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Efficiency and Technology Gap in European Apple Production—A Metafrontier Model for Germany, Italy, and Poland

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ABSTRACT

EU member states have exhibited varying rates of apple production growth. Technical efficiency (TE) estimation is suitable for identifying best-practice farm performance. This study examined whether the development of the apple sector in Germany, Italy, and Poland was influenced by production efficiency, access to technology, as well as technological change, and assessed regional differences. In doing so, a translog stochastic metafrontier model was applied to farm-level data from the Farm Accountancy Data Network (FADN) for the period spanning 2014–2020. The model was estimated with True Random Effects (TRE) and Mundlak True Random Effects (MTRE). We found that the available technology is sub-optimally used in the three countries, with German farms producing at a level closest to the optimum. Furthermore, Poland had the lowest technology level among the three countries, while Germany and Italy produced close to the metafrontier. We found that subsidies significantly increase inefficiency in apple production in the three countries, while the effects of the share of family labor, and specialization in apple production differed among the countries. Therefore, country-specific policies are needed to account for regional differences.

JEL Classification: D24, Q12, Q18

1 | Introduction

Traditionally, based on production quantity and per capita consumption, apples are considered among the most important fruits in Europe (FAO 2023). Commercial apple production amounted to around 10.63 million tons in Europe in 2019 (GAIN 2020). Most of the apple trade in the European Union countries stem from intra-EU trade; only 3%–5% of the total apple supply in the European Union comes from outside the EU, with about 70% of imports originating from Chile, New Zealand, and South Africa (GAIN 2020). Therefore, this investigation focuses only on European apple farms, namely farms in Poland, Italy, and Germany, which are among the top five EU apple producers based on volume of production (FAO 2023).

Poland and Italy are the largest apple exporters in the EU, with a share of 45% and 29% of total European apple exports, respectively (GAIN 2020). Germany is a net apple importer and

Abbreviations: CD, Cobb-Douglas; FADN, Farm Accountancy Data Network; ha, hectares; LR, likelihood ratio; MTE, meta technical efficiency; MTRE, Mundlak True Random Effects; SFA, stochastic frontier analysis; t, tons; TE, technical efficiency; TGR, technology gap ratio; TL, translog; TRE, True Random Effects.

mainly produces for the German domestic market, which had relatively stable production area and quantity over the last decade. For a long time, Italy was the largest apple producer in the EU, holding the main share of production volume until 2011, when Poland produced—for the first time—the largest quantity of apples in the EU. The country started progressively to increase its production area and quantity until 2014, when Russia, its most important trade partner until then, set an import ban for EU apples (GAIN 2020). Since that year, the production area of apples in Poland has been decreasing as the production volume increased (see Figure 1). This reflects the productivity growth of Polish apple farms during the last decade, when Polish producers started to progressively invest in the modernization of orchards. They planted new varieties of apples (Muder et al. 2022) and began to increase their technology levels to obtain higher yields, improve product quality, and better meet market demand (GAIN 2020). However, apple yields in Poland (23.3 t/ha in 2020) are still far below the yields in Germany (30.1 t/ha in 2020) and Italy (44.8 t/ha in 2020). Therefore, the relevant questions in this context are whether producers are making efficient use of available technology, whether there is still a gap in the technology available among the countries, and the extent to which the development of each country's apple sector is associated with technology gaps and efficient use of existing technology.

Technical efficiency (TE) analysis is suitable for identifying best-practice farm performance (Coelli et al. 2005). TE is defined as the ability of a farm to make efficient use of the available technology, either by producing the maximum output with a given set of inputs or by producing a given set of output with minimal inputs. The basic approach of TE, which involves the application of a single production function, is based on the assumption that all producers share the

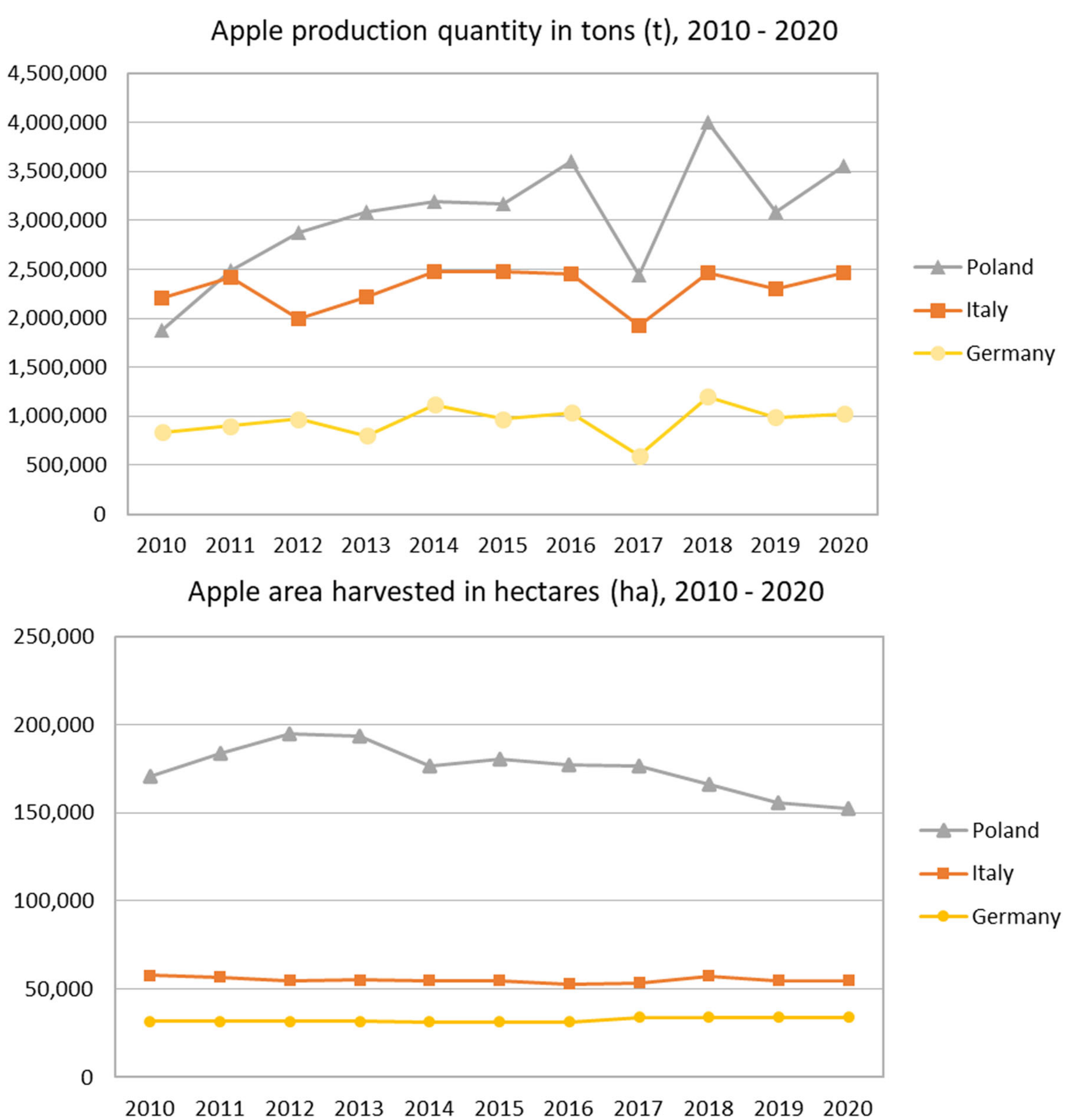

FIGURE 1 | Apple production quantity and harvested area in Poland, Italy, and Germany, 2010–2020. *Source:* Own elaboration based on FAO (2023).

same underlying technology. However, for farms in different regions, production opportunities and technology sets are likely to vary due to, for instance, climatic conditions (e.g., temperature and rainfall), labor and capital endowments, the use of inputs, and the cultivation of different tree varieties. To overcome this shortcoming, the metafrontier model (e.g., Battese et al. 2004; O'Donnell et al. 2008; Huang et al. 2014) was developed based on the assumption that producers in different regions at least have access to the same technology. The model is therefore applied in several studies that compare countries and regions (e.g., Cechura et al. 2017; Alem et al. 2019; Danso-Abbeam and Baiyegunhi 2020; Baráth et al. 2021).

