Farm innovation and technical efficiency of Dutch arable farms: An innovation index and DEA approach

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Abstract

In this article, we analysed the relationship between farm innovation and farm efficiency. We computed an innovation index based on Dutch Innovation Monitor data and ratings from an expert elicitation. The innovation index is an adaptation and extension of an existing innovation index for Irish dairy farms. We computed technical efficiency scores with a Data Envelopment Analysis (DEA). The DEA scores are computed with Farm Accountancy Data Network (FADN) data. We investigated the relationship with pre-registered ordinary least square (OLS) regression analyses in quadratic form and additional Chi-square tests. Unanimously, we reject the first hypothesis that farm innovation and farm efficiency can be described by an inverse parabolic relationship. Early adopters and innovators are not necessarily less efficient than the early and late majority of innovation adopters. We also reject the second hypothesis that innovation front-runners become more efficient. These are preliminary findings.

Keywords. farm innovation, DEA, efficiency

JEL Classification.

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1 Introduction

> *"The lack of good data on innovation makes it difficult to carry out impact analysis for evidence-based policies. We are sailing the innovation flagship without sufficient instruments to evaluate its course. There is work to do in this regard."*
>
> — van Galen & Poppe (2013a), *EuroChoices*

Farm innovations increase the long-term productivity and competitiveness of the Dutch agri-food sector as a whole (OECD, 2015). Yet, the effect of innovations on short-term farm-level efficiency needs to be critically reviewed. It is unclear whether the most innovative farmers are also short-term technically efficient (Walder et al., 2019). Maybe, innovative farmers sacrifice current profits for potential long-term improvements. Thereby, they decrease the farm's short-term efficiency (Bowman & Zilberman, 2013), but the short-term sacrifice may be negligible compared to the long-term gain. In this article, we empirically investigate the relationship between farmers' level of innovation and their technical efficiency.

We classify farmers into five innovation groups: the innovators and early adopters, the early and late majority and the laggards. This is Rogers (1962)'s famous Diffusion of Innovation Theory. According to Rogers' theory, the distribution of innovation adoptions is bell-shaped over time. Upon market entry, innovations are adopted by only a small number of innovators. As the innovation matures it is adopted by the majority of farmers so that only a few laggards adopt the innovation late.

Previous studies have already investigated the relationship between farm innovations and farm efficiency. On the one hand, Emvalomatis et al. (2011) found innovations to be disturbances to the system that prevent farmers to become fully efficient over time. On the other hand, in a study on Germany dairy farms, Sauer & Latacz-Lohmann (2015) found that innovations had a positive effect on efficiency, lasting through the first two years after the innovation adoption. Similarly, DeLay et al. (2021) found that adopters of precision agriculture technologies are significantly more efficiency than non-adopters. They conducted stochastic frontier and meta frontier analyses (SFA, SFMA) and concluded that the early and late majority of innovation adopters are more efficient than non-adopters with diminishing marginal returns. Taken together, it seems that Rogers' innovation groups are related to the efficiency of farms. Early adopters of innovation seem to be less efficient and continue to be inefficient, while the majority of mature technology adopters seem to benefit from adoption, but with a decreasing rate. Therefore, we hypothesise that the relationship between an innovation index as classified into Rogers' innovation groups exhibits an inverse parabolic relationship with technical efficiency scores.

The current body of literature on the relationship between farm innovation and technical efficiency is confined by a strong focus on the dairy sector (Sauer, 2017), and by a simplistic understanding of farm innovation. Because of its complexity, innovation is difficult to measure and surprisingly few studies focused on measuring agricultural innovation (van Galen & Poppe, 2013a; Läpple et al., 2015). Most studies use some sort of simplistic proxy, such as investments (Sauer & Vrolijk, 2019), the number of innovative technologies adopted (Karafillis & Papanagiotou, 2011), the number of patents (when looking at agribusinesses) (Auci et al., 2021) or spending on research and development (when looking at innovations on the national level) (Gutierrez & Gutierrez, 2003). Much of the standard literature focuses on investments as opposed to more detailed empirical analyses of innovation processes within farms (Sauer, 2017).

A simplistic innovation proxy is not able to reflect the complexity of the innovation process. We adopt the view that the innovation process goes beyond the adoption of novel technologies and consists of a broader set of complementary activities. According to the OECD (2015) definition of innovation, innovation refers to all scientific, governmental, business and non-profit activities set out to implement novel or improved products and services. Innovation is a multifaceted process, that necessitate complex interactions of different actors in the agricultural innovation system (Läpple et al., 2016). Therefore, we follow the approach of Läpple et al. (2015) and measured innovation by a multi-component innovation index.

