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## The contribution of innovation to farm-level productivity

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#### Abstract

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Innovation is a key driver of productivity growth. This paper proposes a novel methodology in order to explore the impact of farm-level innovations on farm productivity and its components (i.e. technology, efficiency and scale) using representative data from Irish dairy farms. We measure innovation by an index based on employed production practices, continuous innovation activity and knowledge weighted by expert opinions. The results suggest that more innovative Irish dairy farmers are more productive. Specifically, all farmers improve their production technology and efficiency through their use of innovations, but farmers at specific levels of innovativeness may experience a decrease in productivity due to the small scale at which they operate. This indicates that innovation has a non-linear effect on productivity. We discuss the policy implications for reducing the unequal gains of innovation across farmers.

JEL classification D24 · Q12 · O33

**Keywords** Agricultural Innovation System (AIS) · Total factor productivity · Efficiency · Agriculture · Dairy production · Stochastic frontier analysis

## **1** Introduction

Productivity and efficiency analysis is a particularly popular research topic in agricultural economics (e.g. Alvarez et al. 2012; Brümmer et al. 2002; Emvalomatis 2012; Fuglie et al. 2016; Hadley 2006; Karagiannis et al. 2004; Kellermann 2015; Latruffe 2010; O'Donnell 2012; Sauer and Latacz-Lohmann 2015; Skevas et al. 2018; Zhu and Oude Lansink 2010), due to its important policy implications. Productivity is recognized as an indicator of long-term competitiveness

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in agriculture (e.g. Latruffe 2010; Newman and Matthews 2006), while the efficient use of production factors can be viewed as an indicator of sustainability (e.g. Chambers and Serra 2018; Färe et al. 2005; Malikov et al. 2015; Murty et al. 2012; Sidhoum et al. 2019). For example, the Common Agricultural Policy (CAP) of the EU recognizes the necessity of productivity gains through technology and efficiency improvements at the farm level while reducing environmental pressures (Latruffe et al. 2017): increasing agricultural output with the same or smaller amounts of resources, while minimizing the impact on the environment is referred as sustainable intensification (SI) in the literature and policy documents (e.g. Benton and Bailey 2019; Campbell et al. 2014; Garnett et al. 2013; Godfray and Garnett 2014; Tilman et al. 2011).

Innovation is a key driver of productivity growth and sustainability (e.g. Moreddu and Gruere 2019), and a voluminous literature on the link between innovation and productivity has developed over the years (Sauer 2017; Sauer and Latacz-Lohmann 2015). Innovation is a broad concept, which can be generally defined as the successful utilization of an idea (Knickel et al. 2009). In the case of firms/farms, innovation encompasses both creation and adoption of ideas that can be new to the firm, the market or

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the world (OECD and Eurostat 2005). A firm is characterized as innovative if, during the review period, it has implemented any type of innovation, including (i) new or improved product, (ii) process, (iii) marketing or (iv) organizational method (OECD and Eurostat 2005). Due to the wide nature of the concept of innovation, operationalizing it in applied research is not straightforward and, indeed various approaches to proxy innovation activity at the farm level have been employed. An established approach to measuring innovation is through investment expenditures at the farm level (e.g. Emvalomatis et al. 2011; Minviel and Sipiläinen 2018; Sauer 2017; Sauer and Latacz-Lohmann 2015; Serra et al. 2011; Silva and Stefanou 2007). However, innovation can also be nonphysical (OECD and Eurostat 2005), for example, taking the form of information acquisition, the development and use of tacit knowledge. As such, innovation can be created within the farm through learning-by-doing (Shee and Stefanou 2016; Stefanou 2009), as well as through the interaction with other actors, in particular, farmers interacting with their peers, advisors, academic institutions, input suppliers or other actors, thus forming an Agricultural Innovation System (Klerkx et al. 2012; Lamprinopoulou et al. 2014).

The contribution of AIS actors to supporting SI can be considered more important than physical investments at the farm level, with the CAP and Farm to Fork strategy officially promoting the role of AIS actors to foster a more competitive, resource efficient and sustainable agricultural sector. The reason is that physical investments (e.g in machinery) are not always consistent with the SI vision, since although they result in productivity gains, these may come at the cost of sustainability, e.g. through exerting increasing pressure on the environment (e.g. FAO 2013). To achieve SI, farmers need to combine their own tacit knowledge with information coming from external AIS actors in order to adapt their farming practices, while considering the various environmental, ecological, cultural and socioeconomic characteristics (Laurent et al. 2006; Polanyi 2000; Rossel and Bouma 2016).

This paper builds a framework for examining whether the impact of innovation on farm-level productivity is in line within the wider definition of SI. A stochastic frontier analysis (SFA) model is employed, which examines total factor productivity (TFP) differences across farmers that arise from differences in the innovations they employ. The Irish dairy sector is considered as an interesting case study, given the ambitious growth targets set out for the industry in the post-quota environment, which is predicated on the idea of knowledge adoption augmenting productivity by farmers and other economic agents within the agricultural sector (DAFM 2015). On the basis of an innovation index, which captures the differences in the employed innovations across farmers, we construct a cross-sectional TFP index similar to Orea (2002), by extending the approach taken by Karafillis

and Papanagiotou (2011), where the time dimension in a panel study of productivity growth is replaced by the innovation index. In this setup we are able to examine the contribution of innovation to cross-sectional differences in TFP and its components, i.e. on the production technology, efficiency and scale effects. Hence, the main advantages of the proposed framework is that it can examine whether the contribution of innovation to productivity is in line with the vision of SI and, in particular, the objective of producing more agricultural output with the same or less inputs. Our results suggest a non-linear effect of innovation to productivity. Specifically, more innovative farmers are more productive, which is driven mostly by a positive effect of innovation on technology and efficiency. The scale effect is negative at lower levels of innovation but positive at higher levels of innovation, i.e. innovation has a higher effect on the productivity of larger farmers.

