Q Open, 2024, **4**, qoae032
https://doi.org/10.1093/qopen/qoae032
Advance access publication date: 29 November 2024
Article

Innovation behavior and sustainability performance: Empirical evidence on the farming sector

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Received: October 4, 2023. **Accepted:** November 26, 2024

Abstract

Modern agriculture faces the challenge of supplying a growing world population with high-quality products while minimizing negative environmental and social impacts of its production and ensuring economic viability. Innovation is often considered key to achieving these goals, but its effectiveness remains an empirical question. Our study investigates how the adoption of new technologies affects farm sustainability with respect to its economic and environmental and one indicator of the social dimension. We use a comprehensive dataset on Dutch dairy and arable farms comprising financial and environmental data along with data on innovation activity that allows for a differentiated view on the effects of various innovations. First-difference estimations reveal that simultaneous positive effects across all three sustainability dimensions are not guaranteed. For example, new buildings show a positive association with economic indicators of dairy farms, but the associations between other innovation activities and other economic, environmental, and the social indicator remain inconclusive.

Keywords: New technologies, Productivity, Environment, Emissions, Dairy farms, Arable farms

JEL codes: Q56, Q16, Q12

1. Introduction

Agriculture not only faces the challenge of providing high-quality food, feed, and fiber but also has to meet increasingly ambitious requirements regarding the environmental impact of its production. This is most relevant considering that the agricultural sector and especially the livestock sector are major contributors to environmental problems such as global warming (Leip et al. 2010; Gerber et al. 2013; Grossi et al. 2019). The public discussion focuses not only on agricultural pollutants and resource efficiency, that is, the environmental pillar of sustainability, but also on the social pillar of sustainability of agricultural production. Foremost, concerns over animal welfare and possible ways towards more animal-friendly production are voiced (Lusk 2011).

Finally, the third pillar of sustainability, the economic viability of farms must be taken into account. Farmers traditionally act as price takers and face competition not only from within country borders but also by foreign competitors due to increasing international trade of agricultural goods. Therefore, solely focusing on the farm's environmental performance seems not sufficient considering that a farm is not able to contribute to environmentally friendly production if it is not economically viable in the medium to long run (Läpple and Thorne 2019). That is, the focus must be on all three pillars of sustainability—social, environmental, and economic (Pretty et al. 2010; Llonch et al. 2017; Arvidsson Segerkvist et al. 2020).

To some extent, synergies between different sustainability dimensions can be assumed. For example, input savings per unit of output can imply greater profitability for farmers and also savings in pollutants per unit of output (Gerber et al. 2011; Zehetmeier et al. 2014; Salois 2015; Zehetmeier et al. 2020). Also, the health status of an animal herd can be expected to be positively related to its productivity (Henningsen et al. 2018). In other cases, trade-off situations might be created, for example, cage systems for laying hens score low on animal welfare but emit less particulate matter (Shepherd et al. 2015), by the existence of competing animal breeding goals (Balaine et al. 2020), or when balancing productivity and animal welfare in intensive farming systems (Llonch et al. 2017).

Therefore, improving farm production with respect to all the three dimensions appears as a core challenge for modern farming. The development and successful adoption of innovations that allow farmers to create 'win–win–win' situations with respect to all three sustainability pillars (Leip et al. 2010; Balafoutis et al. 2017; Llonch et al. 2017; Tullo, Finzi, and Guarino 2019; Balaine et al. 2020; Herrero et al. 2020; Simitzis et al. 2022) is of major interest to farmers, policymakers and society. For example, it is acknowledged that new digital technologies have the potential to increase efficiency of farming operations by more precise input use, entailing also economic benefits for farmers (Finger 2023). In the Common Agricultural Policy strategic plans for the upcoming years, the European Commission (2023) highlights the central role of adopting innovative practices and technologies in improving productivity and tackling environmental and animal welfare challenges. To this end, farmers are supported financially when investing in improved capital goods. However, to what extent the adoption of innovations finally contributes to all sustainability dimensions is foremost an empirical question.

As Balaine et al. (2020) remark, there is a general lack of empirical literature that aims at identifying technologies that are able to create win–win or even triple-win situations. In our study, we examine which and to what extent farm-level innovations affect the sustainability performance of farms with respect to the economic, the environmental, as well as one indicator of the social pillar. The study employs a rich and unique panel dataset on Dutch dairy and arable farms that contains comprehensive information on the innovation activity of individual farms as well as information on core indicators for environmental and social sustainability of farming operations. The data allow us to draw conclusions with respect to several environmental impact categories as well as the effects of multiple categories of innovation. Because financial information is included, the data additionally enable us to construct precise measures of economic farm performance. By employing suitable control variables, we adequately address potential bias in parameter estimates due to confounding farm characteristics.

Several recent antecedents of our study exist in the literature. Sauer and Vrolijk (2019) analyze the effect of innovation activity on productivity for Dutch dairy and arable farms. They partly find positive effects for product, process, and organizational innovations with respect to labor, cow, and land productivity. Following a similar research question, Läpple and Thorne (2019) study the impact of innovation on the economic sustainability of Irish dairy farms and to a certain extent identify positive effects on land productivity, profitability, and market orientation. In contrast to these studies, Balaine et al. (2020) also take into account the environmental and social dimension of sustainability. They examine the impact of adoption of milk recording by Irish dairy farms on a variety of economic, environmental, and animal welfare indicators. They find that adoption of the innovation improved the economic and social dimensions (animal welfare) but left the environmental dimension unaffected.

Other studies focus on the link between economic and environmental performance of farms. Zehetmeier et al. (2020) aim at identifying performance measures that link greenhouse gas emissions and profitability of dairy farms in Germany. For example, they identify feed use efficiency as an important indicator of both greenhouse gas emissions and farm profitability, implying that technologies or changes in farm management targeting this variable could generate synergies between environmental and economic goals. Dolman, Vrolijk, and Boer (2012) show for fattening pig farms that there is a high variation in economic, environmental, and societal performance among farms and that farm characteristics related to scale positively affect economic and environmental performance. With a similar dataset as ours, Ang, Kerstens, and Sadeghi (2023) examine the relationship between greenhouse gas intensity and energy productivity for Dutch dairy farms. Counterintuitively, they find a positive relationship between the two.

The next section explores the link between environmental and economic performance from a theoretical perspective. In the subsequent section, the data and the econometric strategy are discussed. The last two sections separately discuss the results for the dairy and arable farms and conclude with policy and management implications.

2. Conceptual framework and empirical model

2.1 Productivity and 'environmental productivity'

In the following we want to show that prominent indicators of economic and environmental farm performance are related but not identical. One widely accepted measure for the economic performance of decision-making units is productivity, and a classical definition of total factor productivity starts out from a production function (van Beveren 2012),

$$Q_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} E_{it}^{\gamma} M_{it}^{\delta} \tag{1}$$

and, hence,

$$A_{it} = \frac{Q_{it}}{K_{it}^{\alpha} L_{it}^{\beta} E_{it}^{\gamma} M_{it}^{\delta}} \tag{2}$$

with Q as the production output, $K, L, E,$ and M as production inputs (capital including land, labor, energy, and intermediates, respectively) of farm i at time t, and α, β, γ, and δ as the corresponding output elasticities. A accounts for differences in technical efficiency between farms and can be seen as identical to total factor productivity in the absence of technical change and variable returns to scale (van Beveren 2012). This definition illustrates that productivity, A_{it}, depends not only on the amounts of inputs consumed in production but also on their relative importance for production (and the substitutional relations between them) because aggregate input is formed by a geometric mean with the corresponding output elasticities as weights (which sum to one with constant returns to scale). As remarked by an anonymous reviewer, productivity differences can also arise because of differing quality in inputs. Depending on whether input quality is included in measurement of input quantity, this might or might not be reflected in the productivity measure outlined in Equation (2). Because input quality is not measured in our data, we will assume that inputs of similar quality are used. Consequently, a proportional reduction in capital use, for example, will result in a smaller increase in total factor productivity than the same proportional reduction in labor, if $\alpha < \beta$.

A common measure for the environmental impacts of production expresses undesirable by-products as a proportion of the amount of desirable output produced. For example, we can define greenhouse gas emission intensity (GI) as

$$GI_{it} = \frac{CO_2eq_{it}}{Q_{it}}, \tag{3}$$

that is, greenhouse gas emissions in CO_2 equivalents per unit of output (Gerber et al. 2013). Greenhouse gas emissions and other environmental impacts are related to the amount of input use—for example, a share of fertilizer leaked to groundwater or converted to nitrous oxide, or dairy cows emitting a certain amount of methane dependent on the feed rations. Accordingly, environmental impacts are often assessed by the use of emission factors assigned to specific input categories (e.g. Zehetmeier et al. 2014). Emission intensity can then be estimated as

$$GI_{it} = \frac{\theta_k K_{it} + \theta_l L_{it} + \theta_e E_{it} + \theta_m M_{it}}{Q_{it}}, \tag{4}$$

with θs as (aggregated) emission factors. By resembling the reciprocal of Equation (2), this definition illustrates that GI is inversely related to (total factor) productivity. However, the key difference between the two measures is the different weights used for input aggregation as well as the functional form (i.e. potential substitutional changes along the production function assumed). Therefore, the two measures are not directly inversely related. This principle generalizes also to less restrictive functional forms than the Cobb-Douglas used for illustration here. For example, labor input might play a crucial role in production, but labor is typically not associated with an emission burden. Consequently, productivity changes that enable input savings only with respect to labor would, by definition, not translate into a reduced environmental impact of the farm products. This emphasizes that an economic indicator solely based on total factor productivity as defined by Equation (2) is not a sufficient indicator for the environmental performance of individual farms. Although the two presented measures are related, the degree to which both are impacted by innovations likely depends on farmers' motivation for adopting them. While profitability-oriented innovations can have a positive side effect for the environmental performance as illustrated, it cannot be ruled out that some innovations are adopted with the primary goal of improved environmental performance (e.g. as a response to stricter environmental regulations).