In this article, we adapt and extend the innovation index of Läpple et al. (2015) to the context of Dutch arable farmers. Our innovation index differs from that of Läpple et al. (2015) in three ways. First, we include investments per agricultural area, because it is often used as a proxy in literature (Sauer & Latacz-Lohmann, 2015; Intellectual Property Organization, 2021). Second, we add a variable for continuity, because previous firm-specific innovation experience can have a positive influence on future adoptions (Sauer & Zilberman, 2012) and because of the importance of ongoing innovation (OECD, 2013; van Galen & Poppe, 2013b). Third, we employ a Benefit-of-the-Doubt approach (BoD) developed by Cherchye et al. (2007) to assign farm-specific weights that are as optimal as possible for each farm.

We use the innovation index to assess farm innovation and Data Envelopment Analysis (DEA) efficiency scores to assess farm performance. In this study, we focus on Dutch arable farms. We empirically investigate the relationship between farm innovation and farm efficiency based on Dutch Farm Accountancy Data Network (FADN) and Innovation Monitor data. We classify innovative farmers into groups using Rogers (1962) Diffusion of Innovation Theory. We test two hypotheses. First, we hypothesise that early adopters and innovators are less efficient than the early and late majority of innovation adopter. We expect that the farm innovation index and the efficiency scores can be described by an inverted parabolic curve. Second, we hypothesise that innovation front-runners become more efficient (expand the efficiency frontier).

In the Methods and Data section 2, we explain how we computed the farm innovation index (2.1) and the DEA efficiency scores (2.2). These preparatory steps feed into the analytical framework, which is explained subsequently (2.3). The hypotheses are tested with simple linear regression analyses in quadratic functional form. We pre-registered[1] the hypotheses and regression analyses. In addition, we analyse the innovation group allocation within the sample as described in (Hansson et al., 2018). In the results section 3, we present the results of the pre-registered as well as additional analyses. We conclude with an overall discussion and limitations section 4.

[1]OSF pre-registration link:
https://osf.io/7m4k6/?view_only=fe774e56a14048e5974b3839c6f943a5

2 Methods and Data

We investigate the relationship between farm innovation and farm efficiency. We analyse the data of Dutch arable farms from 2010 to 2018. The analysis is based on three sets of data that are analysed in three steps. Information from the Dutch innovation monitor were retrieved as a basis for the expert elicitation and used to compute the innovation index. The results from the expert elicitation are used in the computation of the innovation index. Farm Accountancy Data Network (FADN) data are used to compute technical efficiency scores with a Data Envelopment Analysis (DEA). The relationship between the innovation index and the technical efficiency scores is assessed by a linear regression model, as pre-registered, and by additional analyses.

2.1 Innovation index

The innovation index is computed to measure the innovativeness. The aim is to create an innovation index that represents the multifaceted understanding of agricultural innovation as established in the agricultural innovation system approach (AIS). In AIS, innovation is the result of a collaborative and interactive learning process between multiple diverse actors (Klerkx et al., 2010; Dolinska & D'Aquino, 2016). Therefore, we use and extend the innovation index developed by Läpple et al. (2015). To reflect the complexity of the innovation process, the innovation index consists of numerous sub-indices. Our innovation index represents the adoption and investment process, the development and initiation process, and the continuity of the processes.

We compute the innovation index II_{yf} per year y and farm f as shown below .[2] Each summation represents one sub-indicator. The first summation represents whether a certain technology t has been adopted $z_t = 0;1$, how innovative p_t it is and its difficulty of implementation q_t. The second and third summation represent how innovations were developed d ($x_{dyf} = 0;1$) and who initiated their adoption r ($z_{ryf} = 0;1$). The values v_d and v_r represent the average innovation capacity of these actors. The fourth summation represents the investment I_{yf} in euro per utilised agricultural area UAA_{yf} per farm and year. The last summation represents the continuity of innovation processes. It shows whether renewal took place in the past years $c_{yf} \in (0,9)$. The sub-indices were combined by the BoD index developed by Cherchye et al. (2007). The BoD approach uses linear programming to obtain farm-specific weights w being optimal for each farm.

