Cost Efficiency and Farm Self-selection in Precision Farming: The Case of Czech Wheat Production

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Paper prepared for presentation at the 131st EAAE Seminar 'Innovation for Agricultural Competitiveness and Sustainability of Rural Areas', Prague, Czech Republic, September 18-19, 2012

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Annotation: This paper examines allocative and cost efficiency implications of adopting variable-rate fertiliser application using survey data from Czech wheat farms. Data Envelopment Analysis delivered higher efficiency scores for precision farming (PF) adopters. Correcting for selection bias using a one-step endogenous switching regression reveals that farms displaying a lower cost efficiency score are less likely to adopt PF technology. Non-adopters switching to PF technology would likely be affected by a significant decrease in cost efficiency given their production conditions and/or managerial and technical skills. In line with this, results indicate that human capital and farm size increase the likelihood of PF adoption. Cost (allocative efficiency) implications of PF-related changes in input structure only, on the other hand, are not found to have an impact on the choice of technology. A positive allocative efficiency effect of PF technology is brought about mainly by a farm's ability to better extrapolate the soil's productive potential, which is insufficiently reflected in the land rental prices. The allocative as well as cost efficiency implications of PF technology are further related to technology-specific responses to various farm characteristics and technological practices. PF technology makes farms' efficiency more responsive to production conditions, farm specialisation, legal form and other technological practices. The overall efficiency effect the PF practices is, therefore, conditioned on farm characteristics.

Key words: Precision farming, cost efficiency, technical efficiency, allocative efficiency, Czech agriculture, endogenous switching regression.

1 Introduction

Global efforts to improve the management of agricultural production to achieve higher economic performance and sustainability point to the importance of continuously investigating economic and environmental potentials of various production technologies claimed to bring about the more efficient use of farm resources. Precision agriculture adopters strive to produce along these lines, with economic incentives representing the dominant drivers of their technology selection (e.g., Roberts, English and Mahajanashetti, 2000), but positive environmental effects are still being realised (e.g., Khanna 2001). Despite the political interest in precision farming (PF) adoption and its potential for economic benefits, the PF adoption rate is still relatively low (Daberkow and McBride, 2003; Tey and Brindal, 2012). This relatively low rate, as well as the ambiguity of empirical results on PF technology’s economic effects (English, Roberts and Mahajaneshetti, 1998; Batte, 1999) contribute to agricultural economists’ continued interest in analysing the underlying factors that influence PF adoption and illustrate its economic effects.

Whelan and McBratney (2000: 265) offer the following definition of precision farming: “Matching resource application and agronomic practices with soil and crop requirements as they vary in space and time within a field.” Replacing the widely-used uniform application of inputs, not considering within-field production potentials with a system that assesses within-field variability in soil and crops (e.g., through yield or soil nutrition monitoring) and responds with site-specific management practices (Paxton et al., 2011) can be expected to yield economic benefits. Precision farming has been projected (i) to increase revenues by increasing crop yields above the yields achieved with a uniform level of input application, and

(ii) to reduce costs of production by reducing the level of inputs required to achieve a given yield (Roberts, English and Mahajanashetti, 2000).

Adopting PF technology can also be accompanied by cost increases due to new technical demands and input reallocation. Since PF substitutes information and knowledge for physical inputs (Bongiovanni and Lowenberg-Deboer, 2004: 359), implementing PF practices can introduce higher costs of information collection (e.g., soil and yield monitoring for the diagnostic stage), as well as costs related to variable input application. Physical inputs, mainly direct inputs such as fertilisers and other chemicals, are thus replaced by specialised machinery and human capital. This cost effect of PF-related input re-allocation has not received much scientific validation.

This paper examines the impact of PF adoption on economic returns measured by cost efficiency and aims to highlight the role of technology-related input re-allocation in the overall cost effect. This analysis must consider the possibility of self-selection bias, since farmers can be expected to endogenously self-select themselves into a sub-group through their adoption/non-adoption decision instead of being randomly selected from the survey respondents (Khanna, 2001: 36). The farms' self-selection into adopting the PF technology can result from the expectation of technology-related costs and benefits, which depend on the farm's information on the productive or cost-reducing potential of the new technology, as well as their assessment of their own capacity to realise this potential conditioned on their characteristics. More technically efficient farms can, therefore, be assumed to have a greater potential to extrapolate the benefits of new technologies such as PF, and hence to show a higher propensity to adopt the technology. To correct for the self-selection bias, we apply a one-step endogenous switching regression. This study analyses farm-level survey data on Czech wheat-producing farms and focuses on variable rate of fertiliser application as the PF practice of interest.

The paper is structured as follows: The following chapter discusses existing empirical studies on the economic implications of PF technologies and identifies the main added value of our analysis. The subsequent chapter introduces methods, data and variables applied in the analysis. Chapter four presents and discusses the empirical results, while Chapter five summarises the study and derives main conclusions.

2 Previous research

A review of theoretical models (see Feder and Umali, 1993) as well as empirical studies of PF technology's economic implications (see below) points to the thin line between the positive economic effects and PF-related costs and their dynamics, which makes the expectation of the net economic benefits less intuitive. For example, Anselin, Bongiovanni and Lowenberg-DeBoer (2004) identified a profitability-increasing effect of variable rate technology when applying a spatial econometric approach to strip trials data. Most studies have, however, found that the net economic implications of PF technology are conditional on a range of farm, field, market or institutional conditions. For instance, Bongiovanni and Lowenberg-Deboer (2004) find that PF is a modestly more profitable alternative than uniform field management for a wide range of restrictions on nitrogen application levels (e.g, government regulation on nitrogen use). Khanna (2001), by using a double selectivity model on a sequential adoption of PF technologies, came to the conclusion that adopting site-specific technologies leads to gains in nitrogen production on less productive soils. Experiments on cereals fields carried out by Godwin et. al. (2002) showed that the benefits from PF systems outweigh the additional costs in some farm (size) categories, and depending on the sophistication of the PF system. Roberts, English and Mahajanashetti (2000) stress the importance of the quality of the diagnostic stage of the PF practice implementation for drawing benefits from PF technology adoption. They also point out that the economic outcomes of the PF technology are sensitive to input and output prices.