The relationship between indicators of the social sustainability dimension and economic indicators is less straightforward as compared to the case of total factor productivity and greenhouse gas intensity showcased here. As already mentioned, the relation of those variables among each other or their association with other sustainability dimensions might be positive, negative, or non-monotonous (Shepherd et al. 2015; Llonch et al. 2017; Henningsen et al. 2018; Balaine et al. 2020). For the indicator for animal welfare used in our study, we can expect a positive relationship between the animal welfare status and productivity (Pérez-Méndez, Roibás, and Wall 2020). In this sense, animal welfare can be regarded as an important production factor included in A of Equation (1).

2.2 Stylized model of innovation effects and empirical implementation

Continuing from Equation (1), we assume that the farm's level of total factor productivity A_{it} is influenced by its technology level, time-invariant farm-specific factors, and regional and yearly influences, as well as random shocks. Assuming a linear function, this relationship can be expressed as

$$A_{it} = \beta_0 + \beta_1 tech_{it} + \sum_{m=1}^{M} \gamma_m region_{im} + \sum_{s=1}^{T} \delta_s year_{st} + \sum_{k=1}^{K} \theta_k z_{ikt} + a_i + v_{it}, \tag{5}$$

where $year_{st}$ is an indicator variable equal to one if $s = t$, and zero otherwise. The variable $tech$ is the technology status of the farm (i.e. the aggregate of the production techniques currently employed by the farm) (similar to the notion of a firm's knowledge stock as described in Griliches 1998). This variable is not directly observed in our dataset but can be defined as

$$tech_{it} = tech_{it-1} + inno_{it}, \tag{6}$$

that is, last year's technology status plus the introduction of a new production technique (*inno*, which is observed in our data), which augments the technology status of the farm. Equation (5) also contains a set of locational (i.e. regional) and time-related (i.e. yearly) indicators, as well as their interactions. Time-invariant regional effects stem from time-invariant differences in environmental conditions. Regional-invariant yearly effects that are common to all farms in the sample might be generated by weather influences, whereas time–region (variant) interactions absorb regional differences in these yearly effects. a_i contains unobserved time-invariant, farm-specific factors, such as the farmer's average level of management ability or natural conditions such as soil quality. z_{ikt} are time-variant and farm-specific factors that can be explained by changes in management quality. Finally, v_{it} is an idiosyncratic error term.

Estimation of Equation (5) by simple ordinary least squares would be invalidated by the unobserved factors contained in a_i. It must be considered that, for example, the average farmer's management ability influences both the farm's productivity and the decision on modernizing and maintaining the farm's technology status. Several modelling options exist to account for this potential endogeneity. We chose the first-difference transformation to estimate Equation (5). Compared to the within transformation, this estimation strategy tends to be more efficient when v_{it} are serially correlated (Wooldridge 2002). For many of the dependent variables in our models, we cannot rule out that the errors are serially correlated due to path dependency in the dependent variable. Additionally, the first-difference transform offers an intuitive model interpretation in terms of growth of the dependent variable. If both sides of Equation (5) are first differenced, we arrive at our empirical model represented by:

$$\dot{A}_{it} = \beta_1 \boldsymbol{inno}_{it} + \beta_2 \boldsymbol{inno}_{it-1,t-2} + \gamma \boldsymbol{region}_i + \delta \dot{\boldsymbol{year}}_{st} + \theta \dot{\boldsymbol{z}}_{it} + \dot{v}_{it}, \tag{7}$$

where a dot indicates a change in the respective variable relative to the previous year (e.g. $\dot{A}_{it} = A_{it} - A_{it-1}$). Because *inno* is defined as the change in the technology status (Equation 6), only *inno* remains in differenced Equation (7). Deviating from the original model definitions in Equations (5) and (6), additional (binary) innovation indicators are introduced in the vector $\boldsymbol{inno}_{it-1,t-2}$, taking the value of one if an innovation was introduced in $t-1$ or $t-2$. By this, Equation (6) is modified such that the contemporaneous adjustment of the technology status is influenced by not only this year's, but also past innovation activity. The assumption behind this model formulation is that innovations might cause a dip in the farm's economic and/or environmental performance in the year of introduction due to necessary adjustments in farm management as well as required time to learn the efficient use of the new techniques. The innovation is then expected to induce sustained growth in performance over the following years. Hence, we assume lagged effects by innovation of up to two periods based on the findings by Sauer and Vrolijk (2019), who conclude on significant two-period lagged effects by innovation on farms' productivity for a similar dataset as employed in our study. In addition, Diederen, van Meijl, and Wolters (2002) as well as Sauer and Latacz-Lohmann (2015) also report lagged effects by innovation and investments. Graphically, this model can then be illustrated as shown in Fig. 1. Furthermore, region dummy variables would drop out by first differencing. However, we keep them as control variables in Equation (7).

To measure economic or environmental performance at farm level, we do not only employ partial productivity, technical efficiency, and intensity (such as cows or hectares per

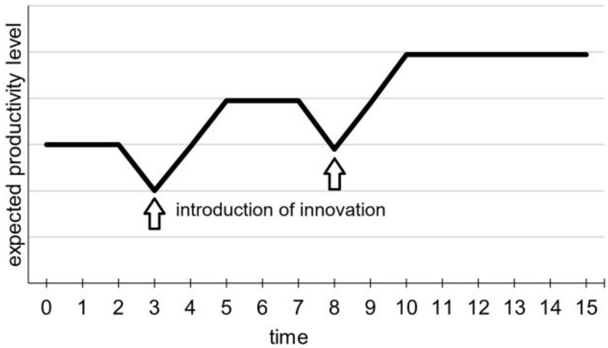

Figure 1. Assumed innovation effects.

worker) measures but also sustainability indicators. For the sake of brevity, in the following explanations the model setup will be exemplary discussed using a (partial) productivity measure as the dependent variable in the regression models.

In Equation (7), $inno_{it}$ represents a vector of dummy variables indicating whether the farmer introduced an innovation (related to the various innovation categories as, e.g. product innovation) in period t. Accordingly, $inno_{it-1,t-2}$ contains dummy indicating whether these innovations were introduced in either of the two preceding periods. The data do not indicate whether multiple innovations within a specific category were introduced by an individual farm for a given year (inno should be a count variable >1 in those cases). Given the relatively low share of farms reporting the introduction of an innovation per year, it is plausible that this would be the case for only few observations, and we deem this not to be a source of relevant measurement error. To account for region-specific and yearly shocks, we include sets of region and year-related dummies in the vectors $region_i$ and $year_t$. Additional control variables are included in z_{it} as discussed below, and finally v_{it} represents a random error term.

Although endogeneity stemming from the time-invariant effect a_i is controlled for, attention must be paid to unobserved time-variant factors that possibly affect the farmer's innovation decisions and dependent variables alike. Most prominently, these might be favorable production or market conditions that lead to higher productivity and profitability and hence provide additional financial resources that can be invested in new farm equipment. However, for example, temporal variation in milk prices and weather conditions are usually highly correlated across farms, especially if the farms are located close to each other, as it is the case for our dataset. Therefore, we can plausibly assume that these effects are controlled for by the year and region-related dummy variables considered in the model.

Additional control variables contained in the vector z_{it} proxy remaining potential sources of endogeneity. The (change in the) standard output of the farm is included as a proxy of farm size because this might change over time, for example, when farmers rent or buy additional land, or expand their dairy herd by investing in new animal housing. Further, we include the change in the binary variable indicating organic production to account for switches between production systems. A switch from organic to conventional production or vice versa might imply the introduction of new production techniques and likely affects farm productivity and environmental performance. This variable is only used for dairy farms because switches did not occur for arable farms. The degree of specialization (share of milk or crop revenue in total revenue for dairy or crop farms, respectively) is considered to account for assumed differences in productivity growth for highly specialized farms. Additional control variables are included in the regression models to proxy differences in farm management characteristics across farms and time: We consider the expenditures for training per year and farm, as well as the age of the farmer (not difference-transformed) in a linear and non-linear (i.e. squared) form to capture a possible U-shaped or inverse U-shaped productivity pattern with respect to the farm manager's age. Based on the farm manager's recorded age, we further build a dummy variable assuming the value one if a new farm manager has taken over farm operations in the respective year (equal to one if the birth year of the manager is different from the preceding year). An additional binary variable ('no successor') takes the value of one if the farm manager's age is above 60 and there is no indication for the presence of a younger farm manager. This variable is meant to capture farms without a farm successor that might soon exit the market and are potentially characterized by lower productivity growth rates and lower probability of introducing costly innovations or investments in general due to a shorter time perspective of farm investments.