The remainder of the paper is organized as follows: Section 2 summarizes previous empirical research regarding innovation and productivity, and explains how this paper extends this stream of literature. Section 3 outlines the conceptual framework, building a TFP index in which the contribution of AIS is incorporated explicitly. Section 4 presents the data and summary statistics. Section 5 reports the results and Section 6 concludes.

## 2 Background and conceptual framework

#### 2.1 Literature review

Many empirical studies have examined the contribution of innovations promoted by specific AIS actors to farm-level productivity and its components, while accounting for the possibility of suboptimal utilization of resources (e.g. Bravo-Ureta and Evenson 1994; Bravo-Ureta et al. 2012; Dinar et al. 2007; Henningsen et al. 2015; Martinez-Cillero et al. 2018; O'Neill et al. 1999; Rao et al. 2012). This vein of research was undertaken using mostly cross-sectional data, possibly due to lack of panel data. The contact of a farmer with an AIS actor is measured usually with a binary variable, indicating whether a farmer contacted an AIS actor during a specific period.

From a methodological perspective, cross-sectional studies either split the samples into farmers who contacted the AIS actor of interest and those who did not, and compare the differences in marginal productivities and efficiency scores between the two groups (e.g. Bravo-Ureta et al. 2012; Henningsen et al. 2015; Rao et al. 2012), or with the use of a metafrontier for more than two groups (DeLay et al. 2022). An alternative methodological approach is to include the innovation variable as part of the technology and/or inefficiency (Dinar et al. 2007; McFadden et al. 2022).

The adopted methodologies of the aforementioned crosssectional studies have a common limitation when one investigates the impact of innovation in SFA framework: the impact of innovation on productivity through the scale effect is not taken into account. The adoption of an innovation changes the production technology and, thus, it may alter the optimal levels of factors of production and, consequently, their optimal usage ratios. In this respect, technical progress, especially embedded technical progress, tends to favor larger farms (e.g. Alvarez and del Corral 2010; Alvarez et al. 2012; Balaine et al. 2020; Läpple and Thorne 2019). During the Green Revolution, physical innovations, such as introduction of specialized machinery, enabled farmers to increase their scale of operation (Weersink et al. 2018) with a commensurate reduction in the total number of farms.

However, knowledge and information, as provided by AIS actors, can assist farmers to sustainably intensify their production processes by reducing the need for large-scale farming. This is because farmers can use knowledge instead of scarce (e.g. labor, land) or harmful (e.g. chemicals) inputs (Bongiovanni and Lowenberg-DeBoer 2004; Finger et al. 2019; Gallardo and Sauer 2018; Lajoie-O'Malley et al. 2020; Mcbratney et al. 2005; Rossel and Bouma 2016) and produce more with the same or less inputs. Thus, when examining the impact of innovation on SI in a productivity and efficiency analysis framework, it is necessary to account for the impact of innovation on the technology, efficiency scores and optimal scale, simultaneously.

Taking a different approach from the aforementioned studies, Karafillis and Papanagiotou (2011) estimated a profit function using cross-sectional farm-level data and constructed a TFP index on the basis of an innovation index. The index consisted of aggregate (mostly physical) technologies that were used at the farm level. The limitation in Karafillis and Papanagiotou (2011), again in relation to SI, is that their TFP index consisted only of the technology and scale effects, neglecting efficiency. Nevertheless, their approach is amenable to modifications which can include the efficiency component of TFP in the analysis. We extend this approach to examine the impact of innovation on the technology, efficiency and scale and their aggregate net effect on TFP using cross-sectional data from Irish dairy farms.

#### 2.2 Conceptual framework

Individual farmers typically have different needs and face different constraints, which leads them to utilize various technologies/sources of information at any point in time (Chavas 2001, 2012). Taking this into consideration, we do not focus on the contribution of a specific actor or technology on productivity, but we consider innovation at the farm level to stem from the contribution of multiple AIS

actors. Previous studies examined the simultaneous impact of multiple innovations on farm level productivity and efficiency (DeLay et al. 2022; Dinar et al. 2007; McFadden et al. 2022). Neglecting to take into account the contribution of various innovations may result in biased estimates, e.g. part of productivity gains may be attributed to a technology that is not included in the analysis.

Furthermore, if one is interested in examining the impact of multiple AIS actors, then it is necessary to consider the relationship between these actors, as these usually form the wider institutional context and regional/national policy objectives (Klerkx and Jansen 2010; World Bank 2006). For instance, Dinar et al. (2007) considered the use of public and private advisors as two separate determinants of production technology and efficiency, utilizing the whole sample in the empirical application. This is because, in the context of their application, private advisors assist farmers with practical problems associated with the use of certain inputs, while public advisors focus on more general problems (Dinar et al. 2007).

In the case of Ireland, the national AIS is one of the most integrated systems in the EU, with an organized and coordinated structure. Specifically, Irish dairy farmers may simultaneously use information or technologies from various Irish AIS actors, who offer complementary technologies/ advice (e.g. Prager and Thomson 2014). These technologies are related to grassland, breeding and financial management, that will, overall, allow dairy farmers to better utilize the lowcost grass-based feed system (Läpple et al. 2019; Thorne et al. 2017) and, as a result, improve competitiveness in a sustainable manner. For instance, a farmer may use milk recording, which provides more information about cows' productive capacity (Balaine et al. 2020) and then contact an advisor for assistance in order to use the information obtained for breeding management (Balaine et al. 2020; Regan 2019).

Capturing the impact of complementary Irish AIS technologies by using separate variables for each technology may create issues such as multicollinearity in the empirical specification. Thus, we use the composite innovation index developed by Läpple et al. (2015) specifically for the Irish dairy sector in 2012, which captures the employed innovations at the farm level that arise from the interaction of various innovations promoted by the Irish AIS: farmers with higher index scores use more innovations promoted by AIS. Thus, the overall index reflects the degree of innovativeness of individual farmers, where innovativeness is defined as "the degree to which an individual, or any other unit of adoption is relatively earlier in adopting new ideas than other members of a system" (Rogers 2003, p. 22).