Numerous studies confirm the importance of the expected economic benefits for PF adoption, and thus farm self-selection into the technology. For instance, Khanna, Epouhe and Hornbaker (1999) concluded that uncertainty in returns due to adoption, high costs of adoption, and a lack of demonstrated effects of advanced site-specific technologies on yields and input use are some of the major reasons for low adoption rates. Considering various stages of technology adoption, Leathers and Smale (1991) found that under uncertain impact of the new technologies, it is rational for the farmers to adopt components of the technology sequentially rather than to adopt the complete technology all at once.

Our data does not allow us to consider sequential adoption. However, the data does include a large range of farm characteristics that allow us to effectively correct for a possible selection bias. Also, the detailed production and technological data permits a closer look at the cost-structural shifts due to technological changes than was possible in any of the previous studies. Most empirical studies use partial production outcome indicators such as profits (Fernandez-Cornejo, 1996) and input productivity such as nitrogen productivity (Khanna, 2001; Roberts, English and Mahajanashetti, 2000), land productivity (Fuglie and Bosh, 1995), or labour productivity (Fleisher and Liu, 1992). These partial (individual input) productivity indicators ignore the production multi-dimensionality with regard to input structure and hence the joint productivity of the input set. Estimating farm-level cost efficiency measures taking into account the multiple-input productivity effect and the possibility of decomposing this measure into its allocative and technical parts thus helps to obtain new insights on the economic effects of PF practices.

Also, previous studies analysing the determinants of PF adoption and its economic implications that controlled for self-selection mostly applied two-step methods developed by Heckman (1976) and Lee (1976). However, the two-step procedure can deliver inconsistent standard errors (Lokshin and Sajaya, 2004: 282). We apply a full-information ML (FIML) method that allows for a one-step (simultaneous) estimation of the efficiency equations and technology choice equation that provides more consistent standard errors.

3 Methodology

In the first step of the analysis, farm-level efficiency measures are obtained by means of a deterministic linear programming method, Data Envelopment Analysis (DEA). Because of the expected physical input and cost reducing effect of precision farming, the cost-minimising behavioural objective is assumed for the specification of the DEA model. It is of interest to derive not only input-oriented technical efficiency measures, but also allocative efficiency, as precision farming has an impact on the inputs' structure. Both efficiency measures represent components of overall cost efficiency, which will be analysed in connection to PF technology in the second step. A joint feasible production set will be assumed in the cost efficiency model for both production practices (PF and non-PF) to create a joint performance benchmark and thus a comparative basis for the efficiency measures.

In the second step of the analysis, determinants of the technology selection and efficiency level are analysed using endogenous switching regression. To illuminate the PF cost effect related to input allocation and the overall cost effect, this analysis is carried out for cost and allocative efficiency separately. The use of switching regression is motivated by the fact that the level of allocative and cost efficiency could differ between PF adopters and non-adopters as a result of the PF technology effect, as well as the fact that adopting PF is a non-random selection choice. As discussed in the introduction, to choose between the two production practices, the farm compares the expected net benefit of both technological alternatives and chooses a practice that delivers the highest returns on its set of characteristics.

Endogenous switching regression models can be estimated by either two-step least square or maximum likelihood (ML) estimation; however, methods estimating one equation at a time are inefficient and derive inconsistent standard errors (Lokshin and Sajaya, 2004: 282). More consistent standard errors can be derived by implementing a full-information ML (FIML) method that simultaneously fits the continuous (efficiency) and the probit (technology choice) equations of the model.

If there is no statistical indication of dependency between the two parts of the switching model, and hence no indication of a self-selection in the PF adoption choice, the efficiency effect of precision technology is estimated using a truncated regression.

3.1 Efficiency measures and Data Envelopment Analysis

For the aim of cost efficiency measurement, we analyse a farm production system with one output variable. We consider a situation where a farm produces output $y \in R_+$, using a vector of k = 1,2,...,K inputs, $x \in R_+^K$. The feasible production set, T, is defined as:

$$T = \left\{ \langle y, x \rangle \in R_+^{M+K} \middle| x \text{ can produce } y \right\}, \tag{1}$$

where the production technology is assumed to be convex and non-increasing in inputs, non-decreasing in outputs, and exhibits strong disposability in both inputs and output[1]. In the cost minimisation context, the output, y, is fixed. Given a vector of k = 1,2,..., K input prices, $p \in R_+^K$, one can define the minimum cost associated with producing a particular output as:

$$E(y, p) = \min_x \left\{ p'x \middle| \langle x, y \rangle \in T \right\}. \tag{2}$$

The cost-minimising input vector is denoted by x_c; where the minimum cost level equals $p'x_c$ and the cost at the observed input vector is equal to $p'x$. The cost efficiency measure of a firm then can be defined as the ratio of minimum cost over observed cost:

$$CE = p'x_c / p'x . \tag{3}$$

This will take a value between zero and one, where a value of one indicates full cost efficiency, implying that it is not technologically feasible to produce the given amount of output with a lower cost.

Cost efficiency, CE, can be further decomposed into two components - a part due to technical efficiency, TE, and a part due to allocative efficiency, AE. It is methodologically simpler to derive TE and calculate AE using the two already derived measures.