$$II_{yf} = \overbrace{w_{Tf}\sum_{t=1}^{T} p_t q_t z_{tyf}}^{\text{technologies adopted}} + \underbrace{w_{Kf} v_d x_{dyf}}_{\text{developer}} + \underbrace{w_{Rf} v_r z_{ryf}}_{\text{initiator}} + \overbrace{w_{If}\frac{I_{yf}}{UAAyf}}^{\text{investment per ha}} + \underbrace{w_{Cf}\sum_{y}^{Y} c_y}_{\text{continuity of innovation}}$$

The innovation index of each farm is computed with data from the Dutch Innovation Monitor of the years 2010 – 2018. The Innovation Monitor is an annual survey among Dutch farmers administered by Wageningen Economic Research (WEcR). It is conducted amongst participants of the so-called information network (*informa-*

[2]code for annotated LaTeX equations by Sibin Mohan

tienet) and its data can be connected to the general FADN data. Being one of the few rich data sets on innovation adoption and innovation processes, data of the innovation monitor have been used in previous research (Diederen et al., 2003; Sauer & Vrolijk, 2019; Sauer, 2017). The Innovation Monitor survey consists of three separate parts: product, process and management innovations. We assess process innovations only.

The complete survey is in attachment XX. Farmers are asked to describe their new or significantly improved process innovations, if they introduced any. This is an open question. We inspected the description of the process innovations, removed all stop-words and culled the most important technologies. These technologies are the technologies t in the first summation of the innovation index. Consequently, the list of technologies is dictated by data availability. Further, farmers are asked to indicated who developed the innovation and who took the initiative. They choose the answers to these questions from two lists of possible options. These lists are incorporated as d and r in the second and third summation of the innovation index.

We obtain the remaining information for the innovation index from the corresponding FADN data set and from an expert elicitation survey. Data on the innovation I_{yf} and agricultural area UAA_{yf} come from the corresponding FADN data set. All qualifying weights come from the expert elicitation survey. With the expert elicitation survey, we expected to gain the views of those that are involved in the industry, particularly in relation to the individual measures of innovation in the agricultural sector. The pdf survey from was sent via e-mail directly to 11 Dutch agricultural and innovation experts and practitioners. To reflect complex AIS, experts with heterogeneous backgrounds were part of the panel. The survey was based on the Irish agri-food innovation survey (Läpple et al., 2015). The complete questionnaire is in attachment XX.

The expert panel rated all technologies t that were obtained from the innovation monitor on an innovation scale from 1 (not innovative at all) to 5 (very innovative) and on an implementation scale from 1 (minor change to the farm) to 3 (major change to the farm). The multipliers p_t and q_t are the respective averages of the expert ratings. Then, the experts were asked to express their opinion in relation to the developers and initiators of the farm innovations. Innovators were defined as actors supporting and initiating the uptake of an innovation. The rating was between 1 (largest innovation capacity) to 5 (lowest innovation capacity). The multipliers v_d and v_r are the respective averages of the expert ratings. Last, the experts were asked to express their opinion on how they would weight the sub-indices in an overall innovation index. The expert opinions were supposed to provide lower and upper bounds for the BoD weights w_f. Through the BoD approach, the weights are endogenised and farm specific.

2.2 DEA: Farm efficiency

Data Envelopment Analysis (DEA) became a popular method to compute technical efficiency. Based on the seminal work by Charnes et al. (1978), it is nowadays frequently used to meaure technical efficiency. See Liu et al. (2013) for a review on DEA literature.

DEA is, in contrast to the stochastic frontier analysis, a non-parametric method.

The benefit of such a non-parametric approach is that only minimal assumptions are required for its estimation. This results in an estimated piece-wise linear efficiency frontier and relative efficiency scores for each farm (Coelli et al., 2005).

We conducted an output-oriented, constant-returns-to-scale DEA, which is computed by the following linear program (Coelli et al., 2005):

$$\begin{aligned} & min_{\theta,\lambda} \quad \theta, \\ s.t. \quad & -q_i + Q\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned}$$

Here, θ is a scalar satisfying $\theta \leq 1$ with a value of 1 being on the frontier and hence a technically efficient farm. Generally, θ represents the efficiency score for the i-th farm. Then, λ is a $I\,x\,1$ vector of constants. The linear programme is solved for each firm separately so that each firm obtains a value of θ. Essentially, the input vector x_i is contracted as much as possible while still remaining within the feasible input set. The inner boundary of this set is the piece-wise linear isoquant, determined by the observed data.

