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The Effect of CAP Subsidies on the Technical Efficiency of Polish Dairy Farms

Jerzy Marzec[*], Andrzej Pisulewski[†]

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Abstract

The main aim of this paper is to analyse the effect of Common Agricultural Policy (CAP) subsidies on technical efficiency of Polish dairy farms. We have distinguished several types of subsidies and provided an analysis to find out which types are most likely to engender systematic differences in technical efficiency. A balanced panel of microeconomic data on Polish dairy farms over an eight-year period (between 2004 and 2011), taken from the Farm Accountancy Data Network (FADN), is used. The translog production function is estimated by employing the Bayesian approach. The empirical results show that the elasticity of production with respect to livestock is the highest, whereas with respect to feed is the lowest. The mean technical efficiency in the covered period is 83%. The research reveals the negative effect of subsidies on technical efficiency.

Keywords: stochastic frontier analysis, dairy farms, Bayesian approach, panel data

JEL Classification: Q12, D24, C11, C23

[*]Cracow University of Economics; e-mail: marzecj@uek.krakow.pl
[†]University of Agriculture in Kraków; e-mail: a.pisulewski@ur.krakow.pl

1 Introduction

Income support policies have always played an important role within the European Union's (EU) Common Agricultural Policy (CAP). The share of the EU budget for CAP was always substantial; on average, CAP constituted half of the budget (European Commission, 2014) making it the most important common policy. Poland joined the European Union on 1 May, 2004, along with nine other countries (Slovenia, Slovakia, Czech Republic, Lithuania, Latvia, Estonia, Malta, Cyprus and Hungary, hereinafter referred to as the new Member States). Poland accession to the EU was just after the Fischler reform, which introduced two schemes of direct payments: the single payment scheme (SPS) and the single area payment scheme (SAPS). Poland adopted SAPS, which is transitional simplified income support for farmers in the new Member States, while Slovenia and Malta adopted SPS. According to council regulation no. 1782/2003, the amount of direct payments granted to Poland was gradually increased. Expressed as a percentage of the then-applicable level of such payments in the Community, the subsequent payments were as follows: 25% in 2004, 30% in 2005, 35% in 2006, 40% in 2007, 50% in 2008, 60% in 2009, 70% in 2010, 80% in 2011, 90% in 2012 and 100% in 2013. Moreover, farmers could receive the complementary national direct payments from the state, but only for agricultural activities, which are supported in the Community. The level of complementary national payments was restricted to the following levels of direct payments in the Community: 55% in 2004, 60% in 2005, 65% in 2006 and, from 2007 onward, up to 30 percentage points above the applicable level of direct payments in a certain year. It is noteworthy that according to Council Regulation no. 1782/2003, only farmers who respect the statutory management requirements (in the following areas: public, animal and plant health, environment, and animal welfare) and maintain their agricultural land in good agricultural and environmental condition are entitled to receive these payments.

Additionally, since 2010, according to article 68 of regulation no. 73/2009, dairy farms in economically vulnerable or environmentally sensitive areas or that engage in economically vulnerable types of farming may be granted specific support. The following regions in Poland were primarily targeted to receive this support: Lubelskie, Małopolskie, Podkarpackie, Śląskie and Świętokrzyskie. In the period 2004-2011, Poland received approximately 16 billion EUR in direct payments and approximately 286.9 million EUR for specific support and approximately 9.5 billion EUR in complementary national payments was paid by the state (ARMR, 2015a).

The farmers in Poland can also benefit from the second pillar of the CAP. This financing mechanism aims to support the sustainable development of rural areas. It was introduced under the Agenda 2000 reform. During the period 2004-2006, Poland received 5.4 billion EUR for rural area development (ARMR, 2015bc). From 2007 to 2013, Poland had planned to spend 17.4 billion EUR for rural development (MARD, 2015).

One of the objectives of CAP stated in article 39 of the Treaty of Rome (Treaty establishing the European Economic Community) is “to increase productivity, by promoting technical progress and ensuring the optimal use of the factors of production, in particular labour.” The objectives of CAP have never been modified. Moreover, they were restated in the unchanged form in the Treaty on the Functioning of the European Union.

The above shortly described mechanisms of financing the Polish agriculture and objectives of Common Agricultural Policy raise the following questions: did the subsidies enhance the improvements in efficiency of the Polish farms and secondly, was the effect of all types of subsidies (decoupled, coupled, rural development) on efficiency the same?

Generally, the agricultural technology varies depending on the type of farming. Therefore, in the present study we have focused on one type of farms. We have chosen the dairy sector, which is one of the most important sectors of agricultural production both in the European Union and in Poland. In 2012, milk was the single largest agricultural product sector in terms of value, with a 13% share of total agricultural output (Marquer, 2013). Milk production is also an important sector in Poland, which is the fourth largest milk producer in the European Union (CSO, 2015).

Since Polish accession to the EU, there have been many structural changes in this sector. It should be noted that the number of dairy farms in Poland has plummeted from 874,000 in 2002 to 424,000 in 2010 as a consequence of introducing dairy quota and cross-compliance rules. Consequently, the number of dairy cows diminished from 2,851.4 thousand heads in 2002 to 2,516.7 thousand heads in 2010. However, in the same period, the average number of cows per farm increased from 3.3 to 5.9 (CSO, 2011) as well as the total production of milk from 11.5 billion litres in 2004 to 12.1 billion litres in 2011 (CSO, 2013a). However, the share of milk production in gross agricultural output (in current prices) decreased from 17.1% in 2005 to 14.9% in 2011 (CSO, 2013a).

Despite the abovementioned structural changes in the Polish dairy sector, it still presents a highly fragmented structure with a large number of small, private family farms (Tonini and Jongeneel, 2009). There are significant differences, in terms of the average size of milk delivery from a farm, between Western European countries and Poland. While in Germany, France and the Netherlands in the quota year 2014/2015 average milk delivery was respectively 431.3, 372.7 and 706.3 tonnes per farm, in Poland it was 80.6 tonnes per farm (Parzonko, 2016). Moreover, Polish dairy sector is also structurally different from the most Central and Eastern European countries. It is because unlike them, Poland did not extensively collectivise its agriculture under communism (Gorton *et al.*, 2001). Therefore, it raises the question whether the subsidies in the Polish dairy sector which is structurally different from dairy sectors in Western European and those CEE countries which collectivised their agriculture, have the same effect on technical efficiency. Additionally, it is interesting to examine if the subsidies have similar impact in the countries like Romania or Bulgaria, which similarly as Poland have a fragmented structure of the dairy sector.