The Farrell (1957) technically efficient input vector[2] for the observed input vector that is not located on the boundary of the technology set, x_t, can be identified by proportionally shrinking the observed input vector, x, until it is projected onto the boundary of the technology set; i.e. by solving the optimisation problem:

$$TE(y, x) = \min_\theta \left\{ \theta \middle| \langle \theta x, y \rangle \in T \right\}, \tag{4}$$

where θ is a scalar that takes a value between zero and one. The technically efficient input vector is calculated as $x_t = \theta x$. The cost corresponding with the technically efficient input level is $p'x_t$. Expressed as a ratio, technical efficiency can be denoted as:

[1] See Coelli et al. (2005) for further discussion of these properties.
[2] This measure considers the production boundary for constant returns to scale technology.

$$TE = p'x_t / p'x = p'(\theta x) / a'x = \theta . \quad (5)$$

Allocative efficiency, which relates to having the correct input mix given observed input price ratios, can then be derived as a ratio between cost efficiency and technical efficiency as follows:

$$AE = CE / TE, \quad (6)$$

which corresponds to the ratio of the cost related to the cost-minimising input vector and the cost related to the technically efficient input vector:

$$AE = p'x_c / p'x_t \ . \quad (7)$$

As mentioned in the introduction, to solve the presented optimisation problems, we apply input-oriented and cost-minimising DEA programs[3] to derive technical and cost efficiency measures, respectively. The purpose of DEA is to construct a frontier over the data points such that the observed output points lay within the production possibility set enveloped by the frontier. To obtain the presented ratio θ representing *TE*, one can solve following a (constant returns to scale) DEA program:

$$\begin{aligned} &\min_{\theta,\lambda} \theta , \\ \text{st} \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & \lambda \geq 0 , \end{aligned} \quad (8)$$

where the vectors x_i and y_i represent data on the *K* inputs and *M* outputs of the *i*-th farm; *X* is the $K \times I$ input matrix and *Y* the $M \times I$ output matrix; θ is a scalar and λ is a $I \times 1$ vector of constants.

The cost-minimising DEA program can be denoted as follows:

$$\begin{aligned} &\min_{\lambda,xic} (p_i' x_{ci}), \\ \text{st} \quad & -y_i + Y\lambda \geq 0, \\ & x_{ci} - X\lambda \geq 0, \\ & \lambda \geq 0 . \end{aligned} \quad (9)$$

The cost efficiency and allocative efficiency scores will be calculated as described in Coelli et al. (2005) and illustrated above in equations (3) and (6), respectively. To derive the efficiency measures, we apply the DEAP software (Version 2.1) developed by Coelli (1996).

The derived farm-level efficiency scores are then analysed using the endogenous switching regression in relation to the PF technology choice.

3.2 Endogenous switching regression model

Since the propensity to select PF technology can depend on the efficiency gains that might result from technology that are conditioned on the set of farm characteristics, we are interested in modelling the interdependence between the efficiency equation and the technology choice equation. We implement FIML to simultaneously estimate the two equations, which provides more efficient parameter estimates and consistent standard errors when compared to fitting one equation at a time by either two-step least squares or ML estimation (Lokshin and Sajaya, 2004).

[3] See Coelli et al. (2005) for a detailed description of the programs.

Drawing from Maddala (1983) and Lokshin and Sajaia (2004), a model is considered which specifies an agent with two regression equations and a criterion function, I_i, that determines the agent's regime - in this case, the technology selection:

$$I_i = 1 \quad \text{if} \quad \gamma Z_i + u_i > 0,$$

$$I_i = 0 \quad \text{if} \quad \gamma Z_i + u_i \leq 0,$$

$$\text{Regime 1:} \quad y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i} \quad \text{if} \quad I_i = 1, \tag{10}$$

$$\text{Regime 2:} \quad y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i} \quad \text{if} \quad I_i = 0, \tag{11}$$

where y_{ji} are the dependent variables in the continuous (efficiency) equations, X_{1i} and X_{2i} are vectors of weakly exogenous variables, Zi is a vector of exogenous variables explaining the endogenous selection dummy I_i; β_1, β_2, and γ are vectors of parameters to be estimated. Error terms u, ε_1 and ε_2 are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\Omega = \begin{bmatrix} \sigma_u^2 & \sigma_{1u} & \sigma_{2u} \\ \sigma_{1u} & \sigma_1^2 & . \\ \sigma_{2u} & . & \sigma_2^2 \end{bmatrix}.$$

The covariance between ε_1 and ε_2 is not defined, as y_{1i} and y_{2i} are never observed simultaneously; σ_u^2 is assumed equal to one. Given the assumption on the error terms, the logarithmic likelihood function for the system of equations (10) and (11) is as follows:

$$\ln L = \sum_i \left(I_i w_i \left[\ln\{\Phi(\eta_{1i})\} + \ln\{\phi(\varepsilon_{1i}/\sigma_1)/\sigma_1\} \right] + (1 - I_i) w_i \left[\ln\{1 - \Phi(\eta_{2i})\} + \ln\{\phi(\varepsilon_{2i}/\sigma_2)/\sigma_2\} \right] \right),$$

where Φ is a cumulative normal distribution function, □ is a normal density distribution function, w_i is an optimal weight for observation i, and

$$\eta_{ji} = \left(\gamma Z_i + \rho_j \varepsilon_{ji} / \sigma_j\right) \Big/ \sqrt{1 - \rho_j^2} \quad \text{j=1, 2.}$$

In this expression, $\rho_1 = \sigma_{1u}^2 / \sigma_u \sigma_1$ is the correlation coefficient between ε_{1i} and u_i, and $\rho_2 = \sigma_{2u}^2 / \sigma_u \sigma_2$ is the correlation coefficient between ε_{2i} and u_i.

