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Drivers and barriers to precision agriculture adoption in Czech agriculture

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Abstract
This study investigates the adoption of precision agriculture technologies (PATs) in the Czech Republic. Using unbalanced panel data from the Czech Farm Accountancy Data Network (FADN) survey spanning the period from 2017 to 2021, it aims to identify the drivers and barriers to the adoption of PATs in Czech field crop production. The estimation of a probit binary choice model with a within-between random effects (WBRE) specification – a novel approach to addressing heterogeneity in panel data choice models – reveals that PATs adoption is significantly influenced by socio-economic factors such as labor intensity, indebtedness, manager education, and farm economic size, as well as environmental factors such as localization and land quality. Furthermore, the adoption of PATs is associated with temporal dynamics in labor intensity, production efficiency, specialization, and land ownership. The findings underscore the need for targeted policy measures to promote the adoption of technology and enhance agricultural efficiency. The contribution of this study lies in deepening the understanding of the determinants and barriers to precision agriculture adoption in the EU context, where empirical research remains relatively scarce.

Keywords Precision agriculture · Adoption · Drivers · Barriers · Field crop production · Czech republic

Introduction

The impact of human activities on environmental degradation has been one of the most widely studied topics in recent years (Lanzi et al., 2018). In this context, agricultural production is particularly significant due to its high environmental footprint (Poore & Nemecek, 2018) and its dependence on the state of the natural environment. Moreover, the agricultural sector faces increasing pressure from the growing demand for food driven by global population growth (Gliessman, 2014). To date, this increasing demand has been met through technological, biological, and chemical advancements; however, these developments have often resulted in production intensification and increased environmental impacts (Sadowski & Baer-Nawrocka, 2018). Addressing these challenges is a key priority for the European

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Union (EU), which allocates a large part of its budget to initiatives that combine environmental protection with sustainable agricultural production (Fantappiè et al., 2020; Czubak & Pawłowski, 2020). One of the EU's key objectives, outlined in the Farm-to-Fork strategy as part of the European Green Deal that sets the direction of EU agriculture for the coming years, is to significantly reduce the use of fertilizers and pesticides in agriculture (Schebesta & Candel, 2020). While these measures offer undeniable benefits for the environment, they also raise concerns about maintaining agricultural productivity at levels sufficient to meet the demand for food, as well as ensuring sufficient incomes for farmers (Adeux et al., 2019).

One promising response to the aforementioned challenges is the adoption of precision agriculture technologies (PATs) (Nath, 2023). These technologies not only enhance farm productivity but also align agricultural practices with environmental sustainability goals. However, the adoption of PATs in the EU remains relatively low (Blasch et al., 2022; Masi et al., 2022), hindering progress in sustainable intensification of agriculture. Researchers have identified multiple factors influencing the adoption of PATs; however, these dynamics remain empirically underexplored within the EU context (Blasch et al., 2022). Despite that, together with the market maturity of individual PATs and better data availability, more empirical studies on the regional adoption emerge (see Table 3 in Žáková Kroupová et al. (2025) for an overview of empirical studies regarding PATs adoption). According to a recent paper by Petrović et al. (2024), the Czech Republic is among the leading adopters of PATs in Central and Eastern Europe. Authors mention mainly the robotization of milking and cleaning in animal production; however, they also point out the use of PATs in tractors. Vrchota et al. (2022) found that PATs in the Czech Republic are adopted more in crop than livestock production, particularly the use of intelligent weather stations data, and navigation and optimising journey systems are present. Moreover, Petrovic et al. (2024) found that the Czech Republic is a regional leader of drone usage for soil monitoring in organic farming. Building on these findings, this paper aims to characterize PAT adopters and identify the drivers and barriers affecting the adoption of PATs among Czech farmers, who can be perceived as regional leaders in this process. To achieve this goal, a panel data probit model with a within-between random effects (WBRE) specification was employed. This approach effectively accounts for unobserved heterogeneity, offers a more precise understanding of PAT adoption, and provides recommendations for future agricultural policy interventions aimed at increasing PAT adoption across the EU.

The novelty of this study lies in the investigation of the adoption of PATs using Farm Accountancy Data Network (FADN) data, which provides a highly representative sample of commercial farms. The FADN is the official harmonized microeconomic database of the European Union. The Czech FADN sample is designed to be statistically representative of the population of commercial farms, i.e., holdings exceeding €8,000 between 2004 and 2019 and €15,000 from 2020 onward in Standard Output (SO) (Institute of Agricultural Economics and Information, 2025). Representativeness is achieved through a stratified sampling procedure that accounts for region, type of farming, and economic size class, and expansion weights are applied to align sample aggregates with the national Farm Structure Survey (FSS) controls. This guarantees that the FADN reflects the structure of Czech agriculture in terms of farm numbers, utilized agricultural area (UAA), livestock units, and labor input (European Commission, 2025). The FADN scope represents commercial farms, which are market-oriented, and earlier assessments confirm that the Czech FADN adequately reproduces the structure and dynamics of commercial agriculture (Prášilová & Zeipelt, 2011; Prášilová et al., 2013).

Moreover, the contribution of this study lies in the use of the WBRE model, which captures both within- and between-farm effects, allowing for the investigation of how farm characteristics and their changes over time influence the adoption of PAT. Therefore, this study offers an improvement on the data sample compared to previous studies, which rely mainly on surveys with a limited sample size. Moreover, regression techniques are employed to ensure the robustness of results and credible inference. Although this is a standard in quantitative research, it is worth mentioning in the case of studies on drivers and barriers of PATs adoption, as so far, in the case of the EU, they remain mainly qualitative, and the number of quantitative studies is still small (Žáková Kroupová et al., 2025). Therefore, the factors driving and hindering PAT adoption in the Czech Republic and the EU remain relatively unexplored, indicating the potential for novel insights in this field. Overall, for the first time, this study provides three key aspects simultaneously: a large representative sample based on a worldwide-acknowledged source, a robust quantitative approach, and a territorial scope of the Czech Republic considered among regional leaders in PATs adoption.

The rest of the paper is organized into four key parts. First, the theoretical background and a review of the current state of research are presented. Second, the data and research methods are described. Third, the results of the study are interpreted and discussed, along with their policy implications. Finally, conclusions are drawn, summarizing the main findings.

Literature review

Precision agriculture (PA) is an approach that is transforming the European agricultural sector by enhancing sustainability and efficiency through the use of advanced technologies (Balafoutis et al., 2017). However, its adoption is influenced by various economic, technological, institutional, and socio-psychological factors, each contributing to the complexity of PA integration (Zarco-Tejada et al., 2014; OECD, 2016).

Financial considerations, including cost, potential return on investment, and access to capital, significantly impact the adoption of PATs (Schimmelpfennig, 2016). Larger farms often have the financial resources to invest in PA, viewing it as a viable option due to the potential to increase efficiency and returns (Pierpaoli et al., 2013; Barnes et al., 2019b). For smaller farms, however, high upfront costs can be prohibitive without external financial support (Sørensen et al., 2010; European Parliament, 2017). At the EU level, the Common Agricultural Policy (CAP) provides subsidies and support for technology adoption, which can significantly influence farmer decisions (Zarco-Tejada et al., 2014; Schimmelpfennig, 2016). Additionally, local government initiatives can either facilitate or restrict PA adoption through zoning laws, environmental regulations, and support programs (Roberts et al., 2004).

The complexity of PA and the need for compatible infrastructure present significant barriers. Farms must be able to integrate new technologies with existing systems, which may require substantial modifications or upgrades (Kutter et al., 2011; Aubert et al., 2012). The rapid evolution of technology also necessitates ongoing education and adaptation, which can be challenging for some farmers (Balafoutis et al., 2017). Studies have found that younger, more educated farmers are generally more open to new technologies (Wolfert et al., 2017; Barnes et al., 2019b). Social influences, including peer adoption and community attitudes toward technology, also play significant roles (Eastwood et al., 2017; Klerkx et al., 2019). Previous scholarship suggests that key barriers to PA adoption include psychological resistance to change, lack of perceived benefits, and insufficient knowledge about operational and long-term advantages (Paustian & Theuvsen, 2017). Moreover, differences in technological literacy and infrastructure across regions can further complicate the adoption process (Pierpaoli et al., 2013; Fleming et al., 2018).

Blasch et al. (2022, p. 34) found that most knowledge about PA adoption is derived from empirical evidence from the United States (U.S.). The authors also noted that EU-related studies are "often qualitative in nature and based on small samples, or specifically focused on early adopters of the technology." However, as shown by Žáková Kroupová et al. (2025), there are some exceptions. According to the authors, a total of six EU-related studies on PATs adoption are eligible for quantitative synthesis, and their effect size can be calculated. Nevertheless, their scope is limited to five countries, namely Austria (Blasch et al., 2021), Denmark (Tamirat et al., 2017), Germany (Michels et al., 2020; Paustian & Theuvsen, 2017; Tamirat et al., 2017), Hungary (Bai et al., 2022), and Italy (Vecchio et al., 2020), and only some specific PATs. In all of these cases, regardless of territorial and technological scope, large farms with young owners are shown to be the most likely PAT adopters. Three more extensive cross-country studies (Knierim et al., 2018; Barnes et al., 2019a, b) stand out as they examine the adoption of PATs across several European countries. Knierim et al. (2018) highlight that PA adoption is influenced more by farmers' perceptions and attitudes toward technology than by demographic factors. In addition to farm size, Barnes et al. (2019a) identify higher income as a factor influencing PA adoption. The authors argue that economic costs pose a significant barrier to adoption and that farmers who are optimistic about the economic benefits of PA are more likely to adopt the technology. Barnes et al. (2019b) further emphasize that, beyond high initial costs and uncertainty about the economic benefits, a lack of trust in the technology remains a major adoption barrier.

As recent evidence indicates, the Czech Republic is among the regional European leaders in PATs adoption (Petrović et al., 2024). Building on this finding, the factors contributing to the high rate of PA adoption are analyzed. The socio-economic and environmental factors behind the adoption of PATs are examined, using detailed data from the Czech FADN. As highlighted in the literature review, socio-economic factors are key to the introduction of PATs. Moreover, in practice, the economic vulnerability of farms is a crucial factor affecting strategic decisions, particularly regarding farm expansion and the adoption of new technologies (Hayden et al., 2021).

Materials and methods

Data

This study focuses on the adoption of PATs in the Czech Republic. The data are obtained from the FADN database, which provides harmonized microeconomic data on agricultural holdings. The FADN database collects detailed information on the use of PATs, broken down into the following categories: A) technologies in crop production, i.e., (i) soil cultivation systems (based on digital soil mapping); (ii) seeding systems; (iii) fertilization systems (e.g., variable rate fertilizer application, remote sensing); (iv) crop protection systems (e.g., variable rate application of plant protection, pesticide spraying robots and drones); (v) autonomous machine guidance; (vi) use of robots in vegetable, fruit, and wine farming; (vii) other technologies in crop production; B) technologies in livestock production, i.e., (a) automated animal systems (e.g., health monitoring sensors, activity monitoring systems, feeding management systems); (b) automatic milking machines; (c) stable and farm management systems (e.g., environmental sensors, video surveillance systems, sound monitoring systems); (d) technologies in pig and poultry farming (e.g., automated control of microclimate, animal growth monitoring, damaged egg detection systems); (e) other technologies in livestock production.

The dataset used in this study is based on national surveys conducted between 2017 and 2021, comprising 2,085 observations from 670 agricultural holdings specializing in field crop production. Farms are classified by FADN into types according to the share of specific production in their Standard Output (SO). Field crop farms are those where the share of field crops in the SO exceeds two-thirds (FADN CZ, 2025a). The sample used in this study represents 53% of cereal production in the Czech Republic (see Table 6 in the Appendix).

Using this comprehensive panel dataset, farms that have adopted PATs (adopters) and those that have not (non-adopters) are statistically characterized in the first and last years of the analyzed period to examine the dynamics of both groups. An adopter is defined in this study as an agricultural producer who utilises at least one of the technologies specified above. In the FADN database, adoption is recorded as a binary variable, which does not, however, allow for assessing the extent of technology use.

The subsequent panel data model-based analysis utilizes an unbalanced panel sample[1], adjusted by removing extreme values (14 observations) and farms with insufficient data (124 observations). Farms with fewer than two observations are excluded to account for unobserved heterogeneity, resulting in a final unbalanced sample of 543 farms, totaling 1,947 observations. More precisely, the sample for the binary choice panel data model includes 1,486 observations of specialist cereals, oilseeds, and protein crops (76%) and 461 observations of general field crops (24%), according to the FADN farm typology. Table 1 presents the structure of this sample.