Previous farm-level studies focused on examining the impact of specific components of the AIS, such as FAS or the use of specific technologies, using binary indicators on efficiency and TFP growth (Parikoglou et al. 2022a, b). However, the TFP growth index and its components are not informative regarding the starting point in productivity, but only measure rates of change. On the contrary, in this study we focus on TFP differences in the dimension of innovativeness. In this regard, we are able to determine, at a specific point in time, whether farms with a higher innovation index are indeed more productive: instead of simply measuring the productivity level for each innovation group and comparing the results (which is particularly difficult to do or requires stronger assumptions compared to measuring productivity changes), we amend the methodology designed to measure productivity differentials across different levels of innovativeness.

At higher levels of innovativeness, farmers experience better information flow, which can inform input use, choices and access to technology embodied in inputs (Batte and Schnitkey 1989). Better information flow may shift the production technology outwards (DeLay et al. 2022; Dinar et al. 2007; McFadden et al. 2022). Furthermore, better information flow may have a twofold impact on efficiency. First, acquisition of knowledge may improve the way inputs are used and lead to higher efficiency. For example, a farmer who starts using a grassland management system could make better use of the available area. Conversely, the introduction of a new product or production method may adversely affect efficiency if the farmer incurs learning costs when implementing the innovation, as predicted by the adjustment-cost theory (Stefanou 2009). For instance, Henningsen et al. (2015) examined cross-sectional productivity differences between contract and non-contract farmers in Tanzania in 2012. The results showed that contract farmers had much lower average technical efficiencies compared to non-contract farmers, although the former were more productive. The authors argue that this finding can be attributed to the lack of advisor services that assist farmers in making better use of the information gained from contract farming.

Lastly, different types of employed technologies may lead to different optimal scales of operation (Varian 2010). For example, some technologies are input saving, e.g. grassland management techniques were developed as a response to the lack of available land. Others may be output-enhancing, such as milk recording. In the latter case, farmers may endure external adjustment costs in relation to these factors of production (Stefanou 2009) and divert resources from production to innovation investments (e.g. Serra et al. 2011). This alters the optimal scale of production, which could cause either a decrease or an increase in productivity. Ultimately, discrepancies in productivity among farmers due to varying levels of innovativeness can be attributed to the aggregate impact on the technology, efficiency and scale.

## 3 Modeling approach and empirical specification

Irish specialist dairy farms produce more than a single output, thus we use an output distance function to represent their production technology (Newman and Matthews 2006). In general, the choice between an input-reducing and output-expanding view does not make a difference when the technology exhibits constant returns to scale (Newman and Matthews 2006; Orea et al. 2004). We choose the distance function to be output-expanding since, despite the quota scheme operating in the period covered by our data, quotas were tradeable within regions.

It is conventional in applications that involve time-series or panel data to capture improvements in the production technology over time by the exogenous passage of time. These improvements result in an outward shift of the technology of the production possibilities set. Following Dinar et al. (2007); Karafillis and Papanagiotou (2011); McFadden et al. (2022), in a cross-sectional setting, differences in the technology employed by farmers are attributed to the level of their innovativeness, captured by I, where, a priori, we expect higher levels of I to result in a similar outward shift of the technology. The output expanding distance function is defined as:

$$D_o(\mathbf{x}, \mathbf{y}, I) = \min\left\{\theta : \frac{\mathbf{y}}{\theta} \in \text{ output possibility set, given } I\right\}$$
(1)

where  $\mathbf{y} \in \mathbb{R}^{M}$  and  $\mathbf{x} \in \mathbb{R}^{N}$  represent, respectively, the vectors of outputs and inputs. Both vectors are assumed to be functions of *I*, as innovativeness affects the employed technology and, thus, the levels of and proportions at which inputs are combined to produce outputs. We also assume that *I* is exogenously determined.<sup>1</sup>

The output distance function in equation (1) reflects the distance of a producer from the boundary of the production possibilities set for each level of the innovation index, with the inverse of the value of the distance function indicating the maximum amount by which the output vector can be expanded to reach this boundary. Technical efficiency can be defined as:

$$D_o(\mathbf{y}, \mathbf{x}, I) = \mathrm{TE} \tag{2}$$

Taking logs of both sides, totally differentiating with respect to *I*, and re-arranging gives:

$$\sum_{m=1}^{M} \frac{\partial \log D_o}{\partial \log y_m} \hat{y}_m + \sum_{n=1}^{N} \frac{\partial \log D_o}{\partial \log x_n} \hat{x}_n + \frac{\partial \log D_o}{\partial I} = \frac{d \log \text{TE}}{d I}$$
(3)

<sup>&</sup>lt;sup>1</sup> We relax this assumption later, treating the variable as endogenous in our empirical framework.

where  $\hat{y}_m, \hat{x}_n$  represent growth rates in outputs and inputs in the *I* dimension  $(\hat{y}_m = \frac{\partial y_m}{\partial I} / y_m = \frac{\partial \log y_m}{\partial I}$  for example). Following the definition of TFP growth in the time dimension, we define TFP change in the *I* dimension as the weighted growth in outputs minus the weighted growth rate in inputs:

$$\frac{\mathrm{d}\log\mathrm{TFP}}{\mathrm{d}I} = \sum_{m=1}^{M} \frac{\partial\log D_o}{\partial\log y_m} \hat{y}_m - \sum_{n=1}^{N} \frac{\varepsilon_n}{\varepsilon} \hat{x}_n \tag{4}$$

with  $\varepsilon_n = \frac{\partial \log D_o}{\partial \log x_n}$ ,  $\varepsilon = \sum_n \varepsilon_n$ . Finally, by inserting (4) in (3) and rearranging we get:

$$\frac{\mathrm{d}\log\mathrm{TFP}}{\mathrm{d}I} = \frac{\mathrm{d}\log\mathrm{TE}}{\mathrm{d}I} - \frac{\partial\log D_o(\mathbf{x}, \mathbf{y}, I)}{\partial I} - (\varepsilon + 1)\sum_{n=1}^N \frac{\varepsilon_n}{\varepsilon} \hat{x_n}$$
(5)

This relationship decomposes TFP differences into three components: (i) efficiency effect, (ii) effect on the technology, and (iii) scale effect. This decomposition is similar to Orea (2002), but here the time variable is replaced by the innovation index. In this way, the contribution of I to each component can be assessed and examined as to whether it is in accordance with the SI vision.