In our model, the input vector contains five variables: the total variable/direct costs (in euro), the costs of tangible assets (in euro), the total working hours (in number of hours), the total land use for production (utilised agricultural area, UAA, in hectares) and assets (in euro). The output vector consists of a single variable, namely total revenue (in euro). Land is a fixed input in the short term and therefore modelled as negative output. The DEA variable choice is based on Adamie &

Hansson (2021). All monetary values are deflated with price indices and expressed in constant 2010 prices. The output is deflated by EUROSTAT price indices of agricultural products, crop output excluding fruits and vegetables .[3] Inputs are deflated by EUROSTAT price indices of the means of agricultural production, goods and services currently consumed in agriculture .[4] We computed the efficiency scores for each year separately and pooled for each year.

2.3 Analytical framework: Hypothesis testing

The computation of the innovation index and the efficiency scores are preparations for the main analysis. We intend to answer the research question ”what is the relationship between farm innovation and farm efficiency" and to test our two hypotheses with a pre-registered quadratic regression analysis.

To test the first hypothesis that early adopters and innovators are less efficiency than the early and late majority of innovation adopters, we set up a regression model with a quadratic functional form. We hypothesise that there is an inverse parabolic relationship between efficiency scores and the innovation index. Both the efficiency scores and the innovation index are bounded between zero and one ($\in [0,1]$). We will fail to reject the hypotheses based on a 0.1α level of the coefficients, or $p \leq 0.1$. The ordinary least squares (OLS) regression has the following quadratic functional form

$$\theta_{yf} = \beta_0 + \beta_1 ii_{yf} + \beta_2 ii^2_{yf} + \epsilon \tag{1}$$

where θ is the efficiency score of a particular farm f in a certain year y as ob-

[3] APRI_PI15_OUTA_custom_1623426 and APRI_PI10_OUTA_custom_1623458
[4] APRI_PI15_INA_custom_1623492 and APRI_PI15_INA_custom_1623426

tained by the DEA, ii is the computed innovation index and the βs are the coefficients. To take on an inverse parabolic shape, β_2 needs to be negative. We pool the data, but use yearly efficiency scores.

To test the second hypothesis that in the long term innovation front-runners become more efficient, we pool the data and add time dummies to control for year effects. The OLS regression equals equation 1 except for additional year dummies y at the end of the equation. The dummies take the year 2010 as a baseline. To be in line with the second hypothesis, we expect all year dummies to be positive and statistically significant (on a 0.1α level) and to increase from year to year. In this analysis we use again year-based efficiency scores. Further, we expect to see a movement of farmers from the bottom right quadrant of the innovation index-efficiency score plot to the upper right quadrant.

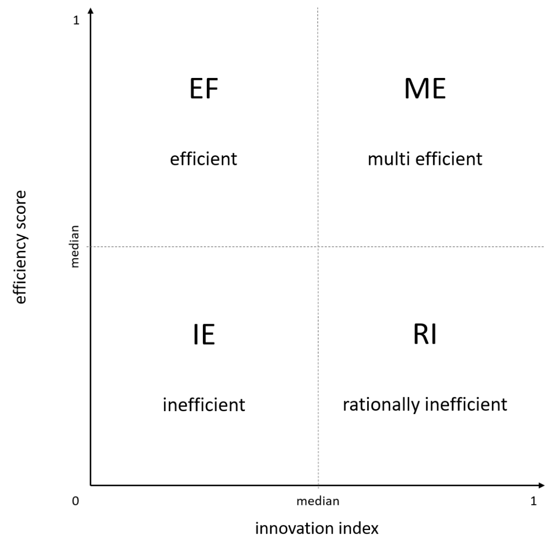


Figure 1. Visualisation of the innovation-efficiency matrix, adapted from Hansson et al. (2018)

In addition to the pre-registered, simple analyses, we conducted some further analyses. We got inspired by the more recent work of Adamie & Hansson (2021) and thereby came across the study of Hansson et al. (2018). Hansson et al. (2018) classify the dairy farmers in their sample into four efficiency groups: the multi-efficient group (ME), the inefficient group (IE), the rationally inefficient group (RI) and the efficient group (EF). In the original work, the classification depends on an animal welfare proxy and efficiency scores. In this study, the classification depends on the innovation index and the DEA score. We took the mean of the two variables to create the four efficiency classifications. See figure 1 for a visualisation. In the original work, and we replicated this method, a Chi-square test was used to investigate whether farms were equally distributed between groups or whether there was an over-representation of farms on either diagonal. An over-representation on the ME-IE diagonal indicates that innovation and efficiency are complements rather than substitutes. An over-representation on the RI-EF diagonal indicates that there is a trade-off between the two. Given an over-representation on the RI-EF diagonal, a two-sample t-test for unpaired data is conducted to see whether farms in the RI group indeed are more innovative than farms in the EF group. For an extensive elaboration and explanation, we would like to refer the reader to the work of Hansson et al. (2018) and Adamie & Hansson (2021).