Table 1 Structure of the sample for binary choice model

Type of farming	PA	Number of observations (farms)				
		2017	2018	2019	2020	2021
Specialist crops farms	Non-adopters	291	300	287	239	217
	Adopters	9	23	32	40	48
General crops farms	Non-adopters	104	103	90	56	40
	Adopters	7	11	17	19	14

Source: Own processing.

[1] It is worth noting that using an unbalanced panel dataset may reduce the statistical robustness of the estimates if the variation is substantial. However, in this study, the variation in the number of observations per year does not exceed 3%, which is relatively low.

Conceptual framework

In agriculture, farmers primarily view the adoption of technologies as an exercise in utility maximization. Technologies that align with their operational needs and economic benefits are more likely to be adopted (Pierpaoli et al., 2013). Accordingly, this study assumes that farmers' decisions regarding the adoption of PATs are driven by utility maximization. The latent net utility derived from the adoption of PA by the i-th agricultural producer is assumed to be:

$$Y_i^* = \mu_i^* + \epsilon_i^* = \boldsymbol{x_i}' \boldsymbol{\beta}^* + \epsilon_i^*, \tag{1}$$

where Y^* represents the latent net utility, ε^* is a random error uncorrelated with the explanatory variables, μ^* is the deterministic utility determined by attributes represented by the regressors $\boldsymbol{x_i}$ (described in Table 2), and $\boldsymbol{\beta}^*$ is a vector of parameters capturing the effects of the explanatory variables on the unobserved utility (D'Antoni et al., 2012; Schulz et al., 2014).

However, the utility function is not directly observable ex-ante; rather, it becomes apparent ex-post after the decision-making process, depending on the perceived utility of the adoption. This allows for the assessment of whether the adoption decision yielded a higher expected utility than non-adoption (Pronti et al., 2024). In other words, the unobservable utility can be approximated by the observed producer's decision to adopt precision agriculture, where ($Y_i = 1$) if the expected utility is positive ($Y_i^* > 0$) and $Y_i = 0$ otherwise (i.e., if the expected utility is negativen, $Y_i^* \leq 0$).

Therefore, the binary choice model can be employed to predict the likelihood of PAT adoption using:

$$Y_i = \boldsymbol{x_i}' \boldsymbol{\beta}, \tag{2}$$

where Y_i is a dummy variable indicating PAT adoption ($Y_i = 1$), $\boldsymbol{\beta}$ is a vector of the parameters to be estimated.

Suppose $P = \Pr(Y_i = 1 | \boldsymbol{x_i}) = \Pr(Y_i^* > 0) = \Pr[\epsilon_i > -\boldsymbol{x_i}' \boldsymbol{\beta}] = 1 - \Phi[-\boldsymbol{x_i}' \boldsymbol{\beta}]$ represents the probability of observing $Y_i=1$ given $\boldsymbol{x_i}$, where $\Phi(\cdot)$ is the standard normal cumulative distribution function. Taking into account the symmetry of the standard normal distribution: $1 - \Phi[-\boldsymbol{x_i}' \boldsymbol{\beta}] = \Phi(\boldsymbol{x}_i' \boldsymbol{\beta})$, $P = \Phi(\boldsymbol{x}_i' \boldsymbol{\beta})$ and the adoption of precision agriculture can be estimated using a probit regression model (Walton et al., 2010).

Empirical model

This study employs an ex-post approach to evaluate the adoption of PATs. Similar to Tamirat et al. (2017), it focuses on actual adoption or non-adoption rather than the intention to adopt. Accordingly, the binary panel data choice model postulates that the probability of adopting PA ($Y_{it}= 1$) of i-th producer at time t is a function of a set of regressors $\boldsymbol{X_{it}} = (\boldsymbol{x_{1it}}, \ldots, \boldsymbol{x_{jit}})$ and unobserved individual-specific effects $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_N)$, where $i = 1,...,N$ and $t = 1,...,T$ (Cruz-Gonzalez et al., 2017)[2]:

[2] It should be noted that the choice of technology is a dynamic process, conditional on past decisions and on the current as well as the expected economic environment (An & Butler, 2012). The dynamic nature of

Table 2 Variables employed in the probit model

Variable	Type	Description	Expected effect
y_PAadoption	B	1 if a farm uses precision agriculture, 0 otherwise	
x_LaborIntensity	C	labor input per 100 hectares (SE010/(SE025/100))	+/-
x_InputOutputRatio	C	total inputs/total production (SE270/SE131)	-
x_CerealsSpecialization	C	share of cereals on total production (SE140/SE131)	+
x_Indebtedness	C	total liabilities/total assets (SE485/SE436)	+/-
x_RentedLandShare	C	share of rented land (SE030/SE025)	-
x_ManagerAge	C	age of manager	-
z_LivestockProduction	B	1 for the livestock production, 0 otherwise	-
z_GeneralFieldCrops	B	1 for general field crops production, 0 otherwise	-
z_Altitude	D	3 categories: less than 300 m a.s.l.; 300 to 600 m a.s.l.; above 600 m a.s.l.	-
z_ConstrainedArea	B	1 if the area faces the natural or other specific constraints	-
z_HighLandProductivity	B	1 for above-average land productivity, 0 otherwise	+/-
z_HighLaborProductivity	B	1 for above-average labor productivity (SE425), 0 otherwise	+
z_AgriculturalEducation	B	1 for farmers with formal agricultural education, 0 otherwise	+
z_FamilyFarm	B	1 for family farm (SE015/SE010 = 1), 0 otherwise	-
z_YoungFarmerSubsidy	B	1 if the farm received subsidies for young farmers, otherwise 0	+
z_InvestmentSubsidy	B	1 if the farm received investment subsidies, otherwise 0	+
z_EconomicSize	D	4 categories: small (standard output (SO) < 50000 EUR); medium (SO 50000–499999 EUR); large (SO 500000–999999 EUR); very large (SO ≥1000000 EUR)	+

B is a binary variable, C is a continuous variable, D is a categorical variable.

Source: Own processing.

$$\Pr\left(Y_{it} = 1 \,|\, \boldsymbol{X_{it}}, \alpha_i, \boldsymbol{\beta}\right) = \Phi\left(\boldsymbol{X'_{it}}\boldsymbol{\beta} + \alpha_i\right) \tag{4}$$

.

Since the panel dataset used in this study is relatively short, employing the fixed effect (FE) specification may lead to an incidental parameter problem (Lancaster, 2000). Furthermore, some of the independent variables are time-invariant. Therefore, it is appropriate to use random effects (RE), assuming that α_i is random, constant over time, and uncorrelated with the explanatory variables. However, this assumption of exogeneity may be too restrictive. To address this concern, the within-between RE model (Bell & Jones, 2015) is employed. This model can be seen as an extension of Mundlak's approach, augmenting the random effects specification by including pseudo-fixed effects (the group means of the time-varying variables). These capture the correlation between regressors and individual effects (Mundlak, 1978).

Bell and Jones (2015) replace the original time-variant variables (x_{it}) with their group-mean centring ($\tilde{x}_{it} = x_{it} - \bar{x}_i$), where $\bar{x}_i$ denotes the group mean of x_{it}, and transform the model in Eq. (4), extending it with time-invariant variables ($\boldsymbol{Z}$) to:

$$\Pr\left(Y_{it} = 1 \,\middle|\, \tilde{\boldsymbol{X}}_{\boldsymbol{it}}, \bar{\boldsymbol{X}}_{\boldsymbol{i}}, \boldsymbol{Z_i}, \boldsymbol{\beta}, \boldsymbol{\gamma}\right) = \Phi\left(\tilde{\boldsymbol{X}}'_{\boldsymbol{it}}\boldsymbol{\beta}_{\boldsymbol{W}} + \bar{\boldsymbol{X}}'_{\boldsymbol{i}}\boldsymbol{\beta}_{\boldsymbol{B}} + \boldsymbol{Z'_i}\boldsymbol{\gamma} + w_i\right), \tag{5}$$

where $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are vectors of parameters to be estimated, $\boldsymbol{\beta}_{\boldsymbol{W}}$ represents within effects (which are identical to the coefficients in FE models), $\boldsymbol{\beta}_{\boldsymbol{B}}$ denotes between effects, and w_i is a time-invariant unobservable component. As Schmid et al. (2023) noted, $\boldsymbol{\beta}_{\boldsymbol{B}}$ differs from the parameters of the panel-level means used in Mundlak's approach. Mundlak's $\boldsymbol{\beta}_{\boldsymbol{B}}$ represents the contextual effects that capture the difference between the within and between effects.

According to Bell et al. (2019) and Schmid et al. (2023), the within-between random effects (RE) model offers several advantages over the fixed effects (FE), RE models, and Mundlak's RE model adjustment. Because it accounts for both sources of heterogeneity, it provides more reliable and comprehensive results compared to the RE and FE models. With temporal data, it is more interpretable than Mundlak's RE model, as the within and between effects are clearly separated. Finally, it deals with collinearity (correlation between x_{it} and $\bar{x}_i$) by group-mean centering, leading to more stable and precise estimates.

The maximum likelihood (ML) method with robust standard errors is used to estimate the parameters of the binary probit model. The estimation is verified using the Wald test, which assesses the joint significance of the regression coefficients. Average marginal effects (AMEs) are calculated with respect to the random effect, integrating the distribution of the random effects (Bland & Cook, 2018). The AME quantifies the average change in the probability of PAT adoption resulting from a one-unit change in a specific time-variant explanatory variable or a discrete change from the base level for time-invariant variables. Robustness checks are conducted by re-estimating the model without identified outliers and

this process could be analyzed using dynamic models (Jaime et al., 2016; Stewart, Stewart, 2007) or duration (hazard) models if the focus is on the timing of economic decisions (Paudel et al., 2021; Canales et al., 2020). However, for an unbalanced panel, as in the case of the FADN data, such an analysis is challenging due to incomplete time-series observations and the lack of precise information on the timing of technology adoption for all farms.

by estimating cross-sectional models. To address the potential endogeneity of explanatory variables, a control function approach is applied, using two-period lags as instruments in the first-stage regression. All statistical analyses are conducted using STATA software, version 18.

The model specification is based on previous studies, available variables in the FADN database, and an assessment of multicollinearity. It has been shown that variables representing efficiency and productivity are closely linked to farm management characteristics, such as the manager's age (Tauer, 1995), education (Phillips, 1994), and risk attitude (Mitra & Sharmin, 2019), which can potentially contribute to multicollinearity issues. For instance, farmers' risk attitudes affect their demand for variable inputs and, consequently, their output levels (Kumbhakar, 2002). Risk-averse producers exhibit a preference for production strategies characterized by lower variance in returns, even when such strategies are associated with reduced expected profitability. Risk attitudes are shaped by farmer characteristics, including age, education, and experience. Mitra and Sharmin (2019) found that education helps reduce risk aversion, whereas risk aversion tends to increase with age. Education, in itself, is identified as a factor exerting a positive impact on farm performance through a more efficient use of resources (Angioloni et al., 2023; Rougoor et al., 1998). However, in Czech field crop production, the correlations between manager education or age and labor productivity or efficiency – measured by the input-output ratio – are low, below 0.25. Specifically, in the example from the year 2021, statistically significant but weak correlations were found between age and productivity (−0.16; p-value = 0.000), and between age and the input-output ratio (0.06; p-value = 0.015). Additionally, the correlation between farmers' formal agricultural education and productivity was 0.21 (p-value = 0.000), and with the input-output ratio 0.12 (p-value = 0.025).

Table 2 provides a detailed description of all variables included in the model. The explanatory variables fall into two categories: continuous variables (x_{it}) and discrete variables (z_i). The continuous variables include time-varying farm characteristics such as labor intensity, production efficiency, specialization, land ownership (share of rented land), level of indebtedness, and manager's age. In the proposed model (Eq. 5), both the between effect, which captures variation among farms, and the within effect, which reflects changes in these farm characteristics over time, are examined.

Labor intensity, defined as the number of workers per hectare, reflects both farm size and the type of crop production system. Smaller farms, as well as those with organic practices or specializing in niche products like herbs or berries, tend to have higher labor intensity (Chiarella et al., 2023). However, Vecchio et al. (2020) found that higher labor intensity often correlates with greater PAT adoption. Since PATs can reduce manual labor needs, farms with higher labor intensity may have a stronger incentive to invest in these technologies. At the same time, certain production characteristics that require high human labor may limit the suitability of PATs, making them less viable for some farms. In such cases, higher labor intensity may be associated with lower adoption rates.