Our identification strategy essentially constitutes a two-way fixed effects approach, assuming that important sources of endogeneity are controlled for by considering both time and farm fixed effects. Additionally, with the described additional covariates controlling for other potentially important, time-variant sources of endogeneity, we are confident that critical sources of endogeneity are taken into account and potential bias is effectively reduced. If residual endogeneity due to time-varying unobservables would still be of concern, the likely direction of the bias would be upwards. For example, some external shock could induce the farmer to attain higher economic or environmental performance, and at the same higher profits can be used to update farm machinery, without there being a direct meaningful relationship between innovation activity and farm performance. However, as can be seen later, such an upwards bias is not a general concern for our results.

An alternative to our strategy is an instrumental variable approach, which we ruled out because of the lack of a suitable instrument in our data. This includes using lags as instruments as in a generalized methods of moments estimation (Blundell and Bond 2000), whose robustness has been questioned when temporal dynamics in the unobservables cannot be ruled out (Bellemare, Masaki, and Pepinsky 2017).

3. Data and indicators

The data for this empirical study were obtained from the Dutch farm accountancy data network (FADN) from Wageningen Economic Research. The Dutch FADN contains a much broader set of sustainability indicators compared to EU FADN (Vrolijk, Poppe, and Keszthelyi 2016). The dataset combines financial accounts data, farm-specific sustainability indicators, and data from specialized surveys on innovation behavior. We focus on specialized dairy and arable farms, which we analyze using separate estimations. The farm classification follows the official Dutch classification system ('NSO'), which considers farms with at least 67 per cent of standard output being generated by one activity to be specialized in that activity. The unbalanced panel spans the period 2008–17 with a total of more than 2,500 observations for dairy farms and 1,000 observations for arable farms (see Tables 1 and 2). Fewer observations had to be used in the estimations due to missing values and data gaps, as indicated in the estimation output tables presented below.

3.1 Innovation data

Data on farms' innovation activity stem from the annual 'innovation survey' focusing on factors and characteristics of farms' innovation behavior (https://www.narcis.nl/research/RecordID/OND1344048; https://www.agrofoodportal.com/ThemaResultaat.aspx?subpubID=2232&themaID=2277). Farms are asked about the number of newly introduced products, processes, or new forms of business organization, along with information on innovation spending (only for process innovation) or innovation cooperation. Following the 'Oslo Manual' (OECD and Eurostat 2005), the farmers were asked about innovation activity in three categories, namely product, process, and organizational or

Table 1. Number of innovations introduced by dairy farms per year.

	Year											Category/group considered
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total	
Any innovation	51	45	43	37	48	57	55	74	59	56	525	
Process innovation	44	35	33	27	33	37	45	52	41	42	389	
Machinery and equipment	31	27	24	17	18	22	35	33	26	30	263	Machinery and equipment
Buildings	16	11	7	7	9	8	8	15	7	4	92	Buildings
Herd management	0	1	1	2	4	3	2	1	0	1	15	Herd and farm management, new techniques
Farm management and new techniques	2	1	2	1	1	0	1	3	2	1	14	
GPS	1	0	0	0	0	1	0	0	0	0	2	
Solar power	0	0	1	4	4	5	3	5	4	5	31	
Windmill	0	0	0	0	0	0	0	0	4	2	6	
New manager	0	0	0	1	0	1	0	0	0	0	2	
Switch to organic	0	0	0	0	0	0	0	0	1	1	2	
Off-farming activity	0	0	0	0	0	0	0	0	0	0	0	
Minor	0	0	0	0	0	1	0	1	1	2	5	
Organizational and marketing	11	16	15	11	18	24	13	26	20	18	172	
Business organization and management	9	12	11	8	14	19	10	22	16	14	135	Business organization and management
Marketing	0	1	0	0	0	1	1	1	1	2	7	Other OM innovation
New partnerships	2	1	3	1	1	4	1	1	0	3	17	
Quality assurance	1	1	1	1	2	1	1	1	3	1	13	
Other	0	2	1	1	2	2	0	1	2	0	11	
Product innovation	0	3	2	1	2	4	0	4	4	4	24	Product innovation
Total observations	227	246	255	257	267	265	253	262	250	261	2543	

Table 2. Number of innovations introduced by arable farms per year.

	Year											
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total	Category/group considered
Any innovation	20	21	24	23	26	42	28	39	29	30	282	
Process innovation	15	16	19	18	18	37	20	30	21	22	216	
Machinery and equipment	8	7	7	9	8	21	16	20	11	17	124	Machinery and equipment
Buildings	1	2	4	2	3	2	2	1	2	0	19	Buildings
Herd management	0	0	0	0	0	0	0	0	0	0	0	
Farm management and new techniques	2	2	4	3	5	1	1	2	3	1	24	Farm management and new techniques
GPS	5	4	4	7	4	9	8	7	9	6	63	GPS
Solar power	0	2	3	0	1	10	1	6	2	4	29	
Windmill	0	0	0	0	0	0	0	0	0	0	0	
Off-farming activity	0	0	0	1	0	0	0	0	0	0	1	
Minor	0	0	0	0	0	0	0	1	0	0	1	
Organizational and marketing	5	5	7	6	5	10	12	13	12	12	87	
Business organization and management	1	4	7	5	5	8	6	11	11	11	69	Business organization and management
Marketing	0	1	1	1	0	0	3	2	0	0	8	Other OM innovation
New partnerships	2	0	0	0	1	1	2	1	0	2	9	
Quality assurance	1	0	1	0	0	1	2	1	0	0	6	
Other	2	0	0	1	0	2	2	0	2	1	10	
Product innovation	1	1	2	2	3	1	0	1	1	1	13	Product innovation
Total observations	88	95	102	90	105	114	106	105	91	111	1,007	

marketing innovations. Regarding the required degree of novelty to be classified as an 'innovation', the definition of the OECD and Eurostat (2005) is adopted. That is, process or product must be 'new or significantly improved' (for the farm, not at the market level) to count as an innovation. Because these are self-reported measures, some degree of subjectiveness must be expected, which cannot be avoided, however. Organizational and marketing innovations were further subclassified in five categories (see Table 1). For process innovation, no subclassification was provided. However, for each innovation, farmers were asked to provide a short description of the innovation introduced. Because process innovations can be related to a wide variety of business activities, we used these descriptions to manually form subcategories (see Table 1). Out of these, only the subcategories with a reasonable number of observations with a value of the innovation indicator of one were considered in the analysis. These are (1) machinery and equipment, (2) buildings, (3) herd or farm management and new techniques, and (4) GPS systems (only for arable farms). The installation of solar panels was not included in the analysis as generated solar power is typically fed into the grid and therefore the installation does not directly influence the production process itself.

For marketing and organizational innovations, we used the subcategories provided by the original questionnaire but aggregated them into two subcategories, 'business organization and management' and 'other' because of limited observations in the latter category (see Table 1).

As summarized in Tables 1 and 2, most innovation activities for both dairy and arable farms are related to new processes implemented in the production process. Fewer innovations are categorized as organizational or marketing innovations and, as expected, only few farms introduce product innovations. Within process innovations, most innovations are related to investments in new machinery and equipment. For dairy farms, the second most relevant process innovation category is investments in new buildings. Arable farms, on the other hand, are more likely to invest in the adoption of GPS-aided systems.

Most of the investments in buildings were related to new animal housing and only few were related to storage capacities for products or machinery. Only a few dairy or arable farms in the sample invested in new herd and farm management techniques. Innovations contained in this category are predominantly concerned with new methods of collecting animal or plant-related data, for example, with the help of sensors. For crop production, these new techniques included methods such as soil analysis, yield recording, or alternative practices of plant nutrition or tillage.

The innovation category 'business organization and management' is a relatively general term recording any changes in the farm's business organization. However, the specific descriptions provided by the respondents revealed that the vast majority of these innovations related to changes in the farm's legal form due to partners entering or leaving the farm business. As can be seen in Tables 1 and 2, the newly introduced category 'Other organizational and marketing' contains new techniques related to the marketing of products or the improvement of product quality. New business partnerships also fall under this category and in contrast to the changes in partnerships subsumed in the first organizational and marketing innovation category, these partnerships relate to new external relationships, for example, with producer organizations or educational institutions.

3.2 Measures of economic farm performance

The analysis of innovation-related impacts on economic performance is based on partial productivity and intensity measures, as well as a technical efficiency measure estimated by a stochastic frontier analysis.