Lokshin and Sajaya (2004) developed a Stata module *movestay*, which allows an implementation of the presented FIML. This module is applied for estimating the switching efficiency-PF technology choice regression model in this paper.

3.3 Data and variables

The study utilises survey data on 93 wheat producing Czech farms during the production year 2007/08[4]. These farms cultivate wheat, on average, on 28% of their total area and achieved yields of 6.31 tons per hectare. This is slightly higher than the national average of 5.77 tons per hectare. This figure reflects the favourable production conditions of selected farms which are mostly situated in two of the best agronomical zones for cereal and sugar beet production, both of which have an average altitude of 260 m.

The economic data shows that average per hectare costs were 16.9 thousand CZK (676 €), with unit production costs of 2,700 CZK/ton of wheat (107 €). Direct inputs - fertilisers,

[4] The data collection was carried out in 2009 within the project 'Economic system of evaluating farm performance with respect to sustainable use of natural resources', No.: QH71016, financed by the Czech National Agency for Agricultural Research.

chemicals and seed - account for 8,301 CZK per ha, while fuels account for 2,177 CZK per ha, capital costs are 3,108 CZK per ha, and labour inputs are 1,148 CZK per ha. Individual per hectare input items are as follows: 0.57 tons of fertilisers; 3.2 kg of chemicals; 240 kg of seeds; 12.3 hrs of labour; 95 litres of fuels. The most intensively used machinery in the crop production - tractors - generates about 164,000 CZK (6,561 €) of costs, which means about 453 CZK (18 €) per ha of wheat. About one-fourth of seeds are purchased and the remaining portion is self-produced. The total amount of all nutrients applied to wheat was 150.5 kg per ha. The larger farm sizes predetermines that field spatial distribution in the sample is relatively high. There are up to 53 wheat fields per farm, with an average of 18 fields. Wheat field size is slightly greater than 30 ha.

This section specifies variables for both models. To make the structure of variables simpler, they will be presented in a tabular form. Table 1 describes variables included in the cost efficiency DEA model and Table 2 presents variables used for the specification of the endogenous switching regression. Table 2 includes two dependent variables for the first (efficiency) part of the model. For each of the variables, the model is estimated separately; the remaining variables are the same for both models. Note that the number of observations to be used in the switching regression decreases due to missing values in some of the variables.

Table 1. Cost efficiency DEA model variables from farm-level 2007/08 survey data (93obs.)

Variable abbreviation	Variable description (unit)	Mean	Stand. dev./ frequency	Min	Max
Output	Wheat production (thousand tons)	2,373.08	1,806.02	263.70	9,580.62
k input variables	k = 1,2,..., *K*, *K* = 5				
Chemicals	Fertilisers, chemicals and seed applied in wheat production (stand. unit)	505.28	410.62	27.46	2533.23
Fuel	Fuel consumed in wheat production (thousand litres)	32.22	26.89	1.56	142.11
Capital	Tractors used in wheat production (motor hrs)	1,142.40	719.08	180.00	2,970.00
Land	Total land used for wheat production (ha)	361.55	247.94	30.00	1,237.69
Labor	Total labor used in wheat production, incl. share of overhead labor (hrs)	4,083.41	3,230.95	370.50	23,541.60
k input price variables					
Price_chem	Fixed price for standardized unit (nitrogen fertilizer) (CZK/ton)	5,934.16	-	-	-
Price_fuel	Fixed price for standardized unit of fuel (gas) (CZK/litre)	24.60	-	-	-
Price_capital	Annual and wheat production share of total value of tractors (CZK/motor hrs)	169.33	119.97	13.17	684.47
Price_land	Paid rent for arable land (CZK/ha)	1,662.63	722.40	250.00	3,530.00
Price_labor	Fixed (to sample average) labour cost (CZK/hr)	125.82	-	-	-

Table 2. Variables in the endogenous switching efficiency-PF selection model (84 obs.)

Variable abbreviation	Variable description (unit)	Mean/ frequency	Stand. dev.	Min	Max
***I. Efficiency equations** (for both regimes)*					
Dependent variable					
CE_tr	log transformation of CE measures	0.442	0.499	-0.632	1.607
AE_tr	log transformation of AE measures	1.254	0.725	-.132	4.701
Explanatory variables					
JSC	Legal form - joint stock company (yes = 1)[D]	26%	n.a.	0	1
Nr. owners	Number of owners	122	197	1	750
Land_rent	Rent paid for land (CZK)	1 680	771	250	4500
Share_crop	Share of crop production in total revenues (%)	72	24	19	100
Share_grass	Share of grass land in total land (%)	3	6	0	51
Field_prep_sow	Field preparation jointly with sowing as an alternative to separate operations (yes = 1)[D]	11%	n.a.	0	1
Fert_b.sowing	Fertilisation before sowing (yes = 1)[D]	49%	n.a.	0	1
Adopt_innov	Farm assessment of its use of technological innovations (1 = very bad, 4 = very good)[K]	2.8	0.62	1	4
Care_machin	Farm assessment of its standards regarding the taking care of machinery (1 = very bad, 4 = very good)[K]	3.18	0.49	1	4
Revenues	Total revenues (mio. CZK)	44.894	36.750	6.500	165.121
II. Technology selection equation					
Dependent variable					
PF-selection	Choice of PF (in fertilization) technology (yes = 1)[D]	42%	n.a.	0	1
Explanatory variables (all explanatory variables from I. part of the model + following variables)					
Probl_qualific	Farm assessment of its problems with labor qualification (0 = no problem, 3 = very large problem)[K]	0.81	0.81	0	3
Field_size	Average field size (ha)	25.5	14.5	6.8	81.1
Share_yield.dam	Estimated share of yield damage (%)	6.8	9.8	0	50

Note: [D] stands for a dummy variable; [K] stands for a categorical (scale) variable.