The input-output ratio serves as a measure of farm efficiency. However, it remains unclear whether higher efficiency (i.e., a lower input-output ratio) acts as a driver of innovation, encouraging PAT adoption, or if an efficient farm may perceive less need for change and thus be less inclined to adopt new technologies. This study hypothesizes that the effect of the input-output ratio is linked to a farm's ability to generate income, with higher income enabling farms to absorb the costs associated with PAT implementation (Tey & Brindal, 2012).

Specialized farms are more likely to adopt PATs, as their specific production systems enable economies of scale, which help reduce cost barriers for adopting capital-intensive innovations such as PATs. Additionally, managerial expertise in specialized operations further enhances the ability to effectively integrate and operate advanced technologies (Kutter et al., 2011; Aubert et al., 2012; Pathak et al., 2019). These farms may be more motivated to adopt PATs, as these technologies aid in managing and mitigating the inherent risks associated with specialized production systems (Watcharaanantapong et al., 2014).

Indebtedness presents a dual challenge. On the one hand, it reflects the availability of credit financing and a manager's willingness to engage with financial risk (Zuo et al., 2021). On the other hand, high debt levels can constrain access to additional external financing and deplete internal resources through interest and debt repayments (Isgin et al., 2008). Beyond external financing, studies have shown that other external factors can influence the decision to adopt PATs. For instance, farmers with a larger share of owned land tend to be more inclined to adopt new technologies (Roberts et al., 2004; Tey & Brindal, 2012), as they experience lower risk aversion in the absence of rental obligations (Block et al., 2023) and have a stronger incentive to maintain productivity on their own land.

Labor structure can also influence PAT adoption. Paustian and Theuvsen (2017) found that farms with a high proportion of external employees are more likely to adopt new technologies than family-run farms. Additionally, research suggests that the age of the manager may impact PAT adoption, with younger farmers typically more open to adopting these technologies (Bai et al., 2022; Walton et al., 2010).

The discrete variables capture key characteristics of agricultural holdings, including farming type; geographical attributes such as areas facing natural or other specific constraints (Areas of Natural Constraints, ANC), altitude, and land quality; labor productivity; farmer education; family farm status; subsidy receipt (including young farmers' and investment subsidies); and economic size. The dataset enables the analysis of the impact of animal production diversification and general field crop production as farming-type variables. Since both variables represent production diversification, their effect is expected to be negative. Diversified operations often pursue risk-minimising strategies (avoiding high fixed costs), have weaker scale economies for capital-intensive PATs, and require heterogeneous training and managerial changes that increase adoption friction.

The integration of PA in ANCs offers potential benefits for overcoming natural and structural constraints (Zieliński et al., 2022). However, achieving widespread adoption requires overcoming economic, technological, and skill-based barriers. Robert (2002) suggests that precision agriculture faces significant socio-economic, agronomic, and technological barriers in ANCs. High costs, lack of skills, inadequate soil information, and insufficient technical support all hinder its adoption in these constrained regions. Therefore, PATs are assumed to be less widely adopted in ANCs.

Land quality plays a complex role in the adoption process of PA. Previous studies show mixed findings regarding the influence of this variable. Kolady et al. (2021) suggest that the effect of land productivity on adoption could be either positive or negative. For instance, a farm with highly productive land may require fewer hectares to remain viable, meaning there is less area over which to distribute capital investment costs, potentially discouraging adoption. Conversely, a farm with low land productivity may need to cultivate more hectares, providing a stronger rationale for adopting PATs due to relatively lower per-hectare costs. To account for the impact of land quality, this study defines a dummy variable based on average land productivity, assigning a value of 1 to farms with land productivity above the dataset's period average.

In contrast to the mixed effects of land quality, farm income – including subsidies and farm net value added per worker, measured as labor productivity – is consistently identified in existing studies as a significant driver of PAT adoption (Barnes et al., 2019b; Kolady et al., 2021). In this study, labor productivity is represented by a dummy variable indicating above-average productivity levels, constructed similarly to the variable for above-average land productivity.

Additionally, previous research frequently suggests that farmers with higher levels of education are more likely to adopt PATs (Žáková Kroupová et al., 2025). Consequently, this study assumes that managers with formal agricultural education are more inclined to integrate PATs into their production practices. Finally, farm size, represented in this study by economic size, is among the factors most frequently associated with higher rates of PAT adoption in previous studies. According to Barnes et al. (2019a), larger farms that benefit from economies of scale are more likely to adopt PATs compared to smaller farms. Larger farms typically have more internal resources and better access to external financing, enabling them to invest in new technologies. They also possess greater management capacities and have access to more data and information to support decision-making (Giua et al., 2022). The positive effect of farm size has been demonstrated across different measures, including land area (e.g., arable land, total utilized agricultural area etc.) (Paustian & Theuvsen, 2017; Franco et al., 2018; Pivoto et al., 2019; Michels et al., 2020; Groher et al., 2020; Kolady et al., 2021), economic size (D'Antoni et al., 2012; Paustian & Theuvsen, 2017; Tamirat et al., 2017; de Souza Filho et al., 2023), number of workers (Schimmelpfennig, 2016), and scale of production (Paustian & Theuvsen, 2017; Gargiulo et al., 2018; Mozambani et al., 2023).

Results and discussion

Precision agriculture adoption in Czech field crop production

The adoption of precision agriculture technologies (PATs) in the Czech Republic has demonstrated a marked upward trajectory in recent years. Since data collection on PATs utilization began in 2017 as part of the national FADN survey, the proportion of farms reporting the implementation of these technologies has increased significantly – from 6% in 2017 to 18% in 2021 (Döbertová et al., 2023; Ministry of Agriculture CR, 2023).

Although most farms using PATs were engaged in mixed production (45%; Ministry of Agriculture CR, 2023), the adoption rate in field crop production – the second most common production type among PAT-adopting farms (34%; Ministry of Agriculture CR, 2023) – has followed a similar upward trend, as illustrated in Fig. 1. Specifically, the proportion of field crop farms adopting these technologies increased from 4% in 2017 to 18% in 2021 within the FADN dataset[3].

In terms of PATs, the most commonly used systems among field crop farms are seeding, fertilization, and crop protection systems, as shown in Table 3. Notably, the adoption

[3] The description in Chap. 4.1 is based on the comprehensive panel dataset, i.e., the dataset before cleaning.

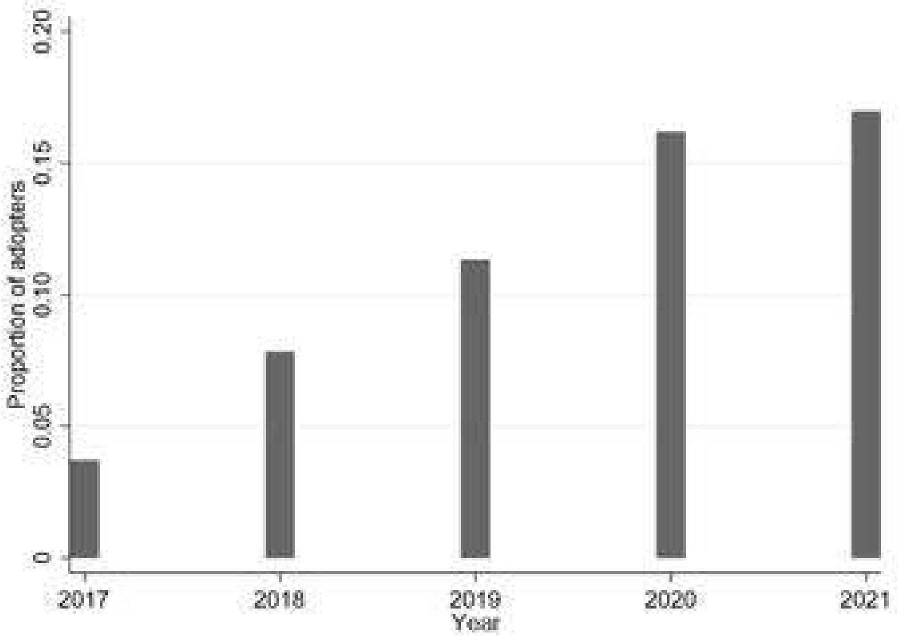

Fig. 1 Diffusion of precision agriculture in the Czech field crop production. Source: own processing based on FADN

Table 3 Number of adopters of individual pats

PA technologies	2017	2021
Soil cultivation systems	12	24
Seeding systems	14	35
Fertilization systems	13	39
Crop protection systems	14	46
Autonomous machine guidance	9	27
Robots in vegetable, fruit, and wine farming	0	0
Other technologies in crop production	0	0
Automated animal systems	1	3
Automatic milking machines	0	2
Stable and farm management systems	0	3
Technologies in pig and poultry farming	0	2

Source: Own processing.

of autonomous systems has increased compared to 2017. In contrast, the adoption of soil cultivation systems has lagged behind the uptake of crop protection, fertilization and seeding systems.

The extent to which these technologies are used together is illustrated in Fig. 2, which presents the distribution of farms by the number of adopted technologies. In 2017, the most common number of PATs adopted by field crop farms was four or five, each accounting for 33% of adopters. The most frequently used combinations included soil cultivation, seeding, fertilization, and crop protection systems or these four, along with autonomous machine

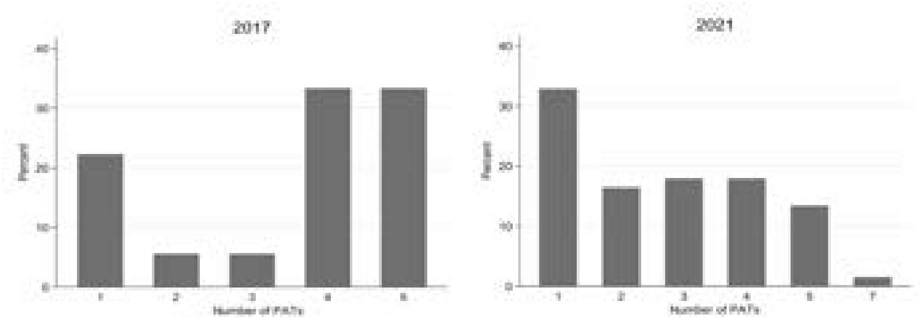

Fig. 2 Proportions of adopters in the sample with a specific number of adopted PATs. Source: Own processing.

guidance. Additionally, 22% of adopters in 2017 used only a single PA technology, most commonly autonomous machine guidance.

In 2021, the situation changed, with a single technology becoming the most commonly used, adopted by 33% of users. Autonomous machine guidance was the dominant choice among single-technology adopters (59%), followed by crop protection systems (27%). An equal proportion of adopters (18%) were using either three or four PATs. Among those using three technologies, the most common combination included seeding, fertilization, and crop protection systems. For those using four technologies, the typical package comprised soil cultivation, seeding, fertilization, and crop protection systems.

The intensity of adoption, reflecting the number of adopted technologies, increased primarily among farms that had already been utilising a greater number of technologies. Among the ten adopters who introduced additional technologies during the analyzed period, seven were already employing more than three technologies. In contrast, only one farm that had initially adopted a single technology (autonomous machine guidance) proceeded to implement additional technologies. This adopter is also the only case where an increase in the intensity of adoption occurred in two consecutive years, first by adopting three additional technologies (soil cultivation systems, seeding systems, and fertilizer systems) and subsequently by incorporating one more (crop protection systems).

Table 4 compares the characteristics of field crop production farms that reported using PATs in 2017 and 2021 with those of non-adopters. Overall, adopters tend to operate on larger farms than non-adopters in both years. In 2017, adopters managed an average of 1,608 hectares, compared to 474.5 hectares for non-adopters. However, by 2021, the average farm size of adopters decreased to 806.3 hectares, though it remained significantly larger than non-adopters, whose average was 383.9 hectares. The decline in the average farm size for adopters suggests that smaller farms increasingly adopted PATs between 2017 and 2021. A higher proportion of rented land is observed among adopters, with 82.6% in 2017 and 68.9% in 2021, compared to non-adopters, who had 70% and 57.3% for non-adopters in the respective years. This suggests that adopters rely more on rented land, possibly because they operate larger farms.