Germany, Italy, and Poland together account for 59% of the EU's total apple production (GAIN 2020). Hence, it is useful to understand how efficient resources are used in the production process and how technology differs among these three countries. Given their interesting narratives and interconnected relationships, we selected these countries as noteworthy cases. When looking to enhance apple production productivity, it is important to understand regional differences in technical efficiency levels, technological differences among the countries, and determinants that affect levels of efficiency. For this reason, a farm-level efficiency analysis applying a stochastic metafrontier model to FADN data of Germany, Italy, and Poland is conducted in this study, and the following research questions are addressed:

1. How efficient are apple farms in Germany, Poland, and Italy taken into account each country's level of available technology?
2. What are the major determinants of apple production inefficiencies? How can efficiency be improved in the investigated countries?
3. Are there differences in production technology between the countries?
4. Has there been technological change in these countries?

2 | Literature Review

Efficiency research on farms that specialize in apple production is scarce, particularly in the EU. Most existing studies refer in this context to China. For instance, one study used a stochastic frontier to determine technical efficiency and environmental efficiency (Bai et al. 2019a), while another measured the technical efficiency and fertilizer use efficiency (Bai et al. 2019b) of apple production in China. Zhu et al. (2021) investigated the impact of internet use on the technical efficiency of apple-farming households in China and found that internet use can considerably increase efficiency due to improved access to technological information. Sun et al. (2023) investigated the technical efficiency of apple production in China's eight major apple production areas, applied a stochastic frontier model, and used urbanization rate as a threshold variable to assess the effects of the transfer of rural labor force on technical efficiency. Overall, the authors identified a negative impact of urbanization on the technical efficiency of apple production. Qu et al. (2020) assessed the impact of cooperative membership on apple farmers' technical efficiency in China. They combined stochastic frontier modeling with propensity score matching and determined that members of a cooperative obtained higher apple production output levels compared to farmers who were not members of a cooperative. Furthermore, Osmani and Kambo (2019) assessed the level of technical efficiency of apple farms in the Korça region in Albania with a stochastic frontier approach, while Yang et al. (2020) considered the impact of training and technology on the technical efficiency of apple farmers in Gilgit-Baltistan in the Kashmir region.

The metafrontier approach can be used to compare efficiencies among various groups that have different production functions. It can compare sectors (e.g., Lakner et al. 2017), farms in different regions (e.g., Alem et al. 2019) or countries (e.g., Martinez Cillero et al. 2021), and the various characteristics of farmers (e.g., Abdul-Rahaman et al. 2023; Missiame et al. 2021) and farms (e.g., Kramol et al. 2015). Bayav (2023) employed a metafrontier model to compare the efficiency of different scales of apple farms in Turkey. The author found that the production functions of large farms were closest to the metafrontier, followed by small farms and then medium-sized farms. The study ultimately concluded that producers were not able to produce on the metafrontier with the existing technology. To the best of our knowledge, none of the existing studies applied a stochastic metafrontier model to FADN data to compare the efficiency and technology level of apple production in different countries. Therefore, this study makes an important contribution to the current applied literature and investigates the efficiency and technology level of apple-producing farms in three major production countries, namely Germany, Italy, and Poland, and identify drivers of inefficiencies. In doing so, it applies the stochastic metafrontier approach developed by Huang et al. (2014), which is used only scarcely in the literature.

3 | The Apple Sector in Poland, Italy, and Germany

While apples are usually produced in small farms, apple farm sizes and structures largely differ across Germany, Italy, and Poland. In contrast to other European countries, Germany has relatively large apple farms—around 55% of its apple output comes from farms with a size of 20 ha or more (Muder et al. 2022). The production in all three countries is labor intensive, with the majority of operating costs consisting of hired and family labor (Dirksmeyer et al. 2014).

In Poland, apple production plays a more important role in agricultural production than in the other two countries. On average, apple production in Poland, Italy, and Germany from 2019 to 2021 accounted for 3.0%, 1.7%, and 0.2%, respectively, of each country's total agricultural production value (Eurostat 2023). The three countries largely differ in their development of production areas. In Germany, total production area increased slightly from 2010 to 2020 (+6.79%) (FAO 2023). This increase is mainly a result of a change in Germany's data collection procedure in 2017 (Muder et al. 2022). In Italy, the total production area slightly decreased from 2010 to 2020 (–5.18%) (FAO 2023); while there was a slight fluctuation in the production area over this time period, overall, a stable trend was identified.

The total production area in Poland had a strong increase from 2010 to 2015 but began to decline since 2015. From 2010 to 2020, there was an overall decline of −10.47% in Poland's production area (FAO 2023). This decrease can be explained by the Russian import embargo, which was set in 2014. Until then, Russia was the foremost importer of Polish apples. Many Polish producers restrained their business and grubbed up older orchards (GAIN 2018). The production quantity in the three countries fluctuated from 2010 to 2020. This is mainly reflected in the volatility of the yields. Apple trees are affected by alternation, a phenomenon where a year with higher yields is followed by a year with significantly lower yields (Krasniqi et al. 2017). This cycle can be caused by various factors, including physiological, biochemical, as well as environmental aspects (Ali et al. 2022) and leads to a fluctuation of yields. Furthermore, climate change and extreme weather events have a significant impact on the yield of apple trees (Gömann et al. 2015). In 2017, apple yield was at its lowest over the decade, caused by an earlier blossom that was then followed by a spring frost at the end of April that occurred in most European countries (GAIN 2017).

According to FAO (2023) Poland has on average the lowest apple yields of the three countries (22.4 t/ha on average between 2018 and 2020), followed by Germany with 31.5 t/ha on average between 2018 and 2020 and Italy with 43.2 t/ha on average between 2018 and 2020. Interestingly, apple yields in Poland are continuously increasing. There is an increase of around 71% from the average yield in the years 2010–2012 to the average yield in the years 2018–2020. In contrast, apple yields in Germany and Italy increased by only 11% over the same time periods (FAO 2023). One explanation for the increase in yields is that it is a side effect of the Russian import embargo: Due to the opening of new export destinations, Polish producers had to adapt to the tastes of new consumers (GAIN 2015) when offered the opportunity to replace old orchards for new varieties, which allowed for a modernization of orchards and a more intense level of production (GAIN 2017). Against the background of this narratives, we selected Poland, Germany and Italy as case studies for our analysis. In doing so, it is interesting to determine the extent of technological change that occurred in the three countries and identify the technological differences that exist between the three countries, particularly in consideration of how the modernization of orchards enabled Poland to catch up with the other countries.

4 | Materials and Methods

4.1 | Theoretical Model

The metafrontier concept (O'Donnell et al. 2008; Huang et al. 2014) is useful for assessing and comparing the efficiency of farms. This model, which was developed by O'Donnell et al. (2008), is estimated in two steps: First, the group frontiers are estimated with stochastic frontier analysis (SFA); then, the metafrontier is estimated with linear programming techniques. Due to the drawbacks of this approach—statistical properties cannot be ascertained and determinants of the production environment cannot be included in the metafrontier model—we opted to apply the approach by Huang et al. (2014), which involved an analysis conducted in two steps: First, the efficiency for the three countries (group models) was calculated with SFA; then, a stochastic metafrontier model was calculated for the pooled sample.