4 Results

DEA analysis delivered results implying that farms in the sample have, on average, the potential to reduce costs by 37%[5] (Table 3). The lower levels of allocative efficiency compared to technical efficiency scores imply that there is a greater potential for decreasing costs through correcting for input combinations (allocation) through different production practices (technologies) than in the radial (proportional) adjustment of input levels as captured by technical efficiency. Differences in all three efficiency scores between PF adopters and non-adopters suggest higher economic returns from precision farming. A two-group mean-comparison test, however, implies that these differences are statistically significant (at a 10% significance level) only in the technical efficiency scores[6].

[5] Despite the intention of collecting data in similar production regions, it needs to be pointed out that a share of the measured inefficiency is attributable to differences in production conditions among farms, which is mainly reflected in the technical efficiency scores. This is due to the deterministic nature of the DEA approach.

[6] This test is not indicative of the causality between efficiency and precision farming practices, nor of the fact that this relationship could not be significant when controlling for other efficiency-determining farm characteristics.

Table 3. Summary of technical, allocative and cost efficiency scores

Type of producers	Nr. Obs.	Mean	Stnd. dev.	Min	Max
TE - total farm sample	93	0.835	0.123	0.578	1.000
AE - total farm sample	93	0.758	0.112	0.467	1.000
CE - total farm sample	93	0.634	0.137	0.349	1.000
TE - PF non-adopters	55	0.818	0.128	0.578	1.000
AE - PF non-adopters	55	0.755	0.115	0.467	0.991
CE - PF non-adopters	55	0.619	0.143	0.361	0.991
TE - PF adopters	38	0.860	0.111	0.628	1.000
AE - PF adopters	38	0.763	0.109	0.531	1.000
CE - PF adopters	38	0.657	0.125	0.349	1.000

Deriving the cost-minimising level of inputs for each observation in the process of cost efficiency measurement also facilitates a closer look at the farm-level use of individual input categories. Table 4 illustrates ratios of actually observed to cost-minimising levels of inputs in given input categories for the sample average, as well as for the two farm groups - farms both adopting and not adopting PF. The table suggests that the most overused input categories are fertilisers and chemicals, and fuel. PF adopters overuse these inputs slightly less than PF non-adopters, which is in line with the more precise and thus reducing practice in fertiliser application. However, this difference is not statistically significant. A similar trend is found in the use of fuel. Compared to PF non-adopters, PF adopters consume fuel in wheat production that is significantly closer to the fuel cost optimum. This could relate to the fact that PF adopters use significantly newer[7] and more fuel-efficient machinery than PF non-adopters.

Interestingly, Table 4 further shows that both groups of farms use less than an optimal amount of capital, which could be given by the relatively low price of capital due to a high degree of machinery depreciation and the frequent (transition-specific) complimentary transfer of machinery from predecessor farms. This result could also relate to the approximation of capital used in this study, which is derived from the amount of tractor hours used in wheat production, and the annual value of these tractors derived from the value at purchase, while the volume of all machinery necessary for wheat production is markedly higher. The last statistically significant difference in the overuse of inputs can be found in land. The ratios in Table 4 suggest that farms applying PF techniques use lesser land for a given level of output than do PF non-adopters (achieve higher land productivity), and thus can be assumed to use land more intensively and. In line with the expectation regarding higher labour intensity of PF technology, PF adopters are, on average, found to use more labour than PF non-adopters. However, this difference is statistically insignificant. Overall, the input structure analysis suggests a positive effect of PF-technology on allocative efficiency given the input prices, which calls for a deeper analysis that will follow.

[7] The average age of tractors in the group of farms adopting PF practices is 9.3 years, while it is 11.7 years in the case of farms not adopting PF practices. The two-group mean comparison-test finds the difference significant at the 5% significance level.

Table 4. Mean statistics for the ratio of real to cost-minimising input levels

Input category	Sample total	PF non-adopters	PF adopters	p-value*
Nr. Obs.	93	55	38	
Chemicals (stand. unit)	1.996	2.055	1.911	0.273
Fuel (stand. unit)	1.742	1.887	1.534	0.047
Capital (motor hours)	0.917	0.929	0.899	0.851
Land (hectares)	1.303	1.349	1.238	0.013
Labor (hours)	1.468	1.388	1.583	0.203

Note: * p-value of the two-group (PF adopters and non-adopters) mean-comparison test.

The relationships between PF adoption and allocative and cost efficiency are further analysed by means of an endogenous switching regression model, the estimates of which are presented in Tables 5 and 7, respectively. Each table includes two models - a complete model, in which the first and second efficiency equations (for the two regimes - PF adoption and non-adoption) contain the same variables, and a more parsimonious model in which some of the most insignificant variables are eliminated to increase the overall fit of the model.

Table 5 presents estimates of the switching regression of the determinants of the PF selection and allocative efficiency. As indicated by the Wald test, both models - i.e. complete and more parsimonious - are overall well-fitted (at the 5% significance level). Since the more parsimonious model is more significant, we interpret the parameters of this model. Parameters of the first equation indicate that among farms adopting PF technology, the chosen legal form, particularly Joint Stock Company, has a positive impact on the level of allocative efficiency. This could relate to the specific capital and ownership structure of legal forms in agriculture related to the form of capital transformation. Joint Stock Companies often acquired more productive capital compared to cooperatives, and progressively invested in new technologies (see Curtiss et al. 2012). Furthermore, the number of owners increases allocative efficiency. This effect can also be observed in the second regime (group of non-adopters), as it is also statistically significant in equation 2. Therefore, the cost efficiency effect of the number of owners is independent of the adoption of PF technology. It is likely that the more owners a farm has, the higher is the share of employees who are simultaneously owners. In this case, the positive impact of the number of owners could approximate the positive incentive structure related to employee ownership. Land rental price, which is included in the model to mainly capture soil quality differences, is also found to have a positive impact on allocative efficiency. The positive effect could suggest that the price does not fully cover the productive potential of the soil. In other words, the increase in productive potential is not sufficiently reflected in the increase of land rental price. The fact that the effect of land rental is significant in the first equation could only suggest that the PF adopters are better at utilising the productive potential of the soil.