Methodologically, the paper does not make any further advances in the stochastic frontier analysis. The statistical modelling and inference is based on the Bayesian Stochastic Frontier Analysis (BSFA), proposed by van den Broeck, Koop, Osiewalski and Steel (1994) and Koop, Osiewalski and Steel (1994, 1997, 1999), which is now regarded as being relatively standard.
This study assess the characteristics of production function, technical efficiency, technical change, and the determinants of technical efficiency over one specialised farm type in the post-accession period. The analysis uses balanced panel data from Farm Accountancy Data Network (FADN) for the years 2004 – 2011. The FADN data is a large and detailed source of information on individual farms. Using these data, we were able to construct large panel dataset for dairy farms. The dataset is considerably larger than those used by previous studies of farm efficiency in Poland. The novelty of this paper does not lie in methodology but in data upon which the analysis is based and in the depth of the empirical analysis.
In this research cost efficiency analysis, as a more useful concept, was not undertaken for two reasons. First, the previous results for Polish dairy farms, presented in the literature, are based on production analysis, constituting a useful reference point for our study. Second, from the estimation perspective, specification of minimum cost function is difficult, because requires information on input prices. Obviously, the prices should vary between farms and over time. All of these are reasons for the popularity of production function as a baseline model in an empirical efficiency analysis.
The aim of the study is to analyse the effect of different types of Common Agricultural Policy (CAP) subsidies on technical efficiency of Polish dairy farms in the post-accession period. This paper is structured as follows: the next section presents the review of existing studies on relationship between technical efficiency and subsidies. In the third section the employed methodology is presented and in the fourth section the data used in this research are described. Section 5 presents and discusses the empirical results and contrasts them with those available in the literature. Finally, the main conclusions are presented.

2 Relationship between Technical Efficiency and Subsidies

According to Zhu and Lansink (2010) there are four theoretical mechanisms by which subsidies can affect the production: “1) by changing relative prices of inputs and outputs and through their impact on input use, 2) through an income effect, changing investment decisions and the quantity and quality of on- and off-farm labour supply, 3) through an insurance effect on risk mitigation, 4) through farm growth and exit”. However, as stated by Kumbhakar and Lien (2010, p. 110), “the effect of subsidies on technical efficiency is an open empirical question”.

According to Kumbhakar and Lien (2010) three approaches to examining the effects of subsidies on farm performance can be distinguished. In the first approach subsidies are treated as traditional input. The second approach analyses the impact of subsidies on productivity through the technical inefficiency. In the third approach, proposed by McCloud and Kumbhakar (2008) and Sipiläinen and Kumbhakar (2010), subsidies are treated as facilitating input, thus affecting both technical efficiency and indirectly output by changing productivity of traditional inputs and shifting the technology. The example of the first approach is Zhengfei and Lansink (2006) who found that subsidies had a significant negative impact on productivity growth. The second approach is the most common in the literature, for example: Giannakas, Schoney and Tzouvelekas (2001), Rezitis, Tsiboukas and Tsoukalas (2003), Iraizoz, Bardaji and Rapun (2005), Karagiannis and Sarris (2005), Zhu and Lansink (2010), Zhu, Demeter and Lansink (2012), Latruffe *et al.* (2012). All the above mentioned studies, indicate the negative impact of subsidies on technical efficiency. Moreover, in all mentioned studies the Battese and Coelli (1995) model was employed. The example of different model application is Sipiläinen, Kumbhakar and Lien (2014), who employed True Random Effects model, however a negative association between technical efficiency and subsidies was also found in that study.

The farms from the CEECs have been the subject of many analyses, among which the most studied were Slovenians (Bojnec and Latruffe 2009, Bojnec and Latruffe 2011, 2013, or Brümmer 2001), Czech (Davidova and Latruffe 2007, Latruffe, Davidova and Balcombe 2008) and Hungarian farms (Mathijs and Vranken 2001, Bakucs, Latruffe, Fertő and Fogarasi 2010). The dominant methodology in the mentioned studies was non-parametric Data Envelopment Analysis (DEA), the exception are Bojnec and Latruffe (2009) and Bakucs, Latruffe, Fertő and Fogarasi (2010), who used parametric stochastic frontier production analysis, namely the Battese and Coelli (1995) model again.

Polish farms have also been the subject of several studies, which report inconsistent results. The conducted studies mainly concern the pre-accession period. The first researchers to analyse the efficiency of Polish farms were probably Brada and King (1993), who compared the efficiency of private and state-owned farms. Poland's economic situation has significantly changed since 1989 due to economic transformation from a centrally planned to a market economy. Studies of the Polish farm sector during the transition period were conducted using both parametric stochastic frontier analysis (e.g. Munroe (2001), Brümmer, Glauben and Thijssen (2002), Latruffe, Balcombe, Davidova and Zawalińska (2004)) and non-parametric methods (e.g. van Zyl, Miller and Parker (1996), Lerman (2002) and Latruffe, Balcombe, Davidova and Zawalińska (2005) and Latruffe, Balcombe and Davidova (2008)).

In the post-accession period technical efficiency of Polish farms sector was considered in Kulawik (2008, 2009), who used Battese and Coelli (1992, 1995) models to analyse farms distinguished according to the type of ownership. Moreover, Czekaj

(2008) conducted efficiency analysis on the panel of Polish farms, however without distinguishing the type of farming. Generally, in Polish scientific papers on efficiency analysis in agriculture, the dominant methodology of research was DEA; see, e.g., Rusielik (2002), Świtłyk (2011), Ziółkowska (2008). The studies considering Polish dairy farms were conducted by Brümmer, Glauben and Thijssen (2002), Rusielik (2002), Rusielik and Świtłyk (2012), Czekaj (2013) and Świtłyk (2016). Rusielik and Świtłyk (2012) and Świtłyk (2016) used parametric Battese and Coelli (1992, 1995) model and non-parametric DEA in their analyses. Czekaj (2013) used parametric and semiparametric stochastic frontier models.

3 Statistical models and methods

3.1 The Stochastic Frontier Production Function Model

In order to measure farm-specific technical efficiency, we use stochastic frontier models, which were simultaneously introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). The general stochastic frontier production function for farm i ($i = 1, \ldots, N$) in period t ($t = 1, \ldots, T$) can be formulated as follows:

$$y_{it} = h(x_{it}; \beta) + v_{it} - z_i \tag{1}$$

where y_{it} is the natural log of the observed output quantity, h is a known analytical form of the production function, x_{it} is the vector of the input quantities used by the farm, β is a vector of k parameters, and v_{it} is a normal random error term with a zero mean and constant variance, representing random shocks, $v_{it} \sim N\left(0, \sigma_v^2\right)$. This random variable represents those effects which cannot be controlled by the farms, such as the environmental factors and weather conditions, etc. Component $z_i \geq 0$ is referred to as inefficiency (errors in the management, e.g., related to low quality of feed, animal diseases or machine performance).

The most popular functional form of the production frontier is a translog. It is a second-order local approximation of any twice-differentiable function and thus is called a (locally) flexible functional form (Christensen, Jorgenson and Lau 1973). The translog satisfies the requirement of Diewert's minimum flexibility for the flexible form. The validity of this specification is tested against the Cobb-Douglas form using the Bayes factor. In this study, the deterministic kernel of the stochastic production frontier is given in translog form:

$$h\left(x_{it}; \beta\right) = \beta_0 + \sum_{j=1}^{J} \beta_j^{(t)} \cdot \ln x_{it,j} + \sum_{j=1}^{J} \sum_{g \geq j}^{J} \beta_{j,g} \cdot \ln x_{it,j} \cdot \ln x_{it,g} + \beta_{trend} \cdot t + \beta_{trend2} \cdot t^2, \tag{2}$$

$$\beta_j^{(t)} = \dot{\beta}_j + \ddot{\beta}_j \cdot t \quad \text{for} \quad j = 1, \ldots, J,$$

