**Beyond the Mean: A Quantile Count Regression Analysis of Precision Farming Technology Adoption Intensity by German Farmers**

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**Abstract**

Understanding technology adoption processes is crucial for agricultural policy and research, yet most studies rely on mean-based models that may obscure distributional differences. This study investigates precision agriculture technology adoption intensity in arable farming using survey data from 342 German farm managers. Adoption intensity is measured as the number of technologies used from 32 technologies and analyzed by quantile count regression alongside negative binomial regression. Results reveal that, among other, that risk attitude shows consistent associations across all quantiles, while farm succession exhibits a monotonically increasing effect. The findings demonstrate limitations of mean-based approaches and provide insights for several stakeholders.

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**Introduction**

Innovation in agriculture refers to technological or managerial changes that alter the production function and thus transform established production practices (Feder and Umali, 1993). The diffusion of such innovations is shaped by substantial heterogeneity among decision makers, as early and late adopters differ systematically in their characteristics (Rogers, 2010). Understanding these heterogeneous adoption processes is particularly important in agriculture, where innovative technologies play a key role in productivity, economic resilience, and environmental sustainability (Chavas and Nauges, 2020). Consequently, identifying the factors and barriers that influence adoption of new technologies has become a central task for research (Ingram et al., 2022), and is of interest for several stakeholders (e.g. policy-makers, suppliers, and developers) (e.g. ISPA, 2025; Ogundari and Bolarinwa, 2018; Thompson et al., 2019). This need has intensified with the digitalisation of agriculture, which supports the development and implementation of precision agriculture technologies (PAT) (Walter et al., 2017; 2023). PAT can enhance farm management and reduce negative environmental externalities by enabling more efficient use of potentially harmful inputs (Tamirat et al., 2018; Finger et al., 2019). Reflecting their economic, environmental and social relevance (Basso & Antle, 2020; Amman et al., 2022; Van der Burg et al., 2024), a substantial body of literature examines the determinants of PAT adoption (e.g. Kroupová et al., 2025; Tey and Brindal, 2022; Pathak et al., 2019; Pierpaoli et al., 2013).

An important strand of this literature examines not only whether farmers adopt specific PATs (e.g. Daberkow & McBride, 2003), but also the intensity with which they use them (e.g. Isgin et al., 2008). In other words, rather than focusing on single tools, these studies conceptualize adoption as a portfolio decision, since farmers display interest to bundle technologies to maximize economic potential of PAT (e.g. Miller et al., 2017). Early contributions by Isgin et al. (2008), based on survey data from Ohio, United States, indicate that farm size, education, soil quality, urban proximity, and indebtedness are positively associated with both adoption probability and adoption intensity. Paxton et al. (2011), analyzing cotton producers in the southern United States, report that within-field yield variability is positively associated with adoption intensity, alongside younger age, higher education, and computer use for farm management. More recent work refines this perspective by accounting for heterogeneity across technology types. Kolady et al. (2021), using data from eastern South Dakota, United States, distinguish between embodied-knowledge and information-intensive technologies and find that cropland size, perceived profitability, and off-farm income are consistently associated with both adoption and intensity, while factors such as land productivity and computer familiarity are associated differently with adoption and intensity depending on the technology category. Hanson et al. (2022) provide evidence from North Dakota, United States, by analyzing adoption intensity in terms of the relation between acres on which PAT are applied to total acreage using a double-hurdle model. Among other they find that increasing cultivated acres also increases autosteer use. Furthermore, evidence from Brazil exists. Mozambani et al. (2023), studying sugarcane farmers in São Paulo, Brazil, find that production scale, information provided by mills, and yield expectations are associated with adoption, whereas adoption intensity is additionally associated with advisory services, prior experience, and access to credit. Most recently, Damasceno et al. (2026) show for soybean farmers in São Paulo, Brazil, that farm size, education, innovativeness, consultancy use, and credit access are robustly associated with both adoption intensity, while perceived costs are negatively associated. While these studies provide important insights, they rely exclusively on mean-based count models (e.g. Poisson, Negative binomial regression) that estimate average effects across all farms. This approach implicitly assumes that the same mechanisms govern technology accumulation among farms with very low adoption intensity and those operating extensive PAT portfolios. If determinants operate differently across the adoption distribution, mean-based estimates may conceal structurally different adoption mechanisms and lead to incomplete policy recommendations. No existing study has tested whether covariate effects vary systematically between low, moderate, and high adopters, representing a substantial methodological gap in the literature.