An unexpected estimation result is that, among PF adopters, the degree of specialisation in crop production has negative implications for allocative efficiency. A detailed data analysis revealed that farms specialising in crop production have a significantly higher capital value[8] than do farms with more diversified production. The higher value of tractors suggests better technical parameters and specialisation of machinery, which has a negative allocative efficiency effect within the group of farms adopting PF. This result could suggest that farms have difficulties to utilise the productive potential of more advanced machinery in relation to its price (the price productivity ratio increases faster for PF adopters that for PF non-adopters), which could relate to the issue of a longer learning curve.

[8] Note that only capital (tractors) applied in wheat production is (are) considered.

Total revenues also have a negative effect on allocative efficiency, in this case in both equations (thus, this is not a technology-specific effect). Further data analysis discloses that total revenues are highly correlated with farm arable land size. Most importantly, land rental prices increase with total revenues, which would suggest that for farms to achieve higher revenues, they had to acquire more land for which they had to offer competitive farm land prices. These farms were thus willing to pay higher prices for a comparatively similar quality of land (which significantly reduces allocative efficiency) to achieve economies of size. In line with this argument is the finding that the effect of revenues is insignificant in the cost efficiency model (economies of size do not outweigh the cost effect of higher land rental prices).

The efficiency model also delivers significance of parameters of two technological variables. The first variable, *Field_prep_sow* depicts an operation in which soil preparation and sowing is performed in one-step when compared to other methods of soil preparation and sowing (mainly as separate sequential operations). This variable's parameter is statistically significant (at the 10% significance level) only in the second allocative efficiency equation, which implies that among farms not applying PF technology, this one-step operation improves allocative efficiency. It is reasonable to expect that those who apply this management in soil preparation are more oriented on advanced practices also in other operations. On the contrary, the second variable *Fert_b.sowing*, representing fertilisation before sowing reduces allocative efficiency in both models. This suggests that this type of fertilisation results in excessive costs, and this cost-increasing effect due to input allocation is not specific for either PF adopters or non-adopters. The size of the negative effect of the fertilisation before sowing is smaller for PF adopters.

The third part of the allocative efficiency-PF switching regression model in Table 5 will be interpreted together with this part of the cost efficiency-PF switching regression model in Table 6.

Important for the interpretation of the allocative efficiency-PF switching regression in Table 6 is the likelihood ratio test of independent equations, which estimates whether the selection bias adjustment is significant. The statistical insignificance of the test suggests that the allocative efficiency and PF adoption models are not jointly determined, and that the allocative efficiency effects of the PF technology themselves do not determine the selection of PF adoption.

Estimates presented in Table 6, however, suggest that the results are different for the cost efficiency-PF relationship. The Wald test of equations' independence is significant at the 10% and 5% significance levels in the complete and more parsimonious models, respectively. Note that this significance is related to the relationship between the PF-adoption equation and the (second) cost efficiency equation for PF non-adopters as depicted by the statistically significant correlation coefficient ρ_2. This suggests that farms choosing not to adopt PF fertilising methods would achieve lower cost efficiency than a random farm from the same sample would have achieved with the non-PF technology. Farms adopting PF fertilisation do statistically no better or worse than a random farm would have.

Table 5. ML estimates of endogenous switching regression model of allocative efficiency and precision farming (84 observations)

	Complete model						More parsimonious model					
	Allocative eff. eqn. 1 (PF adopters)*		Allocative eff. eqn. 2 (PF non-adopters)*		PF choice equation		Allocative eff. eqn. 1 (PF adopters)*		Allocative eff. eqn. 2 (PF non-adopters)*		PF choice equation	
	Par. Est.	P-value	Par. Est.	P-value	Par. Est.	P-value	Par. Est.	P-value	Par. Est.	P-value	Par. Est.	P-value
JSC	0.439	0.053	0.090	0.663	0.109	0.762	0.461	0.028	-	-	0.176	0.622
Nr. owners	0.061	0.113	0.076	0.096	0.008	0.927	0.064	0.093	0.086	0.029	0.014	0.870
Land_rent	0.310	0.090	0.235	0.099	-0.139	0.506	0.340	0.074	0.215	0.156	-0.150	0.490
Share_crop	-0.912	0.038	-0.326	0.446	0.386	0.597	-0.939	0.019	-	-	0.612	0.428
Share_grass	-0.564	0.901	-1.421	0.114	-3.527	0.456	-	-	-1.132	0.136	-4.429	0.337
Field_prep_sow	0.250	0.461	0.718	0.079	-0.539	0.474	0.319	0.238	0.718	0.082	-0.474	0.504
Fert_b.sowing	-0.419	0.111	-0.486	0.125	0.573	0.117	-0.450	0.072	-0.574	0.059	0.471	0.163
Adopt_innov	-0.105	0.594	0.132	0.451	0.399	0.205	-	-	0.145	0.454	0.412	0.201
Care_machin	0.029	0.892	0.225	0.387	0.408	0.276	-	-	-	-	-	-
Revenues	-0.010	0.016	-0.006	0.043	0.010	0.077	-0.011	0.004	-0.006	0.088	0.011	0.071
Probl_qualific	-	-	-	-	-0.335	0.272	-	-	-	-	-0.408	0.105
Field_size	-	-	-	-	0.022	0.062	-	-	-	-	0.022	0.060
Share_yield.dam	-	-	-	-	0.056	0.003	-	-	-	-	0.057	0.003
Constant	2.423	0.001	0.472	0.623	-4.071	0.007	2.173	0.000	0.938	0.054	-2.870	0.007
Wald test of fit			19.23	0.037					17.49	0.015		
Wald test of indep. equations			0.63	0.426					0.75	0.385		
ρ_1 (stnd. dev.)			-0.611	0.678					-0.557	0.529		
ρ_2 (stnd. dev.)			0.337	0.709					0.243	0.802		