For the frontier analysis, separate frontiers were estimated for the two farm types and total output was calculated as the sum of revenues from milk (only for dairy farms), crop, and other farm output, where deflated values have been used based on national price indices. For dairy farms, five production inputs were distinguished: land, labor, dairy cows, intermediates, and capital. Land is the total utilized agricultural area in hectares, labor is the average number of total working units employed on the farm, dairy cows is measured by the average number of dairy cows on the farm, intermediates are measured by the deflated value of the costs of various materials (concentrates, veterinary costs, fertilizers, seeds, pesticides, fuels, electricity, contract work, and other costs), and capital is the deflated book value for buildings and machinery. For arable farms, the same inputs apart from dairy cows were used. The frontier estimations were performed using a translog functional form incorporating time dummies to allow for flexible patterns of technical change and other external yearly shocks. A half-normal distribution for the inefficiency term was assumed and estimations were done using Stata's build-in 'frontier' command, which represents the 'basic' frontier model following Aigner, Lovell, and Schmidt (1977) and treats the data effectively as a repeated cross-sections, allowing the farm-level inefficiency term to have temporal variability. Further details on the frontier estimations and detailed estimation results (Tables S1 and S2) can be found in the supplementary file.

A model recently introduced to calculate technical efficiency scores when individuals self-select themselves into different production regimes is the endogenous switching frontier model (Greene 2010). This model seems not adequate in our estimation of technical efficiency for two reasons. First, the selection-corrected stochastic frontier analysis (SFA) model relies on exogenous variables in the selection equation that are not relevant in the frontier equation, which are unavailable in our data (similar as for the instrumental variable approach already discussed). Second, studies in the stream of selection-corrected SFA focus on long-term management decisions such as adoption of irrigation technology (Vrachioli, Stefanou, and Tzouvelekas 2021) or government programs (Bravo-Ureta, Greene, and Solís 2012). In contrast to this, innovation activity as considered in our case consists of rather short-term decisions, with farms typically changing from being innovators in single years to being non-innovators in the next. This short-term pattern of innovation activity can also be seen in our dataset, with only a few farms innovating in consecutive years (178 of 2,888 for dairy and 88 of 1,334 observations for arable farms). Therefore, adopting a selection-corrected frontier estimation in our context would assume that farms operate with innovative production technology in one year, and revert to the non-innovative production technology in the next. The production–innovation relationship that we assume in our study is that innovation activity adds positively to the technology status of the farm, which makes the technology status a monotonically increasing variable. Therefore, modelling innovation activity as a 1/0 variable in the frontier equation as would be the case in a selection-corrected frontier seems counter-intuitive. Instead, our approach relies on removing unobserved heterogeneity using a panel data estimator and incorporating relevant controls in the second-stage regression.

To gain more detailed evidence on the effects of innovation on the effectiveness and efficiency of specific inputs, we included various partial productivity and intensity measures. Cow productivity was calculated for dairy farms as the natural log of the total production of milk in kilogram per dairy cow. A positive relationship between innovation activity and cow productivity can be expected as a consequence of improved herd management, feed quality, or animal health. As a similar measure, land productivity was calculated for arable farms as the ratio of total output per hectare. Similar to dairy farms, higher land productivity by innovation could be expected, for example, by more precise pesticide or fertilizer application through precision farming technology.

Total farm output per worker was calculated for both dairy and arable farms as total deflated revenues divided by the number of total working units (paid and unpaid workers). We expect innovations to have a positive effect on labor productivity as either new techniques allow for a more efficient use of non-labor inputs or innovations are specifically aimed at introducing labor-saving techniques.

Cows per worker were calculated for dairy farms as the number of dairy cows divided by the farm's number of working units. A similar measure was calculated for arable farms as total utilized agricultural area per working unit. A positive relationship with innovation activity could indicate that farmers use innovations to increase herd size or farmland with the help of labor-saving technologies (see also Gallardo and Sauer 2018).

3.3 Measures of environmental and social farm performance

The selection of variables to assess the environmental performance of farms follows related environmental impact assessment studies on dairy and arable farms (e.g. Djekic et al. 2014). Greenhouse gas emissions were given in the dataset as measures calculated using information on the farm's inputs and appropriate emission factors. The total greenhouse gas emissions in CO_2 equivalents were then related to the output of the farm (CO_2eq per kg of milk for dairy farms). Greenhouse gas emissions were only available for dairy farms.

Similarly, the energy consumption of the farm (expressed in joules) was given in the dataset as a calculated measure summing up the amount of energy consumed on farm, that is, the consumption of fuels, diesel, and electricity for the operation of farm machinery, equipment, and buildings. Like greenhouse gas emissions, energy use was set in relation to the main output of the farm (the physical amount of milk for dairy farms and output in monetary terms for arable farms). As remarked by an anonymous reviewer, calculating 'energy intensity' relative to monetary terms is not a natural way of expressing this measure. However, arable farms typically produce multiple crops and using total revenue circumvents problems with allocating energy use to individual crops. Instead, an aggregate measure is calculated by using market prices (which reflect the relative value of crops) as weights to aggregate outputs from different crops.

Eutrophication potential is included in the analysis by separately considering the average nitrogen and phosphorus balances per hectare of the farm as reported in the dataset. By relating this environmental impact to a land unit, we follow suggestions of other researchers to relate globally relevant emissions (e.g. greenhouse gas emissions) to the farm product, and pollutants that accumulate locally and therefore lead to regionally confined environmental problems (e.g. nutrient surpluses) to farm hectares (Haas, Wetterich, and Geier 2000; Boer 2003; Halberg et al. 2005).

As another impact category, ammonia emissions were included in the analysis. Ammonia emissions significantly contribute to acidification of soils as well as to eutrophication (González-García et al. 2013). Additionally, ammonia emissions pose a human health risk due to their contribution to formation of fine particulate matter (Hristov 2011). Total farm ammonia emissions were given in the dataset and have been calculated as the sum of emissions resulting from animal grazing, animal housing, and manure application. Like nutrient surpluses, ammonia emissions were expressed in relation to the utilized agricultural area of the farm (kg NH_3/ha) to reflect the local relevance of their environmental impact.

The pesticide-related emissions at farm level were reported in the original dataset as environmental impact on groundwater, surface water, and soil. These environmental loads were measured on a point scale quantifying the impact of active substances on groundwater, surface water, and soil, based on the amount and kind of pesticides applied by the farmer. Because we are interested in the overall pesticide impact and because the scores are on an equivalent scale, we aggregated the three measures into one by summing up the three scores. Like nutrient emissions, pesticide use was set in relation to the total utilized area of the farm.

Following previous studies, we adopt somatic cell count as an indicator for the social dimension of sustainability (Arvidsson Segerkvist et al. 2020; Balaine et al. 2020). Somatic

Table 3. Descriptive statistics.

Variable	Dairy farms		Arable farms	
	Mean	SD	Mean	SD
Output (€)	294,148	207,916	338,670	353,416
Land (ha)	61.5	38.6	100.8	78.7
Labor (working units)	1.9	1.2	2.1	1.6
Dairy cows (heads)	108.3	73.9		
Intermediates (€)	146,618	107,578	141,007	124,031
Capital (€)	388,333	326,471	517,703	658,293
Output (€) per worker	152,383	71,389	154,196	78,755
Cows per worker	56.9	26.8		
Hectares per worker			53.9	28.0
Milk (kg) per cow	7,993	1,348		
Output (€) per hectare			3,151	1,521
Technical efficiency (%)	0.89	0.05	0.71	0.15
CO_2eq (kg) per kg milk	1.56	0.30		
Energy (MJ) per unit of output	0.64	0.29	3.57	4.11
Nitrogen surplus (kg N) per hectare	143.7	89.3	92.8	54.3
Phosphorus surplus (kg P_2O_5) per hectare	5.2	24.4	13.6	27.3
Ammonia emissions (kg NH_3) per hectare	44.3	23.7	14.4	10.0
Pesticide load (thousand points)	7.2	36.8	82.1	98.6
Somatic cell count (thousand cells per ml)	200.3	65.8		

Note: The numbers are unweighted averages across the whole sample period (2008–2017). 'Unit of output' is kilograms of milk for dairy farms and euros for arable farms. Monetary values are in real values (2000 = 100).

cell count is an indicator for udder health and therefore for animal welfare (Sharma, Singh, and Bhadwal 2011). Udder infections are painful for the animal and can be prevented by hygiene measures to reduce transmission between dairy cows (Huijps et al. 2010; Krömker and Leimbach 2017). The variable was included in the dataset as results from periodic tests conducted on dairy farms and is measured in thousand cells per milliliter.

Prior to estimation, the dependent variables (the economic as well as the environmental and social indicators) were transformed to their natural logarithm for ease of interpretation of the regression results. The variables were then first differenced to arrive at change measures, as described by Equation (7). This illustrates that the estimated regression parameters can be interpreted in terms of log percentage point changes in physical milk output per cow, monetary output per worker, the number of cows per worker, technical efficiency, CO_2eq per output, energy equivalents per output, and somatic cell count. The exception are nutrient surpluses, ammonia emissions, and pesticide load because a major share of observations showed non-positive (nutrient surpluses and ammonia emissions) or zero values (in cases where farms did not apply pesticides) and the variables were not converted to their natural log to keep these observations in the analysis. Therefore, the regression results with respect to nutrient surpluses, ammonia emissions, and pesticide loads are to be interpreted in their physical units (kg of nutrients, NH_3, and point scores, respectively).