Adopters consistently employ more labor than non-adopters, although this difference declined over time. In 2017, adopters used an average of 21.9 annual work united (AWU) compared to 8.9 AWU for non-adopters. By 2021, adopters had reduced their labor force to 10.7 AWU, closer to the 6.5 AWU of non-adopters. Labor intensity (AWU per 100 hectares)

Table 4 Description of adopters and non-adopters (sample means and proportions)

Year	2017				2021			
Variable	Adopters		Non-adopters		Adopters		Non-adopters	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Total utilized agricultural area [ha]	1608.07	269.55	474.50	32.17	806.33	117.53	383.92	34.22
Labor [AWU]	21.90	2.65	8.90	0.74	10.72	1.52	6.53	0.90
Labor intensity [AWU/100_hectares]	1.70	0.23	2.56	0.22	1.72	0.14	2.33	0.14
Share of rented land [%]	82.58	2.92	70.02	1.90	68.92	2.97	57.26	1.87
Unpaid labor share [%]	2.36	1.77	51.84	2.12	33.94	5.17	60.11	2.41
Input-output ratio [%]	114.73	5.05	111.19	1.40	101.19	2.13	98.04	1.78
Gross farm income [ths CZK]	30088.50	4579.45	8241.87	651.66	18897.38	2843.70	7832.33	766.44
Farm net value added [ths CZK/AWU]	1083.07	103.54	665.57	24.54	1251.64	84.60	1000.84	56.85
Subsidies on investment [ths CZK]	0.00	0.00	98.58	33.85	28.04	13.06	69.97	18.28
Total subsidies - excluding on investments [ths CZK/hectare]	8.50	1.39	8.06	0.23	8.25	0.43	7.54	0.18
Subsidies for young farmers [proportion, %]	0.00		2.28		2.99		1.34	
Indebtedness [%]	40.94	8.13	21.37	1.17	25.97	2.76	16.77	1.26
General field crops production [proportion, %]	38.89		26.48		22.39		17.79	
Livestock production [proportion, %]	50.00		38.59		38.81		44.97	
Specialization on cereals [%]	41.33	3.83	45.78	1.01	47.23	1.98	52.74	1.22
Organic farming [proportion, %]	0.00		2.51		1.49		2.69	
Specific area [proportion, %]	11.11		22.37		20.90		32.21	
Altitude < 300 m a.s.l.[proportion, %]	61.11		59.36		70.15		44.97	
Altitude 300–599 m a.s.l. [proportion, %]	38.89		39.27		26.87		53.69	
Altitude ≥ 600 m a.s.l.[proportion, %]	0.00		1.37		2.99		1.34	
Above-average land productivity [proportion, %]	44.44		24.20		61.90		32.22	
Family farm [proportion, %]	0.00		39.72		22.38		44.63	
Age of manager [years]	52.89	2.83	52.61	0.53	53.66	1.34	54.77	0.66
Formal agricultural education [proportion, %]	88.89		42.24		68.65		40.61	
Basic agricultural education [proportion, %]	11.11		44.98		20.90		37.58	
Only practical agricultural experience [proportion, %]	0.00		12.78		10.45		21.81	

Table 4 (continued)

Year	2017				2021			
Variable	Adopters		Non-adopters		Adopters		Non-adopters	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Male farmer [proportion, %]	100.00		94.29		91.05		92.95	
No. of farms	18		438		67		298	

Source: Own processing.

indicates that non-adopters have a higher labor intensity than adopters, though the gap narrowed slightly by 2021. It can be assumed that reducing labor intensity is one of the motivations for adopting PATs. However, this effect may exhibit a time lag. In the case of farms adopting PATs in 2021, the mean labour intensity in the preceding years (2017–2020) was 1.46 (Std. Dev. = 0.09), increasing to 1.54 (Std. Dev. = 0.18) in 2021.

While in 2017 there were no family farms among adopters, their share increased to 22.4% in 2021. In contrast, the proportion of family farms among non-adopters remained approximately 40% in both years. In general, unpaid labor constituted only 2.4% of total labor among adopters, compared to 51.8% for non-adopters in 2017. By 2021, this share increased for adopters to 33.9% but remained lower than that of non-adopters, which rose to 60.1%. The lower reliance on unpaid labor among adopters may reflect their ability to invest in a more formal workforce, possibly linked to their use of advanced technologies. Adopters also tend to have higher educational levels. In 2017, 88.9% of adopters had formal agricultural education, compared to 42.2% of non-adopters. By 2021, this share declined to 68.7% among adopters but remained higher than that of non-adopters, which stood at 40.6%.

Non-adopters receive more subsidies on investments, particularly in 2017, where adopters received none. By 2021, adopters began accessing these subsidies, though to a lesser extent than non-adopters. Adopters also tend to be more indebted, especially in 2017, with an average indebtedness of 40.9%, which decreased to 26% by 2021. In contrast, non-adopters had much lower indebtedness rates, at 21.4% in 2017 and 16.8% in 2021.

Adopters were also more actively engaged in livestock and field crop production, particularly in 2017. By 2021, however, the share of adopters involved in these activities had declined, while specialisation in cereal production had increased. Non-adopters, by contrast, showed greater specialisation in cereal production from the outset, with their specialisation increasing further over the observed period. The increased specialization in cereal production among non-adopters could indicate a focus on optimizing existing operations without the adoption of new technologies. This approach may be more feasible in regions with lower land productivity or where the perceived benefits of PA technologies do not justify the investment. Adopters are more often located in areas with lower altitudes (<300 m a.s.l.) and regions with above-average land productivity, and this trend strengthened from 2017 to 2021. The concentration of adopters in productive, lowland areas suggests that these regions offer favorable conditions for the implementation of PA technologies. Higher productivity in these areas may enhance the return on investment for PA adoption, making it a more attractive option for farmers. Overall, the observed patterns can be interpreted as a strategic response to the opportunities and challenges presented by PA technologies.

Moreover, the Kolmogorov-Smirnov test identifies significant differences in most farm characteristics between PAT adopters and non-adopters for most of them (see Appendix

– Table 7, results displayed for 2021). Statistical differences between adopters and non-adopters are found for labor, land, specialization in cereals, labor intensity, input-output ratio, gross farm income, farm net value added, indebtedness, and share of unpaid labor. In contrast, no significant differences are found in the share of rented land or the manager‘s age. Pearson‘s Chi-squared test is used to analyze differences in categorical variables between PAT adopters and non-adopters (see Appendix – Table 8, results displayed for the year 2021). Significant differences are observed for farms at altitudes < 300 m a.s.l and 300–599 m a.s.l., above-average land productivity, farmily farm, formal agricultural education, only practical agrarian experience, medium-sized farms, and very large farms. However, no significant differences are found for general field crop production, livestock production, organic farming, specific areas, altitudes ≥ 600 m a.s.l., male farmers, subsidies for young farmers, small farms, and large farms.

Based on the comparison of adopters and non-adopters in 2017 and 2021, it can be concluded that there is a general convergence in some characteristics between adopters and non-adopters, especially regarding labor usage and financial performance. While adopters continue to operate larger farms and achieve higher incomes, they have shown a trend toward smaller farm sizes in 2021 compared to 2017. Although they were more diversified than non-adopting farms, they gradually shifted toward a more specialized operational structure between 2017 and 2021. The educational advantage among adopters remains a key differentiator, emphasizing the role of knowledge and training in the adoption of advanced technologies. Financially, adopters are moving toward lower levels of indebtedness, suggesting a shift toward more sustainable financial management over time. These findings indicate that adopters of PATs in the Czech Republic tend to have larger, more efficient, and better-managed farms, with higher levels of education and greater labor capacity.

Figure 3 illustrates the distribution of economic size among adopters and non-adopters in 2017 and 2021. Farms with an economic size measured in Standard Output (SO) above EUR 499,999 comprised the majority of adopters in both years. However, the share of large farms (SO EUR 500,000–999,999) decreased substantially from 72.2% in 2017 to 17.9% in 2021. At the same time, there was a notable increase in very large farms (SO ≥ EUR 1,000,000) among adopters, rising from a negligible share in 2017 to 37.3% in 2021. The representation of medium-sized farms (SO EUR 50,000–499,999) also increased significantly, from 22.2% to 38.8%. These trends indicate that the adoption of PATs is no longer exclusive to large farms but is increasingly spreading to mid-sized operations. By contrast, non-adopters continue to be dominated by farms with lower economic size. This suggests the persistence of barriers to technology adoption among smaller farms, likely due to limited financial resources, unfavourable cost–benefit perceptions, or restricted access to the necessary infrastructure.

Figure 4 provides a comparative analysis of the characteristics of PAT adopters in their year of initial adoption[4], focusing on attributes that exhibit discernible trends. The findings suggest that the diffusion of PATs in Czech field crop production has gradually shifted from very large farms – where the median total utilized agricultural land was 1,240 hectares in 2017 – toward adoption by farms with less agricultural land, with a median of 110 hectares in 2021. However, these newer adopters exhibit higher efficiency, as evidenced by a decline in the median input-output ratio from 112% in 2017 to 91% in 2021. Additionally,

[4] Each year presents only the data of adopters who reported using PATs for the first time in that year; data on earlier adopters are not included.

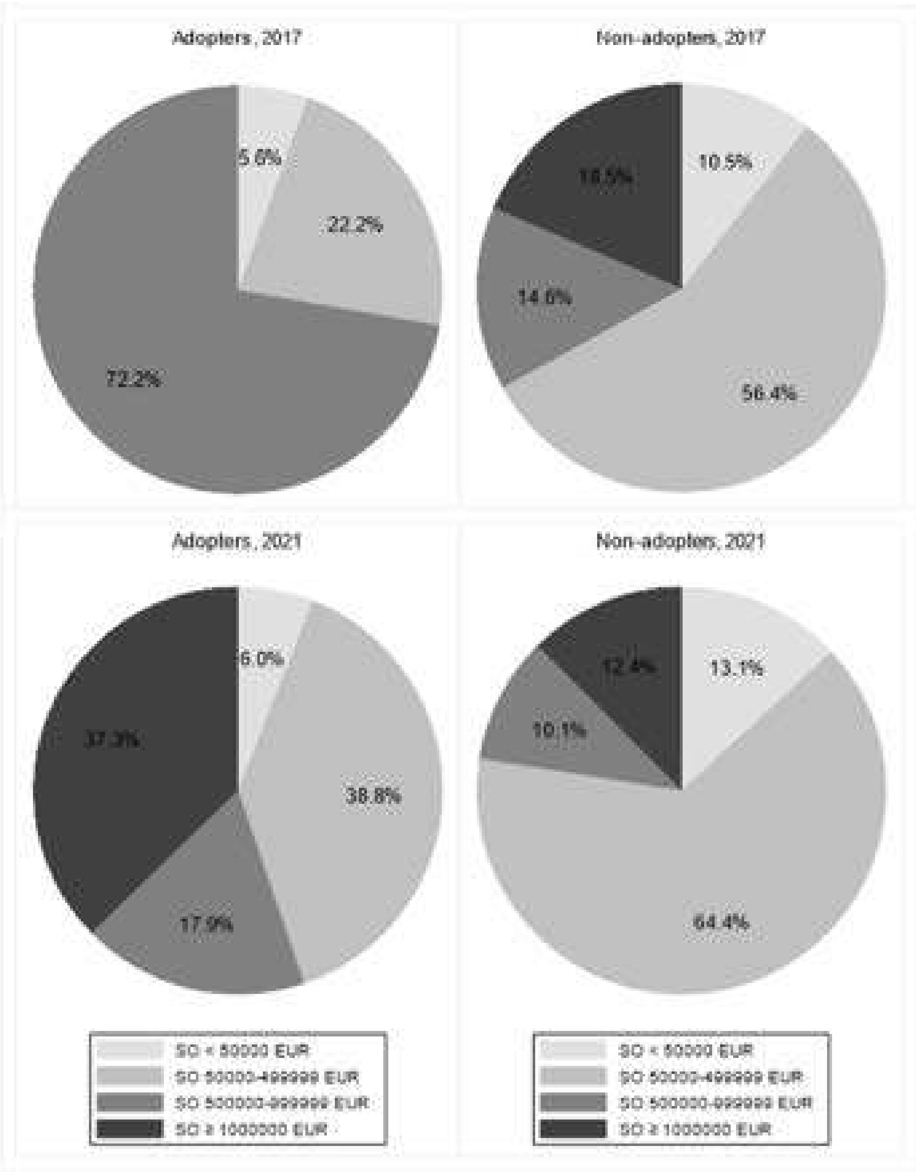

Fig. 3 Economic size of adopters and non-adopters. Note: SO denotes Standard Output. Source: Own processing

the financial structure of adopting farms has evolved considerably, with the median ratio of total liabilities to total assets declining sharply from 34% in 2017 to 6% in 2021, suggesting a shift toward lower reliance on external capital. Another interesting trend emerges in manager demographics: while adopters in 2017 were older managers (median age 57 years), by 2021, PAT adoption had increasingly shifted to farms run by younger managers (median age 40 years). Contrary to expectations, innovators in Czech field crop production are primarily