This methodological limitation is compounded by geographic concentration of existing research. While PAT adoption (intensity) has been examined primarily in United States and Brazilian contexts using mean-based models, evidence for the PAT adoption in Europe is scarce according to Barnes et al. (2019a). This is also holds true for Germany as highlighted by Kehl et al. (2021). Nevertheless, there are few current exceptions for Europe (and Germany) to be named (e.g. Paustian and Theuvsen, 2017; Tamirat et al., 2018; Barnes et al., 2019a; Barnes et al., 2019b, Michels et al., 2020; Blasch et al., 2022; Giua et al., 2022; Gabriel and Gandorfer, 2023; Michels and Mußhoff, 2025a, b). Still, only two studies with a European focus have investigated the adoption intensity regarding PAT. Barnes et al. (2019b) model the number of contingent variable-rate technologies adopted, conditional on the uptake of threshold technologies for variable-rate technologies such as machine guidance. Giua et al. (2022) also analyze adoption intensity by modelling the number of latest PAT (e.g. sensors, drones, satellites, software algorithms, and robots) adopted using a zero-inflated Poisson framework. As a result, both studies focus on a limited set of technologies and estimates only average effects, without considering heterogeneity across the adoption distribution. Thus, despite these important contributions, no European study has examined the intensity of PAT adoption across a comprehensive technology portfolio available for arable farming considering heterogenous effect across the full technology adoption distribution. This is especially crucial, given the current interest of policy makers for digital agricultural transition in Europe (e.g. European Commission, 2025) and Germany (BMLEH, 2025) due to the contribution of PAT to environmental and economic sustainability of the agricultural sector (Finger et al., 2019; Finger, 2023).

Against this background, this paper addresses two research gaps. First, it examines whether the determinants of PAT adoption intensity operate uniformly across the distribution of adopters or whether they differ systematically between low, moderate, and high adopters. Second, it provides contemporary evidence on PAT adoption intensity in German arable farming, where analysis remains limited. The study draws on data from recent computer-assisted telephone interviews (CATI) conducted with 342 German arable farmers between December 2024 and January 2025. Farmers were selected through a random-sampling process. The analysis examines adoption intensity, operationalized as the number of technologies farmers have integrated into their farming operations from a comprehensive portfolio of 32 PAT applicable to arable farming. This technology classification framework is based on the systematic categorization developed by Papadopoulos et al. (2024). In contrast to previous research that relies almost exclusively on mean-based count models, this paper explicitly adopts a distributional perspective on adoption intensity. It combines a conventional negative binomial regression with a quantile count regression framework, allowing the identification of heterogeneous covariate effects along the entire adoption distribution.

## 2 Material and Methods

### 2.1 Survey and Data Collection

The empirical data were collected through a standardized computer-assisted telephone interview (CATI) with active farm managers in Germany between December 2024 and January 2025. The sampling frame was based on a comprehensive database of more than 300,000 agricultural enterprises maintained by *AgriDirect Deutschland GmbH*, covering a wide range of farm types in the German primary sector.

For this study, over 15,000 farm managers were preselected from the database, focusing on arable and mixed arable–livestock farms and excluding pure contract farming enterprises. Within this preselected group, potential participants were contacted randomly by telephone. In total, 366 interviews were completed, of which 342 fully completed questionnaires were retained for analysis after excluding incomplete observations. This procedure constitutes a two-stage sampling design with an initial screening stage followed by randomized contact, resembling a stratified random sampling approach (Lohr, 2021), while acknowledging self-selection due to availability and willingness to participate. Ethics approval was obtained by the German Association of Experimental Economic Research e.V..

### 2.2 Estimation Techniques

Given that our dependent variable, technology adoption intensity, is a count measure representing the number of technologies adopted by each farm, we employ count regression models for our analysis (Greene, 2003). The Poisson regression model serves as the standard starting point for modeling count data. A restrictive feature of the Poisson model is its assumption of equidispersion, where the conditional variance equals the conditional mean (Cameron and Trivedi, 2013). However, count data frequently exhibits overdispersion, where the variance exceeds the mean. To account for this, we employ the negative binomial model, which introduces an additional parameter $\boldsymbol{\theta}$ to accommodate overdispersion. As $\boldsymbol{\theta}$ approaches infinity, the model converges to a Poisson distribution. A lower value of $\boldsymbol{\theta}$ indicates greater overdispersion (Greene, 2003). For ease of interpretation, we transform the coefficients into incidence rate ratios (IRRs) by exponentiating the estimated coefficients: An IRR greater than one indicates that a one-unit increase in the corresponding explanatory variable is associated with a multiplicative increase in the expected number of adopted technologies, conditional on the remaining covariates. Conversely, an IRR below one indicates a decrease in the expected adoption intensity.

While the negative binomial regression provides insights into relationships at the conditional mean of adoption intensity, it may mask heterogeneity in how covariates relate to different points of the conditional distribution of technology adoption. To address this limitation, we employ quantile count regression, which estimates relationships at specified quantiles of the conditional distribution. Quantile count regression extends the quantile regression framework to non-negative count outcomes by directly modeling conditional quantiles of the response variable. Unlike mean-based count models, the coefficients do not describe changes in the conditional mean but quantify how explanatory variables shift different points of the adoption distribution. Positive coefficients indicate higher adoption intensity at a given quantile, while negative coefficients indicate lower adoption intensity. Estimation is implemented using the *qrcm* package in *R*, which applies a parametric quantile regression framework specifically designed for count data.

### *2.3 Sample Characteristics*

The selection of explanatory variables follows the conceptual framework proposed by Pierpaoli et al. (2013), who distinguish between socio-demographic factors (1), competitive and contingent factors (2), and financial resources (3) as the main categories associated with the adoption of PAT. Furthermore, additional factors (4) were considered. This classification guides the specification of all estimated models and ensures consistency across mean-based and quantile-based regressions. Table 1 presents descriptive statistics from the survey of 342 German farmers.

