work adversely impacts farm production or technical efficiency. According to CHANG and WEN (2011), although part-time and full-time rice farms in Taiwan use resources differently, off-farm work was not necessarily associated with lower technical efficiency. Similarly, off-farm work had no impact on the technical efficiency of rice farmers in China (FENG, 2008). CHAVAS et al. (2005) demonstrate mixed effects of off-farm activities on technical, scale, and allocative efficiencies of Gambian farm households. To the best of our knowledge, this is the only existing study investigating the effect of off-fam employment on scale efficiency. Their results show that off-farm income has no significant impact on farms' technical and scale efficiency, but has a positive and significant impact on allocative efficiency.

2.2 Hypothesis on the Determinants of Efficiency

From a policy perspective, it is not sufficient to estimate efficiency scores. Instead, examining the determinants of efficiency differences among farms provides further insights and opportunities for improvements. In general, the determinants of farm efficiency and productivity can be grouped into three main categories: characteristics of the farm manager, farm organizational and technological characteristics, and environmental factors (LATRUFFE et al., 2004).[2] We capture farm manager characteristics through age and education level. Age, as a proxy for experience, is typically expected to have a positive impact on farm performance. This is also true regarding scale efficiency (KARAGIANNIS and SARRIS, 2005; MADAU, 2011; MUGERA and FEATHERSTONE, 2008). More experienced farm managers may be able to better choose the optimal size of their operation. A negative effect of age on scale efficiency is possible if older farmers have no successor and gradually decrease the size of the farm before they retire (VIIRA et al., 2013; WEISS, 1999a). Education level, which proxies farmers' knowledge and skills, is expected to positively influence farm performance, in general, and scale efficiency, in particular (LLEWELYN and WILLIAMS, 1996). According to MUGERA and FEATHERSTONE (2008) and WONGNAA and AWUNYO-VITOR (2019), educated farmers are more likely to have better management skills and adequate knowledge of operating on a more efficient scale. Furthermore, this aligns with several studies that find a positive effect of education on technical efficiency (e.g., ADHIKARI and BJORNDAL, 2012; COELLI and BATTESE, 1996). However, one could also argue that more education provides more possibilities to work off-farm and higher salaries. Hence, a higher education level increases the opportunity costs of working on-farm (HUFFMAN, 2001).

Considering farm organizational and technological characteristics, we focus on land tenancy, type of labor, subsidies, farm debts, arable land rental costs, capital intensity, and farm size. The effect of land tenancy on different dimensions of farm performance is highly debated and typically yields mixed results. On the one hand, we can expect that farmers who own most of their farmland have higher incentives to make long-term investments (e.g., in machinery, irrigation,

[2] Most of the relevant literature discusses the effects of different determinants on technical efficiency. Much less is known about the determinants of scale efficiency. While some determinants may influence technical and scale efficiency similarly, this is not necessarily always the case. Hence, in developing hypotheses on how different determinants influence scale efficiency, we partly rely on the existing literature and our own reasoning.

etc.) and therefore increase their scale efficiency (KELLY et al., 2013; LLEWELYN and WILLIAMS, 1996). Additionally, land ownership often serves as collateral for credits, making it easier for farmers with a high share of owned land to expand (MUGERA and FEATHERSTONE, 2008). On the other hand, some studies have shown that in the presence of secured long-term land leases, farmers with rented land tend to be more motivated toward producing efficiently and on technically optimal scale to recover rental costs (GAVIAN and EHUI, 1999; KARAGIANNIS and SARRIS, 2005). Moreover, renting land could serve as a mechanism to facilitate the transfer of land from less productive farms to more productive ones, implying more (scale) efficient farms with lower owned land shares (FENG, 2008).

Family farms with a higher share of family labor are expected to be more scale efficient (KARAGIANNIS and SARRIS, 2005; WONGNAA and AWUNYO-VITOR, 2019). This is because family labor is mostly non-salaried and readily available to carry out required agronomic activities in a timely and less costly manner, making the farm operation more flexible and easier to operate closer to an optimal scale (WONGNAA and AWUNYO-VITOR, 2019). Moreover, BARTOLINI et al. (2010) argue that the employment status of family members could serve as a motivation factor for farms to grow as this provides the farm with the opportunity to use unemployed family labor on the farm to increase and maintain the farm family income. Related to this, several studies find that the prospect of having a successor within the family and the successor's degree of involvement provides an additional incentive and motivation towards the professionalization and expansion of the farm operation (LARCHER et al., 2019; LARCHER and VOGEL, 2019; STIGLBAUER and WEISS, 2000; VOGEL, 2006). Hence, family labor provides both labor resources and incentives for farm expansion.

The effects of subsidies on the economic performance of farms are highly debated in the literature and results remain ambiguous (BARÁTH et al., 2020; LATRUFFE and DESJEUX, 2016; MINVIEL and LATRUFFE, 2017; ZHU and LANSINK, 2010). Regarding technical efficiency, two main contradicting arguments have been presented. On the one hand, subsidies may reduce farmers' efforts in farming activities through a wealth (income) and insurance (risk mitigation) effect (BOJNEC and LATRUFFE, 2013; ZHU and LANSINK, 2010). On the other hand, subsidies may help farmers overcome financial constraints that impede efficient restructuring or modernization (KUMBHAKAR and LIEN, 2010; LATRUFFE and DESJEUX, 2016). We argue that a similar reasoning is plausible for scale efficiency. On the one hand, if a large part of income is guaranteed by subsidies, there is less need to farm at an optimal size. On the other hand, subsidies can provide liquidity and collateral for credits, allowing farms to expand and increase scale efficiency. This is especially true for decoupled payments in the first pillar of the CAP. This is also true for second pillar payments, e.g., agri-environmental payments, to the extent that these payments are larger than any accompanying costs.

The reasoning with regard to the effect of farm debt on scale efficiency is twofold. KARAGIANNIS and SARRIS (2005) argue that farm debts adversely impact scale efficiency, as farmers under financial stress are unable to make efficient decisions or obtain necessary inputs during critical periods of planting and harvesting. Furthermore, the burden of interest decreases farm liquidity as existing debts make it more difficult to obtain additional credits (JENSEN and MECKLING, 1976; LATRUFFE et al., 2016). However, it can be argued that farmers with larger debt are more motivated to increase their managerial effort and enhance their farm performance to meet these obligations (i.e., repay debts on time). This effect has been reported on the technical efficiency of farms (HADLEY, 2006; LATRUFFE et al., 2016).

Land markets are crucial for farm growth. In situations where land sales markets are tight, which is the case in most EU countries (CIAIAN et al., 2016), rental markets become vital. The higher the rent per hectare for arable land, the less likely it is for crop farms to expand. We expect rental prices of arable land to affect the scale efficiency of crop farms negatively. Likewise, farms with higher capital per hectare of land are expected to attain lower scale efficiency as this could point to overcapitalization of farms (IRÁIZOZ et al., 2003).