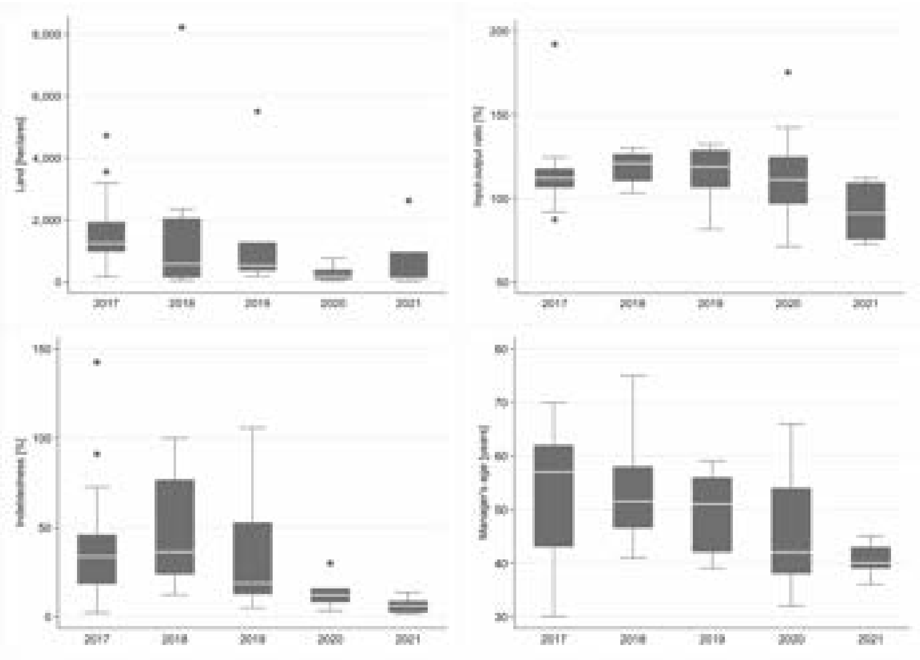

Fig. 4 Characteristics of adopters in the year of PA adoption.
Source: Own processing

middle-aged managers. In 2017, only 25% of adopters were younger than 43 years, while 25% were older than 62 years.

Drivers and barriers to precision agriculture adoption

The estimation results of the probit model are presented in Table 4 in the appendix. The analysis begins with the within-farm effects for time-variant (continuous) variables[5], followed by the between-farm effects, which include the mean values of both continuous and discrete variables. Finally, the random effects statistics and Wald test results are presented. The results suggest that the probit WBRE model captures significant heterogeneity in PAT adoption across farms. Model specification is verified using the Wald test, which confirms the statistical significance of the entire model, as well as each group of variables (within effects, between effects of continuous variables, and binary variables) at the conventional $\alpha=0.05$ significance level. Overall, the results indicate that both time-varying (within effects) and time-invariant (between effects) factors significantly influence PAT adoption.

The model correctly classifies 89% of observations (using a 0.5 probability threshold) into adopters or non-adopters of PATs. The Wald test for endogeneity fails to reject the null hypothesis of exogeneity ($\alpha=0.05$), supporting the use of the model estimates without instrumental variables, as presented in Table 9 in the appendix. Following Jaime et al. (2016), the analysis also considered whether potentially endogenous variables exhibit similar dynamics over time. The results reported in Table 11 indicate that the year-on-year

[5] Descriptive statistics for these variables are provided in Table 10.

growth dynamics do not differ significantly between adopters and non-adopters, further suggesting that endogeneity is unlikely to pose a serious concern in this analysis. A robustness check, using a sample excluding outliers (Table 12 in the appendix), shows stability in both coefficient estimates and marginal effects, suggesting that the results are not influenced by outliers. Furthermore, robustness checks based on cross-sectional estimations for individual years (Table 13 in the appendix) confirm the validity of the results. Differences in estimated marginal effects, taking the probit WBRE model as the basis for comparison, are not statistically significant at the $\alpha = 0.05$ significance level for the majority of variables (Table 14 in the appendix).

Table 5 presents the average marginal effects. The between-farm effects, which capture time-invariant differences across agricultural farms, confirm that at the $\alpha = 0.05$ significance level, PAT adoption is influenced by labor intensity, indebtedness, localization, land quality (productivity), manager's education, and farm economic size. Consistent with previ-

Table 5 Marginal effects (AME) of probit model Estimation

Variable	AME	Std.err.	P>|z|	[95% conf. int.]	
	Within				
x_LaborIntensity	−0.051	0.022	0.018	−0.093	−0.009
x_InputOutputRatio	−0.057	0.033	0.083	−0.121	0.007
x_CerealsSpecialization	0.110	0.040	0.006	0.032	0.189
x_Indebtedness	−0.043	0.066	0.515	−0.172	0.086
x_RentedLandShare	−0.276	0.117	0.019	−0.506	−0.046
x_ManagerAge	0.002	0.001	0.178	−0.001	0.005
	Between				
x_LaborIntensity	−0.026	0.010	0.011	−0.045	−0.006
x_InputOutputRatio	0.044	0.040	0.267	−0.034	0.121
x_CerealsSpecialization	−0.082	0.066	0.218	−0.212	0.048
x_Indebtedness	0.131	0.052	0.012	0.029	0.233
x_RentedLandShare	0.021	0.037	0.560	−0.051	0.094
x_ManagerAge	0.000	0.001	0.593	−0.002	0.001
z_GeneralFieldCrops	−0.020	0.014	0.148	−0.047	0.007
z_LivestockProduction	0.005	0.014	0.726	−0.023	0.032
z_Altitude_300–599 m a.s.l.	−0.075	0.023	0.001	−0.120	−0.029
z_HighLandProductivity	0.055	0.016	0.001	0.023	0.087
z_HighLaborProductivity	−0.008	0.012	0.519	−0.031	0.016
z_AgriculturalEducation	0.041	0.018	0.021	0.006	0.075
z_FamilyFarm	0.009	0.018	0.611	−0.026	0.044
z_YoungFarmerSubsidy	−0.009	0.056	0.866	−0.119	0.100
z_InvestmentSubsidy	0.004	0.011	0.732	−0.018	0.026
z_EconomicSize_Medium	0.025	0.034	0.459	−0.042	0.092
z_EconomicSize_Large	0.066	0.036	0.070	−0.005	0.136
z_EconomicSize_VeryLarge	0.090	0.036	0.013	0.019	0.162

The marginal effects for z-variables represent a discrete change from the baseline level (dummy variable = 0).

Source: Own processing.

ous research, economic size is positively associated with the likelihood of PAT adoption. Specifically, very large farms have a 9.0% point (p.p.) higher probability of adopting PATs compared to small farms. Large farms show a 6.6 p.p. higher likelihood of PAT adoption compared to small farms, although this effect is statistically significant only at the $\alpha=0.1$ significance level. Large and very large farms are better positioned to manage the adaptation costs associated with PAT implementation and are more likely to be managed by professionals capable of effectively integrating new technologies. These farms typically rely more on external labor and land inputs, increasing their flexibility in adopting innovative technologies.

This study shows that economic considerations play a pivotal role in PAT adoption. Larger farms with greater financial resources are more likely to adopt PATs, leveraging economies of scale to offset high upfront costs. This finding aligns with Pierpaoli et al. (2013), who emphasized that farm size and economic resilience significantly influence PAT uptake. Furthermore, the potential for increased profitability and input efficiency serves as a key motivator for adoption, as Barnes et al. (2019a) identified return on investment (ROI) expectations as a primary driver. However, the high initial investment and ongoing maintenance costs present significant barriers, particularly for small and medium-sized farms. Schimmelpfennig (2016) and Sørensen et al. (2010) similarly noted that smaller farms often lack the financial capacity to adopt PATs without external subsidies. While CAP subsidies and national funding programs help alleviate some of these constraints, this study indicates that existing financial support mechanisms remain inadequately tailored to the needs of smaller farms. These findings also show that the potential economic vulnerability inherent in smaller, less financially secure farms acts as a prohibitive factor rather than an incentive to change. Therefore, smaller farms find themselves in a trap where necessary changes are less likely to be adopted. Such findings have particular implications for agricultural policy in the EU, where agriculture is based on family farms.

The adoption of PATs is also positively associated with land quality. Farms with above-average land productivity are 5.5 p.p. more likely to adopt PATs than those with below-average productivity, holding other variables constant. This suggests that farmers perceive PATs as a way to preserve land quality and the productivity of this critical agricultural resource. By adopting technologies such as GPS-guided equipment, soil sensors, and variable-rate applications, farmers can optimize inputs and management practices to maintain the long-term health and productivity of their land. This finding is consistent with Paxton et al. (2011), who observed that farms with more fertile and consistent soil conditions were more likely to adopt yield-monitoring and site-specific management systems. While much of the literature focuses on the role of PATs in managing variability in lower-quality land (e.g., Blasch et al., 2022), this finding highlights that farmers often prioritize technologies where the benefits are more predictable. For instance, high-quality land amplifies the impact of optimized fertilizer and pesticide application, making the initial investment more justifiable.

The manager's education also plays a significant role in PAT adoption. Managers with formal agricultural education are 4.1 p.p. more likely to introduce new technologies into the farm than those with only practical experience or basic agricultural education. This is likely due to their greater familiarity with technological procedures in agricultural production. This finding highlights the importance of specialized knowledge and competencies for the successful implementation of advanced technological solutions in agricultural practice. The study aligns with previous literature identifying that more educated farmers are generally more open to adopting PATs (Tey & Brindal, 2012; Eastwood et al., 2017). However, findings challenge the notion that resistance among older farmers is solely rooted in age-related conservatism or a lack of technical knowledge. This contrasts with Masi et al. (2022), who attributed non-adoption primarily to generational divides and skill gaps. The Czech case indicates that age does not necessarily represent a barrier to the adoption of novel technologies. Demonstrable economic benefits can motivate even more conservative, older farmers.

Furthermore, farms with higher levels of indebtedness are more likely to adopt PATs, as shown in Fig. 5. The positive effect of indebtedness on the likelihood of adopting PATs can be attributed to two potential mechanisms: access to credit financing (Zuo et al., 2021) and a manager's positive attitude toward risk. Farms with higher levels of indebtedness may have established relationships with financial institutions, facilitating access to credit. This access enables them to invest in capital-intensive technologies, such as PATs. For instance, Girma (2022) found that access to credit increases agricultural technology adoption compared to farmers without access to credit. This suggests that financial access can facilitate the adoption of new technologies, which is a key factor in the Czech context. Also, higher debt levels can indicate a greater willingness to take on financial risks, which may correlate with a propensity to adopt innovative technologies. Isgin et al. (2008) observed that farmers with higher debt-to-asset ratios, often considered a proxy for risk preference, tend to adopt more PATs. This implies that higher indebtedness may be linked to a greater willingness to invest in new technologies. Finally, indebted farms may view the adoption of PATs as a strategic move to enhance operational efficiency and reduce long-term costs, thereby improving their financial position. Lowenberg-DeBoer and Erickson (2019) noted that farmers who perceive PATs as tools for reducing costs and increasing yields are often willing to overlook concerns about the initial investment. For indebted farms, adopting such technologies might serve as a calculated risk aimed at stabilizing or improving their financial position.