Table 1. Descriptive statistics – Farmer and farm characteristics (N = 342).

| Cat.[d] | Variable | Description | Mean | SD | Min | Max | German Avg. |
|---|---|---|---|---|---|---|---|
| | *Farmer characteristics* | | | | | | |
| 1 | *age* | Age of the farmer | 51.92 | 11.99 | 21 | 77 | 53 [a] |
| | | ≤ 35 years | 0.10 | - | 0 | 1 | 0.08 [a] |
| | | > 35 to 45 years | 0.14 | - | 0 | 1 | 0.17 [a] |
| | | > 45 to 55 years | 0.26 | - | 0 | 1 | 0.25 [a] |
| | | > 55 years | 0.49 | - | 0 | 1 | 0.51 [a] |
| 1 | *gender* | 1, if the farmer is male | 0.91 | - | 0 | 1 | 0.89 [a] |
| | | Importance of the goals for the farm management on a 7-point scale | | | | | |
| 4 | *goal_econ* | Economic goals (e.g., profit maximization, cost minimization, income security) | 6.03 | 1.01 | 1 | 7 | na |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 4 | *goal_ecol* | Ecological goals (e.g., environmental protection, biodiversity promotion, sustainable resource use) | 5.15 | 1.31 | 1 | 7 | na |
| 4 | *goal_soc* | Social goals (e.g., job satisfaction, work-life balance) | 5.57 | 1.19 | 1 | 7 | na |
| 1 | *highered* | 1, if the farmer has a degree in higher education (University and/or University of Applied Sciences) | 0.21 | - | 0 | 1 | 0.14 [a] |
| 4 | *risk* | Self-assessed risk attitude [c] | 5.44 | 2.08 | 0 | 10 | na |
| 4 | *successor* | 1, if farm succession has already been determined | 0.55 | - | 0 | 1 | 0.37 [a] |
| | *Farm characteristics* | | | | | | |
| 4 | *arable* | 1, if the farm has no livestock | 0.56 | - | 0 | 1 | 0.37 [a] |
| 2 | *arable_land* | Farm size in arable land | 137.67 | 152.85 | 7 | 1,800 | 62.76 [b] |
| | | < 50 hectare | 0.08 | - | 0 | 1 | 0.70 [b] |
| | | 50 to < 100 hectare | 0.41 | - | 0 | 1 | 0.16 [b] |
| | | 100 to < 200 hectare | 0.34 | - | 0 | 1 | 0.08 [b] |
| | | 200 to < 500 hectare | 0.14 | - | 0 | 1 | 0.04 [b] |
| | | > 500 hectare | 0.03 | - | 0 | 1 | 0.02 [b] |
| 3 | *orga* | 1, if the farm is managed part-time | 0.13 | - | 0 | 1 | 0.55 [a] |
| | | 1, if the farm is managed full-time | 0.78 | - | 0 | 1 | 0.45 |
| | | 1, if the farm is managed full-time with additional contracting services | 0.08 | - | 0 | 1 | na |
| 4 | *organic* | 1, if the farm is managed organic | 0.11 | - | 0 | 1 | 0.14 [a] |
| 4 | *red* | 1, if a part of the farm or the whole farm is located in a nitrate vulnerable zone under §13a DüV | 0.48 | - | 0 | 1 | na |
| 3 | *rental* | Share of rental land (% ) | 0.51 | 0.25 | 0 | 1 | 0.55 [a] |
| 2 | *region* | Farm location in Germany | | | | | |
| | | North (Mecklenburg-Western Pomerania, Lower Saxony, Schleswig-Holstein) | 0.32 | - | 0 | 1 | 0.20 [a] |
| | | South (Bavaria, Baden-Württemberg) | 0.31 | - | 0 | 1 | 0.46 [a] |
| | | East (Brandenburg, Saxony, Saxony-Anhalt, Thuringia) | 0.04 | - | 0 | 1 | 0.07 [a] |
| | | West (Hesse, North Rhine-Westphalia, Saarland, Rhineland-Palatinate) | 0.33 | - | 0 | 1 | 0.27 [a] |
| 2 | *soil_hetero* | Soil heterogeneity on a 7-point scale | 3.88 | 1.65 | 1 | 7 | na |
| 2 | *soil_quality* | Soil quality index | 45.14 | 16.39 | 0 | 97 | 62 [e] |

[a] German Farmers‘ Federation (2024)
[b] DESTATIS (2025)
[c] Self-assessment based on an 11-point scale following Michels et al. (2024): “In terms of your behavior on your farm, would you consider yourself a risk-seeking person or do you try to avoid risk?” 0 – risk-averse/ 10 – risk-seeking
[d] Category based on Pierpaoli et al. (2013). 1 = Socio-demographic, 2 = Competitive and contigent, 3 = Financial resources; 4 = Additional
[e] Bundesanstalt für Geowissenschaften and Rohstoffe (2026)
Cat. = Category; na = Not available; SD = Standard deviation; Avg. = Average

For the model estimation, the variables *orga* and *region* were simplified into binary indicators: one indicating whether the farm is managed part-time (*part_time*; 1 = part-time, 0 = otherwise), and another indicating whether the farm is located in the southern region of Germany (*south*; 1 = South, 0 = other regions).