An empirical counterpart to the distance function is needed to evaluate the distance elasticities that enter the formulas of the components of TFP. We depart from the typical translog specification of the distance function and, instead, specify it as Cobb-Douglas in inputs, but translog in outputs and including all interaction terms with *I*. This assumption was dictated by the relatively small sample size and to avoid overparameterization of the distance function.<sup>2</sup> The complete specification is:

$$-\log y_{M,i}^{I} = \alpha_{0} + \sum_{n} \alpha_{n} \log x_{n,i}^{I} + \sum_{m} \beta_{m} \log \left(\frac{y_{m,i}^{I}}{y_{M,i}^{I}}\right)$$
$$\sum_{m} \sum_{\ell} \phi_{m\ell} \log \left(\frac{y_{m,i}^{I}}{y_{M,i}^{I}}\right) \log \left(\frac{y_{\ell,i}^{I}}{y_{M,i}^{I}}\right) + \eta I_{i} + \sum_{n} \lambda_{n} I_{i} \log x_{n,i}^{I}$$
$$+ \sum_{m} \xi_{m} I_{i} \log \left(\frac{y_{m,i}^{I}}{y_{M,i}^{I}}\right) + \nu_{i}^{I} - \log(\mathrm{TE}_{i}^{I})$$
(6)

where *i* is used to index farms,  $y_M$  is the normalizing output,  $\nu_i^I$  is an error term with a normal distribution and  $-\log(TE_i^I) \equiv u_i^I$  is the technical inefficiency term, assumed here to be a draw from an exponential distribution (e.g. van den Broeck et al. 1994), with rate parameter  $e^{\theta + \delta I_i}$ , where  $\theta$  and  $\delta$  are parameters to be estimated. Thus, we assume that technological innovations can result in a shift to the production technology, but also as innovativeness, as a general attitude, can also lead to improvements in the managerial ability of farmers, through the gathering and processing of relevant information, which is translated to improved efficiency.<sup>3</sup>

The dependent variable in eq (6) is negative and  $log(TE_i^I)$  is subtracted from the right-hand side. In this setup, distance elasticities should be negative with respect to inputs and positive with respect to outputs. The innovation index, *I*, plays a similar role as the time-trend variable in panel-data models: as *I* increases from low values to higher ones, the technology of the production possibilities set is expected to move outwards, reflecting an improvement in the employed technology. For a given combination of inputs and outputs, the value of the distance function reduces with an outward shift, as the output vector needs to be divided by a smaller number to reach this new boundary. Thus, the distance elasticity with respect to *I* is expected, a priori, to be negative.

So far, we assumed that innovation is exogenous. However, innovations are "are choice variables that could be correlated with the operator's unobserved managerial ability or human capital, unobserved pest pressure, or other unobservable factors directly correlated with output" (McFadden et al. 2022, page 592). We express this algebraically as:

$$I_i = h(\mathbf{z}_i) + \nu_{2i} \tag{7}$$

where  $I_i$  measures the innovation at the farm level,  $\mathbf{z}_i$  is a vector of farm-specific characteristics that can explain differences in the management practices of farms, and  $\nu_{2i}$  is an error term. Thus, in our empirical framework we estimate eq. (6)–(7) simultaneously in a system, so the latter equation is used as a control function that accounts for potential endogeneity of innovation (e.g. Hausman 1978; Heckman 1978; Heckman and Robb 1985; Wooldridge 2014). The control-function approach has been discussed and used in nonlinear models, including stochastic frontier analysis (Amsler et al. 2016; Griffiths and Hajargasht 2016; Horrace and Jung 2018; Kutlu 2010; McFadden et al. 2022; Shee and Stefanou 2015; Wechsler and Smith 2018; Wechsler et al. 2018).

With estimates of the distance elasticities at hand, the effect on the technology caused by an increase in I

 $<sup>^{2}</sup>$  A simple comparison between the full translog specification and the semi-translog was performed using the Deviance Information Criterion (DIC) (Griffin and Steel 2007). The DIC value for the translog and semi-translog were 460.8 and 405.6 respectively, which suggests that the semi-translog specification is favoured by the data against the translog specification.

 $<sup>^{3}</sup>$  We would like to thank an anonymous reviewer for pointing this out.

becomes:

$$\frac{\partial \log D_o(\mathbf{x}, \mathbf{y}, I)}{\partial I} = \eta + \sum_n \lambda_n \log x_{n,i}^I + \sum_m \xi_m \log \left( \frac{y_{m,i}^I}{y_{M,i}^I} \right)$$
(8)

Analogously to neutral and biased technical progress,  $\eta$  captures the common effect of innovations on the distance function, while the  $\lambda_n$ s and  $\xi_m$ s the impact of innovation on the use of inputs or the production of outputs (Alvarez and del Corral 2010; Alvarez et al. 2012; Finger et al. 2019; Gallardo and Sauer 2018).

The impact of innovations on efficiency (efficiency effect) is calculated as  $\frac{dE(\log TE'_i)}{dI} = \frac{dE(-u'_i)}{dI} = \delta e^{-(\theta + \delta I)}$ . Since the second term in this product is always positive, the sign of  $\delta$  determines the effect of innovation on the expected value of technical efficiency: a positive (negative)  $\delta$  would indicate a positive (negative) effect of *I* on technical efficiency. The effect of *I* on efficiency can be, as discussed, either positive or negative.