where inputs are aggregated into six categories (J=6). Note that the trend variable has been introduced to reflect the influence of technical progress. It captures exogenous technical change, treated as a shift in the production function over time. Furthermore, it is known in the literature as an easy way to analyse changes in productivity. If we introduce time effects in the linear part of the translog production function, they interact with all the inputs, which implies non-neutral technical change. This causes the production function to be more flexible. In particular, it does not assume Hicks-neutral technical change. Consequently, this implies that the elasticities of each of the factors of production and the economies of scale may change over time. One limitation of such a design is that the sign of the change in the elasticity with respect to the production input is either positive or negative during whole period. This feature also applies to an indicator of technical change. The present approach is used e.g. in Battese and Broca (1997) and Koop, Osiewalski and Steel (1999, 2000), where not only a linear trend but also a quadratic trend in the parameters was considered. Further, the Cobb-Douglas production frontier is a special case of the translog frontier in which the coefficients of the second-order terms are zero, i.e. $\beta_{j,g} = 0$, $j \leq g = 1, \ldots, J$. The validity of this specification is tested against the Cobb-Douglas form using the Bayes factor. The measurement of technical change is straightforward (for the ith farm in time period t):

$$\frac{\partial \ln y_{it}}{\partial t} = \beta_{trend} + 2\beta_{trend2} t + \sum_{j=1}^{J} \ddot{\beta}_j \ln x_{it,j}. \tag{3}$$

An alternative way of introducing dynamics into model parameters was proposed by Koop, Osiewalski and Steel (1999). In one of their model specifications they assumed that that frontiers are totally independent across time (so called time specific (TS) model). This refers also to the concept of the DEA method and therefore the translog frontier, the random error distribution and the efficiency distribution are different for each period. But, without a doubt, this idea is unrealistic particularly looking from the point of view of the entrepreneur. The choice of production methods and the factor inputs are interrelated in time. Also, from the statistical viewpoint, the TS model may be over-parameterised. In this context, the model given by (2) represents a compromise between a static production function and the TS or DEA approaches.

Technical inefficiency relative to the stochastic production frontier is represented by the one-sided error component z_i. This firm-specific random term captures the difference between the best practice output and the observed output. Technical efficiency reflects the ability of farms to produce the maximum level of output from a given set of inputs. Output-oriented technical efficiency will be measured as $r_i = \exp(-z_i)$, which is easily quantifiable in the interval (0; 1]. In part of the literature, inefficiency is treated as the firm- and time-varying effect (see e.g. Osiewalski and Steel 1998, Makieła 2014). The assumption about the time invariant inefficiency was chosen in this research; see Marzec, Pisulewski and Prędki (2015). Several distributions have been proposed for z_i, the most common being the half-normal, truncated normal or gamma distribution (see Kumbakhar and Lovell 2000). The conventional assumption is that z_i and v_{it} are distributed independently of each other. A new direction for generalizing (1) is a model with the error components that are correlated and the inefficiency error is assumed to be autocorrelated (see e.g. Das 2015).

Because inefficiency is inherently unobservable, there is a substantial difficulty in identifying it in empirical studies. Therefore, estimates of inefficiency must be derived indirectly. Furthermore, in many situations, the researcher is interested in making inefficiency (i.e. an individual specific effect) depend on certain farm characteristics. It seems reasonable to assume that groups of similar farms, defined, e.g., through their size or other factors, have similar efficiencies (see Kumbhakar, Ghosh and McGuckin 1991). This is achieved by including covariates, which affect the parameters of the one-side error distribution in (1), implying a nested (hierarchical) structure.

In stochastic production frontier models the output-oriented efficiency measure is generally adopted. This can be related to the fact that all production inputs are treated as fixed, in contrast to the conditional factor demand equations obtained from the cost function by using Shephard's lemma. As a result, in production frontier models allocative inefficiency (divergence between observed cost of production and efficient cost) is ignored. The obvious solution to this problem is estimation of a stochastic frontier cost function or cost share equations. However, due to data requirements it is in fact a very complex issue. In our other work we made the first attempt to estimate a short-run cost function for the farms in Poland (see Marzec and Pisulewski 2015).

The vast majority of studies concentrate only on the production function. The duality between production and cost functions suggests the estimation of a complete system that involves the production function and the first-order conditions for profit maximization (cost minimization). The input demands are treated then as random variables which contrasts with the fact that inputs are explanatory variables in the model presented here. According to Zellner, Kmenta and Dreze (1966), in the single period Cobb-Douglas model, inputs are random but do not depend on the symmetric disturbance on the production function. Consequently, they are weakly exogenous for the purpose of estimating the production function parameters. However, Zellner, Kmenta and Dreze (1966) did not introduce a one-sided error into their production function. Thus they did not consider the case of possible inefficiency, which could change their conclusion. An important statistical issue is that the regressors can be correlated with the efficiency term. Therefore, we use the VED model with the factors that affect the levels of efficiency of each farm. These determinants are only weakly correlated with the inputs. Therefore, the problem of endogenous regressors should not occur. The Bayesian concepts of exogeneity were presented, among others, by Osiewalski and Steel (1996) and, in the case of the model with latent variables, by Pajor (2011). An alternative approach to this problem, using modifications of standard techniques (i.e. two stage least squares, limited information maximum likelihood) for the stochastic frontier setting, was considered in Amsler, Prokhorov and Schmidt (2016).

3.2 The Bayesian approach

This study employs the Bayesian Varying Efficiency Distribution (VED) model proposed by Koop, Osiewalski and Steel (1997), which is more flexible than traditional frontier models. They assume that z_i, a firm-specific effect, follows an exponential distribution with a mean (and standard deviation) λ_i. The mean of z_i can depend on additional exogenous variables s_{ij} ($j = 2, \ldots, m$). This implies that the location and scale parameters of the inefficiency distribution are specific for each firm. The parameterisation of the average level of inefficiency can take the form of the equation

$$\ln \lambda_i = -\sum_{j=1}^{m} s_{ij} \cdot \ln \phi_j, \tag{4}$$

where $s_{i1} = 1$ and $\phi_j > 0$ ($j = 2, \ldots, m$) are additional unknown parameters (an intercept ϕ_1 is always included in a m-dimensional vector ϕ). If $m = 1$ exogenous variables s_{ij} are not present; therefore, the inefficiency terms for all units constitute independent, random draws from the common exponential distribution. This important special case is called the Common Efficiency Distribution (CED) model. The CED specification implies that there are no systematic differences in production efficiency. In the VED model, $m > 1$ and the parameter ϕ_j indicates how the mean of the inefficiency distribution changes with the farm characteristics in s_{ij} ($j = 2, \ldots, m$).