Conversely, higher labor intensity and farm localization in altitudes of 300–599 m a.s.l. are associated with a lower probability of PAT adoption. On average, farms located at this elevation have a 7.5 p.p. lower probability of adopting PATs compared to farms at other elevations. Figure 5 illustrates the relationship between labor intensity and the predicted probability of PAT adoption. On average, farms with one unit higher labor intensity have a 2.6 p.p. lower probability of adopting PATs, holding other variables constant. The finding that farms with higher labor intensity are less likely to adopt PATs aligns with broader trends in

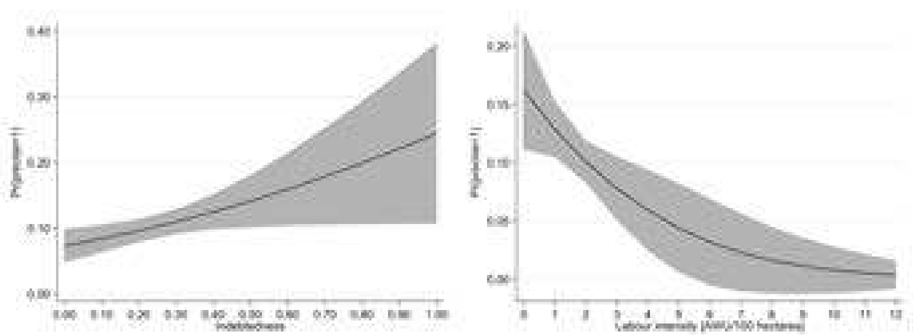

Fig. 5 Predicted probability of PAT adoption by indebtedness and labor intensity (between effects, predictive margins with 95% conf. int.).
Source: Own processing

automation adoption. As Blasch et al. (2022) observed, PATs are often viewed as a substitute for manual labor, offering solutions that reduce labor requirements and enhance efficiency. Farms with high labor intensity may perceive PATs as redundant or may lack the operational flexibility to reallocate human resources to non-manual roles. For instance, Sørensen et al. (2010) highlighted that labor costs significantly influence adoption decisions in regions with higher wages. The findings challenge the assumption that labor-intensive farms would adopt PATs to alleviate workforce constraints. In regions where labor is abundant or inexpensive, the financial incentive to replace manual work with automated systems diminishes.

Figure 6 displays the complex interplay between labor intensity, farm characteristics, and the likelihood of adopting PATs based on between effects. It demonstrates that very large farms have a higher probability of PAT adoption compared to other farm types across all levels of labor intensity.

Within-farm effect estimates, capturing temporal dynamics, reveal that the probability of PAT adoption is significantly influenced by changes in labor intensity, specialization, and land ownership at the $\alpha = 0.05$ significance level. More specifically, the likelihood of adopting PATs increases as farm specialization intensifies. This finding can be attributed to efficiency gains and optimization opportunities that specialization provides. Specialized farms are typically better positioned to capture the benefits of PATs through economies of scale, targeted optimization processes, and managerial expertise aligned with their core agricultural activities. This is consistent with findings by Aubert et al. (2012), who emphasized that specialization enables economies of scale, lowering the cost barriers to adopting capital-intensive innovations like PATs. Moreover, managerial expertise in specialized operations

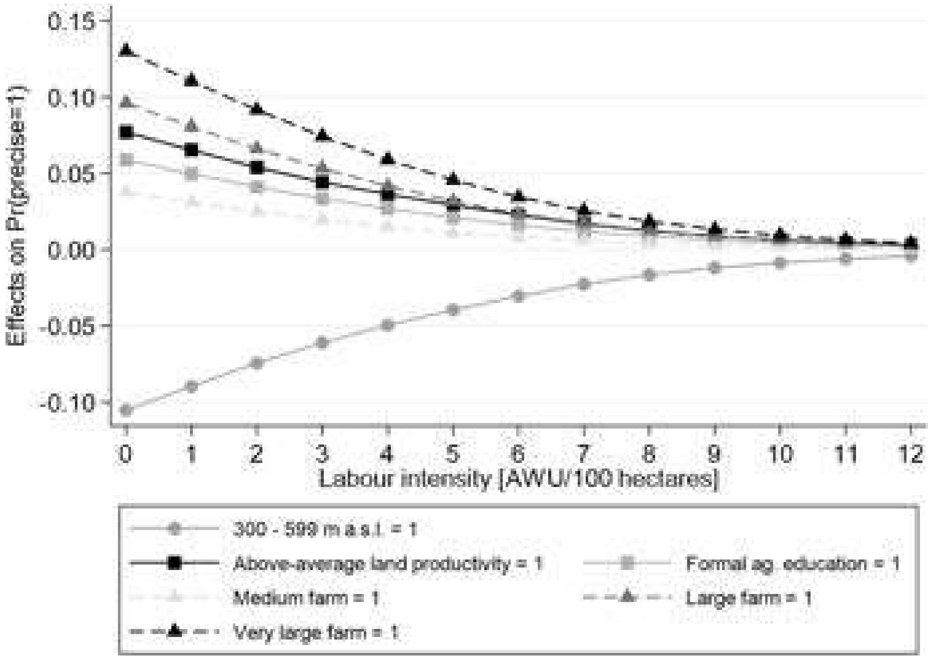

Fig. 6 Average marginal effects of labor intensity (between effects) on PAT adoption by farm characteristics. Source: Own processing

enhances the ability to integrate and operate advanced technologies effectively, as noted by Kutter et al. (2011).

In contrast, higher labor intensity and a larger share of rented land are associated with a decreased likelihood of PAT adoption at the $\alpha = 0.05$ significance level. An increase in labor intensity may indicate a shift toward more labor-intensive production systems, such as organic farming or regenerative agriculture, where the adoption of PATs may face challenges – including higher initial costs and concerns about potential conflicts with the principles of these farming systems. Similar trends were observed by Läpple and Hennessy (2012), who found that farms heavily reliant on manual labor tend to deprioritize technology due to perceived cost-benefit mismatches.

Moreover, insecure land tenure, represented by a greater share of rented land, may reduce farmers' long-term incentives to invest in productivity-enhancing but capital-intensive innovations like PA. This observation aligns with Pedersen et al. (2004), who highlighted that land ownership provides the stability necessary for adopting innovations that require high upfront costs. Conversely, tenant farmers often face uncertainty or short lease durations, reducing their incentive to commit to expensive technologies that may primarily benefit landowners.

Additionally, at the $\alpha = 0.1$ significance level, the probability of PAT adoption decreases as the input-output ratio increases. This negative relationship may suggest that farms with declining efficiency in input utilization are less likely to invest in PATs, potentially due to higher operating costs or lower perceived returns on investment. These findings align with Balafoutis et al. (2017), who observed that farms facing economic pressures are less inclined to adopt new technologies unless direct cost-saving benefits are clearly demonstrated.

Policy implications

The results reveal that the adoption of PATs among Czech field production farms is influenced not only by farm characteristics but also by how these characteristics evolve over time. These findings underscore the importance of targeted policy measures to promote technology adoption and enhance agricultural efficiency. Precision agriculture offers significant potential to optimize resource use, increase productivity, and contribute to the sustainability of the agricultural sector. Therefore, policymakers should prioritize offering financial incentives or subsidies to support investments in these technologies. However, the observed disparities between different farm types emphasize the need for tailored interventions. The following policy recommendations aim to address these gaps, fostering a more competitive, resilient, and sustainable agricultural landscape.

Targeted subsidies and support for small and medium-sized farms: The results indicate that smaller farms face challenges in adopting advanced technologies. Policies should be designed to lower entry barriers for small and medium-sized farms by offering subsidies, low-interest loans, or grants specifically for PA equipment. Policymakers should also promote collaborative approaches by encouraging cooperation among smaller farms through farmer groups or cooperatives. This would allow them to share PATs, split implementation costs, and collectively benefit from economies of scale in PA implementation. Ensuring equitable access to technology could help narrow the productivity gap between small and large farms. To stimulate cooperative formation and cost-effective access to PATs, an integrated policy package is appropriate to reduce upfront and organizational barriers to collective action. Measures could include targeted start-up and co-investment grants (e.g., via CAP rural development funds), credit guarantees or low-interest loans for member cooperatives, fast-tracked legal and tax incentives, subsidised hands-on training and on-farm demonstrations, funding for local extension and matchmaking platforms, and clear data-governance rules that ensure trusted collective use of sensor and farm data while protecting members' rights (Mizik, 2023). Practical examples from Europe demonstrate the feasibility of such mechanisms. Germany's long-standing machinery rings and newer inter-farm digital-technology sharing initiatives illustrate how established cooperation structures can coordinate shared use, invoicing, and service provision for capital-intensive digital tools and thus broaden access for smaller farms (Gscheidle et al., 2025). These measures are most effective when they combine financial support, demonstrable pilot projects, and capacity building to generate visible returns and foster social capital. However, their long-term success depends on sound cooperative governance, sustained advisory and market linkages, and embedding cooperative support within ongoing rural policy instruments to maintain membership incentives and institutional capacity beyond initial public financing (Mizik, 2023).

Strengthening access to investment support: The analysis suggests that adopters of PATs may benefit from greater access to investment subsidies. Policymakers should streamline the process for obtaining investment support, ensuring that smaller farms can access these resources. Enhancing transparency and reducing bureaucratic obstacles in subsidy applications could further improve adoption rates. Smaller farms face prohibitive upfront and maintenance costs, confirming their economic vulnerability trap. Thus, investment support should be redesigned to ensure accessibility for small and medium-sized farms, for instance, by providing differentiated subsidy rates, simplified application procedures, or pooled investment schemes (machinery rings, cooperative ownership). This would directly mitigate the capital barrier highlighted in the results.

Promoting education and skills development: The significant differences between adopters and non-adopters in terms of labor intensity and agricultural education suggest that a skilled workforce is essential for effectively using modern farming practices. Policymakers should invest in training programs and agricultural extension services to enhance farmers' knowledge and capabilities, with a focus on technology and data-driven decision-making in agriculture. Additionally, as the farming population ages, it is crucial to develop training programs that are accessible to older farmers while also encouraging younger generations to enter the agricultural sector. This dual approach ensures that experienced farmers and new entrants can benefit from advancements in precision agriculture.

In the Czech Republic, the diffusion of digital and precision agriculture innovations is strongly shaped by the structure of local micro-networks of farmers, advisors, and innovators, where pioneering adopters and peer learning play a pivotal role in exposing others to new tools and practices (Konečná & Sutherland, 2022). To better bridge the intergenerational digital gap, policymakers should expand the existing Ministry of Agriculture's Demonstration Farms and advisory programs currently under CAP/rural development funding to explicitly incorporate modules tailored for older learners, peer-led field days linking pioneers with their neighbors, and vocational training tracks that welcome new entrants into agri-technology roles; reinforcing local innovation networks and socially embedded learning will be key to embedding precision agriculture more broadly and durably.

Promoting stable land tenure: Given the negative impact of insecure land tenure on PAT adoption, policymakers should focus on regulatory incentives that encourage long-term agricultural lease agreements (e.g., tax benefits), while also establishing mechanisms to protect investments in precision agriculture on rented land. In the Czech Republic, the share of rented agricultural land is among the highest rates in the EU. Under the CAP Strategic Plan for 2023–2027, the EU provides rural development support that could be tailored to this issue, specifically through longer-term lease incentives, tenure security measures, and investment aid for tenants. By linking CAP-funded rural development initiatives to reforms such as land consolidation, extended usufruct leases, and co-investment schemes for renters, Czech policy can directly address tenure-related obstacles to PAT adoption and boost technological uptake across diverse farm sizes.

Addressing regional disparities: The results reveal that localized conditions influence the feasibility of adopting new technologies. Regional policy interventions, such as place-based support programs and tailored extension services, can help overcome the specific barriers faced by farms in less favorable regions. Targeted measures, including area-based payments for PAT adoption or region-specific demonstrations of cost-effectiveness, could support equitable modernization and reduce the risk of regional disparities in competitiveness.

Promoting the adoption of precision agriculture aligns with the EU Green Deal's objectives to mitigate agriculture's environmental impact. By supporting such innovations, governments can improve farm productivity while advancing broader goals related to agricultural sustainability, rural development, and climate change mitigation, thereby fostering a more resilient and sustainable agricultural sector.

Conclusion

This study examined the adoption of precision agriculture technologies (PATs) among Czech agricultural producers, utilizing FADN data, which allows for the replication of this ex-post analysis across other EU member states. By analyzing both between-farm and within-farm effects, the study identified distinct adoption patterns and highlighted socio-economic and environmental factors as significant determinants of PAT adoption among Czech agricultural producers.

The between-farm effects indicate that larger farms with higher land quality and operations managed by professionals with formal agricultural education are significantly more likely to adopt PATs. This is likely due to their stronger financial position to absorb investment costs and their professional management capabilities. The higher adoption rate among farms with better land quality suggests that PATs are viewed as a vital tool for preserving and optimizing this valuable resource. Similarly, managers with formal agricultural education are better equipped to understand and implement these sophisticated technological solutions. Additionally, access to capital and a positive managerial approach toward financial risk are positively correlated with PAT adoption.