The positive effect of farm size on scale efficiency has been documented in several studies (ANANG et al., 2016; FANDEL, 2018; KARAGIANNIS and SARRIS, 2005; KELLY et al., 2013). This seems plausible given that the majority of farms in many countries are still relatively small and operate under increasing returns to scale. Moreover, this result also stresses the central role of land availability to increasing scale, especially for crop farms (BŁAZEJCZYK-MAJKA et al., 2012; KELLY et al., 2013). Moreover, as THIELE and BRODERSEN (1999) noted, capital constraints may be another source of scale inefficiency. Smaller farms with less collateral may be more prone to this situation. However, other studies have found that larger farms may face challenges in undertaking their activities at the optimal time and will therefore not be efficient in using their resources (AMARA et al., 1999; WONGNAA and AWUNYO-VITOR, 2019).

Soil productivity and altitude capture the production environment of the farm. While we cannot derive any hypothesis from the literature, one could argue that land quality substitutes quantity, i.e., it is easier to derive an optimal scale in areas with higher land productivity. Finally, altitude is commonly correlated with steepness. Hence, farm expansion might be easier in lands at lower altitudes.

3 Empirical Model

It is well known that many different stochastic (production) frontier (SF) panel models exist. These models mainly differ in if and how they differentiate between firm heterogeneity, time-invariant inefficiency and time-varying inefficiency. Earlier SF panel models (i.e., KUMBHAKAR, 1987; PITT and LEE, 1981; SCHMIDT and SICKLES, 1984) do not account for firm heterogeneity and treat inefficiency as time-invariant. Others, including AHN et al. (2000), BATTESE and COELLI (1992) and KUMBHAKAR (1990), assume that inefficiency is time-varying and follows a deterministic trend or an autoregressive process, but they do not distinguish firm heterogeneity from inefficiency. GREENE's (2005a, 2005b) true-random and true-fixed effects models were the first to apply standard panel data models to SFA. Hence, they are able to separate firm effects (true or random) from (time-varying) inefficiency. However, they are not able to identify time-invariant (persistent) inefficiency. More recently, COLOMBI et al. (2014) and TSIONAS and KUMBHAKAR (2014) developed models which are able to separate firm heterogeneity, time-invariant and time-varying inefficiencies. However, these models are often burdensome to estimate and impose strong distributional assumptions. Since the main purpose of this study is to estimate scale efficiency, which is derived from estimated technology parameters of the frontier, we opted for GREENE'S (2005a, 2005b) approach, which fully accounts for the panel structure of the data and is one of the most popular models in recent years (ABDULAI and TIETJE, 2007; KUMBHAKAR et al., 2014). In particular, we consider the following general stochastic (production) frontier:

$$y_{it} = f(x_{it}, t; \beta) + \alpha_i + v_{it} - u_{it}, \tag{1}$$

where y_{it} is the log of the output of firm i in time t, x_{it} is the log of a vector of J inputs used by firm i in time t, $t = 1, \dots, T$ is a time variable that serves as a proxy for technical change, β is a vector of unknown parameters to be estimated, α_i captures (unobserved) firm heterogeneity and is assumed to be either fixed or random ($\alpha_i \sim N(0, \sigma_\alpha^2)$), v_{it} represents statistical noise ($v_{it} \sim N(0, \sigma_v^2)$), and u_{it} captures technical inefficiency as a one-sided error term (e.g., $u_{it} \sim N^+(0, \sigma_u^2)$).

In agricultural production systems, capturing heterogeneity is fundamentally relevant given that farms typically face different production, climatic, and environmental conditions (ABDULAI and TIETJE, 2007). The question that remains is whether the farm heterogeneity is modeled as random or fixed effects. KARAGIANNIS (2014) argues that random-effects SF models fit better with agriculture as these models assume no correlation between the regressors and the composite error term ($v_{it} - u_{it}$). Given the time lag between production decisions and harvest, we can assume that the correlation between the predetermined input variables and the largely weather-affected stochastic error term is zero or very small. Moreover, the choice of input quantities to maximize expected profits is subject to human errors (inefficiency), but seems uncorrelated with the error term (GRILICHES, 1963; KARAGIANNIS, 2014). Besides, a random effects formulation allows for the inclusion of "environmental variables" (e.g., altitude, soil productivity, and precipitation) to the frontier, whether they are time-variant or time-invariant. We follow this view and specify the production technology as a translog production frontier:

$$\begin{aligned} y_{it} = \beta_0 &+ \sum_{j=1}^{J} \beta_j x_{jit} + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{K} \beta_{jk} x_{jit} x_{kit} \\ &+ \beta_t t + \frac{1}{2} \beta_{tt} t^2 \\ &+ \sum_{j=1}^{J} \beta_{tj} x_{jit} t + \varphi_p P \\ &+ \sum_{j=1}^{J} \varphi_{pj} P x_{jit} + \sum_{l=1}^{L} \rho_l e_{li} \\ &+ \alpha_i + v_{it} - u_{it} \end{aligned} \tag{2}$$

with symmetry $\beta_{jk} = \beta_{kj}$ imposed. To capture differences in the production technology between part-time and full-time farms, we extend our model in Equation (1) by including a dummy variable (P) equal to one if farms are defined as part-time farms and zero otherwise with φ being a vector of unknown parameters to be estimated. Moreover, given that farms do not have considerable control over the physical production environment, we include a vector of L (time-invariant) environmental variables (e_{li}) to account for geo-climatic heterogeneity with ρ being a vector of unknown parameters to be estimated (KARAGIANNIS, 2014).

Based on the procedure by JONDROW et al. (1982), technical efficiency is estimated as $TE = \exp(\hat{u}_{it})$. Following the parametric approach proposed by RAY (1998), the output-oriented scale efficiency (SE_{it}) is computed from the estimates of the production frontier in Equation (2) as:

$$SE_{it} = \exp\left[\frac{(1-\varepsilon_{it})^2}{2\beta}\right], \qquad (3)$$

where $\varepsilon_{it} = \sum_{j=1}^{J}\left(\beta_j + \sum_{k=1}^{K}\beta_{jk}x_{kit} + \beta_{tj}t + \varphi_{pj}P\right)$ represents the farm-specific scale elasticity and $\beta = \sum_{j=1}^{J}\sum_{k=1}^{K}\beta_{jk}$. The output-oriented scale efficiency measures the distance to the optimal scale once technical inefficiency has been accounted for (KARAGIANNIS and SARRIS, 2005). The optimal size is the output level where scale elasticity ε_{it} and scale efficiency SE_{it} are equal to unity, and the production technology exhibits constant returns to scale (RAY, 1998). A farm is scale-inefficient if the scale elasticity is greater or less than one. At increasing returns to scale ($\varepsilon_{it} > 1$), a firm is sub-optimal and should expand output, while inputs should be scaled-down at the supra-optimal level when the firm exhibits decreasing returns to scale ($\varepsilon_{it} < 1$).

To explain the differences in scale efficiency among farms by different determinants, we utilize a two-stage approach proposed by REINHARD et al. (2002) and applied empirically by MADAU (2011) and KARAGIANNIS and SARRIS (2005). REINHARD et al. (2002) show that this two-stage approach leads to consistent estimates of the coefficients of the determinants as long as the efficiency scores explained in the second stage are calculated from parameters of the first stage rather than parametrically estimated, which is the case for our measure of scale efficiency. Therefore, in the second stage, the scale efficiency scores are regressed against a set of determinants:

$$\ln SE_{it} = \delta_0 + \sum_{h=1}^{H}\delta_h z_{it} + v_{it}^* - u_{it}^*, \qquad (4)$$

where z_{it} is a vector of farm-specific socio-economic and environmental explanatory variables associated with scale efficiency, δ is a vector of unknown parameters to be estimated, $v_{it}^* \sim N\left(0, \sigma_{v^*}^2\right)$ captures the statistical noise, and u_{it}^* is the conditional scale inefficiency that remains after accounting for variation in z_{it} and is assumed $u_{it}^* \sim N^+\left(\delta_0 + \sum_{h=1}^{H}\delta_h z_{it}, \sigma_{u^*}^2\right)$. Therefore, this asymmetric error term u_{it}^* captures the effect of omitted variables on scale efficiency (CARRIAZO et al., 2013; SEIFERT et al., 2020).