2.4 Descriptive Statistics

We used data from the Dutch FADN to conduct the efficiency analysis and data from the Dutch innovation monitor to compute the innovation index. The data comprised the years 2010 to 2018. We analysed conventional arable farms. An arable farm is "an agricultural holding where crop production is the dominant activity, providing at least two-thirds of the production or the business size of an agricultural holding" according to the EUROSTAT glossary .[5] The sample is unbalanced. The data set contained about 30 farms in the years 2010 to 2013 and 80 to 100 farms in the remaining years.

The descriptive statistics are provided in appendix XX. An overview of the means is provided in figure 2. The farmer's mean age was 52 in 2010 and 57 in 2018. The mean number of workers at the farm is two. On average, Dutch arable farms have 100 ha of agricultural land.

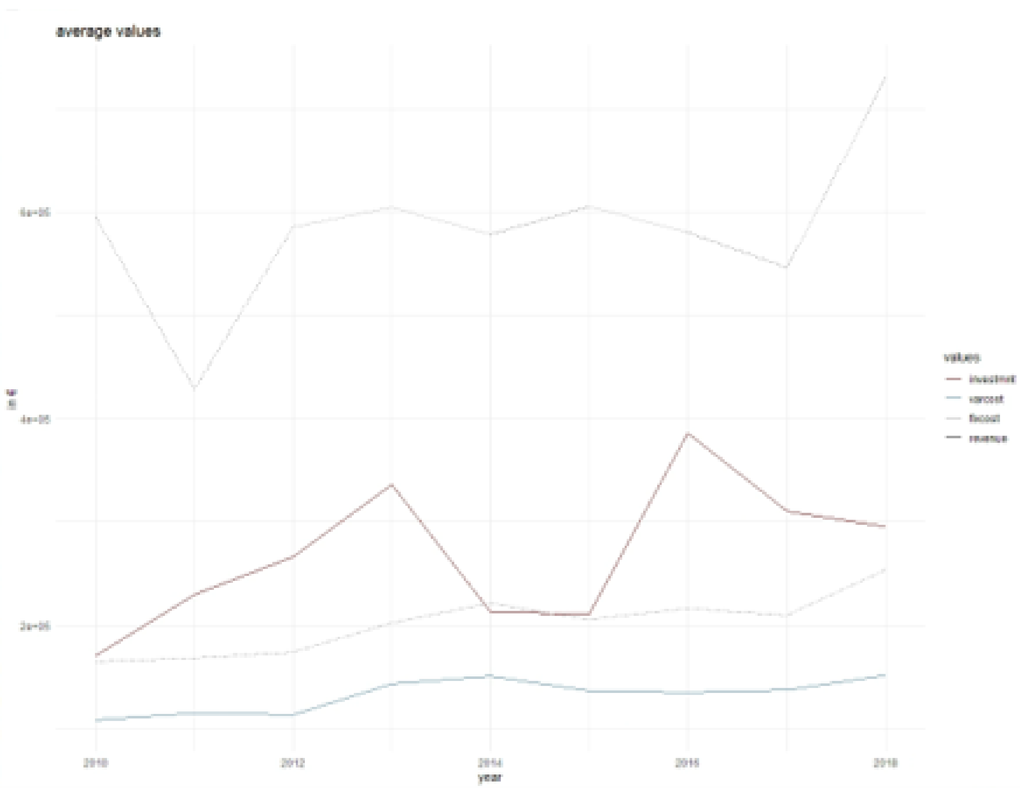


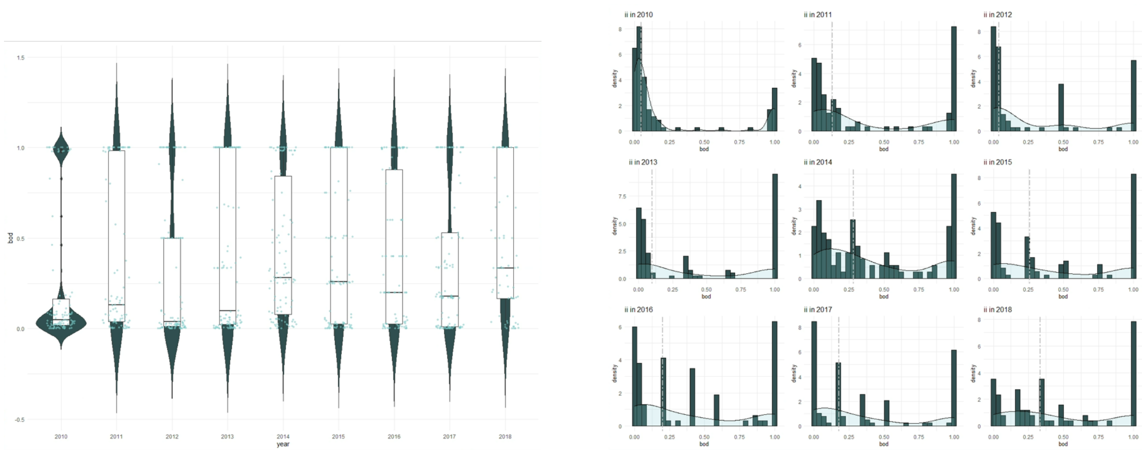
Figure 2. Mean values of the different DEA input and output variables in each year

[5]https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Farm_typology

3 Results

3.1 Innovation

From the farmers' descriptions in the innovation monitor, we derived ten technologies, for example precision farming, irrigation systems, sensors and drones or GPS. The complete list with the definition of each technology is provided in appendix XX. This list of technologies and definitions was given to the expert panel for evaluation. The summary statistics of the expert elicitation is provided in appendix XX.



(a) Violin plot　　**(b)** Histogram

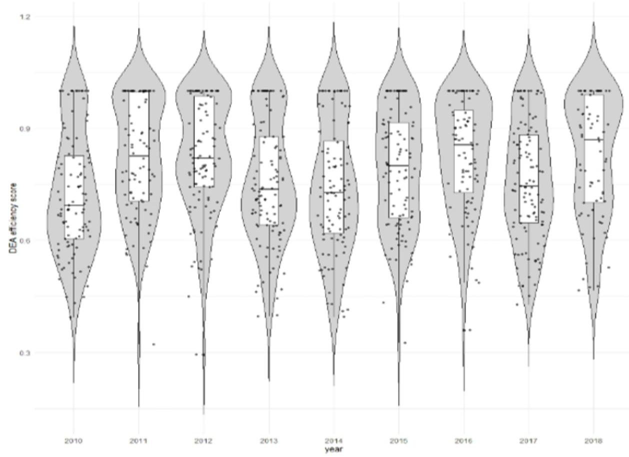
Figure 3. mean and distribution of the innovation index in each year