Finally, the scale effect is calculated as:

$$-(\varepsilon_i+1)\sum_{n=1}^{N}\frac{\varepsilon_{n,i}}{\varepsilon_i}\hat{x}_{n,i}$$
(9)

with  $\varepsilon_{n,i} = \alpha_n + \lambda_n I_i$ ,  $\varepsilon_i = \sum_{n=1}^N \varepsilon_{n,i}$  and  $\hat{x}_{n,i} \left( = \frac{d \log x'_{n,i}}{dI} \right)$  is the rate of change in the quantity of input *n* used in the production process caused by a small change in the value of the innovation index. As discussed in the previous section, the scale effect can be positive or negative and as a result, its sign cannot be determined a priori.

In applications involving time-series or panel data, the components of TFP are calculated over time. No adjustments are required when calculating the effect on the technology when the time index is replaced by I, as in both cases the effect is obtained by differentiating the distance function in the relevant dimension. Calculation of the efficiency change and scale effects, however, a typical TFP growth decomposition involves taking differences of the efficiency scores (for the efficiency change effect) or of the logarithms of inputs (to approximate  $\hat{x}_{n,i}$  in the scale effect) in adjacent time periods. In the cross-sectional setting things are complicated because I is a continuous variable with varying intervals between adjacent observations, but also because one may observe more than a single farm with a specific value of I.

We proceed by transforming the composite innovation index into a discrete innovation variable, which denotes innovation groups. Farmers with similar values are then assigned to each group. More details on the construction of the innovation index and the transformation procedure are presented in the following section. The discrete innovation variable presents clusters of values and, in this setting, the required differences are approximated between each farm in a cluster of values for the innovation index and the average of the relevant variable over farms in the immediately preceding cluster. Therefore, the analysis takes place in two steps. First, we estimate the parameters of the frontier as presented in equation (6) as if I was a continuous variable. Second, using the estimated parameters from the first step, we calculate the three components of TFP change over I as follows:

- The efficiency difference is calculated as the average of the sum of each farmer's logarithm of efficiency in group  $I_g$  with the average logarithm efficiency of farms in group  $I_{g-1}$ .
- The technology difference is calculated as the average value of  $\frac{\partial \log D_o}{\partial I}$  (where  $\log D_o$  is predicted using the estimates of all parameters, including those whose values are restricted when imposing linear homogeneity in the distance function) at each innovation group,  $I_g$ , and the average value  $\frac{\partial \log D_o}{\partial I}$  for the preceding group,  $I_{g-1}$ .
- The scale effect is calculated as the average of the sum of each farmer's scale in group  $I_g$  with the average scale effect of farms in group  $I_{g-1}$ . Similarly, the growth of inputs is calculated as the difference between input *n* of each farmer in  $I_g$  and the average input *n* used in  $I_{g-1}$ .

Ultimately, the net impact of  $I_g$  on TFP is conditional on the aggregated impact on the individual components of TFP. Specifically, for a farm *i* in group  $I_g$ , the difference in TFP relative to the innovation group  $I_{g-1}$  is:

$$\widehat{\text{TFP}}_{i}^{I} = \frac{1}{2} \left( \frac{1}{J_{g}} \sum_{j \in I_{g-1}} \frac{dE(\log TE_{j})}{dI} + \frac{dE(\log TE_{i})}{dI} \right) - \frac{1}{2} \left( \frac{1}{J_{g}} \sum_{j \in J_{g-1}} \frac{\partial \log D_{oj}}{\partial I} + \frac{\partial \log D_{oi}}{\partial I} \right) - \frac{1}{2} \sum_{n=1}^{N} \left( \frac{1}{J_{g}} \sum_{j \in I_{g-1}} \frac{\varepsilon_{j+1}}{\varepsilon_{j}} \varepsilon_{j,n} + \frac{\varepsilon_{i+1}}{\varepsilon_{i}} \varepsilon_{i,n} \right) \cdot \hat{x}_{i,n}$$
(10)

where  $\hat{x}_{i,n} = \frac{d \log x_{i,n}^I}{dI} \approx \log x_{i,n} - \log \left( \frac{1}{J_g} \sum_{j \in I_g} x_{j,n} \right).$ 

Thus, the differences in TFP and its components among farmer groups are decomposed by using sample averages, similarly to Orea (2002). We note two differences in our approach compared to the TFP growth decomposition of Orea (2002). First, we do not go into the details of examining the properties of the decomposition. Second, the productivity growth decomposition is derived with respect to the continuous dimension of time. Nevertheless, the upper bound of the innovation index is unity, implying that farmers with the highest innovation score cannot achieve a higher level of innovation. Taking the derivative with respect to the innovation index has no meaningful interpretation for farmers at this boundary. The latter holds even when discretizing the innovation index; but it allows to calculate TFP differences as discrete differences with respect to innovation groups  $I_G$  (instead of the discrete time dimension as in Orea). The practical implication of the transformation is that we do not focus in examining the absolute but rather the relative effect of innovation across farmers. Classification of farmers to innovation groups is additionally linked conceptually to the agricultural innovation theory. This will be discussed further in the data section when the classification strategy is explained.

We use Bayesian inference to estimate eq. (6)–(7) in a system.<sup>4</sup> The posterior moments are estimated using Markov Chain Monte Carlo (MCMC) techniques (Koop et al. 1995) and the priors on the parameters are based on Griffin and Steel (2007); van den Broeck et al. (1994). We write the error terms of eq. (6)–(7) in vector form as  $\boldsymbol{\nu}_i = \left[\nu_i^I, \nu_{2i}\right]'$  and assume  $\boldsymbol{\nu}_i \sim \mathcal{N}(0, \boldsymbol{\Sigma})$ . For  $\boldsymbol{\Sigma}$  we choose a prior in the inverted Wishart family, with q = 1 degree of freedom and scale matrix  $\mathbf{V} = \mathbf{I} \cdot 1000$ , where **I** is the identity matrix. (e.g. see Koop 2003; Kumbhakar and Tsionas 2016, 2005). A multivariate normal prior is used for the vector of slope parameters that appear in the distance function and an independent bivariate normal prior for a vector that contains the two parameters that enter the specification of the distribution of inefficiency,  $[\theta, \delta]'$ . In both cases the prior mean is a vector of zeros and the covariance matrix with diagonal entries equal to 1000.