## 3 Results and Discussion

### 3.1 Descriptive Results on Technology Adoption Intensity

On average, farms use approximately 8 technologies (mean = 7.92), with half of the farms using between 5 (first quartile) and 11 (third quartile) different technologies. The distribution appears slightly right-skewed, with a range from 0 technologies (minimum) to 22 technologies (maximum) (Table 2). The dispersion index (variance-to-mean ratio) of 2.20 indicates overdispersion in the data, suggesting that technology adoption rates are more variable than would be expected from a random Poisson process. This overdispersion justifies the use of negative binomial regression for analyzing factors affecting technology adoption rather than standard Poisson regression.

Table 2. Descriptive statistics – Technology adoption intensity (N = 342)

| Statistics | Value |
|---|---|
| Minimum | 0 |
| First Quantile | 5 |
| Median | 8 |
| Mean | 7.92 |
| Third Quantile | 11 |
| Maximum | 22 |
| Standard deviation | 4.18 |
| Variance | 17.47 |
| Variance-to-mean ratio (Dispersion index) | 2.20 |

### 3.2 Negative Binomial Regression Results

As shown in Table 2, the distribution of technology adoption intensity is overdispersed, with a variance-to-mean ratio of 2.20, violating the equidispersion assumption of the Poisson model. Accordingly, a negative binomial regression was adopted as the primary modeling approach. Following negative binomial regression model estimation, we conducted diagnostics to assess the validity and robustness of our results. First, we evaluated multicollinearity using Variance Inflation Factors (VIF) with all values falling well below the common threshold of 5, indicating no problematic multicollinearity among predictors. Second, the Q-Q plot of residuals showed reasonable alignment with normality in the central distribution but some deviation at the tails, suggesting the presence of potential outliers or influential observations. Third, to identify influential observations, we calculated Cook's Distance for each observation in the dataset. This analysis revealed several highly influential cases. To assess robustness, the negative binomial model was re-estimated after excluding these cases (sample size reduced from 342 to 322), yielding consistent coefficient directions and magnitudes for variables such as farmers' age, risk attitude, farm size, and succession status.

The results are shown in Table 3. It's crucial to emphasize that these relationships represent associations rather than causal effects. The robust negative binomial model indicates statistically significant associations between adoption intensity and farmers' age (variable age), risk attitude (risk), farm size (*arable_land),* succession status (*successor*), higher education (*highered*), organic farming (*organic*) and economic goal orientation (*econ_goal*). In contrast, several commonly cited factors, including gender (*gender*), environmental and social goals (*goals_ecol; goals_soc*), soil characteristics (*soil_quality; soil_characteristics*), part-time farming (*part_time*), land tenure (*rented*), regional location *(south*), farming without livestock (*arable*) and regulatory exposure (*red*), do not exhibit statistically significant mean effects and IRR coefficients close to 1, which indicates no meaningful relationship. While informative, these average associations may conceal heterogeneous relationships across the adoption distribution, motivating the subsequent quantile analysis.

Table 3. Robust negative binomial regression results for technology adoption intensity (Robust model, n = 322)

| Variable | Coefficient | IRR | 95% CI | p-value |
|---|---|---|---|---|
| *Intercept* | 1.199*** | 3.319 | [2.053; 5.398] | <0.001 |
| *Farmers' characteristics* | | | | |
| *age* | -0.007** | 0.993 | [0.989;0.997] | 0.001 |
| *gender* | 0.085 | 1.089 | [0.900;1.325] | 0.384 |
| *goal_econ* | 0.051* | 1.053 | [1.003;1.106] | 0.040 |
| *goal_ecol* | -0.010 | 0.989 | [0.952;1.028] | 0.581 |
| *goal_soc* | -0.002 | 0.977 | [0.940;1.017] | 0.259 |
| *highered* | 0.097$^{+}$ | 1.102 | [0.098;1.231] | 0.091 |
| *risk* | 0.085*** | 1.089 | [1.063;1.116] | <0.001 |
| *successor* | 0.175*** | 1.192 | [1.084;1.311] | <0.001 |
| *Farm characteristics* | | | | |
| *arable* | 0.042 | 1.043 | [0.947;1.149] | 0.391 |
| *arable_land* | 0.001*** | 1.001 | [1.0008;1.0014] | <0.001 |
| *part_time* | 0.017 | 1.018 | [0.883; 1.171] | 0.805 |
| *organic* | -0.152$^{+}$ | 0.859 | [0.733;1.004] | 0.059 |
| *rented* | <0.001 | 1.001 | [0.999;1.003] | 0.415 |
| *south* | 0.071 | 1.074 | [0.965;1.195] | 0.188 |
| *red* | 0.035 | 1.036 | [0.944;1.137] | 0.453 |
| *soil_hetero* | 0.016 | 1.017 | [0.988;1.046] | 0.266 |
| *soil_quality* | 0.001 | 1.001 | [0.998;1.004] | 0.493 |

Theta = 32.2; log-likelihood = -1633.014; McFadden Pseudo $R^2$ = 0.079; Nagelkerke Pseudo $R^2$ = 0.354
IRR = Incidence Rate Ratio; CI = Confidence Interval
*** p<0.001, ** p<0.01, * p<0.05, $^{+}$ p<0.10

### 3.3 Quantile Count Regression Results

Our quantile count regression analysis using the robust dataset (Table 4) reveals important heterogeneity in factors influencing agricultural technology adoption across different segments of the farming population, providing insights that would be obscured in traditional mean-based regression approaches.