A basic stochastic frontier model is given by the following:

$$y_{it} = f(x_{it}, \beta)e^{(v_{it}-u_{it})} \tag{1}$$

Whereby y_{it} is the output of the i-th farm at time t $= 1, 2..., \mathrm{T}$, x_{it} is a vector (1 x K), containing the logarithms of inputs, β is a vector (K x 1) of unknown parameters that need to be estimated, v_{it} is the random (white-noise) error that should account for statistical noise and be normal distributed with mean zero and a constant variance, and u_i is the non-observable and non-negative random error that describes technical inefficiency for the i-th farm at time t. The error terms v_{it} and u_{it} are independently and identically distributed (iid).

The main assumption of the basic stochastic frontier is that producers operate under the same set of technologies. Therefore, the basic stochastic frontier model does not allow for comparisons among producers in different regions and countries, as they use different sets of technology (Lau and Yotopoulos 1989). To deal with this problem, the metafrontier is a suitable concept as it is based on the assumption that producers in different countries have potential access to the same technology (Battese et al. 2004). If we consider k production regions, the group stochastic frontiers for each region were estimated as follows:

$$y_{it}^k = f^k\left(x_{it}^k, \beta^k\right)e^{(v_{it}^k-u_{it}^k)} \quad i = 1, 2, ..., N(k) \tag{2}$$

Where y_{it}^k is the output of farm i in the kth region at time t. The input is described by the vector x_{it}^k, and β^k is a vector of unknown parameters for region kth. v_{it}^k represents the error term and u_{it}^k is the one-sided error representing technical inefficiency of farm i at time t:

$$u_{it}^k = \delta z_{it}^k + \omega_{it}^k \tag{3}$$

Where z_{it}^k are inefficiency determinants, e.g., institutional and farm-specific characteristics. The unknown parameters to be estimated are given by δ. And ω_{it}^k is a non-negative random variable which captures random inefficiency that cannot be explained by z- variables. The technical inefficiency term is distributed as $u_{it}^k \sim N^+\left(0, \sigma_{vk}^2\left(z_{it}^k\right)\right)$. A mathematical expression of the conditional expectation how the inefficiency components u_{it}^k vary with the inefficiency determinants z_{it}^k is given by:

$$\mathbb{E}\left(u_{it}^k \middle| z_{it}^k\right) = \exp(\gamma^{k'} z_{it}^k) \tag{4}$$

With $\gamma^{k'}$ capturing how the inefficiency determinant z_{it}^k influeneces the expected value of u_{it}^k. The exponential functional form ensures that $\mathbb{E}(u_{it}^k|z_{it}^k)$ has a non-negative value.

To address with heterogeneity concerns among different farms within countries, we applied the True Random Effects (TRE) estimator developed by Greene (2005a; 2005b). This model captures a time-invariant, firm-specific random term (θ_i), which accounts for cross-firm heterogeneity and distinguishes it from time-varying inefficiency (u_i). An alternative to this estimator is the True Fixed Effects estimator. However, as reported by Belotti and Ilardi (2012) the maximum likelihood dummy variable approach used to estimate TFE is appropriate only when the length of the panel is large enough ($T > 10$), which is not the case for our study.

The production function of each group k with TRE is written as follows:

$$y_{it}^k = f^k\left(x_{it}^k, \beta^k\right)e^{(v_{it}^k - u_{it}^k + \theta_i^k)} \quad i = 1, 2, \ldots, N(k) \tag{5}$$

However, the regular TRE does not account for correlation between unobserved factors and explanatory variables, what can cause bias in production frontier coefficients (Abdulai and Tietje 2007). Mundlak (1978) addressed this issue by including the group means of the explanatory variables as additional regressors. Farsi et al. (2005) combined this idea with TRE and proposed a model with Mundlak True Random Effects (MTRE) as follows:

$$y_{it}^k = f^k\left(x_{it}^k, \beta^k, \bar{x}_i^k\right)e^{(v_{it}^k - u_{it}^k + \theta_i^k)} \quad i = 1, 2, \ldots, N(k) \tag{6}$$

Where $\bar{x}_i^k$ represents a mean value of inputs for the i-th farm. By applying the Mundlak auxiliary to the TRE estimator, we can prevent firm-level heterogeneity from distorting inefficiency estimates, and we retain the flexibility of random effects while benefiting from the robustness of fixed effects in handling correlated unobserved heterogeneity (Farsi et al. 2005). To check whether the base model is affected by heterogeneity, we calculated both- the regular TRE and TRE augmented with the Mundlak auxiliary, and compared the findings in the results section.

In step two, based on the work of Huang et al. (2014), we estimated the stochastic metafrontier $f^M\left(x_{it}^k, \beta, \bar{x}_i\right)$, which, by definition, envelops all groups' frontiers $\hat{f}^k\left(x_{it}^k, \beta^k, \bar{x}_i^k\right)$ of k regions (predictions from step one). This is expressed by the following equation:

$$\hat{f}^k\left(x_{it}^k, \beta^k, \bar{x}_i^k,\right) = f^M\left(x_{it}^k, \beta, \bar{x}_i\right)e^{(v_{it}^M - u_{it}^M + \theta_i^M)} \tag{7}$$

Where v_{it}^M is the error term of the metafrontier which is iid as $v_{it}^M \sim N(0, \sigma_{vM}^2)$ and the technical inefficiency term is distributed as $u_{it}^M \sim N^+(0, \sigma_{vM}^2(z_{it}^M))$.

When the country frontiers are estimated (Equation 2), the farm-level technical efficiency can be calculated. Technical efficiency represents the distance of each individual farm from the country frontier. Technical efficiency was calculated as follows:

$$TE_{it}^k = \exp(-u_{it}^k) \tag{8}$$

Country-specific technical efficiency TE_{it}^k does not allow for a comparison of technology among countries—to make these comparisons, technology gap ratio (TGR) is necessary. The TGR is the distance from the respective country frontier to the metafrontier. As the stochastic metafrontier envelops all country frontiers, the TGR must always be less than or equal to 1 (Huang et al. 2014).

$$TGR_{it}^k = \exp(-u_{it}^M) \tag{9}$$

To determine which countries, have the farms that operate closest to the metafrontier, meta technical efficiency (MTE) must be measured. The MTE is the distance of each individual farm to the metafrontier and is defined as the product of TE and TGR:

$$MTE_{it}^k = TGR_{it}^k \times TE_{it}^k \tag{10}$$

We also analyzed the effect of exogenous determinants on inefficiency by scaling its distribution. We allowed heteroscedasticity in u_{it}, and sought to determine the impact of vector of explanatory variables z_i', described by the vector of parameters δ:

$$u_{it}^k \sim \mathrm{E}(\sigma_{ui}^2) \tag{11}$$

$$\sigma_{ui}^2 = \exp\left(z_i'\delta\right)$$

This approach is an improvement to the earlier method, where efficiency was first estimated and then regressed with exogenous variables using an OLS or Tobit model. The greatest issue of this procedure was violation of the iid assumption from the first stage estimation. The method applied in this study is based on the concept that it is possible to relax the constant-variance property of exponential distribution, by allowing the variance to be a function of the exogenous variables. This allows inefficiency, which also depends on the variance of the exponential distribution, to depend on exogenous variables. In doing so, we incorporated exogenous influences on efficiency and furthermore, corrected one source of heteroscedasticity, which would lead to biased estimates of all parameters in the model, and hence to biased estimates of the efficiencies of individual producers (Kumbhakar and Lovell 2000).