Descriptive statistics of the economic variables and environmental indicators are presented in Table 3. Dairy and arable farms are similar in size in terms of monetary output and number of employed working units. The dairy farms in the sample have on average 108 dairy cows, with an average cow productivity of almost 8,000 kg. Dairy farms show a higher average level and a lower dispersion of technical efficiency compared to arable farms, which possibly might be due to a higher dependence on natural conditions and/or a greater diversity of arable products in the case of arable farms. CO_2 emissions per kilogram of milk appear to be at a higher level compared to those reported by other studies (Guerci et al. 2013; Özkan Gülzari, Vosough Ahmadi, and Stott 2018; Zehetmeier et al. 2020). It has to be kept in mind, though, that greenhouse gas emissions per dairy farm were not calculated separately for the dairy operation of the farm but as the total greenhouse gas emissions of the farm.

4. Results and discussion

4.1 Dairy farms

The models outlined before are estimated separately for each farm type. The estimation results for economic effects of innovation activity for dairy farms are reported in Table 4.

Overall, the models estimated show a relatively modest fit in terms of the adjusted R^2 measure, which can likely be traced back to reduced variation in regressors and the dependent variable due to first-differencing. We are cautious when interpreting parameters that are only weakly statistically significant as the probability of one of these parameters being not different from zero is high given the number of estimated models. Nevertheless, some highly significant parameters offer valuable empirical insights.

Our expectation of differing effects by contemporaneous and past innovation activity on the economic performance of dairy farms is partly confirmed. This is the case for innovations in several categories. With respect to all economic indicators in the year of the innovation introduction, investments in new machinery or equipment show a negative influence at least at the 10 percent significance level. This negative effect is also not compensated by positive growth in the following 2 years. Hence, our findings suggest that investments in new machinery or equipment appear not to significantly increase dairy farm productivity in the first years and apparently also no labor-saving induced productivity effect can be identified in the first years after investments.

Investments in new farm buildings show the opposite effect on farms' economic performance. No significant changes in the economic indicators can be found for contemporaneous investments in farm buildings. Considerable and statistically significant positive effects are estimated for cow and labor productivity, as well as for the number of cows managed per worker. That is, new buildings enable farmers to operate a larger dairy herd, which results in greater output per worker. In addition, cow productivity profits from new farm buildings, possibly due to improved feed management, new milking technology simultaneously installed with new buildings, or a higher well-being of the dairy herd. The descriptions given along the innovations were rather short, mostly without giving details on the type of new barns being built or equipment installed. Therefore, they do not allow more precise analysis of possible reasons for this relationship. However, only little and weakly significant positive effects can be observed for farms' technical efficiency. One reason might be that large investments in the capital stock of the farm partly outweigh the output increase by the investment.

Innovative herd or farm management techniques also show significant influence on some economic indicators. Remarkable are the significantly negative lagged effects for cow and labor productivity as well as technical efficiency. This seems surprising considering that, for example, new technologies such as animal sensors should allow the farmer to make more precise judgments on the animals' health status and enable more timely and precise management responses (Tullo, Finzi, and Guarino 2019). However, these investments might also imply an increase in labor and time efforts required to effectively use these techniques in the first years after investment.

Organizational and marketing (OM) innovations show less significant impacts overall. Recalling that innovations in the category 'business organization and management' are primarily related to internal farm management partnerships, it can be anticipated that these innovations do not directly impact the production practices of the farm. Unexpected are, however, rather strong negative effects by (other) organizational and management innovation

Table 4. Economic effects by innovation for dairy farms.

	Milk per cow	Output per worker	Cows per worker	Technical efficiency
Process innovation				
Machinery and equipment in t	−0.011**	−0.019*	−0.017**	−0.006**
	(0.005)	(0.011)	(0.008)	(0.003)
in $t-1$ or $t-2$	0.001	−0.010	−0.002	−0.002
	(0.003)	(0.008)	(0.006)	(0.002)
Buildings in t	0.001	−0.013	−0.006	−0.008
	(0.007)	(0.017)	(0.014)	(0.005)
in $t-1$ or $t-2$	0.017***	0.045***	0.025***	0.007**
	(0.004)	(0.010)	(0.008)	(0.003)
Herd and farm management or new techniques in t	−0.003	−0.019	−0.010	−0.004
	(0.011)	(0.033)	(0.016)	(0.008)
in $t-1$ or $t-2$	−0.012**	−0.050***	−0.022	−0.010*
	(0.006)	(0.017)	(0.014)	(0.005)
Organizational and marketing innovation				
Business organization and management in t	−0.011*	−0.040**	−0.027	−0.005
	(0.007)	(0.017)	(0.017)	(0.004)
in $t-1$ or $t-2$	−0.003	0.005	0.002	0.000
	(0.004)	(0.011)	(0.009)	(0.002)
Other OM innovation in t	−0.014	−0.015	−0.022	0.006
	(0.013)	(0.034)	(0.031)	(0.006)
in $t-1$ or $t-2$	−0.002	−0.060***	−0.025*	−0.014**
	(0.007)	(0.021)	(0.013)	(0.006)
Product innovation in t	0.027	0.025	0.011	−0.009
	(0.016)	(0.038)	(0.027)	(0.018)
in $t-1$ or $t-2$	−0.005	0.009	0.003	−0.001
	(0.010)	(0.034)	(0.022)	(0.009)
Farm size	−0.073***	0.349***	0.694***	−0.032
	(0.027)	(0.055)	(0.055)	(0.017)
Degree of specialization	0.036***	−0.120**	0.073**	−0.066***
	(0.013)	(0.049)	(0.029)	(0.015)
Organic	−0.092**	−0.043	−0.056	−0.032
	(0.041)	(0.075)	(0.061)	(0.035)
Age of farmer	0.000	0.007***	−0.002**	0.002***
	(0.000)	(0.002)	(0.001)	(0.001)
Age of farmer^2	0.000	0.000***	0.000*	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Training	0.008	0.029	−0.023	0.016
	(0.015)	(0.023)	(0.018)	(0.020)
New manager	0.003	0.030	−0.009	0.015***
	(0.007)	(0.025)	(0.023)	(0.005)
No successor	−0.004	0.015	0.013	−0.000
	(0.008)	(0.013)	(0.013)	(0.005)
Year (2009 = base level)				
2010	−0.005	−0.063***	−0.034***	−0.002
	(0.007)	(0.016)	(0.012)	(0.005)
2011	−0.025***	−0.065***	0.000	−0.001
	(0.006)	(0.014)	(0.010)	(0.004)
2012	−0.036***	−0.081***	0.007	−0.002
	(0.007)	(0.014)	(0.011)	(0.004)
2013	−0.016**	−0.156***	−0.117***	−0.009*
	(0.008)	(0.018)	(0.015)	(0.005)
2014	−0.007	−0.058***	−0.002	−0.005
	(0.006)	(0.014)	(0.012)	(0.004)
2015	−0.007	−0.050***	0.000	−0.002
	(0.006)	(0.015)	(0.010)	(0.004)

Table 4. Continued

	Milk per cow	Output per worker	Cows per worker	Technical efficiency
2016	0.002	−0.056***	−0.091***	−0.009*
	(0.008)	(0.017)	(0.014)	(0.005)
2017	0.015**	−0.043***	−0.020*	0.009*
	(0.006)	(0.016)	(0.011)	(0.005)
Region (1 = base level)				
2	−0.003	0.004	0.005	0.001
	(0.002)	(0.006)	(0.005)	(0.001)
3	−0.003	−0.020**	−0.003	−0.007***
	(0.003)	(0.009)	(0.008)	(0.002)
4	−0.001	−0.002	0.011**	−0.004**
	(0.003)	(0.006)	(0.005)	(0.002)
Adjusted R^2	0.097	0.095	0.200	0.034
Number of observations	1,862	1,862	1,862	1,862

Note: Levels of statistical significance are 10% (*), 5% (**), and 1% (***).

on output per worker and technical efficiency. For business organization and management, it can be seen from descriptions given by respondents that in many cases the innovation was related to new partnerships or farm successors entering farm management. A negative effect on output per hectare could therefore be the result of a temporary worker surplus. Because 'other' OM innovation is a wide collection of various innovations, the reason for the negative result is hard to identify. However, the description provided by respondents indicated that engagements in other gainful activities and other various profound changes in farm organization were included in this category, making it credible that in those (few) cases, the farm manager's focus shifted to other activities, leading to lower economic performance of the farming activities.

Finally, the few dairy farms that introduced a product innovation do not show significantly affected economic performance (although coefficients with positive sign are observed). Considering that product innovation activity should not directly affect the technical relationships of the production process (if product innovations are not introduced jointly with process innovations), this is not an unexpected result. On the other hand, because output is measured in monetary units deflated by national price indices, a positive effect on output per worker or technical efficiency could have been a likely scenario assuming that farms achieve higher value added with the introduction of new products (e.g. new cheese variety or branded milk, as mentioned in the descriptions given by respondents).