The joint distribution of the observed y_{it}, the unobserved z_i and all the parameters θ, given exogenous x_{ij}'s and s_{ij}'s, that is the Bayesian model corresponding to equations (1) and (4), can be written as follows:

$$\begin{aligned} p(y, z, \theta \,|X, S) &= p(\theta)\, p(z\,|\theta, X, S)\, p(y\,|z, \theta, X, S) \\ &\propto p(\theta) \prod_{i=1}^{N} \left[f_G \left(z_i \,\middle|\, 1, \prod_{j=1}^{m} \phi_j^{s_{ij}} \right) \cdot \prod_{t=1}^{T} f_N \left(y_{it} \,|h(x_{it}, \beta) - z_i, \sigma^2 \right) \right] \end{aligned} \tag{5}$$

where $p(\theta)$ represents the prior density for the parameter vector $\theta = \left(\beta', \sigma^{-2}, \phi_1, \ldots, \phi_m\right)'$, $f_N(\cdot\,|\mu, \Sigma)$ indicates the normal density with mean vector μ and covariance matrix Σ, and $f_G(\cdot\,|a, b)$ is the gamma density with mean $\frac{a}{b}$ and variance $\frac{a}{b^2}$ ($a = 1$ corresponds to the exponential distribution). Assuming the independence of parameters $p(\theta) = p\left(\sigma^{-2}\right) p(\phi)\, p(\beta)$, Koop, Osiewalski and Steel (1997) propose using a proper prior distribution for precision parameter σ^{-2} and ϕ_j, i.e.,

$$p\left(\sigma^{-2}\right) p(\phi) = f_G\left(\sigma^{-2} \,\middle|\, \tfrac{1}{2}n_0, \tfrac{1}{2}c_0\right) \prod_{j=1}^{m} f_G\left(\phi_j \,|a_j, g_j\right), \tag{6}$$

where hyperparameters n_0, c_0, a_j and g_j ($j = 1, \ldots, m$) are pre-specified constants. In this empirical analysis, setting $n_0 = s_0 = 10^{-6}$ should lead to a very diffuse prior distribution of σ^{-2}. The assumption that the other prior hyperparameters are specified as $a_j = g_j = 1$ for $j > 1$ (Koop, Osiewalski and Steel 1997), indicates that the prior expectation of ϕ_j is one, and thus the impact of the potentially explanatory factors s_{ij} is a priori very uncertain. Additionally, we take $a_1 = 1$ and $g_1 = -\ln(r_{med})$, where r_{med} denotes the prior median of the distribution of the efficiency measure $r_i = \exp(-z_i)$ in the CED model (van den Broeck, Koop, Osiewalski and Steel 1994). Formally, in the VED model, prior median efficiency is slightly lower than r_{med} whenever $m > 1$ (see Koop, Osiewalski and Steel 1997). In our research ($m = 4$), for example, as r_{med} becomes 0.8 (0.7), the prior median efficiency is 0.77 (0.66). This setting implies very weak prior information. Therefore, the hyperparameter r_{med} plays an important role because it informs about the location of the distribution of r_i and represents the researcher's initial knowledge about the efficiency of production units, which are the subject of a study being conducted. We set $r_{med} = 0.8$, a reasonable value for the Polish farm sector (see Brümmer, Glauben and Thijssen 2002).

With regard to the coefficients in the production frontier, it is possible to use an improper prior distribution for β. However, in this research, a truncated normal prior distribution, $p(\beta) \propto f_N(\beta_0, V_0) \cdot I(\beta)$, is used for these coefficients. This was done for two reasons. First, it is common in the frontier literature to impose regularity conditions; see Marzec and Osiewalski (2008). Microeconomic theory requires that production function must satisfy monotonicity in inputs. Consequently, we assume $I(\beta) = 1$ if the production frontier is non-decreasing in inputs for this value of β. The imposition of regularity conditions is relatively simple when employing Bayesian techniques compared to classical estimation. In this case, the vector β_0 reflects that the production function takes a Cobb-Douglas form with average elasticities of all inputs equal to $\frac{1}{6}$ and the constant returns to scale. Every other element of β_0 equals zero. Thus, we initially assume no technical change. The covariance matrix, V_0, is either the identity matrix or it is a diagonal with positive entries. Additionally, in the translog model all variables have been normalized (centered), by subtracting from each output and input (in logs) its sample mean. Accordingly, at the geometric mean of the original data the elasticity with respect to each input is normally distributed with the mean of $\frac{1}{6}$ and the standard deviation of 1. Our results, which are presented in the fifth chapter, are robust to changes in the prior distribution. Summarising, the above assumptions do not introduce any strong subjective information about these parameters.

The second reason to adopt proper priors is that the use of improper priors creates problems with Bayesian model comparison. Testing for Cobb-Douglas versus translog was associated with the employment of informative priors, especially for these parameters in β, which differ across models.

The inference about parameters is based on the posterior distribution, i.e. the conditional distribution of the parameters given the data. Unfortunately, in this case, neither the posterior distribution nor any of its summary measures can be obtained in closed form, and thus, they must be evaluated numerically. The complexity of the stochastic frontiers model requires advanced statistical methods to analyse posterior distributions. It is reasonable to use Monte Carlo methods, e.g., MCMC, that attempt to draw samples from the posterior distribution. As Koop, Osiewalski and Steel (1997, 1999) and Osiewalski and Steel (1998) showed, Gibbs sampling, a special case of MCMC, is an efficient tool for generating samples from the posterior distribution. It is necessary, however, that two conditions are met. The frontier production function must be linear in the parameters, and all variables s_{ij} must be binary. The first condition is clearly met. In the VED model, however, there may be a variable – at least one variable s_{ij} – that is not binary. Then, the conditional posterior distribution of parameter ϕ_j is a non-standard distribution. In this research, we will assume that these determinants of efficiency may be continuous. This will allow a more precise measurement of these variables. Therefore, there is a need to use other numerical techniques than the pure Gibbs sampler. In the case of the continuous variables s_{ij}, the usage (within a Gibbs procedure) of the random walk Metropolis-Hastings steps with an asymmetric proposal density might be an appropriate solution (Koop, Osiewalski and Steel 1994). To generate candidate draws we use the gamma distribution. Preliminary runs are used to calibrate a parameter of the proposal density used in this algorithm. The MCMC algorithm involved 200.000 cycles, and the first 100.000 were discarded.

As with any statistical model of an economic process, there is inherent uncertainty as to whether the model discussed above accurately reflects the information contained in the sample. Obviously, the stochastic frontier model given by equations (2) and (4) has been subjected to verification testing. The complexity of the model permits the formulation of the hypotheses in such a way that they are equivalent to different non-nested models. We apply the Bayesian model comparison approach, which selects the model that receives the most support from the data; i.e. precisely that which corresponds to the maximum posterior probability. In this case, it will be used to perform variable selection in the deterministic part of the production frontier and the choice of the determinants of inefficiency. The results of this approach will inform researchers about the adequacy for the model given the data and other information. The Bayesian procedure for comparing two models is based on the posterior odds ratio, which is the product of the prior odds and the Bayes' factor (see, e.g., Osiewalski and Steel 1993, Raftery 1995); this last one requires numerical calculation of the marginal likelihoods, $p(y)$, for each of these models. We approximate $p(y)$ using the harmonic mean (HM) estimator proposed by Newton and Raftery (1994), which is the most popular method due to its simplicity and wide applications. However, the HME is heavily criticized for commonly overestimating and for a numerical instability due to large outliers in the posterior simulation. The convergence of the standard HME is often very slow. But in this research, we performed very long MCMC runs in order to check numerical stability of this estimator. Furthermore, one of these models turned out to be strongly supported by the data sets (see model marked as M_5 given in Table