4 Study Region and Data

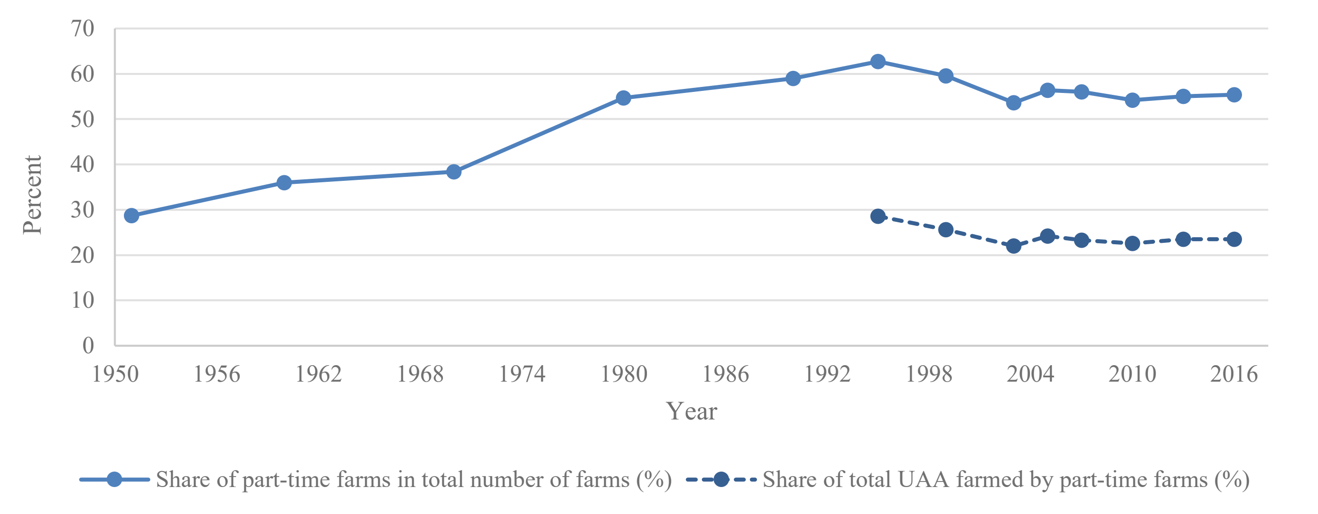
4.1 Part-Time Farming in the EU and Austria

In the EU, farming is predominantly a family business, with a high share of farmers and other family members working only part-time on the farm while pursuing other gainful activities outside the farm. For example, of the 10.5 million farms in the EU in 2016, around 95% can be categorized as family farms,[3] utilizing 81% of the regular agricultural labor force, cultivating around 62% of the total utilized agricultural area (UAA), holding 63% of all livestock, and producing about 60% of the agricultural output (EUROSTAT, 2019b). In the same year, only 17% of the 20.5 million people constituting the EU's total agricultural labor force were employed full-time on the farm. The remaining 83% undertook agricultural activity as a part-time or secondary activity (EUROSTAT, 2018b). The importance of part-time farming becomes evident because the 20.5 million farmers in the labor force translate into 9.5 million full-time equivalents, i.e., the average farmer works less than half-time (EUROSTAT, 2018b). This phenomenon clearly distinguishes the farming sector from any other sector.

However, the importance of part-time farming is not consistent across the EU. While full-time farm enterprises are dominant in some regions and sectors of agriculture, in others, part-time farming is significant and persistent (SCHUH et al., 2019). For example, in the Czech Republic, France, Luxembourg, and Belgium, slightly more than 50% of the regular labor force in agriculture worked full-time. In comparison,

[3] While no uniform definition of the term 'family farm' exists (GARNER and DE LA O CAMPOS, 2014), in this paper it refers to any farm under family management where 50% or more of the regular agricultural labor force is provided by family members (EUROSTAT, 2019a).

Figure 1. Part-time farms' share in total number of farms and total UAA



Sources: own illustrations based on data from different agricultural censuses

it is less than 10% in Malta, Austria, and Cyprus (EUROSTAT, 2017). Moreover, certain farm types, such as olive farms and grazing and livestock fattening farms, are particularly associated with off-farm labor participation. At the same time, it is less common for specialist dairy and horticulture farms (HILL and BRADLEY, 2015). Moreover, having other gainful activities is more prevalent among younger farmers than older ones (HILL and BRADLEY, 2015; MCNAMARA and WEISS, 2005), as well as among small farms compared to larger ones (EUROPEAN COMMISSION, 2013).

In Austria, the country investigated in this study, 90% of total farms are family farms cultivating about 86% of the country's UAA. As depicted in Figure 1, the share of part-time farms increased from 29% in 1951 to 63% by the middle of the 1990s and has remained relatively stable at around 55% during the last two decades.[4] Moreover, part-time farms cultivate approximately 23% of the total UAA.

4.2 Data

Our empirical analysis uses the information collected for the Austrian fraction of the EU's Farm Accountancy Data Network (FADN) from 2010 to 2017. The panel represents the heterogeneity of Austrian agriculture and stratifies farms according to standard output (SO), primary production activity, and topography.[5] We select (field) crop farms based on the EU's Type of Farm (TF14) grouping. In particular, our sample includes farms specialized in cereal, oilseed, and protein crops (TF15) and other field crops (TF16) (EUROPEAN COMMISSION, 2009). With its high share of part-time farms, Austria is an ideal case study. Although an important agricultural activity, crop farming in Austria has not received much attention in the efficiency literature, with the majority of studies focusing on dairy farms (HAMBRUSCH et al., 2006; KARAGIANNIS et al., 2012; LAKNER et al., 2015; ORTNER et al., 2006). To analyze the impact of off-farm activities on efficiency, we distinguish between part-time and full-time farms based on the proportion of annual working days the farm manager (or couple) spent on agricultural activities. On-farm agricultural activities include agriculture, forestry, secondary agriculture-related business, and agri-tourism. A farm is categorized as part-time if the farm manager (or couple) spends less than two-thirds of his or her annual working days on agricultural activities. Our utilized sample is an unbalanced panel of 344 crop farms

[4] According to the official classification, a farm is a part-time farm in Austria if the farm manager (and her/his spouse) spend less than 50% of the work time on-farm (BMLRT, 2020).

[5] Within the FADN methodology, the SO of an agricultural product (crop or livestock) is the average monetary value of agricultural output at farm-gate prices, either in euros per hectare or per head of livestock. The sum of SO per hectare of crop and per head of livestock in a farm is a measure of its overall economic size, expressed in euros.