#### 4 Data

Our data are from the Teagasc National Farm Survey (NFS) database, which is part of the Irish FADN data. The NFS data are collected annually through face to face interviews by professional farm recorders, providing a statistically representative sample of Irish farming. Then, farms are classified into "specialised" farming systems conditional on their major enterprise which is calculated on a standard gross margin basis (Läpple et al. 2015). We use a representative sample of specialist Irish dairy farmers in 2012, where a supplementary survey was carried out on the topic of new technologies and knowledge transfer. We define two outputs and four categories of inputs, similar to Newman

and Matthews (2006). The main output  $(y_1)$  is value of milk sold<sup>5</sup> and other output  $(y_2)$ , such as sales of meat and other products. In relation to inputs, we account for capital (K) as the sum of the value of machinery and buildings, plus the value of livestock, land (A) as the utilized agricultural area, measured in hectares, labor (L) as both unpaid and paid labor units, and materials (M), including expenditures in seeds and plants, fertilizers, crop protection, energy, contract work, purchased feed, upkeep of buildings, machinery hire and upkeep of land. As a measure of the state of innovativeness at the farm level, the innovation index developed by Läpple et al. (2015) is used. Knowledge transfer and innovation experts collaborated in selecting and weighting three indicators from different components of the Irish AIS (e.g. research, education, agribusiness and advisory services etc.) that capture process innovations at the dairy-farm level.

The three selected innovation indicators and their respective weights (weights reflect the perceived importance of each component of the Irish AIS) are: (i) innovation adoption with weight 0.45, which is comprised of five selected innovative technologies relating to improving farm performance (E-profit monitor usage, ICT usage, soil testing, reseeding application and milk recording), weighted by how innovative the technologies were considered and their implementation effort by farmers; (ii) continuous innovation with weight 0.15, which measures whether a farmer renewed some of his machinery, underlining the need for ongoing innovation (OECD 2013);<sup>6</sup> (iii) acquisition of knowledge with weight 0.40, taking into account the importance of knowledge development for innovation (Spielman and Birner 2008). The acquisition of knowledge is measured by whether a farmer had a contract with Teagasc Farm Advisory Services (FAS), without the contact being for environmental scheme assistance only (Cawley et al. 2018; Läpple et al. 2015; Parikoglou et al. 2022a). This is an important distinction because in the latter case, farmers participate for the purpose of fulfilling bureaucratic requirements to receive subsidy payments instead of receiving technical advice regarding breeding, financial and grassland management. On the contrary, farmers who are not contacting FAS for scheme assistance only, are contacting FAS for technical advice that will allow them to be more productive in line with the sustainable intensification vision.

 $<sup>\</sup>frac{1}{4}$  Estimating system of equations in Bayesian inference for accounting for endogeneity has been previously suggested in the literature (see Chan and Tobias 2020, 2015).

<sup>&</sup>lt;sup>5</sup> The quantity of milk produced in kilograms could be used alternatively. However, monetary measures are preferred, as these also capture partly differences in quality, which are reflected in prices.

<sup>&</sup>lt;sup>6</sup> As pointed out by an anonymous reviewer, renewal of machine in a given year may have an impact on the production possibilities set not only in the year the expenditures occur, but in subsequent years as well. However, this would require re-constructing the innovation index and imposing additional ad hoc weights for lagging effects. We leave this for future work.

By aggregating them, the innovation index is constructed with values bounded between zero and one. Hence, a farmer with a score of one uses all available innovations from all three presented indicators in relation to the AIS to the greatest extent (meaning he applies more of the examined technologies, replaced higher amounts of machinery etc.), while the opposite applies for a farmer with a score of zero. Switching from zero to a higher value implies that a farmer is using more innovations, resulting in a higher level of innovativeness.

We categorise farmers into groups in order to accommodate the calculation of TFP differences with respect to the innovation index. Beyond this, the categorization of farmers also offers a conceptualization explaining differences in productivity: similar to the treadmill hypothesis, differences in productivity are explained by differences in innovativeness (Cochrane 1958). Classification of farmers have been previously used in empirical studies, considering three innovation groups (Diederen et al. 2003; Läpple et al. 2015; Läpple and Thorne 2019). Rogers (2003) suggests considering five innovation groups that could be expanded potentially to six groups, allowing in this way for cases of non-adoption. The choice of six groups could also be relevant for the Irish dairy context: accounting for a smaller number of groups would require farmers to be aggregated into larger groups, which implies loss of important information regarding less innovative, smaller farms.<sup>7</sup> In this paper, we use the K-means clustering approach to identify the innovation groups that will be used for the TFP differences, avoiding in this way to select the number of the innovation groups and their cut-off points arbitrarily.<sup>8</sup> The results of the K-means clustering indicate that there are three innovation groups  $(I_G)$ . In Appendix A, we briefly explain how the approach resulted in the three innovation groups.

Furthermore, following Läpple et al. (2015) we choose marital status (binary=1 if farmer is married), off-farm income (binary=1, if farmer has off-farm income), education (binary=1, if farmer has formal agricultural education) and farm size (measured in ha) to be the vector of Z variables included in the control function estimation. In general, the use of a control function, either in linear or non-linear settings, requires the use of suitable instruments, such as prices (Bound et al. 1995; Smith and Landry 2021). As McFadden et al. (2022) note, the control function tends to

Table 1 Summary statistics: Irish dairy farms, 2012

	Means for each Innovation Group $I_G$			
Variables	1	2	3	
	(N = 45)	(N = 69)	(N = 140)	
Milk output (1000 €)	71.05	100.95	141.57	
Other output (1000 €)	30.46	39.81	62.29	
Capital (1000 €)	158.88	239.98	343.17	
Labor (Units)	1.46	1.48	1.80	
Area (Ha)	46.8	50.3	70.3	
Materials (1000 €)	45.80	63.91	82.56	
Innovation score I	0.16	0.51	0.85	
Married (binary)	0.8	0.8	0.7	
Higher education (binary)	0.5	0.8	0.7	
Off-farm income (binary)	0.1	0.0	0.0	