3). Potential computational instability of HM estimator should not affect the choice of the single “best” model.
Lenk (2009) identified the source of computational bias and proposed several ways of improving the accuracy of the computed HME and its performance in model selection; see also Osiewalski and Osiewalski (2013), Pajor and Osiewalski (2013-14). Additionally, another method, which was motivated mainly by Lenk’s approach, is the corrected arithmetic mean estimator proposed by Pajor (2016). The practical application of these new numerical tools to calculate $p(y)$ is still an unresolved issue in this study and it will be subject of the further research.
We use the Bayesian methods to stochastic frontier analysis although Data Envelopment Analysis and non-Bayesian SFA are the dominant methodology in the efficiency research. The standard DEA approach has the disadvantages of assuming no statistical noise (the difference between output and unobserved maximal output is interpreted only as inefficiency) and the piecewise linear production frontier. However, it is non-parametric, so it is sometimes said that this method allows the data to ‘speak for themselves’; see Odeck and Bråthen (2012). Furthermore, DEA is useful in handling with multiple outputs. On the other hand, a formal statistical testing of hypotheses is not possible except by employing bootstrapping techniques proposed by Simar and Wilson (2000). Empirical fitting a boundary function to data requires a sample of relatively homogeneous firms (DEA is sensitive to outliers). From the viewpoint of DEA it is not obvious how to handle panel data to get models comparable with SFA models. In this research, we use quite a large panel dataset that contains both small and large farms. Therefore, this sample is clearly heterogeneous. Thus, we prefer BSFA to the above-mentioned method, which is, however, more often used in practice. The extensive discussion about the advantages and limitations of these two approaches can be found in Koop, Osiewalski and Steel (1999) and Growiec, Pajor, Górniak and Prędki (2015). A comparative study using this dataset and both methods was presented by Marzec, Pisulewski and Prędki (2015). The methodological advantage of BSFA over non-bayesian statistical approach has been discussed in detail by van den Broeck, Koop, Osiewalski and Steel (1994).

4 Data

The estimation of the Bayesian frontier model in this study utilises balanced panel data from 1,212 Polish dairy farms over the period 2004-2011, provided by the Farm Accountancy Data Network (FADN). The selected panel contains dairy farms, which, in the covered period, were predominantly classified as specialist dairy farms according to FADN methodology. According to FADN typology, specialist dairying is defined as a farm in which dairy cows constitute more than $\frac{3}{4}$ of the total grazing livestock, and grazing livestock is more than $\frac{1}{3}$ of the grazing livestock and forage. The construction of the variables is based on other studies on dairy farms in which FADN data were used (Emvalomatis, Stefanou and Lansink 2011, Reinhard, Lovell and Thijssen 1999).

In the stochastic production function the output (Q) is specified as the deflated total net farm revenues from sales excluding the value of feed, seeds and plants produced on the farm. Six categories of inputs are used in the specification of the model:

1. Building and machinery (K) are measured in terms of the deflated book value. This includes fixed capital such as buildings, fixed equipment, machines and irrigation equipment.

2. Total labour (L) is measured in hours. Both hired and family labour declared by the farmer during the interview are included in this measure.

3. Total utilised agricultural area (A) is measured in hectares. It includes both owned and rented land.

4. Materials and services (M) are measured in terms of deflated values. This category of input consists of six other subcategories: purchased seeds and plants, fertilisers, crop protection, crop- and livestock-specific costs and energy. To deflate the total reported expenditure on materials and services, we used price indices provided by the Central Statistical Office (2013b) for each subcategory. In order to avoid double measurement of costs of producing the feed within the farm, the total expenditure on materials was diminished by the value of feed produced within the farm.

5. Livestock (H) is expressed in standardised livestock units (LU). This is a weighted measure, provided by FADN, that shows the amount of the cattle present on the farm during the year. It is constructed by assigning weights to different categories of cattle. Dairy and cull cows are assigned a weight 1, whereas younger cattle (0-2 years) are assigned weights from 0.4 to 0.6.

6. Feed (F) is measured in deflated value. This includes feed and concentrated feedstuffs purchased and produced within the farm. Distinguishing this input is due to the fact that Polish dairy farms use generally their own feed.

The construction of the exogenous variables, which explain possible systematic differences in efficiency levels are based on Zhu and Lansink (2010) and Zhu, Demeter and Lansink (2012). According to the abovementioned articles, the two main types of subsidies can be distinguished: coupled and decoupled. The former directly influence the quantity of input or output, while the latter are designed such that they do not affect production decisions of farmers (Bezlepkina, Lansink and Oskam 2005). The list explanatory variables selected from FADN database is as follows:

1. Less favoured areas subsidies – the ratio of less favoured areas subsidies received by the farm to gross farm income.
2. Investment subsidies – the ratio of investment subsidies received by the farm to gross farm income.

3. Coupled subsidies – the ratio of coupled subsidies (namely, these are the sum of the following subsidies selected from the FADN database: subsidies for crops, subsidies for livestock – according to FADN methodology specific support subsidies are included in this category, subsidies on intermediate consumption, subsidies for external factors) received by the farm to gross farm income.

4. Decoupled subsidies – the ratio of decoupled subsidies received by the farm to gross farm income.

5. Rural development subsidies to gross income ratio (as an optional factor for LFA areas subsidies, because they are correlated).

Tables 1 and 2 provide basic descriptive statistics of the farms being analysed. These statistics confirm that, as stated before, in Poland, the largest group is comprised of small farms. All variables are skewed right, particularly output and feed. Moreover, the medians of the original data are roughly equal to the means of a logarithmic transformation. This implies that the empirical cumulative distribution functions of output and input can be approximated by a lognormal distribution. The results in the next table show that many of the selected farms did not receive EU subsidies. This phenomenon occurred in the initial period of accession. Nonetheless, the subsidy share of the total farm income is over 22%, suggesting that farmers' current income derived from agricultural activities is small compared to what they could have potentially earned.

Table 1: Description of the dataset: Average (per annum) values for the period 2004-2011*

Variable	Mean of log**	Mean	StDev	Percentile				
				5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Output ('000 PLN)	87	125	133	21	50	87	152	353
Capital ('000 PLN)	215	287	252	59	134	214	355	745
Labour (in hours)	4,251	4,449	1,528	2,504	3,652	4,378	4,994	6,600
Materials ('000 PLN)	31	42	44	10	19	30	51	111
Utilised agricultural area (in hectares)	23	29	29	9	16	22	35	66
Livestock (in Livestock Unit)	25	31	26	8	16	25	39	75
Feed ('000 PLN)	23	34	40	6	13	22	40	97

* – Figures in PLN were deflated (with base year 2004) using the price indices.
** – Output and input (excluding labour, area and livestock) were calculated as the arithmetic mean on the logarithmic scale and converted back to the base currency.

Table 2: Summary statistics for the analysed farms: Average (per annum) value of subsidies for the period 2004-2011*

Variable	Mean	StDev	Percentile				
			5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Subsidies for LFA	3	4	0	0	2	4	9
Subsidies for investment	2	5	0	0	0	1	8
Coupled subsidies	3	6	0	0	1	4	12
Decoupled subsidies	7	10	0	2	5	9	21
Rural development subsidies (LFA incl.)	7	11	0	1	4	8	24
Total gross farm income	85	83	14	35	61	105	234

* – Note: All values (in thousand PLN) were deflated (see above).

5 Empirical Results and Discussion

We have applied the Bayesian model comparison to test hypotheses about the specification of the production frontier model and the technical inefficiency components. Bayes factors (BF) and posterior odds ratios are used (see Osiewalski and Steel 1993, Kass and Raftery 1995, Koop 2003) in order to conduct a model selection.