*Variables with stable effects across the distribution*

Farmers' age (*age*) shows a consistently negative and statistically significant association with adoption intensity across all quantiles. Coefficients range from β = −0.052 to β = −0.064, indicating modest but meaningful decreases in adoption with increasing age. This stability suggests that age operates as a structural constraint on cumulative technology adoption rather than differentiating specific adopter groups. Each additional year of age corresponds to a downward shift of about 0.05–0.06 technologies in the conditional quantiles. Farmers' risk attitude (*risk*) exhibits one of the strongest and most stable associations with adoption intensity, with positive and statistically significant coefficients at every quantile. Estimates range from β = 0.537 at the 10th quantile to β = 0.653 at the median, indicating that a one-unit increase on the risk attitude scale (0–10) is associated with roughly 0.5–0.65 additional adopted technologies throughout the distribution. Farm size, measured by arable land (*arable_land*), shows a consistent and statistically significant positive association across all quantiles. Coefficients increase only slightly from β = 0.010 at Q10 to β = 0.012 at higher quantiles, indicating a stable relationship throughout the distribution. Given that arable land is measured in hectares, the coefficients imply approximately one to 1.2 additional technologies per 100 hectares across quantiles.

Table 4. Results of quantile count regression for technology adoption intensity (Robust model, n = 322)

| Variable | Q10 (10%) | Q25 (25%) | Q50 (50%) | Q75 (75%) | Q90 (90%) |
|---|---|---|---|---|---|
| *Intercept* | 1.610 | 0.676 | 1.867 | 3.858 | 4.17 |
| *Farmers' characteristics* | | | | | |
| *age* | -0.064** | -0.052** | -0.055* | -0.061* | -0.055* |
| *gender* | -0.674 | -0.622 | 0.039 | 1.234 | 2.117* |
| *goal_econ* | 0.094 | 0.351 | 0.395⁺ | 0.298 | 0.335 |
| *goal_ecol* | -0.029 | -0.093 | -0.113 | -0.093 | -0.096 |
| *goal_soc* | -0.024 | -0.052 | -0.171 | -0.199 | -0.085 |
| *highered* | 0.423 | 0.156 | 0.515 | 1.069 | 1.106⁺ |
| *risk* | 0.537** | 0.590*** | 0.653*** | 0.649*** | 0.601*** |
| *successor* | 0.711 | 0.959+ | 1.323* | 1.675** | 1.904*** |
| *Farm characteristics* | | | | | |
| *arable_land* | 0.010*** | 0.011*** | 0.012*** | 0.012*** | 0.012* |
| *arable* | -0.067 | 0.185 | 0.250 | 0.415 | 0.824⁺ |
| *organic* | -0.574 | -1.034⁺ | -1.685⁺ | -1.992⁺ | -1.913** |
| *part_time* | -0.144 | -0.146 | 0.523 | 0.691 | -0.096 |
| *red* | 0.814 | 0.289 | 0.016 | -0.044 | -0.238 |
| *rented* | -0.004 | -0.004 | <0.001 | 0.007 | 0.011 |
| *south* | 0.689 | 0.730 | 0.456 | 0.311 | 0.554 |
| *soil_hetero* | 0.189 | 0.221 | 0.140 | 0.104 | 0.205 |
| *soil_quality* | 0.001 | 0.013 | 0.022 | 0.009 | -0.010 |

Values show quantile regression coefficients (β) for the conditional quantiles of the number of adopted technologies (not IRR). Kolmogorov–Smirnov: 0.029 (p = 0.28). Cramér–von Mises: 0.041 (p = 0.26).
*** p<0.001, ** p<0.01, * p<0.05, ⁺ p<0.10

*Variables with increasing effects*

Farm succession (*successor*) reveals the most pronounced heterogeneity in the dataset, with a strong monotonic increase in effect size across quantiles. While the association is not statistically significant at the 10th quantile (β = 0.711), it becomes statistically significant at the 25th quantile (β = 0.959) and strengthens further toward higher quantiles (β = 1.675 at Q75; β = 1.904 at Q90). Overall, the effect nearly triples from low to high adopters (0.7 vs. 1.9 technologies). Organic farming (*organic*) shows consistently negative associations across all quantiles, with coefficients ranging from β = −0.574 at Q10 to β = −1.913 at Q90. Organic farms adopt approximately 0.6 to 2.0 fewer technologies than conventional farms, with the strongest negative associations observed among medium and high adopters. The status of an arable farm without livestock (*arable*) exhibits a clear monotonic increase across quantiles, from β = −0.067 at Q10 to β = 0.824 at Q90 (statistically significant). While no meaningful differences are observed among low adopters, specialized arable farms at high adoption levels use approximately 0.8 more technologies than non-specialized farms. Higher education (*highered*) displays a similar pattern of monotonic increase, with coefficients rising from β = 0.423 at Q10 to β = 1.106 at Q90 (statistically significant at Q90). Having a university degree is associated with approximately 0.4 to 1.1 additional technologies, but the effect is concentrated among farms at the highest adoption levels.