4.2 | Empirical Model

Built on the studies of Battese and Coelli (1995) and Battese et al. (2004) and adjusted with the specifications detailed by Huang et al. (2014) and Greene (2005a; 2005b), we used a translog stochastic metafrontier model with TRE and MTRE estimators. The study's functional form was based on the results of a likelihood ratio (LR) test, which revealed that a translog production function is an adequate fit for the given dataset. The distribution of the inefficiency terms was assumed to be exponential. The country k frontier for the model with MTRE is defined as:

$$\ln y_{it}^k = \beta_0^k + \sum_{j=1}^{4} \beta_i^k \ln X_{jit} + \frac{1}{2}\sum_{j=1}^{4} \beta_{jj}^k (\ln x_{jit})^2 + \frac{1}{2}\sum_{j=1}^{4}\sum_{l=1}^{4} \beta_{jl}^k \ln x_{jit} \ln x_{lit} + \sum_{j=1}^{4} \beta_i^k \ln \bar{x}_{ji}^k + \beta_t^k t + \frac{1}{2}\beta_{tt}^k t^2 + \theta_i^k + v_{it}^k - u_{it}^k \quad (12)$$

Where y_{it} is defined as vector of total farm output, x_{jit} is a vector of inputs ($j = 1, \ldots, J$) by farms ($i = 1, \ldots, N$) over time ($t = 1, \ldots, T$), v_{it} is the white-noise error term, u_{it}^k is the inefficiency component, θ_i^k is a farm-specific component for capturing time-invariant unobserved heterogeneity, and $\bar{x}_i^k$ represents the group means of inputs. This model extends the basic stochastic frontier model by distinguishing between unobserved heterogeneity (farm effect) and TE, and the model with a general TRE estimator by accounting for correlation between unobserved factors and input variables. For the model with general TRE, we dropped the group means of inputs and their respective coefficients from the MTRE specifications. The trend variable t indicated technological change. The model was estimated using STATA 17. Furthermore, the variables were normalized using the ratio of each variable and its mean value; therefore, the first-order parameters were directly interpreted as partial production elasticities at the geometric mean of the data (Coelli et al. 2005).

4.3 | Data and Description of Variables

We analyzed individual farm data from the Farm Accountancy Data Network (FADN) for the years 2014–2020. National FADN datasets for each EU country include bookkeeping data with standardized definitions of each variable, which enables us to use the FADN data to make cross-country comparisons. We considered only farms that specialize in apple production, meaning that more than two-thirds of the standard output comes from this activity. The FADN database is an unbalanced panel, as rotational sampling was applied. The sample sizes for Poland, Italy, and Germany were 1210, 1612, and 469, respectively.

As it is not possible to assign expenditures and revenues to special farm operations within the FADN database, we considered the whole farm specialized in apple production." Apple's total output" was part of the aggregated variable "pome fruit excl. table grapes total output" until 2013; therefore, we set the first year of our analysis to 2014, when FADN changed the data collection procedure and indicated "apples total output" as its own variable. In the production model, we set total farm output in Euro as an output variable. The total farm output in Italy is, on average, 2.37 times higher than that in Poland, while the output in Germany is 6.21 times higher than in Poland. We furthermore used land, labor, capital, and materials as input variables. Table 1 provides an overview of the variables used, their respective FADN codes, and the mean, standard deviation, minimum, and maximum for each variable in each country.

TABLE 1 | Descriptive statistics for the research sample.

Variable	Mean	Std. Dev.	Minimum	Maximum
Poland ($N = 1210$)				
Output (SE131)	49175.60	51082.65	1564.11	528337.70
Land (SE025)	11.99	8.28	1.71	67.83
Labor (SE011)	6562.60	4500.36	676.00	44116.00
Capital (SE360 + SE340)	15342.02	12238.71	638.46	99451.09
Materials (SE285 + SE305 + SE295 + SE300 + SE356 + SE345)	14008.33	16713.70	1012.03	237657.20
Italy ($N = 1612$)				
Output (SE131)	116760.00	118491.30	1388.00	1367822.00
Land (SE025)	7.32	7.23	0.85	90.03
Labor (SE011)	4578.98	3483.63	800.00	42160.00
Capital (SE360 + SE340)	15835.71	16603.57	100.00	239005.60
Materials (SE285 + SE305 + SE295 + SE300 + SE356 + SE345)	27047.91	26110.01	646.00	338371.00
Germany ($N = 469$)				
Output (SE131)	305563.80	258852.50	11595.00	1767611.00
Land (SE025)	22.25	13.69	3.43	75.51
Labor (SE011)	9648.35	6170.27	1689.02	50094.24
Capital (SE360 + SE340)	69024.30	57263.23	1365.29	320342.20
Materials (SE285 + SE305 + SE295 + SE300 + SE356 + SE345)	83499.58	69243.31	1588.73	513094.30

Source: Own study.
FADN abbreviations: SE131—Total output in Euros; SE025—Total utilized agricultural area in ha; SE011—Labor input in hours; SE360—Depreciation in Euros; SE340—Machinery and buildings current costs in Euros; SE285—Seeds and plants in Euros; SE305—Other crop specific costs in Euros; SE295—Fertilizers in Euros; SE300—Crop protection in Euros; SE356—Other direct inputs in Euros; SE345—Energy in Euros.

We used total utilized agricultural area measured in ha as a variable for land. In our sample, the average apple farm size in Germany was 1.9 times larger than in Poland and 3.0 times larger than in Italy. We measured labor input in working hours and found that the average German farm uses 1.5 times more labor than the average Polish farm and 2.1 times more labor than the average Italian farm.We define capital as the sum of depreciation and current costs for the upkeep of machinery and buildings. The mean capital costs in the sample are similar between Poland and Italy, Germany's costs are around four times as high, which implies that apple production in Germany is more capital-intensive. The materials variable includes young plants, fertilizers, crop protection, energy, other direct inputs, and other crop-specific costs. In our sample, German apple farms use around 3.1 times more materials than Italian apple farms and 6.00 times more materials than Polish apple farms.

Based on existing literature, we included shares of family labor and CAP subsidy (excl. on investment) to farm output ratio and the degree of specialization in apple production as variables for explaining inefficiency (z-variables) in our model. Since apple farming is a labor-intensive business and the majority of operating costs involve hired and family labor (Dirksmeyer et al. 2014), we consider it worthwhile to more closely examine the effect of the share of family labor on efficiency. Previous studies came to ambiguous results and identified both positive (e.g., Rade et al. 2018; Addo and Salhofer 2022) or negative (e.g., Kourtesi et al. 2016) effects of family labor on farm efficiency. The effects of subsidies on technical efficiency have been controversially discussed in recent literature. Most studies (54%) found a negative estimated effect on technical efficiency of farms, 22% found a null (nonsignificant) effect and 24% found a significant positive effect (Minviel and Latruffe 2017). However, these results are hardly comparable, as these studies differ in terms of production sector, time period, subsidy variable, and type of subsidy used (Minviel and Latruffe 2017). Agostino et al. (2024) confirmed that this impact depends on the type of subsidy. Furthermore, Fertő and Bojnec (2023) considered the impact of CAP subsidies on the technical efficiency of Hungarian wine farms and found negative effects. As this study considers a horticultural production system during a similar time period, we expect similar results. Regarding the specialization of farms, the current literature found either positive (e.g., Addo and Salhofer 2022) or negative effects (e.g., Náglová and Rudinskaya 2021). As apples are highly vulnerable to extreme weather events, crop diversification can reduce production risk. Conversely, specialized farms have better opportunities to acquire advanced technology (e.g., for storage and orchard maintenance).

The z-variables included in our analysis were limited with respect to the data that were available in the FADN database. Unfortunately, not all variables that we would have liked to include existed in the database (e.g., the ages of the trees). Other variables were collected for only one or two countries in our sample (e.g., irrigation, organic, and PDO/PGI). Hence, with respect to the metafrontier, we could not include these variables.