Table 1. Descriptive statistics

Variable	Part-time farms (N = 721)			Full-time farms (N = 731)		
	Mean	Min.	Max.	Mean	Min.	Max.
Output (euros)	90,172	5,234	635,461	146,885	12,918	738,184
Capital (euros)	154,510	1,915	703,336	199,777	2,010	834,870
Labor (AWU)	0.90	0.09	4.30	1.54	0.28	10.92
Land (hectares)	56.24	10.20	198.68	72.54	11.07	306.59
Materials (euros)	36,452	5,460	166,743	54,461	4,899	413,879
Time	5.09	1.00	8.00	5.16	1.00	8.00
Soil productivity (index)	49.00	15.00	86.00	49.00	15.00	84.00
Altitude (meters)	247.40	113.00	820.00	233.40	120.00	630.00
Age (years)	50.00	17.00	78.00	50.00	18.00	81.00
Higher education, dummy	0.52			0.66		
Owned land share	0.64	0.00	1.00	0.58	0.00	1.00
Family labor share	0.96	0.32	1.00	0.91	0.10	1.00
1st pillar payments ratio	0.23	0.03	1.10	0.20	0.01	0.61
2nd pillar payments ratio	0.15	0.00	1.86	0.13	0.00	0.71
Debt/revenues ratio	0.06	0.00	2.05	0.08	0.00	2.91
Rental cost/ha (euros)	318	0.00	1,000	320	0.00	1,000
Capital intensity (euros)	3,500	69.00	21,203	3,595	80.00	67,060
Standard output (euros)	63,814	6,906	492,376	96,556	10,181	403,856
Small size, dummy	0.40			0.19		
Medium size, dummy	0.44			0.44		
Altitude, dummy	0.42			0.50		

Notes: Time is used as a proxy for technological change. Since our dataset covers the period 2010-2017, 1 indicates 2010, and 8 indicates 2017.
Sources: own calculations based on the FADN

with 1,452 observations, of which 49.7% are part-time farms.[6] Each farm is observed for a minimum of two consecutive years. On average, farms have a duration of 4.2 years in the sample. Table 1 presents descriptive statistics. Given the topography of Austria, most crop farms in our sample are located in favored agricultural areas in the northern and eastern parts of the country.

Farm output is total farm revenues (i.e., revenues from crops, livestock, forestry, and other agricultural activities) in euros converted into a constant-price quantity index using an official crop output price index with 2010 as the base year. We include four inputs in the production function: i) capital (in euros) is the end-of-year value of buildings, machinery, livestock, and forestry assets, and assets for other agriculture-related activities; ii) labor input (measured in AWUs) includes family and hired labor;[7] iii) land is the total UAA in hectares; and iv) materials (in euros) capture variable costs such as expenses for plant production (seeds, pesticides, fertilizers, etc.), insurance, energy, bought services, and other agriculture-related expenses. Capital and materials are deflated with appropriate official price indices for agricultural investments and operating inputs, respectively, with 2010 as the base year. Since the translog specification is considered a second-order Taylor series expansion around the point of approximation, we normalize all variables around the sample mean.[8] Finally, to account for geo-

6 We excluded observations with implausible values, i.e., extremely large (small) values in a specific year that is an outlier to other observed years or generally large (small) values that don't correspond to a farm's operational size, such as a relatively small farm reporting extremely large labor unit use. Observations with zero values for production inputs and output variables are also eliminated after all avenues for calculation within the data have been exhausted. Additionally, farms not observed for a minimum of two consecutive years were also eliminated to maintain the panel structure of the data.

7 AWU is the standard unit for measuring agricultural labor input in the EU and is used to define the number of full-time equivalent. In Austria, 1 AWU implies 270 working days per year. However, a person can obtain a maximum of 1 AWU even if they work for more than 270 days per year.

8 Our dataset suffers from several shortcomings which are common with the FADN and any other datasets based on farm accounting. These shortcomings include: i.) capital stock may be underestimated as yearly deprecia-

climatic differences in production conditions, we include an existing measure of soil productivity and farm altitude. This soil productivity measure is an index between 1 (lowest productivity) and 100 (highest productivity). It is mainly based on soil properties and includes some other regional conditions like exposure to hail and drought, the steepness of plots, and the average size of plots.[9]

The variables explaining scale efficiency differences among farms are categorized into three groups: i) farm manager characteristics; ii) farm organizational and technological characteristics; and iii) environmental factors. Farm manager characteristics include the age of the farmer measured in years and the education level of the farm manager as a dummy equal to one if the farmer has a higher agricultural education (i.e., diploma, university degree, or advanced certificate in agriculture) and zero otherwise. To capture farm organizational and technological characteristics, we include the share of owned land in the total UAA, the share of family labor in total farm labor, the ratio of first pillar payments to total farm revenues, the ratio of second pillar payments to total farm revenues,[10] the ratio of farm debts to total farm revenues, the average rental cost per hectare of arable land, and the capital-to-land ratio (which captures capital intensity). Moreover, based on SO, farms are grouped into three economic sizes. Small-scale farms have an SO less than €40,000, medium-scale farms have an SO between €40,000 and €100,000, and large-scale farms have an SO greater than €100,000. Therefore, we include dummies for small- and medium-scale farms. Regarding environmental factors, we include the soil productivity index and an altitude dummy (equal to one if the farm's altitude is less than or equal to 200 meters) and zero otherwise.

Descriptive statistics in Table 1 reveal that, on average, part-time farms produce significantly lower output (61%) compared to full-time farms using considerably lower amounts of all inputs (i.e., more than 70% less capital and land, 67% less materials, and 58% less labor). However, only minor differences are observed regarding environmental factors. In addition, while the average age of farm managers is the same between part-time and full-time farms, full-time farm managers have, on average, a higher level of agricultural education than their counterparts. Part-time farms are considerably smaller, own more of the land they farm, use more family labor, get more subsidies in relative terms, and have more debt in relative terms. However, only minor differences are observed regarding rental costs and capital intensity.

5 Results and Discussions

5.1 Production Structure and Technical Change

Table 2 presents the estimates of the production frontier. About 61% of the estimated coefficients (17 of 28) of the production frontier are statistically significant at the 5% level. Furthermore, the dummy variable for part-time farming and its interaction with the input variables are jointly significant at the 5% level based on the log-likelihood ratio test with a test statistic of 11.4. This indicates significant differences in the production frontier of part-time and full-time farms, justifying the inclusion of dummies in the empirical specifications of the estimated production frontier. Moreover, the estimated value of γ indicates that, on average, 72% of the deviations from the production frontier are due to technical inefficiency, supporting the need to estimate a stochastic production frontier instead of a mean production function.

Given that the translog specification accounts for interactions between the input variables, it is meaningful to compute the output elasticities and the scale elasticity of farms (see Table 3). As SAUER et al. (2006) noted, the translog specification fails to satisfy the regularity conditions (i.e., monotonicity and curvature) of the production function globally. Still, it is possible to check if these conditions are met locally. At the point of approximation, we find that all first-order estimates are positive, statistically significant, and less than unity, implying that marginal products

tion follows tax laws rather than physical wastage; ii) labor is self-reported and may be overestimated; iii) all monetary values are deflated with sectoral price indices rather than farm-specific prices; and iv) land is assumed to be of homogeneous quality.

[9] Multiplied by a pre-assigned monetary value to measure the potential profitability, this index is the basis for taxation of (most) farms in Austria.