It is noteworthy that, using the Cobb-Douglas for, the posterior probability of positive elasticity for a typical farm, with respect to area, was very small (ca. 0.01). As a result, the forementioned production function specification was definitely rejected by the data; see model M_9 given in Table 3. Therefore, in the further part of the study, we present only the results based on the translog production function.

Eight translog models have been considered in this research. Under equal prior odds of each model, as in this case, Bayes factor equals the posterior odds ratio. The natural logarithms of the marginal data density values and the set of Bayes factors for pairwise comparison with the base model, M_5, are presented in table 3. In addition, it is important to state that the hypothesis, which claims that there was no technical change, has been rejected - although, for the sake of brevity, detailed results are not mentioned.

Firstly, the test examines whether the production frontier varies over time. The linear trend in the parameters is generally preferred over the static, non-dynamic form of production function. Another model comparison refers to the joint tests of the parameters of the variables which explain technical inefficiency.

The quantitative evidence that the data supports the VED model over the CED model was very strong. Furthermore, we have conducted an additional analysis to find out which factors − rural development subsidies or LFA subsidies − are most likely to explain systematic differences in technical efficiency. Bayes factor clearly indicates that the model with rural development subsidies ratio was strongly supported by the data. It is easily noticeable that most posterior probability (almost 0.95) is attributed

Table 3: Bayesian model comparison (equal prior model probabilities, i.e. $p(M_r) = 0.111$)

M_r	Translog model – specification	$\ln(p(y\|M_r))$	Bayes Factor	$p(M_r\|y)$	Model rank
M_1	CED ($\phi_j = 1$ for $j = 2, \ldots, m$)	-1296.1	≈ 0	≈ 0.000	8
M_2	CED without a dynamic component ($\ddot{\beta}_1 = \ldots = \ddot{\beta}_6 = 0$)	-1346.2	≈ 0	≈ 0.000	9
M_3	VED with $m = 4$ (including LFA subsidies rate)	-339.0	$1.58 \cdot 10^{-21}$	≈ 0.000	6
M_4	VED with $m = 5$ (including LFA and investment subsidies rates)	-336.8	$1.43 \cdot 10^{-20}$	≈ 0.000	5
M_5	VED with $m = 4$ (including rural development subsidies rate)	-291.1	1	0.949	1
M_6	VED with $m = 5$ (including rural development and investment subsidies rates)	-318.4	$1.43 \cdot 10^{-12}$	≈ 0.000	4
M_7	M_5 without a dynamic component ($\ddot{\beta}_1 = \ldots = \ddot{\beta}_6 = 0$)	-296.4	$5.16 \cdot 10^{-3}$	0.005	3
M_8	M_6 without a dynamic component ($\ddot{\beta}_1 = \ldots = \ddot{\beta}_6 = 0$)	-294.1	$4.89 \cdot 10^{-2}$	0.046	2
M_9	C-D: M_2 with $\beta_{j,g} = 0$ for $j, g = 1, \ldots, J$	-1165.6	≈ 0	≈ 0.000	7

to M_5. Therefore, further empirical analysis will be based on M_5.

We have employed the stochastic frontier panel data model with individual effects. In order to confirm the assumption about the time invariant inefficiency, we estimated the CED model for cross-sectional data separately for each year in the sample. The average posterior means for the technical efficiency are very similar for the eight models, ranging from 0.87 in 2008 to 0.91 in 2007. In other periods, the efficiency level was ca. 0.88. In our opinion, these results justify the treatment of inefficiency as a firm specific term.

Bayesian estimates, based of model M_5, of the parameters of the production frontier for dairy farms are presented in Table 4. It is important to note that for translog models, the posterior standard deviations for some parameters are slightly higher than the absolute values of the estimated coefficients. However, the parameters of interest, such as input elasticities, defined as a function of the data and the parameters of the model, are significantly different from zero; see Table 5, where the posterior means and standard deviations for the characteristics of the production function are presented for a typical farm (with average values of logs of the production inputs).

We use the Bayesian approach to incorporate the theoretical regularity restrictions into a translog production function. In this research, monotonicity conditions are imposed for the average values of logarithms of explanatory variables (i.e., for a typical farm). We estimated the posterior probability that all six inputs' elasticities are positive to be 0.99. Thus, the parameter estimates are consistent with the microeconomic theory, although it is not possible to impose the global conditions (i.e. for all farms) using the local approximation of the "true" production function. The estimated elasticities are less than unity for all inputs, farms and time periods.

Moreover, with respect to capital, materials and livestock, the elasticities invariably have the expected signs. In general, with respect to other inputs, the elasticities take values greater than zero for the majority of observations. However, about 19 percent of the estimated labour elasticities are slightly negative. Furthermore, the percentage of negative elasticities with respect to area and feed is approximately 19% and 23%, respectively; see Table 5. Additionally, the law of diminishing marginal productivity is checked for a typical farm. The sufficient conditions, which are quite strong for translog, are fulfilled for all inputs except labour and area (but these elasticities are quite small). Formally testing or imposing the hypothesis of quasi-concavity could be the subject of further research (Marzec and Osiewalski, 2008).

Table 4: Posterior means and standard deviations of the parameters in the VED translog model, M_5

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
1	0.168	0.008	$\ln M \cdot \ln F$	0.031	0.018
$\ln K$	0.112	0.008	$\ln A \cdot \ln H$	0.002	0.031
$\ln L$	0.061	0.013	$\ln A \cdot \ln F$	−0.116	0.018
$\ln M$	0.347	0.009	$\ln H \cdot \ln F$	0.135	0.022
$\ln A$	0.057	0.011	$\ln^2 K$	0.011	0.009
$\ln H$	0.533	0.013	$\ln^2 L$	0.103	0.027
$\ln F$	0.045	0.007	$\ln^2 M$	0.064	0.016
$\ln K \cdot \ln L$	−0.077	0.024	$\ln^2 A$	0.049	0.017
$\ln K \cdot \ln M$	−0.018	0.018	$\ln^2 H$	0.007	0.021
$\ln K \cdot \ln A$	0.015	0.019	$\ln^2 F$	−0.011	0.008
$\ln K \cdot \ln H$	0.026	0.022	t	0.001	0.001
$\ln K \cdot \ln F$	0.001	0.014	t^2	0.002	0.001
$\ln L \cdot \ln M$	0.030	0.031	$t \cdot \ln K$	−0.003	0.002
$\ln L \cdot \ln A$	−0.082	0.033	$t \cdot \ln L$	−0.012	0.004
$\ln L \cdot \ln H$	0.011	0.041	$t \cdot \ln M$	−0.004	0.003
$\ln L \cdot \ln F$	0.007	0.025	$t \cdot \ln A$	−0.002	0.003
$\ln M \cdot \ln A$	0.001	0.023	$t \cdot \ln H$	0.001	0.004
$\ln M \cdot \ln H$	−0.187	0.029	$t \cdot \ln F$	0.010	0.002