	Full Sample statistics $(N = 254)$					
Variables	Mean	St. Dev.	Min.	Max.		
Milk output (1000 €)	118.04	76.65	12.29	471.14		
Other output (1000 €)	50.54	35.17	3.29	276.29		
Capital (1000 €)	282.17	196.02	13.49	1006.13		
Labor (Units)	1.65	0.68	0.5	5.31		
Area (Ha)	60.88	30.43	8.06	198.1		
Materials (1000 €)	70.98	48.79	6.79	306.14		
Innovation index	0.6	0.2	0	1		
Married (binary)	0.8	0.3	0	1		
Higher education (binary)	0.7	0.4	0	1		
Off-farm income (binary)	0.1	0.1	0	1		

be more robust when the choice of the selection variables is not clear (Heckman and Navarro-Lozano 2004). Alternative methods to account for potential endogeneity such as propensity score matching tend to be quite sensitive to the choice of conditioning variables (Heckman and Navarro-Lozano 2004).

Table 1 reports summary statistics for the entire sample and for each of the three innovation groups. It can be observed that, on average, farmers with higher values of I utilize input quantities at different proportions and produce more of both outputs. This corroborates the assumption in our conceptual framework that farmers at different states of innovativeness utilize inputs at different proportions. Notably, the average amount of employed capital is almost two times larger in group three than in group one. Farms in group three utilize, on average, much more labor and land compared to farmers in group one and two; the differences in terms of the utilized labor and area between group one and two are very small. Regarding the use of materials, farms in group three have 50% higher expenditures than farms in group two; similarly, farms in group two have 50% higher expenditures than farms in group one.

 $<sup>\</sup>overline{}^{7}$  Smaller farms are important for the SI of the Irish dairy sector, because they play a number of socio-economic roles, such as increasing welfare by keeping rural areas populated, contributing to the rural non-farm economy and providing environmental public goods, for example, attractive landscapes (Dillon et al. 2017). The exit of small farms results in higher poverty, financial losses from non-farm enterprises, depopulation (especially in remote areas), but also in environmental degradation (Dillon et al. 2017).

<sup>&</sup>lt;sup>8</sup> We would like to thank the Editor Christopher Parmeter for the motivation to endogenize the categorization of farmers.

Table 2 Posterior means (and standard deviation)

Stochastic frontier (eq. (6))		Innovation equation (eq. (7))			
Variable	Mean (St. dev.)	Variable	Mean (St. dev.)		
constant	-0.156 (0.023)	constant	-1.714 (0.327)		
$\log K$	-0.198 (0.036)	married	-0.284 (0.237)		
$\log L$	-0.067 (0.037)	higher education	0.852 (0.208)		
$\log A$	-0.139 (0.046)	off-farm income	-1.145 (0.515)		
$\log M$	-0.549 (0.040)	size	0.015 (0.003)		
$\log y_2$	0.345 (0.024)				
Ι	-0.043 (0.029)				
$I \cdot \log K$	0.013 (0.024)				
$I \cdot \log L$	-0.097 (0.023)				
$I \cdot \log A$	0.061 (0.027)				
$I \cdot \log M$	-0.025 (0.025)				
$I \cdot \log \log y_2$	-0.007 (0.017)				
$\log y_2 \cdot \log y_2$	0.118 (0.026)				
Inefficiency ef	fects				
constant	2.237 (0.206)				
Ι	0.193 (0.087)				
Average TE	0.90 (0.01)	$\nu_2$	1.82 (8.9)		
$ u_i^I$	0.02 (0.01)	$\nu_i^I \nu_2$	-0.70 (0.66)		
RTS	0.95				

### **5 Results**

#### 5.1 Frontier estimates

Table 2 reports the estimated posterior means of the model's parameters, along with the standard deviations. These are estimated with Markov Chain Monte Carlo (MCMC) techniques that used 60,000 iterations and a burn-in of 30,000 in order to reduce the influence of the initial values. Prior to estimation the data for inputs and outputs are normalized by their geometric mean and the sample average of the innovation index is subtracted from the farm-specific  $I_i$ s. These transformations allow interpretation of the parameters associated with the first-order terms directly as distance elasticities at the mean of the data (sample mean for *I* and geometric mean of inputs and outputs).

The estimated distance elasticity of other output indicates that if the farmer produces 1% more of this output category (for given amounts of inputs and milk output) then the value of the distance function is increased by 0.34%, moving the farmer closer to the production technology. The negative sign of each of the input variables implies that increases in inputs push the farmer away from the production technology. Materials were estimated to have the highest elasticity, where an 1% increase is expected to lead, *ceteris paribus*, to a decrease in the value of the distance function by 0.54%. The negative sign of the coefficient associated with the interaction between L and I, indicates that, at higher levels of innovativeness, an increase in the amount of labor moves the farmer even further away from the frontier, i.e. I has a labor-saving effect at the farm level, on average (e.g. Gallardo and Sauer 2018). In contrast, the positive sign of the parameter associated with the interaction term between M and I implies that innovations assist farmers in applying materials such as feed, fertilizers, etc., more efficiently (e.g. DeLay et al. 2022; Finger et al. 2019).

The returns to scale (RTS) is close to unity (0.95) at the geometric mean of the data, indicating almost constant RTS. This is very close to Newman and Matthews (2006), who estimated a stochastic frontier model of specialist Irish dairy farmers using NFS data between 1984 and 2000. Parikoglou et al. (2022a) found specialist Irish dairy farmers to operate under decreasing RTS between 2008-2017, accounting for unobserved technological heterogeneity and the dynamic evolution of efficiency.

The positive sign of the parameter on I indicates that switching to a more innovative group leads to a decrease in the distance function by 0.014%. In the efficiency specification, the positive effect of I suggests that switching to the adjacent innovation group increases efficiency (or decreases inefficiency). The calculated marginal effect of innovation on efficiency is 1.7%. Therefore, this result implies that farmers at higher innovation states are utilizing their inputs more efficiently.