[10] Second pillar payments include agri-environmental payments and less favored area payments. We do not include, for example, investment subsidies as they account for only a relatively small share of total second pillar payments and occur in an erratic manner. According to BMNT (2018), first pillar payments account for 59%, agri-environmental payments for 36%, and less favored area payments for about 2% of total farm subsidies for an average crop farm in Austria in 2017. Hence, our two categories (first pillar and second pillar payments) include about 97% of total payments to crop farms.

Table 2. Parameter estimates of the translog production frontier

Variable	Estimate	Standard error
β_0	-0.146**	0.058
β_1 (capital)	0.092***	0.034
β_2 (labor)	0.165***	0.041
β_3 (land)	0.248***	0.061
β_4 (materials)	0.547***	0.045
β_{11}	-0.019	0.020
β_{22}	-0.031	0.046
β_{33}	-0.110**	0.052
β_{44}	0.145***	0.036
β_{12}	0.096***	0.027
β_{13}	-0.007	0.037
β_{14}	-0.054*	0.028
β_{23}	-0.115***	0.042
β_{24}	0.083**	0.035
β_{34}	-0.068*	0.041
β_t (time)	0.041***	0.011
β_{tt}	-0.007***	0.002
β_{t1}	0.012***	0.004
β_{t2}	0.020***	0.005
β_{t3}	-0.012	0.008
β_{t4}	-0.012**	0.006
φ_p (part-time, dummy)	-0.052*	0.030
φ_{p1}	-0.083**	0.034
φ_{p2}	-0.044	0.046
φ_{p3}	0.009	0.066
φ_{p4}	0.026	0.048
β_l (soil productivity)	0.368***	0.096
β_a (altitude)	0.008	0.014
σ_u	0.211***	0.018
σ_v	0.132***	0.009
$\lambda = \sigma_u / \sigma_v$	1.594***	0.026
$\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$	0.717***	0.060

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.
Sources: own calculations

are positive and diminishing, satisfying monotonicity and quasi-concavity conditions of the estimated production function.

The estimated output elasticities show that irrespective of how farms are managed, either part-time or full-time, materials contribute the most to crop production, followed by land, labor, and capital. This finding is consistent with the existing literature estimating crop production frontiers (BRÜMMER, 2001; GIANNAKAS et al., 2001; RIZOV et al., 2013; TIEDEMANN and LATACZ-LOHMANN, 2013). However, there are differences regarding output elasticities. For full-time farms, output elasticities are higher for capital, labor, and materials, but are lower for land. On average, farms exhibit increasing returns to scale (i.e., the estimated scale elasticity of 1.09 is statistically different from 1). However, average returns to scale are larger for full-time farms (1.12) compared to part-time farms (1.05).

We estimate an average annual technical progress of 0.6% among full-time farms and no significant technical change among part-time farms. Technological change is capital- and labor-using, material-saving, and neutral with respect to land. The relatively low technical progress of field crop farms, especially over the last few decades, is supported by similar studies. A comparative study of farm productivity from 2001 to 2007 by LATRUFFE et al. (2012) estimates overall technical progress of 6.7% and 3.9% and 1.1% and 0.6% per year among Hungarian and French crop farms, respectively. Among crop farms in France, DAKPO et al. (2019) find an overall technical regress of 6.2% (or 0.5% per year) between 2002 and 2015. Contrary to our result, the authors find that technological change of crop farms seems to be capital-saving. Among Hungarian crop farms, BARÁTH and FERTO (2015) find a positive but decreasing technical change which is labor-saving and material-using.

Table 3. Output elasticities, returns to scale, technical change, technical efficiency, and scale efficiency

Elasticities with respect to	Part-time		Full-time	
	Estimate	Standard Error	Estimate	Standard Error
Capital	0.051***	0.020	0.159***	0.020
Labor	0.202***	0.027	0.229***	0.027
Land	0.333***	0.039	0.254***	0.038
Materials	0.463***	0.032	0.482***	0.028
Returns to scale	1.049***	0.030	1.124***	0.035
Technical change	-0.001	0.003	0.006**	0.003
Technical efficiency	0.878***	0.011	0.873***	0.010
Scale efficiency	0.951***	0.004	0.888***	0.017

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.
Sources: own calculations

5.2 Technical Efficiency

We estimate an average technical efficiency over farms and time of 87.8% and 87.3% for part-time and full-time farms, respectively. This indicates that, on average, there is no significant difference between the two farm groups based on a two-sided Welch test

Table 4. Frequency distributions of efficiency scores

Efficiency scores	Technical efficiency (%)		Scale efficiency (%)	
	Part-time	Full-time	Part-time	Full-time
< 60	3.33	3.56	0.14	4.65
60–70	3.61	3.56	1.53	2.87
70–80	6.24	8.76	2.50	8.07
80–90	29.54	32.42	9.99	22.16
90–100	57.28	51.71	85.85	62.24
90–92.5	19.97	14.36	7.77	11.49
92.5–95	22.33	23.26	9.57	12.04
95–97.5	14.70	13.54	17.48	14.50
97.5–100	0.28	0.55	51.04	24.21

Sources: own calculations

(t = 0.84).[11] The distribution of technical efficiency in Table 4 shows that more than half of the farms achieved technical efficiency scores over 90%, with a few very inefficient farms (with efficiency scores < 60%). This distribution is similar between part-time and full-time farms. However, we find that the efficiency scores of full-time farms are slightly more dispersed, with more farms being very inefficient (TE < 60%) or very efficient (with TE > 97%).

In the previous literature, the impacts of off-farm activities and income on technical efficiency yielded mixed results based on different methods and various study regions (AHMED and MELESSE, 2018). Our results show, on average, no effect of off-farm work on technical efficiency, similar to findings reported by CHAVAS et al. (2005) and LIEN et al. (2010) for Gambian and Norwegian crop farms, respectively. LIEN et al. (2010) argue that the efficiency loss by part-time farms due to lack of time for farm management might be offset by the incentive to increase efficiency and make the best use of the hours available for on-farm work. On the other hand, KILIC et al. (2009) and SABASI et al. (2019) find adverse effects of off-farm activities on technical efficiency among Albanian farms and U.S. dairy farms, respectively. They argue that the time foregone in managing the farm is detrimental to efficiency. On the contrary, AHMED and MELESSE (2018) and BOJNEC and FERTŐ (2013) find that off-farm activities increased technical efficiency among Ethiopian maize producers and Slovenian farms. The authors surmised that by participating in off-farm activities, farms allocate family labor resources efficiently (i.e., surplus labor is employed off-farm) and invest off-farm incomes into more advanced farm technology, thus increasing technical efficiency.