5 | Results and Discussion

5.1 | Tests for Model Specification

Six main hypotheses were tested with LR tests to specify the model (Table 2). In test (i), we tested whether the model is better represented by a stochastic production function without an efficiency term, which was rejected. In test (ii), we tested if a Cobb-Douglas (CD) functional form is more appropriate than the translog (TL) form. The null hypothesis was rejected, and hence, we applied the translog functional form in our model.

TABLE 2 | Specification test results by country and metafrontier.

		Likelihood ratio				
Test		**Poland ($N = 1210$)**	**Italy ($N = 1612$)**	**Germany ($N = 469$)**	**df**	**Critical Value ($\alpha = 0.01$)**
(i) No inefficiency	TRE	112.37***	150.68***	80.98***	1	5.41[a]
	MTRE	112.92***	155.13**	84.93***	1	5.41[a]
(ii) Cobb–Douglas versus translog	TRE	35.02***	47.71***	41.01***	10	23.21
	MTRE	27.14**	31.80***	41.01***	10	23.21
(iii) Heteroscedas-ticity	TRE	117.67***	160.28***	44.43***	3	11.35
	MTRE	112.13***	157.52***	43.39***	3	11.35
(iv) Technological change	TRE	66.93***	11.93**	63.66***	2	9.21
	MTRE	54.56***	11.34**	70.12***	2	9.21
(v) Pooled model versus metafrontier	TRE		1014.84***		16	32.00
	MTRE		1034.40***		20	37.57
(vi) Constant returns to scale	TRE	55.49***	26.78***	30.47***	5	15.09
	MTRE	6.59	20.37**	15.8**	5	15.09

Source: Own study.
**test p-value < 0.01,
***test p-value < 0.001,
[a]Critical values for (i) according to Kodde and Palm (1986), the other critical values are obtained from the Chi-squared distribution.

The TL production function provides a more flexible form, which allows negative elasticities at the individual data points. This can lead to a violation of monotonicity and quasiconcavity properties (Diewert 1973). Violating regularity properties can affect the accuracy of calculated technical efficiencies (Henningsen and Henning 2009; Sauer et al. 2006). To alleviate concerns about potential effects of the functional form on TE, we compared TE results of the TL and CD model (Owusu and Bravo-Ureta 2022). The results are presented in the section "Technical Efficiency Scores". In (iii), we tested a model without heteroscedasticity in the inefficiency component, which was rejected. Hence, the exogenous variables were included in our model. In (iv), we tested a model without time variables, which was rejected. In (v), we did a joint estimation of the group frontiers (pooled model) to test if the model is better represented by a pooled than a metafrontier model. In line with metafrontier literature (O'Donnell et al. 2008; Huang et al. 2014) we performed an LR test. The null hypothesis was rejected. However, the LR test relies on the assumption that the difference in dimensions between the null and alternative hypothesis is defined. If $k = 0$, the chi-squared distribution would be undefined. To overcome this issue, we also performed a Wald-test to see, if the k-group production functions structurally differ from the pooled model. The values for the Wald-test statistic (see table A1) were significant and the null hypothesis was rejected. Hence, the application of a metafrontier is justified by both tests. In test (vi) we tested a model with constant returns to scale. The null hypothesis was rejected for all groups except for the Polish model with MTRE. Although we could not reject it in that case, we did not add a constant returns to scale restriction to our model due to the need for a common model for the three countries, as well as the highly significant result for the Polish model with TRE.

5.2 | Stochastic Group Frontiers and Metafrontier Estimates

The estimates of the variables of the production function for the group models and the metafrontier model are found in Table 3. The first-order coefficients of the TL production model can be interpreted as partial production elasticities at sample mean because the inputs of the model were normalized by their geometric means. This means that the coefficients indicate how a relative change of 1% in one input factor would change the relative output with all other input factors remaining constant. The coefficients are positive and range between zero and one, satisfying the theoretical requirements of monotonicity and quasiconcavity of the production frontier at the sample mean. The relative importance of the production factors differs among the three investigated countries, which justifies the application of the metafrontier approach. In Germany and Italy, labor was the coefficient with the largest effect on production, which implies that any change in the labor input would affect the total farm output more than a relative change in any other input would. This shows that improving access to qualified labor forces could strongly improve the productivity of this labor-intensive business. Materials were found to be the most important production factor in Poland. In Italy, it is the second most important factor, closely following labor. In Germany, materials are the second most important production factor in the model with MTRE, whereas in the model with TRE, capital is more important. Generally, in the model with TRE, capital plays a more significant role. In Germany and Poland, it is insignificant in the model with MTRE but not in the TRE model, and the values are higher for all countries. In the model with MTRE, the variable land was insignificant in all three countries, while in the TRE model, it was only insignificant in Germany. This may be due to the fact that, during the examined period, the farm areas did not change significantly. In both estimations all parameters of the metafrontier were highly significant and came to similar results.

The estimated time trend variable (t) represents the average annual rate of technological change (Wang and Ho 2010) and is significant and positive for all countries and the metafrontier. This implies that a technological improvement in apple production took place in Germany, Italy, and Poland between 2014 and 2020. For Italy and the metafrontier, the variable t^2 is significant and slightly negative, implying a nonlinear (concave) trend. The negative sign of t^2 reflects a strong increase in technological change at the beginning that declines after some years but exhibits an overall positive trend. A potential explanation for the slowdown in Italian apple production after some years might be the change in its production orientation over time. Italy more than doubled the size of organic apple production between 2015 and 2019 (Muder et al. 2022). With more than 14% of cultivated apple areas in 2019 were organic (Muder et al. 2022), Italy is one of the largest organic apple producers in the EU (GAIN 2021, 2016). This change in production orientation might also explain the slight regression that followed the initial outward shift in the production function, but with an overall trend remaining positive. As there is no variable for organic fruits and vegetables in Italy given in the dataset, we cannot further investigate the interaction between organic production and technological change. The variable t^2 was not significant for Germany and Poland, which means that there is no clear evidence of a slowdown or a nonlinear trend. The findings are consistent with other author's findings (e.g., Moreira and Bravo-Ureta 2010). The estimated theta values are low (far from 1) what indicates an important role of the unit-specific effects and thus, is a justification for a model with random effects.

5.3 | Determinants of Technical Inefficiency in Apple Production

In addition to serving as a benchmark for producer's TE, stochastic frontier analysis also identifies factors that affect the TE of farms (Kumbhakar and Lovell 2000). Table 3 presents a set of explanatory variables that affect the TE of apple-producing farms. Since these variables affect inefficiency, a positive sign means that the variable increases inefficiency and therefore leads to decreased TE.

Regarding the share of family labor in total labor, the explanatory variable was positive for all group frontiers. However, it was only significant in Italy, which implies that a higher share of family labor decreases TE in Italy. The effects of family labor on the efficiency of farms are controversially discussed in the

TABLE 3 | Estimation results for model with True Random Effects (TRE) and Mundlak True Random Effects (MTRE).