*Variables with sign-reversals*

Gender (*gender*) exhibits a pronounced sign reversal across the distribution. At lower quantiles, male farmers are associated with fewer adopted technologies (β = −0.674 at Q10; β = −0.622 at Q25), the effect crosses zero at the median, and becomes increasingly positive at higher quantiles (β = 1.234 at Q75; β = 2.117 at Q90, statistically significant). This shift from approximately -0.6 technologies at low adoption levels to +2.1 technologies at high adoption levels represents one of the most striking examples of heterogeneity in the dataset. Designation as a nitrate-vulnerable zone (*red*) also shows a pattern of sign reversal across the distribution. The coefficient is positive and substantial at the 10th quantile (β = 0.814), declines through the middle quantiles (β = 0.289 at Q25; β = 0.016 at Q50), and becomes negative at higher quantiles (β = -0.044 at Q75; β = -0.238 at Q90). Although none of these effects are statistically significant, the clear directional shift from positive to negative suggests heterogeneous responses to regulatory pressure.

*Variables with non-monotonic effects*

Economic goals (goals_econ) show an inverted U-shaped pattern across quantiles, with coefficients rising from β = 0.094 at Q10 to a peak of β = 0.395 at Q50 (statistically significant), then declining to β = 0.298-0.335 at higher quantiles. Part-time farming (*part_time*) shows negative coefficients at lower quantiles (β = -0.144 at Q10-Q25), which become positive at middle to upper-middle quantiles (β = 0.523 at Q50; β = 0.691 at Q75), and returning to negative at Q90 (β = -0.096). Ecological goals (*goals_ecol*) and social goals (*goals_soc*) show consistently small negative coefficients across all quantiles (ranging from approximately β = -0.02 to β = -0.20), with no statistically significant effects and no clear monotonic pattern. Soil heterogeneity (*soil_hetero*), soil quality (*soil_quality*) exhibit no statistically significant associations and no systematic patterns across quantiles. Coefficients remain close to zero throughout the distribution, indicating that these farm characteristics do not meaningfully differentiate adoption intensity.

*Comparison with mean-based estimates*

When comparing the quantile count regression results (Table 4) with the robust negative binomial model (Table 3), clear differences emerge in how factors influence technology adoption across the distribution. While the negative binomial regression identifies associations at the conditional mean, the quantile approach uncovers substantial heterogeneity that remains hidden in the mean-based specification.

For variables with stable effects across quantiles (*age*, *risk*, *arable_land*), the mean-based estimates from the negative binomial model provide reasonable approximations of the effects throughout the distribution. In these cases, the direction and relevance of effects are broadly consistent across quantiles, suggesting that average relationships are informative.

However, for variables with strong heterogeneity (e.g. successor) the mean estimates obscure critical differences between low and high adopters. The negative binomial model estimates a modest mean effect for succession (IRR = 1.192), but the quantile analysis reveals that this average mask a tripling of the effect from low to high adopters (0.7 vs. 1.9 additional technologies).

Similarly, variables that show no statistically significant mean effects in the negative binomial model (e.g. *gender*) are revealed by the quantile analysis to have substantial effects specifically among high adopters, effects that are diluted in the mean-based specification. Conversely, economic goals (*goals_econ*) appear statistically significant in the mean-based model but the quantile analysis shows this effect is concentrated at the median and not generalizable across the distribution.

Most importantly, variables exhibiting non-monotonic patterns or sign reversals cannot be adequately captured by mean-based models, which estimate a single average effect. Even where individual quantile estimates do not reach conventional levels of statistical significance, the systematic variation in sign and magnitude across the distribution suggests meaningful heterogeneity that is averaged out in mean-based approaches.

## 4 Concluding Remarks

This study addressed two research gaps in PAT adoption. Methodologically, it demonstrated that mean-based count models mask substantial heterogeneity in how determinants operate across the adoption distribution. Empirically, it provided contemporary evidence from German arable farming on the adoption intensity across a comprehensive portfolio of 32 PAT. While the robust negative binomial model identifies clear associations for age, risk attitude, farm size, and farm succession at the mean, the robust quantile count regression reveals that these relationships are far from uniform. More generally, the results demonstrate that conclusions about “what drives technology adoption” are inherently conditional on the position of farms within the adoption distribution. For future research it could be of interest to develop a typology of farmers based on the used technologies by applying a cluster analysis. Future research could also complement our results by weighting technologies according to complexity or investment requirements.

## References


Ammann, J., Umstätter, C., & El Benni, N. (2022). The adoption of precision agriculture enabling technologies in Swiss outdoor vegetable production: a Delphi study. *Precision Agriculture*, *23*(4), 1354-1374. https://doi.org/10.1007/s11119-022-09889-0

Barnes, A. P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., ... & Gómez-Barbero, M. (2019a). Exploring the adoption of precision agricultural technologies: A cross regional study of EU farmers. *Land use policy*, *80*, 163-174. https://doi.org/10.1016/j.landusepol.2018.10.004

Barnes, A. P., Soto, I., Eory, V., Beck, B., Balafoutis, A. T., Sánchez, B., ... & Gómez-Barbero, M. (2019b). Influencing incentives for precision agricultural technologies within European arable farming systems. *Environmental science & policy*, *93*, 66-74. https://doi.org/10.1016/j.envsci.2018.12.014

Basso, B., & Antle, J. (2020). Digital agriculture to design sustainable agricultural systems. *Nature sustainability*, *3*(4), 254-256. https://doi.org/10.1038/s41893-020-0510-0