Next, we attend to the results for the environmental and animal welfare indicators, as reported in Table 5. Compared to the economic indicators, innovations seem to have only minor impacts on these measures. On one hand, this appears plausible considering that the primary motivation for farmers to introduce innovations is the improvement of farm profitability. On the other hand, as discussed in the conceptual framework, the farm's environmental impact should be inversely related to economic performance measures as, e.g. productivity or efficiency. Additionally, investment subsidies or tax redemptions, especially in the intensive livestock sector, have been granted conditionally on the farm accomplishing improvements in animal welfare or emission reductions.

Greenhouse gas emissions appear to be unaffected by most forms of innovation. A significant positive effect is identified for the contemporaneous impact of newly introduced techniques in herd and farm management. Also, farms with a product innovation experience lower greenhouse gas emissions per kilogram of milk in the year of the innovation and increasing greenhouse gas emissions in the subsequent years. This result can possibly be traced back to the indirect effect of innovation on emissions per unit of output as discussed

Table 5. Environmental and social effects by innovation for dairy farms.

	CO_2eq per kg milk	Energy per kg milk (MJ)	Nitrogen surplus per ha (kg)	Phosphorus surplus per ha (kg)	Ammonia emission per ha (kg)	Pesticide load (index points)	Somatic cell count
Process innovation							
Machinery and equipment in t	0.008	0.040***	−11.8	−5.0**	−0.6	−13.8	−0.004
	(0.008)	(0.014)	(7.6)	(2.4)	(1.0)	(17.6)	(0.015)
in $t-1$ or $t-2$	−0.001	0.004	8.2*	1.6	−0.7	−2.8	0.010
	(0.006)	(0.010)	(4.6)	(1.6)	(0.7)	(6.5)	(0.012)
Buildings in t	−0.007	0.077***	−13.3	−4.1	2.3	14.9	0.033
	(0.014)	(0.026)	(11.8)	(4.4)	(2.7)	(10.8)	(0.032)
in $t-1$ or $t-2$	−0.005	−0.030**	−3.6	−1.1	−0.5	−1.9	−0.022
	(0.008)	(0.013)	(5.6)	(2.1)	(1.1)	(9.9)	(0.017)
Herd and farm management, new techniques in t	0.050**	0.015	−9.4	0.6	3.7	167.1	0.019
	(0.022)	(0.038)	(14.8)	(5.5)	(3.7)	(153.2)	(0.049)
in $t-1$ or $t-2$	0.012	0.044**	−2.1	−3.2	−0.1	−47.9	0.016
	(0.010)	(0.020)	(9.1)	(4.2)	(2.3)	(57.9)	(0.025)
Organizational and marketing innovation							
Business organization and management in t	−0.008	−0.017	0.3	−1.2	−1.9	−50.6*	0.014
	(0.013)	(0.015)	(10.4)	(3.5)	(1.3)	(30.3)	(0.047)
in $t-1$ or $t-2$	0.001	0.008	−4.1	0.2	0.1	16.7***	0.012
	(0.008)	(0.011)	(5.1)	(1.9)	(1.1)	(6.3)	(0.015)
Other OM innovation in t	−0.003	−0.014	−−1.1	4.2	−4.8***	−15.9	0.018
	(0.020)	(0.040)	(10.3)	(3.9)	(1.6)	(13.9)	(0.034)
in $t-1$ or $t-2$	0.012	0.035	2.5	−0.3	3.2	−6.1	−0.010
	(0.014)	(0.022)	(8.2)	(3.2)	(2.6)	(12.6)	(0.023)
Product innovation in t	−0.042**	0.004	0.5	−1.2	3.2	16.0	−0.051
	(0.021)	(0.042)	(14.2)	(4.9)	(2.4)	(11.3)	(0.053)
in $t-1$ or $t-2$	0.042**	0.027	1.3	3.8	−0.3	5.2	0.047
	(0.016)	(0.049)	(13.0)	(5.0)	(1.5)	(10.6)	(0.033)
Farm size	−0.133***	−0.518***	−56.5*	−12.6	4.9	28.6	0.056
	(0.050)	(0.084)	(31.4)	(11.8)	(7.0)	(63.7)	(0.099)
Degree of specialization	−0.031	−0.147***	82.0***	17.7***	3.6	71.5	0.002
	(0.019)	(0.042)	(20.8)	(6.1)	(2.9)	(52.6)	(0.041)
Organic	−0.049	0.224*	−50.1**	−5.2	−12.7***	−21.3	0.058
	(0.069)	(0.120)	(19.6)	(5.2)	(4.0)	(14.2)	(0.057)
Age of farmer	0.001	0.004**	−1.9***	−0.6***	−0.1	−2.4	−0.002
	(0.001)	(0.002)	(0.6)	(0.2)	(0.1)	(1.7)	(0.001)

Table 5. Continued

	CO_2eq per kg milk	Energy per kg milk (MJ)	Nitrogen surplus per ha (kg)	Phosphorus surplus per ha (kg)	Ammonia emission per ha (kg)	Pesticide load (index points)	Somatic cell count
Age of farmer²	0.000	0.000*	0.0**	0.0***	0.0	0.0	0.000
	(0.000)	(0.000)	(0.0)	(0.0)	(0.0)	(0.0)	(0.000)
Training	−0.023	−0.064	12.1	0.7	0.3	28.3	−0.015
	(0.033)	(0.046)	(16.4)	(10.2)	(1.7)	(46.5)	(0.043)
New manager	−0.007	0.042**	−12.0	−3.1	−0.3	17.0	−0.046
	(0.012)	(0.018)	(10.1)	(3.3)	(1.8)	(12.4)	(0.034)
No successor	0.013	−0.008	3.4	1.6	0.9	0.4	0.021
	(0.014)	(0.030)	(8.8)	(3.0)	(2.1)	(12.1)	(0.037)
Year (2009 = base level)							
2010	0.059***	0.060***	12.3	6.6	10.6***	29.7*	n.a.
	(0.012)	(0.021)	(11.5)	(4.1)	(2.5)	(17.6)	
2011	0.015	0.024	−2.6	0.1	0.6	27.2	n.a.
	(0.010)	(0.019)	(9.0)	(3.1)	(1.4)	(18.8)	
2012	0.031***	0.017	−12.0	−3.6	−0.7	40.5	Base level
	(0.009)	(0.019)	(8.4)	(3.0)	(1.3)	(39.9)	
2013	0.187***	0.048**	2.5	9.1**	8.6***	17.4	0.038
	(0.014)	(0.022)	(9.4)	(3.7)	(1.7)	(47.0)	(0.038)
2014	0.001	0.026	−31.9***	−17.9***	0.0	2.4	0.034
	(0.009)	(0.019)	(8.7)	(3.3)	(1.3)	(19.0)	(0.022)
2015	0.003	−0.003	−2.1	9.1***	−2.3*	−11.9	−0.011
	(0.010)	(0.018)	(8.4)	(3.2)	(1.3)	(19.2)	(0.022)
2016	−0.022	0.061***	5.6	1.7	−0.8	−9.9	0.088***
	(0.013)	(0.022)	(10.4)	(3.8)	(1.6)	(15.5)	(0.028)
2017	−0.090***	0.007	−30.2***	0.6	2.6*	27.2*	−0.052**
	(0.011)	(0.019)	(9.6)	(3.4)	(1.4)	(14.8)	(0.022)
Region (1 = base level)							
2	0.012***	0.013**	−1.6	−1.1	−0.2	−3.8	−0.015
	(0.004)	(0.006)	(2.5)	(0.8)	(0.7)	(7.8)	(0.010)
3	0.006	0.015	6.1*	1.4	−1.2	−0.8	−0.009
	(0.005)	(0.010)	(3.3)	(1.0)	(0.8)	(4.6)	(0.013)
4	0.005	0.003	−0.3	−0.7	−0.8	5.2	0.007
	(0.004)	(0.008)	(3.2)	(1.0)	(0.8)	(5.2)	(0.010)
Adjusted R^2	0.313	0.077	0.020	0.062	0.084	−0.008	0.051
Number of observations	1,811	1,861	1,862	1,862	1,862	1,862	1,293

Note: Levels of statistical significance are 10% (*), 5% (**), and 1% (***).

in the conceptual framework (lower emissions per unit of milk were mirrored in higher cow productivity, if also the product innovation effects on cow productivity were statistically insignificant).

The energy use per kilogram of milk shows the strongest dependence on innovation activities and mirrors the impacts explored earlier for the economic indicators. Investments in machinery and equipment are accompanied by increased energy consumption in the year of introduction, possibly due to lower technical efficiency or cow productivity as previously discussed. Furthermore, the replacement of outdated machinery (such as tractors) by more powerful machines that are not necessarily energy saving might be relevant in this context. A significant positive effect is estimated for contemporaneous investments in farm buildings and energy savings are estimated for the years after the actual investment. This could also be due to lower cow productivity in the year of investment and increased productivity thereafter, as discussed for the economic effects.