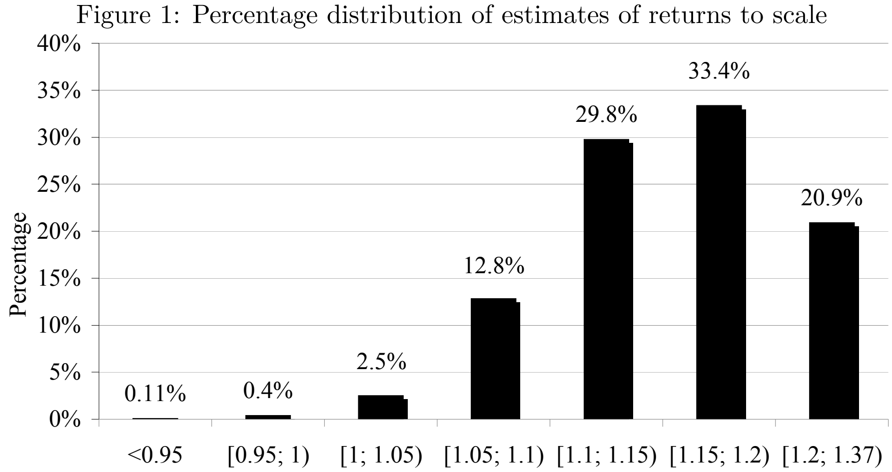
The empirical results in Table 5 show that the highest is the elasticity of production with respect to livestock, whereas the lowest is the elasticity of production with respect to feed. Similar to Brümmer, Glauben and Thijssen (2002) and Latruffe, Balcombe, Davidova and Zawalińska (2004), the elasticity with respect to labour is found to be very low. However, in contrast to Brümmer, Glauben and Thijssen (2002) and Latruffe, Balcombe, Davidova and Zawalińska (2004), who showed that the intermediate production (consumption) factors elasticity of production (i.e. raw and auxiliary materials, veterinary services, repairs and maintenance, and other services) is the highest, we found that the highest is elasticity of production with respect to livestock.

Almost all dairy farms have increasing returns to scale (Figure 1). This result is in line with that of Latruffe, Balcombe, Davidova and Zawalińska (2005), who reported that 64% livestock farms had an increasing RTS in 2000. A typical Polish farm is characterised by increasing returns to scale, which is approximately 1.155 (±0.013). Among the farms investigated, 54.1% operated under increasing returns to scale greater than 1.15. Figure 2 indicates that the farm average of the returns to scale estimates decreases over time from 1.19 in 2004 to 1.12 in 2011. It is noteworthy that estimates of the elasticities of production and RTS noticeably vary across farms, making the Cobb-Douglas model inadequate to describe dairy production. This observation supports the previous conclusion.

Table 5: Posterior moments for elasticities of output with respect to input (in a typical farm)

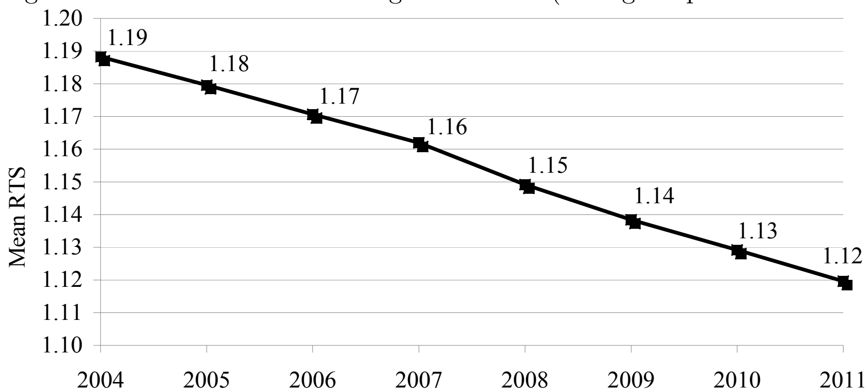
Elasticities of production	Mean	Std. dev.	Incorrect sign (%)
Livestock (H)	0.533	0.013	0
Materials and Energy (M)	0.347	0.009	0
Capital (K)	0.112	0.008	0.0
Labor (L)	0.061	0.013	19
Area (A)	0.057	0.011	21
Feed (F)	0.045	0.007	23
RTS	1.155	0.013	–

Figure 1: Percentage distribution of estimates of returns to scale



As shown in Table 6, during the whole period 2004-2011 technical progress occurred in the typical farm. The average annual growth rate of production due to the technical

Figure 2: Returns to scale – changes over time (average of posterior means)



change was about 1.9%. On the contrary, Brümmer, Glauben and Thijssen (2002) reported a technical regress (nearly 9% p.a.) from 1991-1994 for dairy farms. The negative rate of technical change was also found for livestock farms from 1996-2000 by Latruffe, Balcombe and Davidova (2008). So after 2004, when the EU extended its membership eastwards, there was strong productivity growth in the Polish milk sector.

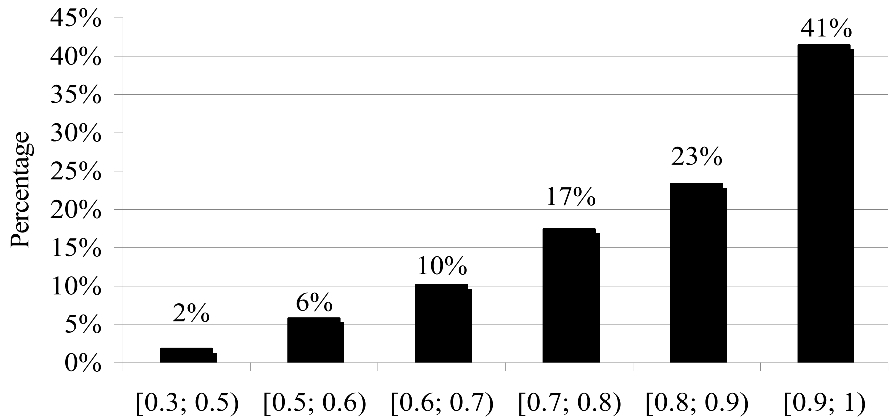
Table 6: Estimates of technical change (in percentage points) - see (3)

Period	2004	2005	2006	2007	2008	2009	2010	2011
Mean	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
St. dev.	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8

Regarding the technical efficiency score, it can be seen that average posterior mean exceeds the prior value (which is below 0.8) and amounts to 0.83 with the average posterior standard deviation equals 0.05. This implies that, on average, Polish dairy farms can potentially increase production by as much as 20%, at the given input levels. It can be noted that large farms tend to be more efficient than small ones. Namely, the correlation coefficient between the individual farm's efficiency posterior mean and average farm's production (in logs) is 0.55.
Additionally, we have examined the sensitivity of the estimation results to various initial values of r_{med}, and it did not change the conclusions of our study. For example, for the values of r_{med} equal to 0.7, 0.8 and 0.9 the average posterior mean of technical efficiency was very close to 0.83 with the average posterior standard deviation 0.049. This score is consistent with the results obtained by Latruffe, Balcombe, Davidova and Zawalińska (2004), who reported an average technical efficiency of 0.88 for a livestock farm panel in 2000. In other research conducted by Brümmer, Glauben and Thijssen (2002) for a sample of dairy farms in the Poznań region, the average

efficiency over the period 1991-1994 was equal to 75%. The mean total technical efficiency obtained by Latruffe, Balcombe, Davidova and Zawalińska (2005) using the DEA method for a sample of livestock farms in 2000 was 0.71. Czekaj (2013) reported an average technical efficiency score for a cross-sectional sample of dairy farms from 2010 between 85% and 88%.