The means of the innovation indices are all below 0.5 in all years. The overall innovation index mean is 0.23. At the same time, the standard deviations of the innovation indices are all close to 0.4 and the overall innovation index standard deviation is 0.37. Thus, the variation within a year is large and the majority of farmers could become more innovative. In itself, these figures seem reasonable at first sight. However, when we examined the sub-indices separately, we saw that numerous farmers score zero on a high number of sub-indices. The issue is most severe with the technology indicator, showing that the majority of farmers did not adopt any of the ten technologies on the previously defined list. However, also with the developer and initiator sub-indices there are numerous zero scores. This leads to a high number of innovation indices with the value of zero. The summary statistics of the overall innovation index and its sub-indices is in appendix XX. In figure 3 the mean and distribution of the innovation index are visualised.

As described in the previous section, we wanted to use the expert opinions on the sub-index weights as lower and upper bounds in the BoD approach. However, when we impose these restrictions, the mean innovation indices are even smaller and less varied. That is because there is generally consensus on the weighting of factors, but there are some outliers (see figure XX in appendix XXX). Consequently, we did not impose any restrictions on the weights w_f.

3.2 Efficiency scores

The mean technical efficiency is 0.78 with a standard deviation of 0.16. The mean efficiency score is relatively stable over the years as can be seen from table in figure 4. The number of fully efficient farms varies per year. We found the highest proportion of fully efficient farms in 2018 with 24.32% and the lowest proportion in 2017 with 9.73%.