Table 6 Representativeness of FADN and field crops farms sample

Year	Number of represented farms by FADN	Number of farms in the Czech Republic	Represented area of Cereals [hectare] - Fieldcrops	Area of cereals in the Czech Republic [hectare]	Sample representativeness [%]
2017	17,660	48,033	710,721	1,352,450	52.6
2018	17,798	48,699	714,430	1,339,056	53.4
2019	17,801	48,472	751,020	1,353,556	55.5
2020	13,506	47,160	703,787	1,336,290	52.7
2021	13,506	42,678	709,666	1,334,331	53.2

Sample representativeness is calculated as the ratio of the cereal area represented by the sample of field crop farms to the total cereal area in the Czech Republic.

Source: FADN (2025b), Ministry of Agriculture CR (2025), and Czech Statistical Office (2025a).

The within-farm effects highlight that temporal changes, especially increasing specialization, positively influence PAT adoption. Specialized farms can better leverage economies of scale and optimize specific production processes, making them more likely to integrate PATs. Conversely, higher labor intensity and an increasingly larger share of rented land over time are associated with lower adoption rates, suggesting challenges in more labor-intensive or tenure-insecure settings. These findings indicate that PAT adoption is influenced by both structural characteristics and temporal changes within farms, suggesting that targeted policies supporting education and access to financing may effectively promote adoption across various farm types.

This analysis also reveals methodological limitations due to the use of the FADN database. Despite its high representativeness, the current panel's imbalance limited the ability to model state dependence, which assumes that substantial PAT investments create a path dependency in continued use. The binary dependent variable can, to a certain extent, mask the variation in the intensity and, in particular, the quality of adoption. Moreover, the current model is unable to account for potentially underutilized PATs. It is related to the fact that some farmers may buy new machinery with PA features only as an equipment update. Such a case may not necessarily reflect a deliberate decision to adopt PATs for precision management purposes. Instead, it may indicate routine equipment replacement or upgrading, with the precision features potentially underutilized. Predominantly, it may concern autonomous machine guidance, which is slowly becoming a standard in Europe, and, as the data shows, it is the most frequently used PAT among farms using only one type of PAT. Therefore, the interpretation of adoption used in the article reflects the presence of the technology on the farm, but actual utilization intensity may slightly vary. However, the aim was to estimate the average effects, which reveal important patterns in farm adoption, as the data do not allow for a more detailed analysis. Future research could extend beyond binary adoption decisions to examine the determinants of adoption intensity, providing deeper insights into the factors shaping the extent and progression of PAT implementation in agricultural holdings.

Appendix

See Tables 6, 7, 8, 9, 10, 11, 12, 13, 14

Table 7 Comparative analysis of farm characteristics between adopters and non-adopters: Descriptive statistics and K-S test results (2021)

	Min.	1. Q	Median	Mean	3. Q	Max.	Std. D.
Labor [AWU] (Kolmogorov–Smirnov test D = 0.330; *p*-value = 0.000)							
Non-adopters	0.2	1.5	2.4	6.5	5.1	215.4	0.9
Adopters	0.6	2.1	6.0	10.7	16.3	69.3	1.5
Land [hectares] (Kolmogorov–Smirnov test D = 0.318; p-value = 0.000)							
Non-adopters	13.3	66.1	136.7	383.9	391.3	3872.3	34.2
Adopters	16.0	122.9	512.5	806.3	1137.8	4650.7	117.5
Specialization on cereals [%] (Kolmogorov–Smirnov test D = 0.208; p-value = 0.018)							
Non-adopters	0.0	39.7	51.7	52.7	66.3	99.5	1.2
Adopters	15.8	36.8	45.3	47.2	55.2	86.6	2.0
Labor intensity [AWU_100 hectares] (Kolmogorov–Smirnov test D = 0.226; p-value = 0.007)							
Non-adopters	0.1	1.2	1.8	2.3	2.6	26.0	0.1
Adopters	0.5	1.0	1.4	1.7	2.2	8.4	0.1
Input-output ratio [%] (Kolmogorov–Smirnov test D = 0.187; p-value = 0.044)							
Non-adopters	27.2	76.9	95.2	98.0	114.8	207.0	1.8
Adopters	68.4	86.7	102.7	101.2	110.9	152.2	2.1
Subsidies on investment [ths. CZK] (Kolmogorov–Smirnov test D = 0.037; p-value = 1.000)							
Non-adopters	0.0	0.0	0.0	70.0	0.0	3150.0	18.3
Adopters	0.0	0.0	0.0	28.0	0.0	531.4	13.6
Total subsidies – excluding on investment [ths. CZK/hectare](Kolmogorov–Smirnov test D = 0.186; p-value = 0.023)							
Non-adopters	4.4	6.0	6.8	7.5	7.9	36.5	0.2
Adopters	5.6	6.5	7.3	8.3	8.3	23.9	0.4
Gross farm income [ths. CZK] (Kolmogorov–Smirnov test D = 0.308; p-value = 0.000)							
Non-adopters	−182.3	1102.2	2521.5	7832.3	7643.1	92256.6	766.4
Adopters	333.1	2359.9	7971.6	18897.4	28686.5	117325.4	2843.7
Farm net value added [ths. CZK/AWU] (Kolmogorov–Smirnov test D = 0.242; p-value = 0.003)							
Non-adopters	−681.6	430.6	810.3	1000.8	1286.3	9512.1	56.9
Adopters	46.0	777.2	1200.9	1251.6	1540.9	3508.4	84.6
Indebtedness [%] (Kolmogorov–Smirnov test D = 0.287; p-value = 0.000)							
Non-adopters	0.0	1.7	9.2	16.8	24.9	213.0	1.3
Adopters	0.1	8.4	20.8	26.0	36.8	103.2	2.8
Share of rented land [%] (Kolmogorov–Smirnov test D = 0.173; p-value = 0.076)							
Non-adopters	0.0	26.3	65.3	57.3	83.5	100.0	1.9
Adopters	0.0	51.5	75.3	68.9	89.4	100.0	3.0
Share of unpaid labor [%] (Kolmogorov–Smirnov test D = 0.327; p-value = 0.000)							
Non-adopters	0.0	18.8	69.0	60.0	100.0	100.0	2.4
Adopters	0.0	0.0	0.0	33.9	82.8	100.0	5.2
Age of manager [years] (Kolmogorov–Smirnov test D = 0.091; p-value = 0.760)							
Non-adopters	27.0	46.0	55.0	54.7	63.0	84.0	0.7
Adopters	29.0	44.0	53.0	53.7	62.0	77.0	1.3

Statistically significant differences between adopters and non-adopters were found in labor, land, specialization in cereals, labor intensity, input-output ratio, total subsidies, gross farm income, farm net value added, indebtedness, and the share of unpaid labor (p-value < 0.05).

Source: Own processing.

Table 8 Statistical analysis of categorical variables between pats adopters and non-adopters: pearson's Chi-squared test (2021)

Variable	Pearson chi2(1)	*p*-value
General field crops production	0.765	0.382
Livestock production	0.843	0.358
Organic farming	0.323	0.570
Specific areas	3.329	0.068
Altitude < 300 m a.s.l.	13.877	0.000
Altitude 300–599 m a.s.l.	15.775	0.000
Altitude ≥ 600 m a.s.l.	0.913	0.339
Above-average land productivity	19.593	0.000
Family farm	11.226	0.001
Formal agricultural education	17.344	0.000
Only practical agricultural experience	4.461	0.039
Male farmer	0.291	0.590
Subsidies for young farmers	0.913	0.339
Small farms (standard output (SO) < 50000 EUR)	2.666	0.103
Medium farms (SO 50000–499999 EUR)	14.931	0.000
Large farms (SO 500000–999999 EUR)	3.305	0.069
Very large farms (SO≥1000000 EUR)	24.047	0.000

Source: Own processing.

Table 9 Probit model estimation

Variable	Coef.	Std.err.	$P>\lvert z\rvert$	[95% conf. int.]	
	Within				
x_LaborIntensity	−1.278	0.511	0.012	−2.280	−0.276
x_InputOutputRatio	−1.425	0.835	0.088	−3.062	0.211
x_CerealsSpecialization	2.773	0.982	0.005	0.848	4.697
x_Indebtedness	−1.078	1.652	0.514	−4.315	2.160
x_RentedLandShare	−6.949	3.065	0.023	−12.957	−0.941
x_ManagerAge	0.048	0.036	0.181	−0.022	0.117
	Between				
x_LaborIntensity	−0.643	0.247	0.009	−1.127	−0.158
x_InputOutputRatio	1.105	0.981	0.260	−0.818	3.029
x_CerealsSpecialization	−2.057	1.706	0.228	−5.402	1.287
x_Indebtedness	3.306	1.150	0.004	1.052	5.559
x_RentedLandShare	0.540	0.944	0.567	−1.310	2.391
x_ManagerAge	−0.010	0.019	0.588	−0.048	0.027
z_LivestockProduction	−0.182	0.372	0.625	−0.910	0.547
z_GeneralFieldCrops	−1.104	0.547	0.044	−2.176	−0.032
z_GeneralFieldCrops#z_LivestockProduction	0.047	0.490	0.924	−0.914	1.008
z_Altitude_300–599 m a.s.l.	−1.655	0.642	0.010	−2.913	−0.398
z_ConstrainedArea#z_Altitude < 300 m a.s.l.	1.990	0.678	0.003	0.661	3.319
z_ConstrainedArea#z_Altitude 300–599 m a.s.l.	−0.398	0.502	0.428	−1.382	0.586
z_ConstrainedArea#z_Altitude > 600 m a.s.l.	1.444	0.807	0.074	−0.138	3.027
z_HighLandProductivity	1.270	0.315	0.000	0.652	1.889

Table 9 (continued)

Variable	Coef.	Std.err.	*P*>|z|	[95% conf. int.]	
z_HighLaborProductivity	−0.194	0.302	0.521	−0.786	0.398
z_AgriculturalEducation	1.031	0.393	0.009	0.260	1.802
z_FamilyFarm	0.225	0.436	0.606	−0.629	1.079
z_YoungFarmerSubsidy	−0.246	1.522	0.871	−3.230	2.737
z_InvestmentSubsidy	0.096	0.278	0.729	−0.449	0.642
z_EconomicSize_Medium	0.832	1.284	0.517	−1.686	3.349
z_EconomicSize_Large	1.840	1.316	0.162	−0.739	4.418
z_EconomicSize_VeryLarge	2.343	1.287	0.069	−0.180	4.865
_const.	−6.441	2.217	0.004	−10.786	−2.095
lnsig2u	2.622	0.343		1.950	3.293
sigma_u	3.710	0.635		2.652	5.190
Rho	0.932	0.022		0.875	0.964
Wald chi2(28)	144.200		0.000		
Wald chi2(6): within effects	26.730		0.000		
Wald chi2(6): between effects	20.720		0.002		
Log likelihood	−331.629				
Percentage of correctly predicted values	89.009				
Wald chi2(3): InputOutputRatio_res, Indebtedness_res, and LaborIntensity_res	0.620		0.892		

Alternatively, a model including a time factor was also estimated; however, it was not statistically significant. For the year dummy variables, Wald chi2(4) = 0.770, p-value = 0.943, with p-values for each year dummy greater than 0.410. For the time variable, Wald chi2(2) = 1.830, p-value = 0.400. Furthermore, the stability of the within effects with respect to price changes was tested using an estimate based on the input–output ratio, where total output was deflated using the Agricultural Producer Price Indices (Total agricultural products, 2015 = 100; CZSO, 2025b) and total input was deflated using the Agricultural Input Price Indices (Input total, 2015 = 100; Czech Statistical Office, 2025c). The test of differences in the marginal effect (difference in AME = 0.007 for x_InputOutputRatio) does not reject the null hypothesis of zero difference (t-statistic = 0.162, p-value = 0.872), thus supporting the validity of the results.

Source: Own processing.

Table 10 Description of continuous variables of probit model

	Min.	1. Q	Median	Mean	3. Q	Max.	Std. dev.
x_LaborIntensity	0.352	1.158	1.695	2.387	2.515	87.526	3.370
x_InputOutputRatio	0.272	0.873	1.047	1.054	1.210	2.987	0.276
x_CerealsSpecialization	0.000	0.347	0.471	0.476	0.605	1.024	0.203
x_Indebtedness	0.000	0.045	0.131	0.195	0.286	1.104	0.197
x_RentedLandShare	0.000	0.498	0.723	0.650	0.877	1.000	0.287
x_ManagerAge	20.000	45.000	54.000	53.498	61.000	84.000	11.185

Source: Own processing.