	TRE								MTRE							
	Poland ($N = 1210$)		Italy ($N = 1612$)		Germany ($N = 469$)		Metafrontier ($N = 3291$)		Poland ($N = 1210$)		Italy ($N = 1612$)		Germany ($N = 469$)		Metafrontier ($N = 3291$)	
Land	0.23*	(0.093)	0.16***	(0.037)	0.04	(0.092)	0.20***	(0.010)	0.25	(0.166)	0.07	(0.074)	0.16	(0.116)	0.19***	(0.011)
Labor	0.24***	(0.070)	0.50***	(0.043)	0.65***	(0.091)	0.34***	(0.008)	0.20*	(0.090)	0.32***	(0.064)	0.59***	(0.101)	0.24***	(0.007)
Capital	0.23***	(0.059)	0.20***	(0.026)	0.32***	(0.059)	0.19***	(0.006)	0.15	(0.083)	0.11**	(0.036)	0.06	(0.083)	0.08***	(0.005)
Materials	0.51***	(0.076)	0.27***	(0.034)	0.21***	(0.068)	0.32***	(0.005)	0.49***	(0.076)	0.25***	(0.034)	0.20**	(0.065)	0.28***	(0.004)
t	0.05*	(0.026)	0.07***	(0.020)	0.07**	(0.023)	0.07***	(0.003)	0.05*	(0.026)	0.07***	(0.019)	0.08***	(0.023)	0.06***	(0.003)
t^2	−0.001	(0.003)	−0.01***	(0.002)	−0.003	(0.003)	−0.01***	(0.0004)	−0.0004	(0.003)	−0.01***	(0.002)	0.0004	(0.003)	−0.01***	(0.000)
Constant	10.62***	(0.059)	11.63***	(0.042)	11.10***	(0.060)	11.10***	(0.016)	10.66***	(0.059)	11.63***	(0.043)	11.04***	(0.062)	11.20***	(0.011)
Inefficiency model coefficient and standard error (in brackets) estimates																
Share of family labor	0.26	(0.474)	3.44***	(0.583)	0.856	(1.106)	1.12	(3.723)	0.19	(0.477)	3.53***	(0.610)	1.17	(1.033)	1.03*	(0.519)
Subsidies	4.84***	(0.619)	7.04***	(0.837)	6.54***	(1.553)	0.48	(0.367)	4.73***	(0.617)	7.06***	(0.841)	6.00***	(1.464)	0.73*	(0.368)
Specialization in apples	−3.55*-**	(0.932)	1.89*	(0.825)	−5.61*	(2.622)	−4.44	(4.215)	−3.36***	(0.932)	2.05*	(0.843)	−5.39*	(2.510)	−2.17*	(1.060)
Constant	−0.67	(0.857)	−7.66***	(0.997)	−0.79	(2.114)	−6.76	(5.232)	−0.77	(0.858)	−7.90***	(1.036)	−0.97	(2.049)	−4.81***	(0.934)
Model statistics																
Vsigma	−2.60***	(0.094)	−2.92***	(0.092)	−3.45***	(0.128)	−5.64***	(0.037)	−2.61***	(0.095)	−2.95***	(0.090)	−3.54***	(0.127)	−6.02***	(0.074)
Theta	0.22***	(0.016)	0.22***	(0.014)	0.19***	(0.017)	0.428***	(0.010)	0.22***	(0.016)	0.23***	(0.014)	0.18***	(0.016)	0.435***	(0.006)
LogLike	−633.04		−693.31		−2.36		2227.00		−626.12		−676.70		11.12		2411.20	

Source: Own study.
translog interaction variables omitted, [a]first-order parameters in production model can be interpreted as partial production elasticities at the geometric mean of the data; [b]values of lambda from the model without Usigma predictors;
***test p-value < 0.001,
**test p-value < 0.01,
*test p-value < 0.05;

literature. Some authors have found that family labor increases TE (Idris 2013; Rade et al. 2018; Addo and Salhofer 2022), arguing that principal–agent problems that are linked to hired labor are avoided (Giannakas et al. 2001), motivation and incentives are higher for residual claimants (Rade et al. 2018; Addo and Salhofer 2022), and the support of family members during the peak seasons reduces losses in quality and quantity of the output (Idris 2013). In line with the findings of this study, other authors have found that family labor negatively impacts TE (Karagiannis and Sarris 2005; Latruffe et al. 2008; Kourtesi et al. 2016), concluding that contractual agreements can provide high incentives for hired labor (Kourtesi et al. 2016) and that hired labor might be more qualified to perform specialized tasks (Latruffe et al. 2008). Therefore, we argue that apple production is a labor-intensive business that relies on seasonal workers who can cope with work under physical stress and in return receive incentives for efficient work. Therefore, it is plausible that these specialized labor forces work more efficiently than family laborers.

Furthermore, we analyzed the effects of subsidies on the TE of apple production and identified a significant negative effect in all investigated countries. In line with us, Fertő and Bojnec (2023) found that CAP subsidies had a negative effect on the TE of Hungarian wine farms. They argued that the reduction of CAP subsidies would create market pressure and enforce less efficient wine farms to leave the market. Furthermore, other authors have identified the negative effects of CAP subsidies on technical efficiency (e.g., Marzec and Pisulewski 2017; Latruffe et al. 2017; Zhu et al. 2012). However, these studies considered a time frame in which other CAP reforms were enforced; therefore, they are only partially comparable with our results. The main argument for the negative effect of subsidies on TE is that farmers tend to use subsidies as an additional source of income rather than as a financial means to adapt to the market (Marzec and Pisulewski 2017). This lowers their incentive to increase their production efficiency, as they receive an income without actively engaging in any farming activities (Minviel and Latruffe 2017).

Regarding the specialization of farms in apple production, this study yielded ambiguous results. We only included farms in the investigation that had 66% of their total output come from apple production, which is already a notable degree of specialization. We investigated whether higher degrees of specialization affected the level of production efficiency. For Germany and Poland, we identified a positive effect of specialization on efficiency, whereas for Italy, we found a negative effect. Interestingly, the average levels of specialization in Poland and Germany were similar (around 86%); Italy had a higher level of specialization (92%). This leads to the assumption that the effect of specialization might not be linear. The results are significant in Poland at 0.1% level and in Italy and Germany at 5% level. We argue that the structures of apple farms differ among European countries (Muder et al. 2022). Therefore, specialization could have different effects on TE depending on the country. Other authors found both positive (Karagiannis and Sarris 2005; Addo and Salhofer 2022) and negative (Náglová and Rudinskaya 2021) effects of specialization on efficiency. The first associated specialization with a higher level of skills (Addo and Salhofer 2022) and greater motivation resulting from the pressure of relying on a single farm activity for most of the farm's output (Karagiannis and Sarris 2005).

For the inefficiency terms of the group frontier, both estimators—the TRE and the MTRE—produced very similar results at the same significance levels. However, for the metafrontier, the results vary depending on the estimator. While all inefficiency variables are insignificant with the TRE estimator, they become significant at the 5% level when applying the MTRE estimator, suggesting that these variables influence the technology gap. While the determinants have ambiguous effects within the countries, the share of family labor and subsidies decrease efficiency in the overall metafrontier, whereas specialization in apples increases efficiency.

5.4 | Technical Efficiency Scores

We calculated the TE, TGR and MTE for the three countries and for both—the model with TRE and the model with TRE augmented with the Mundlak auxiliary. The results