Blasch, J., van der Kroon, B., van Beukering, P., Munster, R., Fabiani, S., Nino, P., & Vanino, S. (2022). Farmer preferences for adopting precision farming technologies: a case study from Italy. *European Review of Agricultural Economics*, *49*(1), 33-81. https://doi.org/10.1093/erae/jbaa031

BMLEH (2025). Digitalisierung in der Landwirtschaft. Federal Ministry of Agricultural, Food and Regional Identity. Online available at: https://www.bmleh.de/DE/themen/digitalisierung/digitalisierung-landwirtschaft.html

Bundesanstalt für Geowissenschaften und Rohstoffe (2026): Arable yield potential of soils in Germany. Online available at: https://www.deutsche-rohstoffagentur.de/DE/Themen/Boden/Nachhaltiges-Bodenmanagement/Bodenfunktionen-Bodenempfindlichkeiten/Ertragspotential/Ertragspotential_node.html

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data* (No. 53). Cambridge University Press.

Chavas, J. P., Nauges, C. (2020). Uncertainty, learning, and technology adoption in agriculture. *Applied Economic Perspectives and Policy*, *42*(1), 42–53. https://doi.org/10.1002/aepp.13003

Cook, R. D. (1977). Detection of influential observation in linear regression. *Technometrics*, *19*(1), 15-18. https://doi.org/10.1080/00401706.1977.10489493

Daberkow, S. G., & McBride, W. D. (2003). Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the US. *Precision agriculture*, *4*(2), 163-177. https://doi.org/10.1023/A:1024557205871

Damasceno, R., Carrer, M. J., Pagliuca, L. G., Vinholis, M. D. M. B., & Souza Filho, H. M. D. (2026). What drives the adoption of digital technology? An empirical assessment of multiple technology adoption by soybean farmers in São Paulo, Brazil. *Precision Agriculture*, *27*(1), 7. https://doi.org/10.1007/s11119-025-10295-5

DESTATIS (2025). Landwirtschaftliche Betriebe mit Ackerland, Landwirtschaftlich genutzte Fläche: Deutschland, Jahre, Ackerkulturen, Größenklassen des Ackerlandes. CODE 41271-0005. *Deutsches Statistisches Bundesamt*. Federal Statistical Office of Germany.

European Commission (2025). Digitalising the EU agricultural sector. Online available at: https://digital-strategy.ec.europa.eu/en/policies/digitalisation-agriculture

Feder, G., Umali, D. (1993). The adoption of agricultural innovations. A Review. *Technological Forecasting and Social Change*, *43*, 215 – 239. https://doi.org/10.1016/0040-1625(93)90053-A

Finger, R., Swinton, S. M., El Benni, N., Walter, A. (2019). Precision farming at the nexus of agricultural production and the environment. *Annual Review of Resource Economics*, *11*, 313-335. https://doi.org/10.1146/annurev-resource-100518-093929

Finger, R. (2023). Digital innovations for sustainable and resilient agricultural systems. *European Review of Agricultural Economics*, *50*(4), 1277-1309. https://doi.org/10.1093/erae/jbad021

Gabriel, A., & Gandorfer, M. (2023). Adoption of digital technologies in agriculture—an inventory in a european small-scale farming region. *Precision Agriculture*, *24*(1), 68-91. https://doi.org/10.1007/s11119-022-09931-1

German Farmers‘ Federation (2024). Situationsbericht 24/25. Deutscher Bauernverband (2024) Online available at: https://www.situationsbericht.de/

Giua, C., Materia, V. C., & Camanzi, L. (2022). Smart farming technologies adoption: Which factors play a role in the digital transition?. *Technology in Society*, *68*, 101869. https://doi.org/10.1016/j.techsoc.2022.101869

Greene, W. H. (2003). *Econometric analysis*. New Jersey: Pearson Education.

Hanson, E. D., Cossette, M. K., & Roberts, D. C. (2022). The adoption and usage of precision agriculture technologies in North Dakota. *Technology in Society*, *71*, 102087. https://doi.org/10.1016/j.techsoc.2022.102087

Ingram, J., Maye, D., Bailye, C., Barnes, A., Bear, C., Bell, M., Cutress, D., Davis, L., ... Wilson, L. (2022). What are the priority research questions for digital agriculture?. *Land Use Policy*, *114*, 105962. https://doi.org/10.1016/j.landusepol.2021.105962

Isgin, T., Bilgic, A., Forster, D. L., & Batte, M. T. (2008). Using count data models to determine the factors affecting farmers' quantity decisions of precision farming technology adoption. *Computers and electronics in agriculture*, *62*(2), 231-242. https://doi.org/10.1016/j.compag.2008.01.004

ISPA (2025). Economics Community – Justification and Interest/scope. Online available at: https://www.ispag.org/communities/Economics

Kehl, C., Meyer, R., Steiger, S. (2021). Digitalisierung der Landwirtschaft: gesellschaftliche Voraussetzungen, Rahmenbedingungen und Effekte. TAB-Arbeitsbericht Nr. 194.