Nitrogen and phosphorus surpluses seem largely unaltered by farm-level innovation activity. Innovations in machinery and equipment show a negative influence on the average phosphorus surplus of the farm, and a similar but insignificant relationship with nitrogen surpluses. Ammonia emissions are likewise unaffected by innovation activity except for other organizational and marketing innovations, which show a significantly negative impact. Again, possible reasons for this relationship are hard to identify because of the manifold nature of this innovation category.

Pesticide emissions as well as somatic cell count seem to be largely determined by other factors than those considered in the regression analyses. The only statistically significant association is found for the effect of organizational and marketing innovations on the pesticide load, suggesting that farms with new business organization show higher pesticide use in the following years. This might indicate that farm successors (as mentioned, this innovation category was frequently related to children entering the farm management) apply more intensive production methods with respect to pesticide use. For the other innovation variables, we find no significant effect. For the somatic cell count, this is in contrast to other findings, for example, by Balaine et al. (2020). However, in their study, Balaine et al. investigated the effects of a specific innovative technique (milk recording), where a positive effect on animal health might be more clear-cut compared to the rather broad innovation categories used in our study.

4.2 Arable farms

Estimation results for the economic effects by farm-level innovation activities for arable farms are summarized in Table 6. Somewhat higher model fits are observed for these farms, likely because of a stronger dependence of farming operations on climate and other yearly varying preconditions, which makes the yearly dummy variables better predictors. The generally observed trend of negative performance effects in the year of innovation introduction and positive effects in the following years can be confirmed for some model results. However, almost all estimated parameters for innovation-related variables are statistically insignificant. One of the exceptions is a weakly significant parameter for past innovations in new farm management techniques with respect to their effect on the number of hectares cultivated per worker. A straightforward explanation can be given because some respondents considered the lease of additional land as an innovation in this category.

Many arable farmers in our dataset adopted GPS-based systems during the study period. These systems should enable farmers to apply fertilizers more precisely and facilitate more efficient tillage routines (Balafoutis et al. 2017). The estimated coefficients are all positive; however, only the number of hectares per worker shows a significant positive association with the past introduction of GPS systems.

Table 6. Economic effects by innovation for arable farms.

	Output per ha	Output per worker	Ha per worker	Technical efficiency
Process innovation				
Machinery and equipment in t	0.007	−0.016	−0.022	−0.021
	(0.022)	(0.028)	(0.018)	(0.015)
in $t-1$ or $t-2$	0.004	0.005	0.000	−0.002
	(0.020)	(0.022)	(0.013)	(0.011)
Buildings in t	−0.007	−0.053	−0.046	−0.031
	(0.063)	(0.054)	(0.035)	(0.030)
in $t-1$ or $t-2$	−0.015	−0.012	0.004	−0.001
	(0.040)	(0.037)	(0.020)	(0.022)
Farm management, new techniques in t	−0.030	0.016	0.046	−0.034
	(0.056)	(0.067)	(0.035)	(0.042)
in $t-1$ or $t-2$	−0.010	0.036	0.047**	−0.005
	(0.052)	(0.055)	(0.020)	(0.030)
GPS systems in t	0.035	0.053	0.018	0.019
	(0.032)	(0.042)	(0.032)	(0.017)
in $t-1$ or $t-2$	−0.008	0.038	0.046**	0.003
	(0.029)	(0.030)	(0.019)	(0.016)
Organizational and marketing innovation				
Business organization and management in t	−0.020	−0.011	0.009	−0.006
	(0.039)	(0.042)	(0.024)	(0.018)
in $t-1$ or $t-2$	0.021	0.000	−0.021	0.000
	(0.024)	(0.027)	(0.015)	(0.014)
Other OM innovation in t	0.024	0.043	0.019	0.040
	(0.076)	(0.066)	(0.026)	(0.047)
in $t-1$ or $t-2$	−0.009	−0.024	−0.015	0.005
	(0.040)	(0.049)	(0.030)	(0.031)
Product innovation in t	−0.042	−0.047	−0.005	−0.016
	(0.051)	(0.048)	(0.035)	(0.019)
in $t-1$ or $t-2$	0.002	0.052	0.050*	0.008
	(0.043)	(0.048)	(0.027)	(0.021)
Farm size	0.224***	0.537***	0.313***	0.149***
	(0.085)	(0.078)	(0.082)	(0.041)
Degree of specialization	0.148**	0.233***	0.085	0.070**
	(0.074)	(0.068)	(0.057)	(0.030)
Age of farmer	−0.002	−0.002	0.000	−0.003**
	(0.003)	(0.003)	(0.003)	(0.001)
Age of farmer²	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Training	−0.027	0.007	0.034	−0.012
	(0.088)	(0.077)	(0.056)	(0.053)
New manager	−0.049	−0.082	−0.033	−0.028
	(0.057)	(0.052)	(0.039)	(0.033)
No successor	−0.010	0.006	0.016	−0.004
	(0.029)	(0.027)	(0.022)	(0.010)
Year (2009 = base level)				
2010	0.056	−0.061	−0.117***	−0.007
	(0.039)	(0.046)	(0.037)	(0.024)
2011	−0.335***	−0.410***	−0.075***	0.005
	(0.043)	(0.046)	(0.026)	(0.024)
2012	0.296***	0.229***	−0.067**	0.048**
	(0.036)	(0.040)	(0.026)	(0.021)
2013	−0.368***	−0.478***	−0.110***	−0.037*
	(0.038)	(0.042)	(0.031)	(0.022)
2014	−0.141***	−0.213***	−0.072**	−0.000
	(0.031)	(0.037)	(0.032)	(0.018)

Table 6. Continued

	Output per ha	Output per worker	Ha per worker	Technical efficiency
2015	0.012	−0.106**	−0.118***	0.009
	(0.037)	(0.045)	(0.028)	(0.023)
2016	−0.225***	−0.341***	−0.117***	−0.048**
	(0.049)	(0.050)	(0.031)	(0.024)
2017	−0.101**	−0.121***	−0.020	0.067**
	(0.049)	(0.046)	(0.032)	(0.026)
Region (1 = base level)				
2	−0.005	−0.014	−0.009	−0.009
	(0.019)	(0.023)	(0.020)	(0.010)
3	0.004	0.020	0.015	0.002
	(0.023)	(0.025)	(0.018)	(0.012)
4	−0.004	0.001	0.005	−0.008
	(0.016)	(0.020)	(0.014)	(0.008)
Adjusted R^2	0.378	0.426	0.119	0.045
Number of observations	590	590	590	590

Note: Levels of statistical significance are 10% (*), 5% (**), and 1% (***).

Organizational and marketing innovations are not a statistically significant predictor for any of the economic indicators. For past product innovations, a positive relationship is estimated for the number of hectares per worker, which might well be due to the cultivation of additional land to produce new products. However, the low statistical significance prevents a definite conclusion.

The effects on environmental performance of arable farms are summarized in Table 7. As expected from the ambiguous results for the economic indicators previously reported, the results lack statistical significance for almost all estimated innovation-related parameters. New machinery and equipment or the adoption of GPS-aided systems can be expected to allow farmers more precise and more economical application of fertilizers and pesticides. Also, new farm management techniques such as soil analyses or plant disease monitoring could support the farmer in finding the appropriate amount of fertilizer and pesticide. However, we could not robustly identify significant and desirable effects for the types of innovation considered in this study. Instead, new farm management techniques imply slightly higher nutrient surpluses in the following years. New farm buildings might lead to lower ammonia emissions in the year of construction, which are, however, followed by higher emissions in the subsequent years. To some degree, higher emissions are associated with the introduction of GPS-aided systems, while past organizational and marketing innovations lead to slightly lower ammonia emissions. Product innovation seems to result in higher nutrient surpluses to some extent. Perhaps, this is related to lower yields of new crops in the year of introduction due to missing farmers' experience in cultivation of the crop. For pesticide use, no statistically significant effects are estimated for any of the innovation activities. The only clear desirable effects seem to be associated with other organizational and marketing innovations, which seem to some degree facilitate lower nutrient surpluses and ammonia emissions in the years following their introduction.

5. Conclusions

To meet the sustainability goals of agriculture in the future, high expectations are put on the investment in new technologies. Undoubtedly, progress in agricultural productivity also ensuring resource efficiency can only be made by implementing new production techniques. Accordingly, an important strategy of agricultural policy has been to foster

Table 7. Environmental effects by innovation for arable farms.