Figure 3: Percentage distribution of technical efficiencies of Polish dairy farms



The obtained result is consistent with the study conducted for Hungarian farms (Bakucs, Latruffe, Fertő and Fogarasi 2010), where a technical efficiency score of 0.73 was reported. A more recent study of dairy farms' technical efficiency in Central and Eastern Europe shows that the technical efficiency (total technical efficiency) for Hungarian farms in the period 2001-2007 was also 0.73 (Latruffe, Fogarasi and Dejeux 2012).

The reported technical efficiency score for English and Welsh dairy farms was 0.897 (Hadley 2006). Areal, Tiffin and Balcombe (2012) found that the average technical efficiency score of English and Welsh dairy farms is 0.86. The analysis of French dairy farms conducted by Latruffe, Fogarasi and Dejeux (2012) shows that their technical efficiency is 0.74.

The reported average technical efficiency score of 0.88 of dairy farms in eleven "old member states" of the European Union from 1990-2007 by Latruffe *et al.* (2012) – was higher than that of dairy farms in Poland. To enable comparisons with the results obtained by Latruffe *et al.* (2012) and Sipiläinen, Kumbhakar and Lien (2014), who used an input distance function, we computed the corresponding output-oriented technical efficiency as $\mathrm{TE}_{OUT}=(\mathrm{TE}_{IN})^{RTS}$, which is a rough approximation (the equality holds in fact for homogenous production functions).

The distribution of farms' technical efficiency scores is presented in Figure 3. Most of the farms (41%) operate with a technical efficiency above 0.9, and 23% of the estimates of the efficiencies are between 0.8 and 0.9. According to our analysis, a large group

of farmers (17%) works with a low efficiency, i.e., below 0.7. The minimum technical efficiency score is 0.3 and such small efficiency estimate probably identifies an atypical farm (an outlier).
The variability in the technical efficiencies can be explained by allowing the mean inefficiency term to vary in relation to specified farms' characteristics. Posterior means and standard deviation for coefficients $\ln(\phi_j)$ are given in Table 7.
Among five potential factors that may influence the efficiency of dairy farms, two are found to be insignificant. The results of the joint and individual tests indicate that, e.g., the ratio of investment subsidies or less favoured areas subsidies do not significantly explain the difference in the efficiency between groups of farms. Therefore, these variables are omitted in the final model.
One of the most important findings from this research is the determination of the influence of subsidies on technical efficiency (r_i). Our results show that each of the three different types of subsidies have a significant negative effect on technical efficiency. The results indicate that an increase in the share of decoupled subsidies in gross farm income causes decrease in r_i, whereas an increase in the share of coupled subsidies in gross farm income leads to decrease in r_i. Rural development subsidies have a negative impact too, although it is the weakest of the three.
These findings are consistent with those obtained for other CEE countries but not necessarily for dairy farms: Bakucs, Latruffe, Fertő and Fogarasi (2010) for Hungarian farms, Bojnec and Latruffe (2009) for Slovenian farms, and Latruffe *et al.* (2008) for Hungarian, Czech, and Slovenian farms. The findings contradict the results obtained by Latruffe *et al.* (2008) for Romanian farms.
These results are in line with Zhu, Demeter and Lansink (2012), who reported a negative effect of subsidies (defined as the share of total subsidies in total farm income) for dairy farms in Germany, the Netherlands and Sweden. The negative influence of subsidies on technical efficiency can be explained by income and insurance effects of subsidies (Zhu and Lansink 2010); i.e., farmers treat subsidies as an additional source of income but not as an incentive to innovate or adopt new technologies. These results are also consistent with those obtained for a panel of dairy farms from eleven European Union countries, where subsidy dependence negatively influenced the technical efficiency score (Latruffe *et al.*, 2012). A negative relationship between technical efficiency and subsidies was also reported for Finnish and Norwegian dairy farms by Sipiläinen, Kumbhakar and Lien (2014).
Our results contradict the findings of Hadely (2006), who reported a positive effect of subsidies on the technical efficiency of English and Welsh dairy farms. The same result was obtained by McCloud and Kumbhakar (2008) for Danish, Finish and Swedish dairy farms. However, in the latter case, the authors treat subsidies as "facilitating input" that may affect output through the technology parameters.

Table 7: Sources of variation in technical efficiency (r_i) across dairy farms

Variable	Mean in the dataset – farms' average	Posterior mean (st. dev.) of $\ln(\phi)$
Coupled subsidies (rate)*	4.2%	-0.045 (± 0.019)
Decoupled subsidies (rate)*	10.3%	-0.101 (± 0.010)
Rural development subsidies (LFA incl., rate)*	10.1%	-0.025 (± 0.005)

* – Note: Subsidisation rates are defined as subsidies divided by gross farm income.

6 Conclusions

The dairy sector is one of the most important agricultural sectors in the EU and, in particular, in Poland. Accession to the EU caused structural changes in Polish dairy sector. For example, the changes were visible in sharp decrease in the number of dairy farms. In the EU countries, agriculture has been heavily subsidized. Poland, as a new member of the EU, has also benefited from the financial support granted under CAP. The share of the EU budget, spent on agricultural policy, has always been substantial, making it the most important common policy. Therefore, the crucial empirical question is about the effect of subsidies on the technical efficiency in member states. There are numerous analyses exploring this issue in old member states, whereas the literature concerning the technical efficiency and the impact of CAP subsidies in the post-accession period in CEE countries is rather scant. The aim of this paper was to provide an answer to the abovementioned issue.

In this paper, we have conducted an econometric efficiency analysis of a large group of Polish dairy farms in the period 2004-2011. We have specified a single-output stochastic production function. Furthermore, to reflect the specific dairy production by means other than the commonly used inputs, i.e., capital, labour, materials, and area, we have defined two more inputs: livestock and feed. The use of Bayesian Stochastic Frontier Analysis allows us to formally choose the optimal model based on information in the data.

Our results show that the production elasticity with respect to livestock is the highest, whereas production elasticity of feed is the lowest, and area elasticity of production is slightly higher than feed elasticity of production. According to our results the majority of Polish dairy farms operate under increasing returns to scale. However, returns to scale for a typical farm diminished steadily in the covered period. We found also that since 2007, there has been technical progress, which is an additional positive indicator for the development of the Polish dairy sector.

We find that the average technical efficiency (TE) of Polish dairy farms from 2004 to 2011 is about 83%. The majority of dairy farms have a TE score above 90%, and the lowest TE score found is 30%. We have also estimated the effects of dairy

farm characteristics on technical efficiency, especially we have examined the impact of subsidies on efficiency of these farms. Applying the continuous variables reflecting the effect of subsidies enabled us to determine the direction and relative magnitude of the impact. In regard to the effect of CAP subsidies on the average technical efficiency, a negative relationship has been revealed. Comparing the values of the parameter estimates related to the subsidy variables, we have found that decoupled subsidies have the greatest negative effect on the average TE score, while rural development subsidies have the least negative effect.
These results seem to be interesting from a practical point of view. However, our current study is based on the concept of production function, so it has many limitations, which are discussed in the previous sections. Applications of a cost function-based analysis of productivity and efficiency will be of the subject of future research.

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