Note: Values of cost efficiency are log transformed to gain a more normal distribution. The robust Huber/White/sandwich estimator of the variance is used in place of the conventional MLE variance estimator; *AE_lt is the dependent variable.

Table 6. ML estimates of endogenous switching regression model of cost efficiency and precision farming (84 observations)

	Complete model						More parsimonious model					
	Cost efficiency eqn. 1 (PF adopters)*		Cost efficiency eqn. 2 (PF non-adopters)*		PF choice equation		Cost efficiency eqn. 1 (PF adopters)*		Cost efficiency eqn. 2 (PF non-adopters)*		PF choice equation	
	Par. Est.	P-value	Par. Est.	P-value	Par. Est.	P-value	Par. Est.	P-value	Par. Est.	P-value	Par. Est.	P-value
JSC	0.604	0.004	0.300	0.203	0.165	0.640	0.567	0.011	0.245	0.314	0.131	0.700
Nr. owners	0.069	0.142	0.127	0.009	0.031	0.696	0.062	0.192	0.142	0.006	0.034	0.671
Land_rent	0.170	0.018	0.227	0.114	-0.130	0.608	0.160	0.010	0.237	0.178	-0.123	0.616
Share_crop	-0.754	0.065	-0.386	0.377	0.385	0.627	-0.789	0.017	-	-	0.566	0.399
Share_grass	-5.520	0.024	-1.469	0.063	-4.337	0.332	-5.040	0.048	-1.447	0.062	-3.830	0.363
Field_prep_sow	0.466	0.046	0.559	0.294	-0.462	0.575	0.442	0.077	-	-	-0.787	0.349
Fert_b.sowing	-0.356	0.196	-0.265	0.236	0.571	0.093	-0.289	0.175	-	-	0.684	0.029
Adopt_innov	0.224	0.226	0.316	0.074	0.382	0.259	0.212	0.224	0.214	0.138	0.303	0.369
Care_machin	-0.115	0.619	0.233	0.320	0.332	0.358	-	-	0.317	0.217	0.384	0.277
Revenues	-	-	-	-	0.012	0.090	-	-	-	-	0.012	0.033
Probl_qualific	-	-	-	-	-0.502	0.029	-	-	-	-	-0.526	0.017
Field_size	-	-	-	-	0.021	0.230	-	-	-	-	0.023	0.162
Share_yield.dam	-	-	-	-	0.057	0.023	-	-	-	-	0.058	0.016
Constant	0.588	0.624	-0.971	0.267	-3.713	0.016	0.237	0.718	-1.232	0.151	-3.862	0.010
Wald test of fit			34.41	0.000					32.30	0.000		
Wald test of indep. equations			2.85	0.091					4.72	0.030		
ρ_1 (stnd. dev.)			0.164	(0.971)					0.247	(0.771)		
ρ_2 (stnd. dev.)			0.560	(0.290)					0.657	(0.234)		

Note: Values of cost efficiency are log transformed to gain a more normal distribution. The robust Huber/White/sandwich estimator of the variance is used in place of the conventional MLE variance estimator; *CE_lt is the dependent variable.

In this context, switching regression allows us to use the parameters for the PF adopters equation to predict the cost efficiency values for the PF non-adopters, were they to adopt the PF practice, and vice versa. This results in four sets of predicted values for cost efficiency that are summarised in Table 7. The hypothetical predictions assume that the coefficients obtained in the switching regression for PF adopters would apply to PF non-adopters were they to apply the PF technology, and analogically, the coefficients obtained for PF non-adopters would apply to PF adopters were they to revert.

Table 7. Summary of predicted values for cost efficiency

	Type of producers	Mean	Stnd. dev.	Min.	Max.
1.	PF adopters (in PF mode)[1)]	0.651	0.069	0.495	0.797
2.	PF adopters (in non-PF mode) [2)]	0.805	0.060	0.680	0.917
3.	PF non-adopters (in PF mode) [2)]	0.603	0.118	0.156	0.802
4.	PF non-adopters (in non-PF mode) [1)]	0.640	0.086	0.438	0.840

Note: [1)] predictions of real state, [2)] predictions of hypothetical state.

The results in Table 7 show that the average predicted cost efficiency for the PF non-adopters in their real regime (line 4) is higher than their level of cost efficiency for the hypothetical situation, i.e. were they to apply PF (line 3). Adopters of PF would do much better were they to return to non-PF technology (line 2), however, their predicted cost efficiency values (line 1) still accede the cost efficiency of PF-non adopters (line 4). This could imply that only more cost efficient farms are willing to undergo losses of new-technology adoption as they expected to do better than a random farm and improve in the course of the learning curve. These results support the expected self-selection into the technology. However, only the proof of self-selection of less efficient farms into conventional (non-PF) technology is statistically significant.