Kolady, D. E., Van der Sluis, E., Uddin, M. M., & Deutz, A. P. (2021). Determinants of adoption and adoption intensity of precision agriculture technologies: evidence from South Dakota. *Precision Agriculture*, *22*(3), 689-710. https://doi.org/10.1007/s11119-020-09750-2

Kroupová, Z. Ž., Aulová, R., Rumánková, L., Bajan, B., Čechura, L., Šimek, P., & Jarolímek, J. (2025). Drivers and barriers to precision agriculture technology and digitalisation adoption: Meta-analysis of decision choice models. *Precision Agriculture*, *26*(1), 17. https://doi.org/10.1007/s11119-024-10213-1

Lohr, S. L. (2021). *Sampling: design and analysis*. Chapman and Hall/CRC, New York. https://doi.org/10.1201/9780429298899

Michels, M., Rieling, J. A., & Musshoff, O. (2024). Risk attitude, innovativeness, and financial literacy—A cross-occupational comparison of German farmers and foresters. *Q Open*, *4*(1), qoae007. https://doi.org/10.1093/qopen/qoae007

Michels, M., & Mußhoff, O. (2025a). Exploring barriers to map-based variable-rate nitrogen fertilization adoption: A COM-B framework analysis of German farmers. *Environmental Research Communications*. DOI 10.1088/2515-7620/ae256e

Michels, M., & Mußhoff, O. (2025b). Status Quo der Digitalisierung auf Ackerbaubetrieben in Deutschland. *Berichte über Landwirtschaft-Zeitschrift für Agrarpolitik und Landwirtschaft*. https://doi.org/10.12767/buel.v103i2.543

Michels, M., von Hobe, C. F., & Musshoff, O. (2020). A trans-theoretical model for the adoption of drones by large-scale German farmers. *Journal of rural studies*, *75*, 80-88. https://doi.org/10.1016/j.jrurstud.2020.01.005

Miller, N. J., Griffin, T. W., Bergtold, J., Ciampitti, I. A., & Sharda, A. (2017). Farmers' adoption path of precision agriculture technology. *Advances in Animal Biosciences*, *8*(2), 708-712. https://doi.org/10.1017/S2040470017000528

Mozambani, C. I., de Souza Filho, H. M., Vinholis, M. D. M. B., & Carrer, M. J. (2023). Adoption of precision agriculture technologies by sugarcane farmers in the state of São Paulo, Brazil. *Precision Agriculture*, *24*(5), 1813-1835. https://doi.org/10.1007/s11119-023-10019-7

Ogundari, K., Bolarinwa, O. D. (2018). Impact of agricultural innovation adoption: a meta-analysis. *Australian Journal of Agricultural and Resource Economics*, *62*(2), 217-236. https://doi.org/10.1111/1467-8489.12247

Paustian, M., & Theuvsen, L. (2017). Adoption of precision agriculture technologies by German crop farmers. *Precision agriculture*, *18*(5), 701-716. https://doi.org/10.1007/s11119-016-9482-5

Pathak, H. S., Brown, P., Best, T. (2019). A systematic literature review of the factors affecting the precision agriculture adoption process. *Precision Agriculture*, *20*(6), 1292-1316. https://doi.org/10.1007/s11119-019-09653-x

Paxton, K. W., Mishra, A. K., Chintawar, S., Roberts, R. K., Larson, J. A., English, B. C., ... & Martin, S. W. (2011). Intensity of precision agriculture technology adoption by cotton producers. *Agricultural and Resource Economics Review*, *40*(1), 133-144. https://doi.org/10.1017/S1068280500004561

Pierpaoli, E., Carli, G., Pignatti, E., Canavari, M. (2013). Drivers of precision agriculture technologies adoption: a literature review. *Procedia Technology*, *8*, 61-69. https://doi.org/10.1016/j.protcy.2013.11.010

Rogers, E. M. (2010): Diffusion Of Innovations, Vol. 4., Free Press, London.

Shockley, J. M., Dillon, C. R., & Stombaugh, T. S. (2011). A whole farm analysis of the influence of auto-steer navigation on net returns, risk, and production practices. *Journal of Agricultural and Applied Economics*, *43*(1), 57-75. https://doi.org/10.22004/ag.econ.100640

Tamirat, T. W., Pedersen, S. M., & Lind, K. M. (2018). Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. *Acta Agriculturae Scandinavica, Section B—Soil & Plant Science*, *68*(4), 349-357. https://doi.org/10.1080/09064710.2017.1402949

Tey, Y. S., & Brindal, M. (2022). A meta-analysis of factors driving the adoption of precision agriculture. *Precision Agriculture*, *23*(2), 353-372. https://doi.org/10.1007/s11119-021-09840-9

Thompson, N. M., Bir, C., Widmar, D. A., & Mintert, J. R. (2019). Farmer perceptions of precision agriculture technology benefits. *Journal of Agricultural and Applied Economics*, *51*(1), 142-163. https://doi.org/10.1017/aae.2018.27

van der Burg, S., Giesbers, E., Bogaardt, M. J., Ouweltjes, W., & Lokhorst, K. (2024). Ethical aspects of AI robots for agri-food; a relational approach based on four case studies. *Ai & Society*, *39*(2), 541-555. https://doi.org/10.1007/s00146-022-01429-8

Walter, A., Finger, R., Huber, R., Buchmann, N. (2017). Opinion: Smart farming is key to developing sustainable agriculture. *Proceedings of the National Academy of Sciences*, *114*(24), 6148-6150. https://doi.org/10.1073/pnas.1707462114