	Energy per output	Nitrogen surplus per ha	Phosphorus surplus per ha	Ammonia emissions per ha	Pesticide load
Process innovation					
Machinery and equipment in t	0.063	4.4	5.7	0.7	−10.8
	(0.043)	(6.2)	(4.6)	(0.8)	(57.1)
in $t-1$ or $t-2$	0.024	−2.4	−0.6	0.4	−39.8
	(0.034)	(5.3)	(2.8)	(0.9)	(35.8)
Buildings in t	0.139	−16.7	2.2	−2.1**	34.7
	(0.148)	(13.6)	(9.5)	(0.9)	(78.8)
in $t-1$ or $t-2$	−0.029	10.4	−1.4	3.9***	−38.5
	(0.069)	(9.5)	(5.7)	(1.3)	(91.5)
Farm management, new techniques in t	0.080	11.6	1.3	0.7	−57.9
	(0.104)	(12.7)	(3.5)	(2.2)	(110.9)
in $t-1$ or $t-2$	−0.036	19.6*	9.5***	0.0	667.7
	(0.084)	(10.1)	(3.4)	(1.2)	(632.6)
GPS systems in t	−0.031	1.7	−3.7	1.9*	44.6
	(0.061)	(7.4)	(4.9)	(1.1)	(52.9)
in $t-1$ or $t-2$	−0.050	−5.7	−1.1	0.0	2.5
	(0.040)	(4.6)	(2.4)	(0.7)	(47.5)
Organizational and marketing innovation					
Business organization and management in t	−0.007	−4.9	−2.4	−2.1	38.9
	(0.060)	(8.8)	(5.0)	(1.8)	(97.9)
in $t-1$ or $t-2$	−0.012	2.0	−2.6	−0.6	−61.9
	(0.037)	(5.7)	(2.9)	(1.4)	(79.8)
Other OM innovation in t	−0.006	10.1	16.8	1.3	−41.0
	(0.144)	(17.6)	(10.9)	(2.8)	(118.0)
in $t-1$ or $t-2$	−0.046	−26.5*	−15.5***	−5.7*	153.6
	(0.065)	(13.7)	(4.5)	(3.3)	(154.7)
Product innovation in t	−0.017	48.6*	15.4*	3.7	−43.0
	(0.089)	(27.9)	(8.6)	(2.7)	(126.2)
in $t-1$ or $t-2$	0.005	−7.8	0.7	−3.2	36.2
	(0.096)	(9.1)	(3.9)	(2.0)	(58.3)
Farm size	−0.179	−22.6*	−8.3	1.4	−12.5
	(0.131)	(13.6)	(8.2)	(2.8)	(144.9)
Degree of specialization	−0.104	19.7	5.4	2.0	−190.7
	(0.084)	(12.2)	(6.4)	(2.3)	(117.5)
Age of farmer	0.000	−0.6	−0.4	−0.1	−3.5
	(0.003)	(0.5)	(0.3)	(0.1)	(4.7)
Age of farmer^2	0.000	0.0	0.0	0.0	0.0
	(0.000)	(0.0)	(0.0)	(0.0)	(0.1)
Training	0.015	−12.7	−19.2	3.5	−57.2
	(0.125)	(17.3)	(16.8)	(5.3)	(147.4)
New manager	0.063	−1.6	−9.0	1.0	−114.4
	(0.077)	(16.2)	(7.8)	(2.4)	(72.7)
No successor	0.013	−2.6	−3.4	0.0	−77.0
	(0.082)	(4.6)	(3.3)	(0.9)	(75.6)
Year (2009 = base level)					
2010	0.073	7.9	16.8**	1.3	91.0
	(0.083)	(15.2)	(7.8)	(1.9)	(146.1)
2011	0.430***	11.6	7.9	0.1	662.3***
	(0.058)	(10.5)	(6.1)	(1.5)	(216.3)
2012	−0.277***	−19.2*	−0.7	0.5	−36.1
	(0.063)	(11.0)	(5.6)	(1.5)	(238.7)
2013	0.336***	32.5***	9.7	6.2***	181.8
	(0.073)	(10.9)	(6.2)	(1.8)	(144.0)

Table 7. Continued

	Energy per output	Nitrogen surplus per ha	Phosphorus surplus per ha	Ammonia emissions per ha	Pesticide load
2014	0.261***	2.5	12.3**	1.7	292.2**
	(0.055)	(11.3)	(5.9)	(1.6)	(116.0)
2015	0.179***	17.1	8.6	1.2	172.7
	(0.065)	(11.3)	(6.3)	(1.5)	(123.6)
2016	0.156**	37.8***	17.0***	−1.6	250.1*
	(0.067)	(11.7)	(5.6)	(1.5)	(128.6)
2017	0.148	−10.6	−0.4	1.7	238.9**
	(0.090)	(10.4)	(5.5)	(1.5)	(111.6)
Region (1 = base level)					
2	0.001	6.7*	5.5***	0.0	−26.4
	(0.024)	(3.7)	(1.9)	(0.8)	(69.0)
3	0.012	0.6	0.5	−0.7	50.8
	(0.030)	(3.4)	(2.5)	(0.9)	(62.1)
4	−0.033	−0.8	2.9*	0.5	7.8
	(0.025)	(3.4)	(1.6)	(0.5)	(33.9)
Adjusted R^2	0.187	0.074	0.048	0.066	0.015
Number of observations	590	590	590	590	590

Note: Levels of statistical significance are 10% (*), 5% (**), and 1% (***).

exploration, adoption, and diffusion of new sustainable production technologies. To this end, farmers typically receive financial support to update capital goods and farm equipment to state-of-the-art technology. To what extent newly implemented technologies can live up to the expectations and contribute to more sustainable production is finally an empirical question, taking into account specific production settings and environments. Our study contributes to this empirical literature by employing a comprehensive dataset that allows us to robustly explore the impacts of a wide variety of innovations on farm-level indicators with respect to several pillars of sustainability. If also a positive effect on all sustainability pillars cannot be expected for every form of innovation, farmers' primary aim is to increase or stabilize profitability by introducing such innovations. That is, a positive effect on the economic pillar of sustainability can be expected.

The results of our study suggest that farm-level innovations cannot be per se attributed to a general positive effect on any of the sustainability dimensions. Nevertheless, some statistically robust findings support the expectation of positive effects for some forms of innovation. This evidence can help to identify most promising new technologies that most likely will contribute to more than one sustainability indicator and dimension. The most significant positive effects on economic performance were found for investments in buildings by dairy farmers. However, simultaneous positive effects regarding the environmental and social farm performance could not be unambiguously confirmed.

For other forms of innovation and with respect to arable farms, the empirical results remain inconclusive. Although positive links with economic performance were estimated for some techniques (e.g. GPS-aided systems), these relationships appeared not statistically robust. For some innovation categories, this might be due to the way the particular innovation category has been defined. If innovations subsumed in the same category are heterogenous and their effects potentially conflicting, ambiguous estimation results might arise. For other innovations, unexpected negative relationships with respect to farm performance were estimated (e.g. for herd and farm management techniques on dairy farms). These findings are puzzling and need to be explored further based on more precise measures for innovation.

Compared to the results of Sauer and Vrolijk (2019)—which is based on a similar sample than the present study—we find fewer statistically significant results with respect to the economic performance indicators. However, the results are not contradictory and differences in statistical significance can likely be explained by the different methodological approaches along with differing variable definitions applied by the studies.

The starting hypothesis of our study was that innovations could offer a way to dissolve competing relationships between sustainability dimensions. Recently, results by Ang, Kerstens, and Sadeghi (2023) for similar data as ours show that win–win situations might be tricky to achieve, even for related impact measures within the same sustainability dimension. In part, this can be an explanation for our ambiguous results. If relationships between different sustainability indicators are inherently competitive rather than complementary, innovation targeting one indicator cannot be expected to contribute to the other equally well.

As was expected before, in our study farm-level innovations are not found to be a panacea with respect to the sustainability challenges lying ahead for agricultural production. Public support for modernizing farm technology should therefore be considered wisely and should focus on the most cost-effective strategies. Furthermore, the right incentives must be created for farmers to foster the adoption of technologies with promising environmental benefits. To identify those technologies, studies based on observational data such as ours should at least complement results on potential input savings of new technologies, given that farmer behavior plays an important role in realizing the technologies' potential. For example, rebound effects have been discussed in the context of energy-saving technologies (Pan et al. 2021; Ang, Kerstens, and Sadeghi 2023).

As discussed in the description of the empirical strategy, identification of causal innovation effects is impeded by the highly endogenous nature of innovation activity and time-variant unobservables are of particular concern for the identification strategy. Future studies could test the robustness of our findings with alternative approaches, for example, with datasets including suitable instruments, if also these are hard to come by.

Our study did not consider the risk aspect in innovation adoption. A key motivation for farmers to adopt new technologies besides the improvement of mean farm performance is likely the reduction in performance variability. For example, DeLay, Thompson, and Mintert (2021) find that variance in technical efficiency is lowest for early adopters of precision farming technologies in their sample of US corn farmers. If farm-level innovations are adopted solely for risk reduction purposes, there might be no positive effects on the mean environmental impact via input savings, as discussed in the conceptual framework. Nevertheless, a positive effect on the distribution of economic performance measures (e.g. a reduction in downside risk) might also imply positive effects on the distribution of environmental impacts. Another aspect, which remains unexplored in our study, is possible cost implications of innovation activity, for example, via allocative efficiency. These aspects should also be addressed in future studies.

Supplementary material

Supplementary data are available at *Q Open* online.

Data availability

The data underlying this article cannot be shared publicly due to privacy of farmers who participated in the survey and personal information such as financial data and socio-economic variables.

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