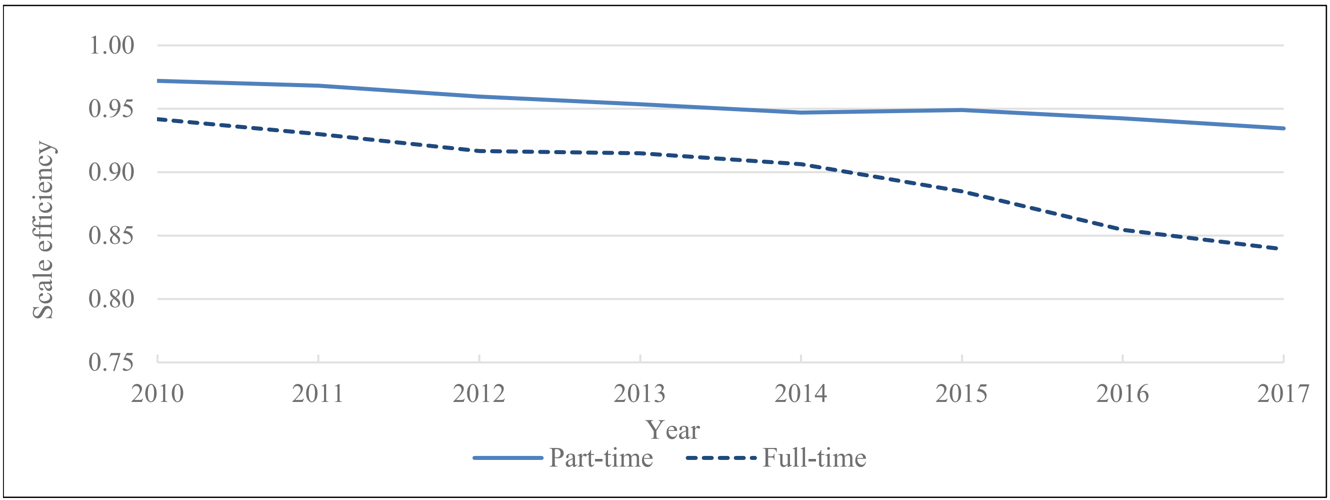
[11] Note that in the presentation and discussion of our results, we treat each farm in each year as an independent observation, i.e., as if we observe 1,452 farms rather than 344 farms for an average of 4.2 times.

5.3 Scale Efficiency

We estimate a relatively high average scale efficiency of 91.9% for our entire sample. Splitting our crop farms into part-time and full-time farms, we derive efficiency scores of 95.1% and 88.8%, respectively (Table 3). Based on a two-sided Welch test (t = 11.63), part-time farms are significantly more scale efficient than full-time farms. This is also reflected in the frequency distributions in Table 4. Considerably more part-time farms (85.9%) than full-time farms (62.2%) achieved efficiency scores above 90%. This is also true for very high efficiency scores of more than 97%, with 51% of part-time farms and 24.2% of full-time farms in this category. Moreover, a larger proportion of very inefficient farms (< 60%) are full-time farms. Although scale efficiency decreases over time, part-time farms are consistently more scale efficient than their full-time counterparts, with the gap considerably increasing over time (Figure 2). A decreasing scale efficiency over time may indicate that farms do not adjust quickly enough in size given changes in technology, which seems more relevant for full-time farms. For example, with labor-saving technology change, farms would need more land to employ the same amount of labor and part-time farms are more flexible than full-time farms in adjusting the share of off-farm work.

To the best of our knowledge, CHAVAS et al. (2005) is the only other study to estimate the scale efficiency of part-time farms; however, no study exists which compares the scale efficiency of part-time and full-time farms. CHAVAS et al. (2005) report a mean scale efficiency of 82% for farms in the Gambia. Moreover, we can compare our efficiency scores to studies on farms of similar production orientation and geographic areas. Our estimates of the scale efficiency of crop farms in Austria are in a range comparable with results by LATRUFFE et al. (2005) and LATRUFFE et al. (2012). LATRUFFE et al. (2005) investigate the technical and scale efficiency of crop and livestock farms in Poland. They find average scale efficiency scores for crop farms in Poland of 93% and 86% in 1996 and 2000, respectively. Comparable to our results, they find that technical inefficiency poses a greater challenge to farms than scale inefficiency. LATRUFFE et al. (2012) derive scale efficiency scores for crop farms in Hungary and France. They estimate a mean scale efficiency of 93% for French crop

Figure 2. Temporal patterns of scale efficiency of part-time and full-time farms



Sources: own illustrations based on own calculations

farms and 89% for Hungarian crop farms. Moreover, VASILIEV et al. (2008) report average scale efficiency scores of 90% for Estonian grain farms.

In contrast, RASMUSSEN (2010) finds a lower mean scale efficiency of crop farms in Denmark (78%). Interestingly, this is comparatively lower than the scale efficiency of dairy (89%) and pig farms (88%). Moreover, while the scale efficiency for dairy and pig farms increased over time, this was not the case for crop farms. RASSMUSSEN (2010) surmised that restrictions in land acquisitions severely inhibited crop farms' ability to expand to optimal scales. A low average scale efficiency of 80% is also reported by OXOUZI et al. (2012) for crop farms in mountainous and other less favorable agricultural areas of Greece. For Austria, thus far, scale efficiency has only been measured for dairy farms. Applying data envelopment analysis (DEA), HAMBRUSCH et al. (2006) derive an average scale efficiency of 94%. In a similar attempt, but based on stochastic frontier analysis (SFA), KARAGIANNIS et al. (2012) estimate an average scale efficiency of 90% for conventional and 84% for organic dairy farms. Regarding the development of scale efficiency over time, LATRUFFE et al. (2012) do not find any significant change in scale efficiency for crop farms in France and Hungary between 2001 and 2007. DAKPO et al. (2019) find that four different types of French farms (including field crop farms) experienced a decrease in scale efficiency and a stagnation of scale efficiency for mixed farms between 2002 and 2015. In contrast, BARÁTH et al. (2020) report for a sample of Slovenian farms that scale efficiency increased by 4% between 2006 and 2013.

To further investigate the scale efficiency of farms in terms of scale elasticity, farms are grouped into the following categories: i) (almost) optimal (operating close to constant returns to scale: $0.995 \leq \varepsilon_{it} \leq 1.005$); ii) sub-optimal (increasing returns to scale: $\varepsilon_{it} > 1.005$); and iii) supra-optimal (decreasing returns to scale: $\varepsilon_{it} < 0.995$). According to our definition, results in Table 5 show that 2.2% of farms are operating on an optimal scale, 16.2% at a supra-optimal scale, and 81.6% at a sub-optimal scale. Hence, the majority of farms are too small to be scale efficient. This is especially true for full-time farms, with 94.5% having a sub-optimal scale, while this is only true for 68.5% of part-time farms. At the same time, 28.2% of part-time farms are too large, while this is only the case for 4.4% of full-time farms. Moreover, while part-time and full-time farms operating at the supra-optimal scale are close to scale efficiency, this is not the case for sub-optimal farms. Full-time farms at the sub-optimal scale exhibit the highest inefficiency.