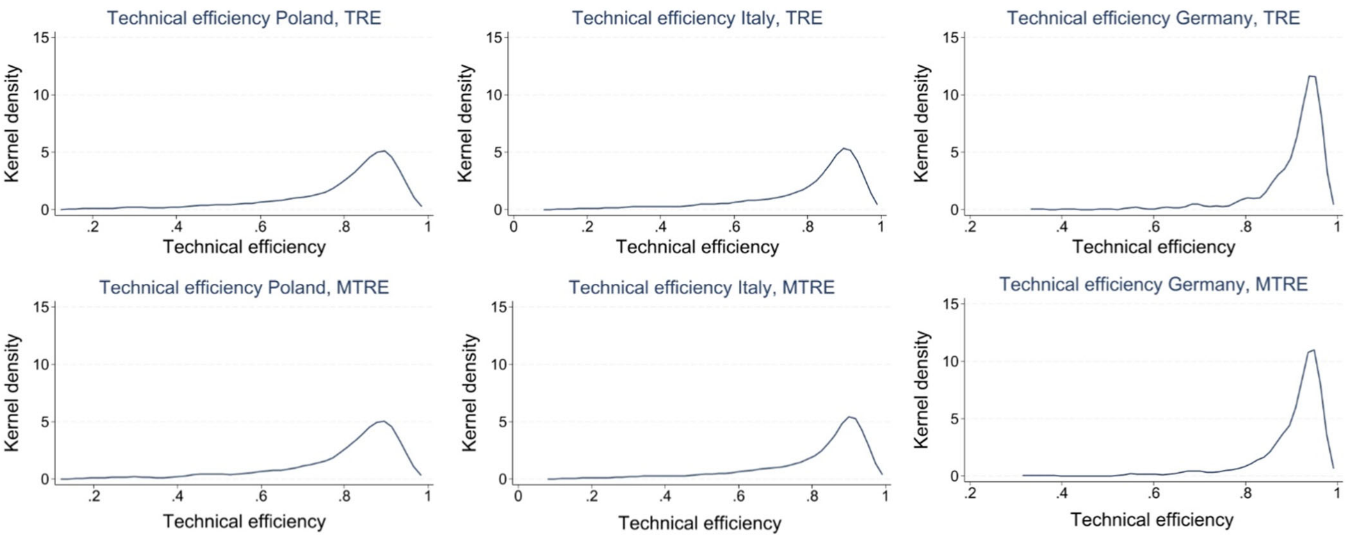

FIGURE 2 | Kernel density plot technical efficiency (TE) with respect to the country frontier for the models with True Random Effects (TRE) and Mundlak True Random Effects (MTRE). *Source:* Own study.

show that overall TE differs among the three countries (Figure 2).

The estimated efficiency scores of both estimators are very similar, in mean values as well as in minimum, maximum, and standard deviation (Table 5). The mean country-specific TE is the highest in Germany (around 90%), which implies that apple farmers in Germany produce at a level close to the maximum possible output with regard to environmental conditions and the production technology available in the country. The TE levels in Poland (around 79%) and Italy (around 80%) are lower, which means that there is still room to improve their respective outputs by around 21% and 20%, respectively, factoring in their technological and environmental conditions.

To alleviate concerns that violated regularity properties affect the correctness of TE, we calculated the TEs also for a CD model. A comparison of the results can be found in Appendix B (see Tables B1 and B2). The findings confirm, that the average TE scores are almost identical across TL and CD for both estimators. Also, the minimum and maximum TE values as well as the standard deviation are very close. The difference in the mean TE is for all groups < 0.8%, for most groups even < 0.2%. The Spearman rank correlation coefficients (Table 4) are very high and indicate that there is a statistically significant and strong relationship between the TE results from TL and CD. The findings are in line with Owusu and Bravo-Ureta (2022), and confirm that the TE indices of the TL closely resemble the patterns of the CD. Hence, the decision between CD and TL has negligible effects on the TE results. The descriptive statistics of the TEs of the group frontiers, TGRs, and MTEs are presented in Table 5. The TGR was the highest in Italy, followed by Germany and Poland (Figure 3). The results imply a relatively small gap between the metafrontier and the group frontiers of Italy and Germany. In contrast, there is a larger gap between the Polish group frontier and the metafrontier, which suggests that there is a difference in the technology that is available in Poland compared to the other two countries (Moreira and Bravo-Ureta 2010).

TABLE 4 | Comparison of TE results from TL and CD and Spearman correlation results.

	Poland	Italy	Germany
MTRE	TL & CD	TL & CD	TL & CD
	0.9908***	0.9912***	0.9552***
TRE	TL & CD	TL & CD	TL & CD
	0.9860***	0.9870***	0.9511***

Source: Own study. Spearman rank correlation was computed between TE scores from translog (TL) and Cobb-Douglas (CD) models.
***$p < 0.01$

This finding suggests that although many apple orchards in Poland were modernized during the last decade, Poland still has not fully caught up with other European major producers in terms of technology level. While the mean TGRs are very similar between the TRE and MTRE estimators for Germany and Italy, there is a larger difference for Poland. The TGR for Poland is higher when applying the TRE estimator. Although the mean TGR values are similar for Italy and Germany, the standard deviation is smaller for TRE, indicating that individual data points are more concentrated and closer to the optimum. The differences in TGR are driven by variations in the metafrontier model, which had only insignificant coefficients of inefficiency variables when applying the TRE estimator.

TABLE 5 | Technical efficiency (TE), Technology gap ratio (TGR), and meta technical efficiency (MTE) estimates of apple farms in Poland, Italy, and Germany (2014–2020) for estimation with TRE and MTRE.

	Poland		Italy		Germany	
	MTRE	**TRE**	**MTRE**	**TRE**	**MTRE**	**TRE**
TE estimates						
Mean	0.791	0.790	0.800	0.797	0.900	0.903
SD	0.153	0.156	0.164	0.164	0.083	0.081
Min.	0.145	0.149	0.105	0.107	0.327	0.344
Max.	0.958	0.959	0.967	0.959	0.979	0.980
TGR estimates						
Mean	0.663	0.906	0.991	0.996	0.979	0.994
SD	0.093	0.099	0.016	0.001	0.033	0.003
Min.	0.357	0.417	0.665	0.989	0.751	0.971
Max.	0.987	0.994	0.997	0.998	0.998	0.998
MTE estimates						
Mean	0.524	0.719	0.793	0.794	0.881	0.899
SD	0.124	0.171	0.163	0.164	0.090	0.081
Min.	0.084	0.106	0.102	0.107	0.321	0.342
Max.	0.863	0.945	0.963	0.962	0.969	0.976

Source: Own study.

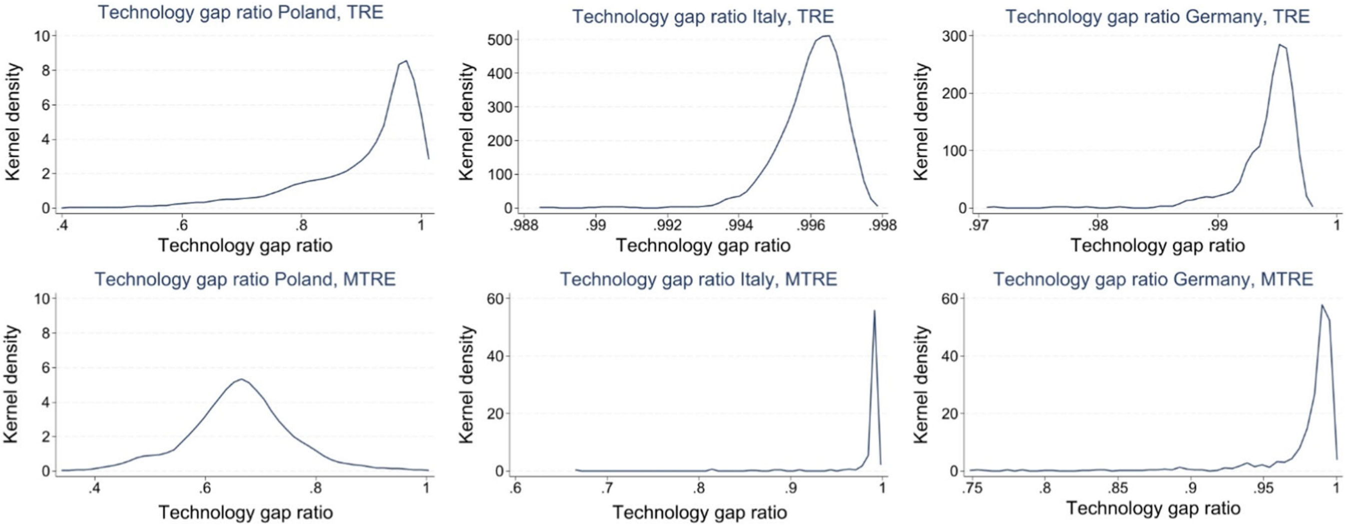

FIGURE 3 | Kernel density plot technology gap ratio (TGR) for the models with True Random Effects (TRE) and Mundlak True Random Effects (MTRE). *Source:* Own study.