(a) Violin plot

DEA results - efficiency scores

year	count	mean	sd	% fully efficient
2010	103	0.72	0.16	12.62
2011	92	0.82	0.15	23.91
2012	107	0.82	0.15	21.5
2013	113	0.76	0.16	16.81
2014	103	0.74	0.17	13.59
2015	105	0.79	0.16	16.19
2016	92	0.83	0.15	19.57
2017	113	0.76	0.16	9.73
2018	74	0.82	0.16	24.32

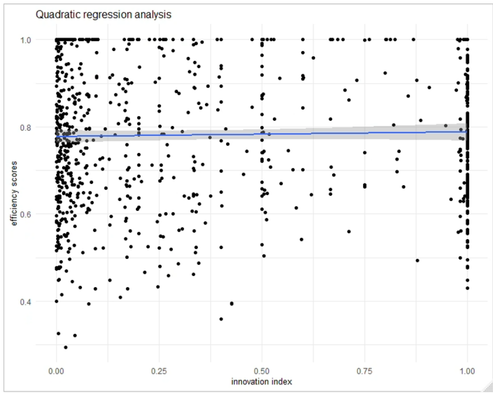
(b) summary statistics of efficiency scores

Figure 4. mean and distribution, summary statistics of DEA efficiency scores

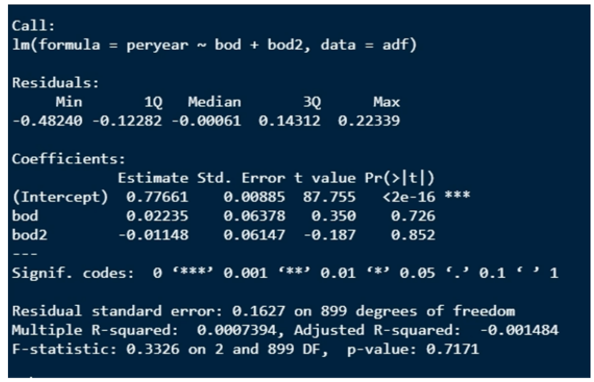
3.3 Main results: Farm innovation and farm efficiency

We hypothesise that there is an inverse parabolic relationship between innovation and technical efficiency. The results of the OLS regression are indicative of an inverse parabolic relationship because β_1 is positive and β_2 is negative. However, none of the estimates are significant and when inspecting the plot in figure 5 no inverse parabolic relationship can be detected. Consequently, we reject this hypothesis. The model has a poor fit. The model summary is provided in table 5 along with a visualisation.

We aimed to find evidence that early adopters and innovators are less efficient than the early and late majority of innovation adopters. In retrospect, we have the impression that a quadratic regression analysis is not entirely fit for the task. Therefore, we added an additional analysis step as described before. While previous studies assigned farmers to groups based on the medians of the values, we found



(a) innovation index and efficiency scores



```
Call:
lm(formula = peryear ~ bod + bod2, data = adf)

Residuals:
     Min       1Q   Median       3Q      Max
-0.48240 -0.12282 -0.00061  0.14312  0.22339

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.77661    0.00885  87.755   <2e-16 ***
bod          0.02235    0.06378   0.350    0.726
bod2        -0.01148    0.06147  -0.187    0.852
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1627 on 899 degrees of freedom
Multiple R-squared:  0.0007394, Adjusted R-squared:  -0.001484
F-statistic: 0.3326 on 2 and 899 DF,  p-value: 0.7171
```

(b) summary statistics of quadratic regression analysis

Figure 5. Visualisation of quadratic regression analysis (later, table will be provided, not image)

that the distribution of our innovation index is not fit to do so. As depicted by the grey stripe-dotted lines in figure 3, the medians of the innovation indices are very low. That means that for instance a farmer with an innovation index of only 0.1 would be called early adopter or innovator in 2010 and 2012. Alternatively, we wanted to use Rogers (1962)'s percentiles, as mentioned in the pre-registration, but the top 16% have an innovation index of almost always equal to one. This does not provide a fit measure for a sensible classification due to the lack of variation. Consequently, we followed the classification of Läpple et al. (2015). They cut the sample in top and bottom 25%. We define the top 25% of the sample as innovators. Doing so, leaves us with the most reasonable data of all. An overview of all measures is provided in table 6.