The differences in the parameters of the first two equations in Tables 5 and 6 are related to the technology-specific effects of the selected variables on technical efficiency, the second component of cost efficiency. One of the differences refers to the effect of revenues. Total farm revenues as a proxy for farm size were found to have a highly insignificant effect on cost efficiency in both equations[9]. This suggests that the negative effect of revenues on overall cost due to related allocative inefficiencies is eliminated by their positive effect on technical efficiency, likely due to associated economies of scale. Analogous to the allocative efficiency model, the legal form of Joint Stock Company and land rent continue to have a significant positive effect on overall cost efficiency among PF-adopters. The parameter for the number of owners lost its significance in the first equation; however, it is still significant in the second equation. Among PF adopters, specialisation in crop production also has a negative implication for overall cost efficiency. Contrary to the allocative efficiency model, the share of grass land in total cultivated land has a significant negative effect for total cost efficiency in both equations. Land has been turned into grass land mainly in less favourable areas for agricultural production, which suggests that the share of grass land could proxy for the farm producing in worse production conditions. In contrast to previous results, the negative effect of the technological operation of applying fertilisers before sowing is not significant for cost efficiency, and carrying out sowing jointly with field preparation has a positive effect for cost efficiency only within the PF regime.

[9] In combination with the variable Land_rent, the variable Revenues caused a collapse of the model. The model with Revenues, without the variable Land_rent, provides good estimates; however, the parameter for Revenues is highly insignificant. On the other hand, the model with Land_rent without Revenues is overall better fitted, and the parameter for Land_rent is statistically significant, as shown in Table 6.

Finally, we interpret the parameters of the PF adoption model. We focus on the estimates presented in Table 6, since the overall fit of the cost efficiency-PF switching regression, when compared to the allocative efficiency-PF switching regression, is greater (see the Wald test statistics). Similar to Khanna (2001) or Khanna, Epouhe and Hornbaker (1999), we find that farm size (revenues) and human capital[10] positively increase the farms' likelihood of adopting PF technology. The propensity of PF adoption also increases with the estimated yield damage due to seasonal weather conditions, which could indicate that farms experiencing greater yield volatility are more likely to adopt PF technology, or they are more likely to adopt the technology because they have a greater capacity to estimate yield responses to changing weather conditions. The last significant parameter in the PF choice model is the parameter for the variable fertilisation before sowing. This result suggests that farms that are more concerned with soil nutrition sufficiency are more likely to adopt PF in fertilisation, since the results of some of the steps in fertilisation (incl. the first productive fertilisation) are known to be sensitive to the application method.

5 Conclusion

This paper examines the economic implications of adopting the variable-rate application of fertilisers and the determinants of adopting this PF technology utilising data from Czech wheat farms during the 2007/08 production year. Economic indicators are represented by cost efficiency and its two components - technical and allocative efficiency - which allows for a separation of the PF technology-related allocative cost effect due to changes in input structure with regard to price relations, and the technical efficiency effect that embodies the cost differences due to technology-specific ratios of the real to technically optimal input levels. The relationship between PF adoption and efficiency scores is analysed by means of a one-step endogenous switching regression.

The efficiency analysis revealed that there are marked potentials for cost efficiency improvements among the analysed farms. The greatest inefficiencies are found in the use of variable inputs (fertilisers and chemicals) and fuel. Significant differences in input use optimality (input productivity) between PF technology adopters and non-adopters are found in the use of fuel and land, with PF adopters showing higher partial productivities. Results on overall efficiency scores also show that PF adopters can be characterised as more efficient. However, as estimates of the switching regressions suggest, the causal relation is not straightforward.

The results of the first endogenous switching regression disclose statistical independence between the determination of allocative efficiency and the PF technology choice. The results thus do not confirm the self-selection hypothesis with regard to the expected efficiency influencing the PF technology choice when only allocative efficiency (effect of technology-related input structure change) is considered. Despite the expected negative impact of PF technology on allocative efficiency due to the intensification of information/knowledge and machinery innovation, the PF technology is found to have overall rather a positive effect on allocative efficiency given the input prices in the Czech market during the analysed period. The allocative efficiency increases relate mainly to the fact that the PF technology significantly increases the farms' ability to abstract the soil's productive potential, while land prices remain the same for PF adopters and non-adopters.

Contrary to the relationship between allocative efficiency and PF technology choice, total cost efficiency and the technology-choice regressions are found to be significantly dependent. The estimates show that farms not adopting PF practices do significantly better without the

[10] In our case, human capital is approximated by problems with workers' qualification, for which the parameter estimate is negative.

technology switch than if they were to adopt the PF technology. Similarly, farms adopting the PF technology are found to display lower cost efficiency in reality when compared to a hypothetical situation of non-adopting the technology. However, these differences are found to be insignificant. Also, the PF adopters' predicted cost efficiency values in the PF adoption regime are still higher than the predicted cost efficiency values for PF non-adopters in their real non-adoption regime. In general, the results suggest that less efficient farms are less likely to adopt PF technology, as they expect increases in overall costs given their production conditions and/or managerial and technical skills. In line with this argument, it was found that a farm's problems with workers' qualifications, which represents lower human capital, significantly decreases the likelihood of PF adoption. On the other hand, a farm size generating economies of scale is a factor that increases the farm's propensity of choosing PF technology.

The impact of PF technology is mainly observed through changes in the allocative and total cost efficiency effects of some farm characteristics and accompanying technological practices. Precision Farming technology makes the farm cost efficiency more responsive to land quality and more sensitive to production conditions, farm specialisation, as well as legal form and other technological practices such as one-step field preparation and sowing.

Acknowledgements

This research study was carried out as part of the project "Economic system of evaluating farm performance with respect to sustainable use of natural resources" No.: QH71016, and financed by the Czech National Agency for Agricultural Research, NAZV. The authors would like to thank the NAZV and the other people who worked on the project for their great help in formulating the questionnaire, organising the survey, and processing the data.

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