Table 11 Differences in growth rates - t-test

Variable	Difference in growth rates	t-test statistic	*p*-value
LaborIntensity	2.489	1.386	0.166
InputOutputRatio	2.235	1.268	0.205
Indebtedness	37.901	0.843	0.400

Source: own processing

Table 12 Probit model Estimation for outlier robustness check (N=1,883)

Variable	Coef.	Std.err.	*P*>|z|	AME	Std.err.	*P*>|z|
Within						
x_LaborIntensity	−0.887	0.506	0.080	−0.036	0.021	0.089
x_InputOutputRatio	−1.424	0.788	0.071	−0.057	0.031	0.066
x_CerealsSpecialization	2.809	0.996	0.005	0.113	0.041	0.006
x_Indebtedness	−0.710	1.623	0.662	−0.029	0.065	0.662
x_RentedLandShare	−5.732	3.118	0.066	−0.230	0.121	0.057
x_ManagerAge	0.039	0.036	0.278	0.002	0.001	0.273
Between						
x_LaborIntensity	−0.580	0.198	0.003	−0.023	0.008	0.006
x_InputOutputRatio	0.888	0.985	0.367	0.036	0.040	0.372
x_CerealsSpecialization	−1.591	1.718	0.354	−0.064	0.068	0.346
x_Indebtedness	3.247	1.130	0.004	0.130	0.051	0.011
x_RentedLandShare	0.397	0.893	0.656	0.016	0.035	0.652
x_ManagerAge	−0.013	0.019	0.506	−0.001	0.001	0.515
z_LivestockProduction	−0.333	0.369	0.367	−0.002	0.014	0.900
z_GeneralFieldCrops	−1.084	0.533	0.042	−0.021	0.014	0.125
z_GeneralFieldCrops#z_LivestockProduction	−0.122	0.492	0.803			
z_Altitude_300–599 m a.s.l.	−1.726	0.650	0.008	−0.076	0.024	0.001
z_ConstrainedArea#z_Altitude < 300 m a.s.l.	1.897	0.673	0.005			
z_ConstrainedArea#z_Altitude 300–599 m a.s.l.	−0.383	0.504	0.447			
z_ConstrainedArea#z_Altitude > 600 m a.s.l.	1.403	0.825	0.089			
z_HighLandProductivity	1.089	0.296	0.000	0.047	0.015	0.002
z_HighLaborProductivity	0.026	0.278	0.924	0.001	0.011	0.924
z_AgriculturalEducation	0.990	0.385	0.010	0.040	0.018	0.022
z_FamilyFarm	0.160	0.435	0.713	0.006	0.018	0.716
z_YoungFarmerSubsidy	−0.322	1.413	0.820	−0.012	0.051	0.810
z_InvestmentSubsidy	0.074	0.263	0.779	0.003	0.011	0.781
z_EconomicSize_Medium	0.676	1.220	0.580	0.022	0.035	0.536
z_EconomicSize_Large	1.576	1.254	0.209	0.058	0.037	0.116
z_EconomicSize_VeryLarge	2.110	1.229	0.086	0.085	0.038	0.025
_const.	−5.943	2.149	0.006			
lnsig2u	2.575	0.358				
sigma_u	3.623	0.649				
Rho	0.929	0.024				
Wald chi2(28)	158.270		0.000			
Wald chi2(6): within effects	19.540		0.003			
Wald chi2(6): between effects	21.026		0.002			
Log likelihood	−321.670					
Percentage of correctly predicted values	89.007					

Source: Own processing.

Table 13 Probit model estimation – cross-sectional data

Variable	Model 2021				Model 2020				Model 2019				Model 2018			
	Coef.	Std.err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.
x_LaborIntensity	−0.165**	0.068	−0.034**	0.014	−0.251**	0.106	−0.049**	0.020	−0.198**	0.096	−0.028**	0.014	−0.351**	0.145	−0.040**	0.016
x_InputOutputRatio	0.248	0.335	0.052	0.070	0.594*	0.346	0.116*	0.068	1.285***	0.480	0.179***	0.066	−0.012	0.449	−0.001	0.051
x_CerealsSpecialization	−0.786	0.569	−0.164	0.117	0.639	0.629	0.125	0.123	−0.076	0.614	−0.011	0.086	−0.446	0.861	−0.051	0.097
x_Indebtedness	0.449	0.390	0.094	0.082	0.408	0.433	0.080	0.084	0.349	0.293	0.049	0.041	0.467*	0.269	0.053*	0.030
x_RentedLandShare	0.182	0.319	0.038	0.067	0.614	0.387	0.120	0.074	−0.102	0.421	−0.014	0.059	0.475	0.485	0.054	0.056
x_ManagerAge	−0.008	0.008	−0.002	0.002	−0.006	0.008	−0.001	0.002	−0.003	0.009	0.000	0.001	−0.004	0.009	0.000	0.001
z_GeneralFieldCrops	−0.128	0.243	−0.026	0.048	0.341	0.246	0.072	0.055	0.326	0.273	0.049	0.044	0.076	0.292	0.009	0.034
z_LivestockProduction	−0.088	0.179	−0.018	0.038	−0.105	0.192	−0.021	0.037	−0.141	0.203	−0.019	0.028	−0.276	0.197	−0.030	0.021
z_Altitude 300–599 m a.s.l.	−0.724***	0.206	−0.153***	0.042	−0.534***	0.198	−0.104***	0.038	−0.353*	0.202	−0.049*	0.028	−0.089	0.226	−0.010	0.025
z_HighLandProductivity	0.643***	0.205	0.144***	0.048	0.712***	0.216	0.154***	0.049	0.524*	0.288	0.083	0.051	0.439	0.294	0.055	0.041
z_HighLaborProductivity	−0.270	0.240	−0.055	0.048	0.004	0.230	0.001	0.045	0.364	0.249	0.051	0.034	−0.095	0.249	−0.011	0.029

Table 13 (continued)

Variable	Model 2021				Model 2020				Model 2019				Model 2018			
	Coef.	Std.err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.
z_AgriculturalEducation	0.381**	0.189	0.081**	0.040	0.435**	0.210	0.086**	0.042	0.701***	0.205	0.096***	0.028	0.594**	0.247	0.065**	0.026
z_FamilyFarm	0.012	0.236	0.002	0.049	0.057	0.245	0.011	0.048	−0.862***	0.288	−0.093***	0.025	−0.441	0.348	−0.044	0.030
z_YoungFarmerSubsidy	0.680	0.569	0.173	0.167	−0.579	0.739	−0.091	0.088								
z_InvestmentSubsidy	−0.181	0.293	−0.036	0.055	0.004	0.267	0.001	0.052	0.383	0.283	0.060	0.050	0.530*	0.273	0.074*	0.045
z_EconomicSize_Medium	−0.228	0.321	−0.049	0.070	−0.445	0.462	−0.092	0.108	−0.677	0.560	−0.114	0.112	−1.267*	0.570	−0.197	0.124
z_EconomicSize_Large	0.126	0.445	0.027	0.100	0.010	0.536	0.002	0.129	−0.756	0.634	−0.124	0.120	−1.128	0.682	−0.186	0.134
z_EconomicSize_VeryLarge	0.353	0.424	0.081	0.107	−0.066	0.516	−0.016	0.123	−0.383	0.603	−0.071	0.120	−0.481	0.659	−0.101	0.144
_const.	−0.208	0.876			−1.738*	0.981			−2.119**	1.062			−0.240	1.090		
Wald chi2(18/17)	69.290***				68.230***				89.270***				66.46			
Log likelihood	−137.425				−128.381				−112.753				−95.416			

Table 13 (continued)

Variable	Model 2021				Model 2020				Model 2019				Model 2018			
	Coef.	Std.err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.	Coef.	Std. err.	AME	Std. err.
Percentage of correctly predicted values	83.562				84.615				87.302				91.939			
Number of observations	365				364				441				459			

The estimates use the original, uncleaned data.

Source: Own processing.

Table 14 Differences in AME estimates - t-test

Variable	Difference in AME					t-test statistic					p-value				
	M_outlier	M_2021	M_2020	M_2019	M_2018	M_outlier	M_2021	M_2020	M_2019	M_2018	M_outlier	M_2021	M_2020	M_2019	M_2018
x_LaborIntensity	−0.003	0.008	0.023	0.002	0.014	−0.234	0.465	1.014	0.093	0.724	0.815	0.642	0.311	0.926	0.469
x_InputOutputRatio	0.008	−0.008	−0.072	−0.135	0.045	0.141	−0.099	−0.918	−1.754	0.700	0.888	0.921	0.359	0.080	0.484
x_CerealsSpecialization	−0.018	0.082	−0.207	−0.071	−0.031	−0.190	0.610	−1.483	−0.660	−0.269	0.849	0.542	0.139	0.509	0.788
x_Indebtedness	0.001	0.037	0.051	0.082	0.078	0.014	0.381	0.517	1.248	1.302	0.989	0.703	0.605	0.213	0.193
x_RentedLandShare	0.005	−0.017	−0.099	0.035	−0.033	0.098	−0.222	−1.197	0.507	−0.491	0.922	0.824	0.232	0.612	0.624
x_ManagerAge	0.001	0.002	0.001	0.000	0.000	0.707	0.894	0.621	0.270	0.326	0.480	0.372	0.535	0.787	0.745
z_GeneralFieldCrops	0.001	0.006	−0.092	−0.069	−0.029	0.051	0.120	−1.621	−1.493	−0.775	0.960	0.905	0.106	0.136	0.439
z_LivestockProduction	0.007	0.023	0.026	0.024	0.035	0.354	0.568	0.641	0.787	1.404	0.724	0.570	0.522	0.432	0.161
z_Altitude_300–599 m a.s.l.	0.001	0.078	0.029	−0.026	−0.065	0.030	1.629	0.658	−0.707	−1.896	0.976	0.104	0.511	0.480	0.059
z_HighLandProductivity	0.008	−0.089	−0.099	−0.028	0.000	0.365	−1.759	−1.926	−0.529	−0.005	0.715	0.079	0.055	0.597	0.996
z_HighLaborProductivity	−0.009	0.047	−0.009	−0.059	0.003	−0.553	0.950	−0.188	−1.631	0.092	0.580	0.343	0.851	0.104	0.927
z_AgriculturalEducation	0.001	−0.040	−0.045	−0.055	−0.024	0.039	−0.912	−0.992	−1.656	−0.756	0.969	0.362	0.322	0.098	0.450
z_FamilyFarm	0.003	0.007	−0.002	0.102	0.053	0.118	0.134	−0.044	3.311	1.513	0.906	0.893	0.965	0.001	0.131
z_YoungFarmerSubsidy	0.003	−0.182	0.082			0.040	−1.033	0.783			0.968	0.302	0.434		
z_InvestmentSubsidy	0.001	0.040	0.003	−0.056	−0.070	0.064	0.713	0.059	−1.112	−1.517	0.949	0.476	0.953	0.267	0.130

Table 14 (continued)

	Difference in AME					t-test statistic					*p*-value				
Variable	M_outlier	M_2021	M_2020	M_2019	M_2018	M_outlier	M_2021	M_2020	M_2019	M_2018	M_outlier	M_2021	M_2020	M_2019	M_2018
z_Economic-Size_Medium	0.003	0.074	0.117	0.139	0.222	0.061	0.951	1.039	1.188	1.731	0.951	0.342	0.299	0.235	0.084
z_Economic-Size_Large	0.008	0.039	0.064	0.190	0.252	0.155	0.367	0.474	1.516	1.822	0.877	0.714	0.635	0.130	0.069
z_Economic-Size_VeryLarge	0.005	0.009	0.106	0.161	0.191	0.096	0.080	0.824	1.289	1.290	0.924	0.937	0.411	0.198	0.198

Note: M_outlier denotes the model in Table A7, and M_2021, M_2020, M_2019, and M_2018 denote the models in Table A8. The between effects from the WBRE model in Table A4 serve as the basis for comparison

Source: own processings

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Data availability The data supporting the findings of this paper are available from the Farm Accountancy Data Network – Czech Republic. However, access to these data is restricted as they were used under license for this study. Data can be obtained from the authors with permission from the Institute of Agricultural Economics and Information.

Declarations

Competing Interests The authors report there are no competing interests to declare.

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