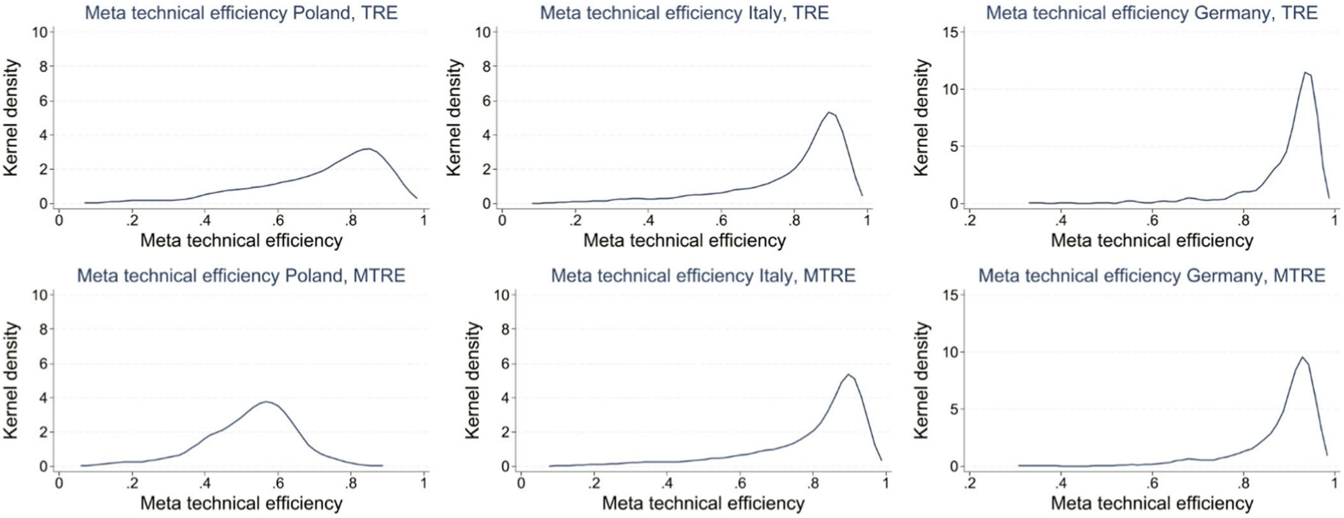

FIGURE 4 | Kernel density plot meta technical efficiency (MTE) for models with True Random Effects (TRE) and Mundlak True Random ETffects (MTRE). *Source:* Own study.

Considering the TE of producers with respect to the metafrontier (Figure 4), German producers are on average closest to the metafrontier, followed by Italy and Poland. As the MTE is a product of TE and TGR, the findings regarding the differences in TRE and MTRE apply also to the MTE.

Interestingly, the lower levels of MTE in Italy and Poland, compared to Germany, are caused by different circumstances. In Poland, not all farmers use available technology in the best way possible, and additionally, there are also gaps in the available technology. In contrast, in Italy, the level of technology is high, but not all farmers utilize the best available technology. Therefore, our results show that different approaches in the investigated countries are needed to improve productivity. As suggested by Moreira and Bravo-Ureta (2010), in the context of Poland, additional research would be needed to apply technology from neighboring countries to local conditions and to adapt the best farming practices from the neighboring countries. In contrast, in Germany and Italy, where the country frontier is already close to the metafrontier, research on new technologies or the adaption of technologies from distant areas could help improve farm performance. For the three countries in this study, we would further suggest supporting investments and farm cooperatives to provide producers the opportunity to become more efficient through using the best available technology. Farm cooperatives could assist in exchanging machinery and sharing cooling and storage technology, which is especially helpful to small farms. In Italy, in particular, where many small farms operate and available technology is not used in the most efficient way, organization into cooperatives could benefit producers. Because a lack of capital is a primary reason for declines in apple production (Muder et al. 2022), the provision of credits is necessary to provide producers access to the available technology.

To determine the significance of the differences in the estimated efficiency parameters, we conducted MANOVA analysis (Table 6).

TABLE 6 | Tests for the differences in efficiency among countries.

	TE		TGR		MTE	
	TRE	MTRE	TRE	MTRE	TRE	MTRE
Wilks's lambda	0.9397***	0.9447***	0.6578***	0.1233***	0.8768***	0.4944***
Pillai's trace	0.0603***	0.0553***	0.3422***	0.8767***	0.1232***	0.5056***
Lawley–Hotteling trace	0.0641***	0.0586***	0.5203***	7.1077***	0.1405***	1.0226***
Roy's largest root	0.0641***	0.0586***	0.5203***	7.1077***	0.1405***	1.0226***
Tukey HSD test						
Italy versus Poland	0.0073	0.0088	0.0900***	0.3283***	0.0755***	0.2691***
Germany versus Poland	0.1137***	0.1086***	0.0882***	0.3160***	0.1798***	0.3571***
Germany versus Italy	0.1064***	0.0997***	−0.0018	−0.0123***	0.1043***	0.0880***

Source: Own study.
***test p-value < 0.001.

The tests showed that efficiency differed significantly across the three countries. Post hoc tests identified the exact sources of these differences. The Tukey HSD test revealed that there was no significant difference in TE between Poland and Italy for both estimators. However, the TGR differed between the TRE and MTRE estimators. The TGR values for Germany and Italy are very similar with TRE, and the Tukey test confirmed that there are no significant differences. In contrast, both TGRs differ significantly when using the MTRE estimator. These results confirm the differences in metafrontier estimation between the two estimators.

6 | Conclusions

This study analyzed the technical efficiency of apple farms in Germany, Italy, and Poland and applied a metafrontier model to assess technological differences among these three countries. Farmer's output in Poland and Italy lagged behind its potential, with a mean TE of around 79% and 80%, respectively, and Germany had the highest mean TE at around 90%-level. The results indicate that there are farmers in all three countries who use the available technology sub-optimally, meaning that they produce lower output with the same input compared to the best-performing farms in the country.

For Italy and Germany, we found a TGR very close to 1, which means that the technology level in both countries is high. In contrast, in Poland, the TGR was lower; therefore, the country was further away from the metafrontier, meaning that there was a gap in the available level of technology. We found that Germany had the highest MTE, with those of Italy and Poland being much lower. The low MTE in Italy is mainly caused by a low TE, while Poland's low MTE was the result of having a low TE and the lowest TGR.

Our results suggest that different policy measures for the countries are needed for each to catch up to the metafrontier. To increase the technology level in Poland, research regarding adapting technology from neighboring countries to local conditions is necessary. To improve the application of the available technology in all countries, the support of farm cooperatives, access to credits, and support via investments are key. Our analysis was limited to the variables available in the FADN database.

We applied a TL model with TRE and MTRE and compared both. The results for the group frontiers were quite similar across both approaches. However, the metafrontier results showed greater differences between the two estimators, which was also reflected in variations in the TGR. Our results show that accounting for the correlation between unobserved factors and explanatory variables has a significant effect on the TGR.

Furthermore, the findings confirm that labor is one of the most important variables in production function. We therefore conclude that access to the labor is a key element of apple production and that strict regulations on the employment of seasonal workers can negativly impact production. Furthermore, the explanatory variables family labor, and specialization in apple production had different effects among the countries. Hence, we conclude that there exist regional differences that cause inefficiency. Therefore, country-specific policies are needed to target these inefficiencies.

Future empirical research should include further relevant countries in the analysis and should consider a longer time period. Moreover, it could be interesting to include more horticultural crops in the analysis to identify crops which perform best and to provide recommendations about the most efficient crop compositions. From a theoretical perspective, further research is needed to examine the relationship between different stochastic production function estimators and how they influence the estimation of the metafrontier and the TGR.

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Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The analyzed individual farm dataset from the FADN is not publicly available due to privacy reasons but the data can be requested from the DG agri unit of the European Commission.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.