We split the sample in two innovation and two efficiency groups, based on the innovation index and the efficiency scores respectively. To split the sample into

year	median_ii	rgrs86ii	bottom25ii	top25ii
<fct>	<dbl>	<dbl>	<dbl>	<dbl>
2010	0.0476	0.979	0.0194	0.163
2011	0.132	1	0.0395	0.983
2012	0.0388	1	0.0140	0.5
2013	0.0978	1	0.0228	1
2014	0.281	0.983	0.0787	0.842
2015	0.260	1	0.0256	1
2016	0.2	0.998	0.0253	0.877
2017	0.179	1	0.0101	0.529
2018	0.334	1	0.167	1

Figure 6. *becomes table later*

efficiency groups, we used the median. We do so for each year separately. The Chi-square test (null hypothesis = there is no association) reveals that there is no over-representation of farmers in any of the groups. In other words, there is a similar number of observations in all quadrants and thus there is no relationship between the two dimensions. As there is no over-representation of a group, there is no point in doing a t-test. All in all, we find sufficient evidence to reject the first hypothesis that innovators are less efficient than the majority of innovation adopters.

We also reject the second hypothesis that innovative farmers become more efficient over the years. The results of the second regression analysis are summarised in table 7. Further, we visualised how farmers move from one efficiency group to another over the years with a sankey diagram in the same figure. Again, there is no clear pattern to be detected.

4 Preliminary Discussion

In this preliminary discussion, we discuss our findings and the limitations to this research. We do not find a relationship between the farm innovation index and the

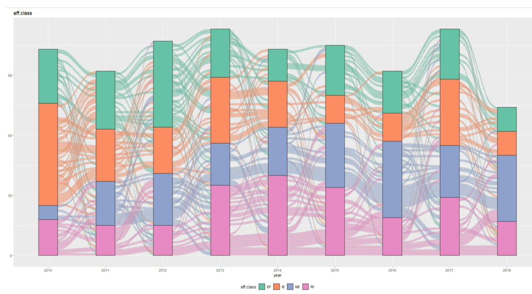
```
Call:
lm(formula = peryear ~ bod + bod2 + year, data = adf)

Residuals:
     Min       1Q   Median       3Q      Max
-0.52855 -0.11619 -0.00544  0.13587  0.27800

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.72200    0.01626  44.400  < 2e-16 ***
bod          0.00367    0.06457   0.057  0.95470
bod2         0.00249    0.06194   0.040  0.96794
year2011     0.09449    0.02291   4.124 4.07e-05 ***
year2012     0.10116    0.02199   4.600 4.83e-06 ***
year2013     0.03219    0.02180   1.477  0.14009
year2014     0.01546    0.02264   0.683  0.49495
year2015     0.06320    0.02233   2.830  0.00476 **
year2016     0.10201    0.02306   4.423 1.09e-05 ***
year2017     0.03401    0.02187   1.555  0.12030
year2018     0.09687    0.02473   3.917 9.66e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.159 on 891 degrees of freedom
Multiple R-squared:  0.05462,	Adjusted R-squared:  0.04401
F-statistic: 5.147 on 10 and 891 DF,  p-value: 2.386e-07
```

(a) *becomes table*



(b) Sankey diagram

Figure 7

technical efficiency. Farmers with a low innovation index are as likely to be highly efficient as the farmers with a high innovation index. This can be interpreted in multiple ways. First, this could be seen as an indication that innovation activities have no effect on efficiency - neither positive, nor negative. We see innovation as a holistic process, looking at how innovations are developed and initiated, which technologies are adopted, whether innovation is continuous and how much is invested in innovations. Thus, the innovation process does not put the innovative farmer into a favourable competitive place. Second, our results can be seen as an indication that farm innovations might not be as effective in stimulating farm-level efficiency as hoped.

We believe that the innovation index, as extended from Läpple et al. (2015), reflects the innovation level of a farmer quite well. The index strikes the balance between comprehensiveness and simplicity. Since it can be easily computed based on survey data, the effort of computation is limited. However, the quality of the index depends on the underlying data.

The general data availability on farm innovation is limited. The Dutch Innovation Monitor is one of the few rich data sets investigating farm innovation systematically. However, also this data set hat its limitations. For example, there is no structural monitoring on which technologies have been adapted. Farmers describe in an open-ended question which technologies they adapted in the past year. The descriptions can be filtered and coded, but the process might introduce inaccuracies to the data. If the survey included a multiple choice list of technologies and an open question in addition, these inaccuracies could be prevented. This would in the end also improve the quality of the innovation index.

To conclude, we believe that the methodology, especially with the additional analyses is able to provide a satisfactory answer to our research question on the relationship between farm innovation and farm efficiency. We trust our findings in the sense that the data at hand do not provide an indication of any relationship between the two variables. However, we do not entirely trust the Innovation Monitor data that were used to compute the innovation index. In that sense, our study should be replicated with better data on innovation indices.

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