Our result that the majority of Austrian crop farms operate under increasing returns to scale is in line with previous studies. For example, THIELE and BRODERSEN (1999) find that the majority of crop farms in East Germany (71%) and West Germany (88%) exhibit increasing returns to scale. They find similar results for all other types of farms. Similarly, LATRUFFE et al. (2005) derive increasing returns to scale for 86% of Polish crop farms. RASMUSSEN (2010) reports for a sample of Danish crop farms that almost all of these farms have an elasticity of scale above one. LATRUFFE et al. (2012) confirm increasing returns to scale for the majority (54%) of French crop

Table 5. Relationship between scale elasticity and scale efficiency

Farms	Optimal scale		Sub-optimal scale		Supra-optimal scale	
	N (%)	Mean SE_{it}	N (%)	Mean SE_{it}	N (%)	Mean SE_{it}
Part-time	24 (3.3%)	1.00	494 (68.5%)	0.936	203 (28.2%)	0.981
Full-time	8 (1.1%)	1.00	691 (94.5)	0.881	32 (4.4%)	0.994
Total	32 (2.2%)	1.00	1,185 (81.6%)	0.904	235 (16.2%)	0.983

Notes: N is the number of observations.
Sources: own calculations

Table 6. Relationship between the efficiency and farm size

Farm size	Scale elasticity		Scale efficiency				Technical efficiency			
	Part-time	Full-time	Part-time	Full-time	t-statistic	Overlap	Part-time	Full-time	t-statistic	Overlap
Small	1.090	1.170	0.928	0.828	-8.099***	0.585	0.859	0.821	-3.170***	0.864
Medium	1.027	1.117	0.963	0.902	-8.478***	0.622	0.877	0.864	-2.066**	0.933
Large	1.009	1.100	0.974	0.900	-8.332***	0.332	0.904	0.908	-0.295	0.981

Notes: The t-statistic is for a two-sided Welch test. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Overlap measures the overlap between areas of two density functions. Farm size is calculated based on the farms' standard output (i.e., small-scale farms have an SO less than €40,000, medium-scale farms have an SO between €40,000 and €100,000, and large scale farms have an SO greater than €100,000).
Sources: own calculations

farms, but find decreasing returns to scale for the majority (55%) of their Hungarian counterparts. Evaluated at the sample mean, ZHU and LANSINK (2010) find increasing returns to scale for crop farms in Sweden and the Netherlands, but find decreasing returns to scale for Germany. Analyzing all EU-15 countries and based on sample means, RIZOV et al. (2013) report increasing returns to scale for farms in most countries, especially North European countries, while farms in Greece and Italy are characterized by slightly decreasing returns.

Table 6 depicts the scale elasticity, scale efficiency, and technical efficiency for small (SO < €40,000), medium (€40,000 ≤ SO ≤ €100,000), and large-scale (SO > €100,000) part-time and full-time farmers. On average, all groups exhibit increasing returns to scale, which decrease with size. Based on a two-sided Welch test, scale efficiency is significantly higher for part-time farms compared to full-time farms for all size groups. As illustrated by the coefficient of overlap, the two density functions of the scale efficiency of part-time and full-time farms do only overlap between 33.2% (large farms) and 62.2% (medium farms). Regarding technical efficiency, we also observe that technical efficiency increases with size for both groups. Part-time farms are only slightly more efficient, though statistically significant, among small and medium-sized farms and almost equally efficient among large farms. The general observations that technical and scale efficiency increase with farm size are not novel. Many other studies have confirmed this, including BLAZEJCZYK-MAJKA et al. (2012), LATRUFFE et al. (2004, 2005, 2008), and VASILIEV et al. (2008) for crop farms and KARAGIANNIS and SARRIS (2005), MADAU (2011), and PAUL et al. (2004) for other types of farms.

5.4 Determinants of Scale Efficiency

Based on Equation 4, we estimate separate models for both part-time and full-time farms to examine the impact of determinants of scale efficiency. Results are presented in Table 7. Most of the determinants have a statistically significant coefficient and all significant coefficients have the expected sign. Regarding the farm manager characteristics, we find a statistically significant effect only for the education level of the farm manager on the scale efficiency for full-time farms. This suggests that a higher education level of the farm manager may not only increase technical efficiency, as indicated by many previous studies (ADHIKARI and BJORNDAL, 2012; COELLI and BATTESE, 1996; LLEWELYN and WILLIAMS, 1996), but may also help find the optimal scale of the farm operation. This aligns with findings by LLEWELYN and WILLIAMS (1996), MUGERA and FEATHERSTONE (2008), and WONGNAA and AWUNYO-VITOR (2019). On the other hand, we did not find any significant effect of the farm manager's age, which is a proxy for farming experience, on scale efficiency. This is in line with the findings of ANANG et al. (2016), but

Table 7. Determinants of scale efficiency

	Part-time		Full-time	
Variable	**Estimate**	**Standard error**	**Estimate**	**Standard error**
Age	0.0002	0.0003	-0.0007	0.0007
Higher education, dummy	0.0071	0.0048	0.0301***	0.0109
Owned land share	-0.0320***	0.0103	-0.0651***	0.0224
Family labor share	0.2258***	0.0223	0.2308***	0.0343
1. Pillar payments ratio	0.1778***	0.0333	0.2513***	0.0769
2. Pillar payments ratio	-0.0021	0.0201	0.3363***	0.0722
Debt/revenues ratio	-0.0033	0.0123	0.0247	0.0226
Rental cost/ha[a]	-0.0033*	0.0018	-0.0218***	0.0044
Capital intensity[a]	-0.0006***	0.0001	-0.0022***	0.0001
Small size, dummy	-0.0591***	0.0077	-0.1383***	0.0168
Medium size, dummy	-0.0275***	0.0071	-0.0304***	0.0115
Soil productivity[a]	0.0774***	0.0195	0.1874***	0.0415
Altitude, dummy	0.0169***	0.0050	0.0406***	0.011
Constant	-0.2831***	0.0285	-0.3104***	0.0485

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Variables with superscript a are divided by 100.
Sources: own calculations

contradicts those of KARAGIANNIS and SARRIS (2005), MADAU (2011), and MUGERA and FEATHERSTONE (2008), who find positive effects of experience on scale efficiency.

Land ownership negatively affects the scale efficiency of both part-time and full-time farms. In other words, farms with a higher share of rented land achieve higher scale efficiency scores. This is in line with results reported by KARAGIANNIS and SARRIS (2005) and indicates that renting land may be a potential way for farmers to achieve optimal scale and improve scale efficiency. Moreover, FORBORD et al. (2014) note that complicated societal and institutional norms (i.e., the process of purchasing agricultural land with its legal requirements, family involvement, and high economic costs) make renting farmland a more attractive option for farm expansion. Therefore, observing a low rental share for a particular farm could reveal different underlying reasons. On the one hand, it may indicate that the farmer is reluctant to expand through renting land because of financial constraints or risk aversion. On the other hand, it could be that the rental market in the specific area is thin. The estimated impact is much more substantial for full-time farms. This seems reasonable, given that full-time farms are, on average, less scale efficient and can gain more by increasing their size.

Furthermore, in line with KARAGIANNIS and SARRIS (2005), we find that the share of family labor positively impacts the scale efficiency of both part-time and full-time farms at a very similar level. This result could indicate that the flexibility of family labor enhances farms' ability to derive the optimal scale or that the employment status of family members could serve as a motivation factor for farms to grow. This is in line with WEISS (1999b), who finds a positive relationship between family size and farm growth, with the effects more distinct for full-time farms than part-time farms in Austria. He argues that family labor provides both labor resources and incentives for farm expansion.

The effects of different subsidies on technical efficiency have been extensively discussed with mixed results. MINVIEL and LATRUFFE (2017) performed a meta-analysis on this issue based on 68 studies and 195 distinct model results. For decoupled payments, including first pillar payments of the CAP, they find that 46 out of 86 models find a significant negative effect of subsides, 20 report a significant positive effect, and the remainder report non-significant effects. For agri-environmental payments and less favored area payments, they find that 50% of the 40 model results are significantly negative, 25% significantly positive, and 25% have non-significant effects. We find differences between both payment categories and farm types. In particular, first pillar payments have a significantly positive impact for both part-time and full-time farms. This sounds reasonable, as decoupled subsidies provide monetary means to buy (or rent) additional land or other input factors and expand the size of the farm. Financial constraints faced by farmers due to credit market imperfections may be mitigated by subsidies (CIAIAN and SWINNEN, 2009; GARRONE et al., 2019). The effect is larger for full-time farms, as they have a higher necessity to increase in size. Moreover, part-time farms have additional off-farm income that provides liquidity to reinvest and expand the farm, in addition to subsidies. A positive impact of government payment on scale efficiency is also reported by LAMBERT and BAYDA (2005) for crop farms in North Dakota. Second pillar payments have only a significantly positive effect for full-time farms, while it is close to zero and insignificant for part-time farms. This may again stress the importance of transfers for full-time farms compared to part-time farms. However, the large difference in the subsidy effects between part-time and full-time farms and the fact that second pillar payments have a larger effect than decoupled first pillar payments for full-time farms are to some extent puzzling. The first result may indicate that the costs of participating in agri-environmental programs are smaller for full-time farms. This makes sense if participation implies additional labor requirements and part-time farms have higher opportunity costs of working on-farm. The strong impact of second pillar payments for full-time farms may suggest large windfall profits, i.e., payments exceed additional costs.

As expected, land rental costs negatively affect the scale efficiency of farms and the impact is again stronger for full-time farms. The higher the rent per hectare for arable lands, the less likely it is for farms to expand. Furthermore, we find that more capital-intensive farms (i.e., higher capital to land ratios) are less scale efficient. This may point to overcapitalization (HOPPICHLER, 2007; SINABELL, 2014). In fact, PAWLAK et al. (2021) report that Austria's capital to land ratio is above the EU-28 and EU-15 average, while the output to capital ratio is below. We find no effect of debt on scale efficiency. This is similar to LAMBERT and BAYDA (2005), who find no significant impact of short-term and long-term debt on scale efficiency among crop farms in North Dakota. Moreover, the negative and statistically significant coefficients of the dummies included for small- and medium-sized farms in our regression further confirm our results in Table 6.

Regarding environmental factors, we find that both soil productivity and low altitudes positively impact the scale efficiency of part-time and full-time farms. Farms with higher soil productivity, on average, attain relatively higher scale efficiency. This may indicate that the quality of the land may substitute for quantity to some extent. In addition, farms on plains with altitudes less than 200 meters are more scale-efficient compared to those at higher elevations. This might indicate that it is easier for farms to expand to an optimal scale in areas at lower altitudes.

6 Concluding Remarks

Part-time farming has been an integral part of the agricultural sector in the EU and beyond for decades. It has been argued that the combination of off-farm employment and farm activity could be a farm survival strategy that increases and stabilizes farm household income, helps cope with market risk, and provides capital for investments (BREUSTEDT and GLAUBEN, 2007; CHANG and MISHRA, 2008; PFEIFFER et al., 2009; SHITTU, 2014). However, there are also concerns regarding the adverse effects of off-farm activities on farm performance. Reallocation of time from on-farm to off-farm may alter management practices, lead to less informed farm decisions, and decrease efficiency (SABASI et al., 2019). So far, most studies have analyzed the impact of part-time farming on technical efficiency (BRÜMMER, 2001; PFEIFFER et al., 2009; BOJNEC and FERTÖ, 2013; LIEN et al., 2010). To the best of our knowledge, CHAVAS et al. (2005) is the only study that estimates the scale efficiency of part-time farms and there has been no study thus far that has compared the scale efficiency of part-time and full-time farms.

We investigate this issue based on an unbalanced panel of about 350 specialized crop farms over eight years. Since working off-farm is a continuous rather than a discrete decision, we split our sample by defining a part-time farm where the farm manager (or couple) spends less than two-thirds of his or her annual working days on agricultural activities. Based on this, we find several interesting results. First, we find differences in the production technology between part-time and full-time farms, indicating that part-time farms are not just a smaller version of full-time farms. Instead, they are organized differently. On average, part-time farms use about the same value of capital per hectare, but use significantly less labor and material per hectare, i.e., they produce less extensively. Moreover, part-time farms use more land per output, although the average quality of utilized land is about the same. Based on our translog production frontier, we estimate output elasticities, i.e., the contribution of an input to the output, to be higher for land and smaller for capital in the case of part-time farms compared to full-time farms.

Second, evaluated with regard to their production technology, part-time farms are, on average, closer to the optimal scale than full-time farms. Almost all full-time farms in our sample are too small to be scale efficient. Our results regarding scale efficiency shed some new light on the discussion about the effect of part-time farming on farm performance. The interpretations of our findings are in line with SCHMITT (1988, 1989a, 1989b) and MITTENZWEI and MANN (2017), who argue that given imperfect factor markets, which often prevent farm growth that would allow for the full use of the available family labor force on the farm, combining on-farm and off-farm jobs is an economically superior strategy. To put it differently, part-time farming is a possibility to cope with factor market constraints. This is also in line with two related findings: i) we find a low but significant technical change for full-time farms, but not for part-time farms, and ii) the gap in scale efficiency between part-time farms and full-time farms increases over time. A possible interpretation of these findings is that full-time farms, depending on profits from farming, invest in new technology, but are not able to adjust the scale of the other inputs accordingly, while part-time farms' technology is more persistent and, hence, there is less necessity to increase in size. In the case of crop farms, the main constraint is most likely the availability of land. As in many other EU countries, agricultural land sales markets are relatively thin (CIAIAN et al., 2016). Moreover, according to EUROSTAT (2018a), Austria had the third-highest rental prices of the 20 EU Member States for which data was available in 2016.

Third, for our sample, but in contrast to many other studies, we find no difference between the technical efficiency of part-time and full-time farms. However, we find a positive correlation between farm size and technical efficiency as well as scale efficiency for part-time and full-time farms. Given these different effects of part-time farming on scale efficiency, technical efficiency, and technical change, both on average and over time, the overall impact remains ambiguous and suggests further investigation.

Lastly, in investigating the impact of different farm socio-economic and environmental factors on scale efficiency, we find that the factors facilitating farm growth also increase scale efficiency. This is true for better access to and lower costs of land rental (higher rental share and lower rental rates), flexibility or availability of labor supply (higher share of family labor), higher subsidies, and being located in lowlands (altitude). Moreover, we also find that scale efficiency increases with the farmer's education level, but that the age of the farm manager has no impact. The impact of all of these factors is stronger for full-time farmers, likely because they have a higher necessity to adjust in scale.

From a policy perspective, our results are ambiguous. On the one hand, most crop farms in Austria are still too small to be technically efficient and scale efficient, with full-time farms exhibiting higher technological progress. Hence, the government should support farm growth and structural change to improve farm performance. Most important in this regard, in particular for crop farms, is probably access to and affordability of land. Land sales markets in Austria, as in many other EU countries, are relatively thin. Moreover, sales prices and rental prices in Austria are among the highest of all EU Member States (SALHOFER and LEONHARDT, 2021; VRANKEN et al., 2021). On the other hand, given these restrictions in land availability, part-time farming seems to be a substitute for farm growth, at least to some extent.

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