The calculated average efficiency score is 0.90. This is much higher compared to the Irish dairy cross-sectional efficiency analysis of Kelly et al. (2012) and Kelly et al. (2013), using Data Envelopment Analysis (DEA) on NFS data of Irish dairy farms from 2008. The former study estimated average efficiency at 0.757 under constant returns to scale (CRS) and at 0.799 under variable returns to scale (VRS). The latter study found average efficiency to be 0.785 under CRS and 0.833 under VRS. Of course, DEA does not distinguish between efficiency and statistical noise. This, along with the fact that input-oriented technical efficiency (which is a very reasonable assumption given that the data are from 2008 in the analysis), as employed in both studies, will potentially lead to different efficiency estimates compared to SFA. In panel-data analyses, the average efficiency of specialist dairy farmers between 1984-2000 was found to be approximately 0.7 (Newman and Matthews 2006); and 0.85 between 2008 and 2017 (Parikoglou et al. 2022a). The differences in the estimated average efficiency can be explained by the different methodological approaches and time periods of the data employed.

Finally, the results in eq. (7) show that farmers who completed a formal agricultural training are more innovative. This suggests that more educated farmers are more aware of the benefits of the use of the available innovations and more likely to adopt them; and also more educated farmers are

Table 3 Differences in TFP and its components (%)

Groups	Technology	Efficiency	Scale	TFP difference
Group 1 - Group 2	5.204	0.021	-1.087	4.139
Group 2 - Group 3	4.272	0.020	0.949	5.241
Average	4.744	0.020	-0.069	4.690

more able to process faster and more effectively new information (El-Osta and Morehart 1999; Läpple et al. 2015; Lin 1991). Furthermore, larger farms are found to be more innovative, which is consistent to the wider innovation adoption literature (e.g. Sauer and Zilberman 2012). We also find that Irish dairy farmers who have off-farm income are less innovative. This indicates that farmers with off-farm income may allocate less time in information acquisition regarding the availability of relevant innovations and in turn, they are less likely to adopt them (Läpple et al. 2015). Finally, we find that married farmers tend to be less innovative. This is possibly because married farmers, tend to be older and at their later stages of the farm life cycle, innovating less and dis-investing (Zhengfei and Oude-Lansink 2006).

### 5.2 TFP differences

Table 3 presents the means of the differences in TFP and its components across the 3 innovation groups of Irish dairy farmers. The results can be interpreted as the impact on the TFP components and, hence, to aggregate TFP, if farmers were to switch from one innovation group to the one right above the one they currently belong.

The technology effect column reports the differences in TFP between groups due to differences in the technology caused by a different state of innovativeness. For example, the estimated TFP of farmers in group 2 due to the effect on the technology is 5.204% higher when compared to group 1. On average, farmers at higher state of innovativeness have 4.744% higher TFP due to the effect on the technology. Likewise, the efficiency column indicates the differences in TFP due to the efficiency effect. For example, group 2 is almost 0.02% more efficient than group 1. The average difference in TFP among groups due to the efficiency effect is 0.02%.

The average difference in TFP due to the scale effect is -0.069%. Parikoglou et al. (2022a, b) found that, despite the fast technical progress, negative scale effects were slowing down the TFP growth of specialist dairy farms between 2008 and 2017. This result indicates that, likely due to the importance of the grass-based feed system and low land mobility in the sector, Irish dairy farmers cannot operate close to the optimal scale of production. In this study, we are able to examine the scale effect in more detail, with the use of an innovation index that takes into account multiple innovations from the Irish AIS, instead of the

<b>Table 4</b> Posterior means and standard deviatio	Table 4	Posterior	means	and	standard	deviations
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Variable	Mean	Std. dev.
Constant	-0.153	0.017
log K	-0.203	0.027
$\log L$	-0.068	0.029
$\log A$	-0.157	0.031
$\log M$	-0.548	0.030
$\log y_2$	0.347	0.018
Ι	-0.014	0.007
$\log y_2 \cdot \log y_2$	0.118	0.019
$I \cdot \log K$	0.017	0.017
$I \cdot \log L$	-0.093	0.017
$I \cdot \log M$	0.053	0.019
$I \cdot \log A$	-0.027	0.018
$I \cdot \log y_2$	-0.004	0.012
Inefficiency effects		
Constant	2.241	0.154
Ι	0.187	0.061
Average TE	0.90	0.040
$\sigma_{\nu^{I}}^{2}$	0.020	0.002
RTS	0.97	

contribution of FAS specifically. In particular, we observe mixed effects when differences between specific innovation groups are considered. The interpretation of the scale effect in this estimation is as follows: if a farm moves from group 1 to group 2, TFP will be reduced by -1.087% due to moving away from the optimal scale of operation, given the technology under the level of innovativeness in group 2. This suggests that farms in groups 1 and 2 would not have the necessary investments/scale to operate close to the optimal scale, had they switched to the next group. In the same way, if a farm moves from group 2 to group 3, it will experience a positive scale effect that will result in a growth in TFP by 0.949%.

The aggregate net effects of each component on TFP differences between groups are reported in the last column of Table 3. On average, the estimated TFP difference with respect to innovation is 4.69%. The highest contributors to TFP are the effect on the technology and scale, followed by the efficiency effect. Overall, a positive TFP change is observed for both changes to a groups of higher innovativeness.

In Appendix B, we present the results in Table 4 and 5 when potential endogeneity is not accounted (i.e. eq. (7) is

Table 5 Differences in TFP and

its components (%)

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Groups	Technology	Efficiency	Scale	TFP difference
Group 1 - Group 2	1.969	0.021	-0.359	1.631
Group 2 - Group 3	1.082	0.019	0.525	1.626
Average	1.525	0.020	0.082	1.629

not estimated). Furthermore, in Appendix B we report and discuss the results of a few robustness checks.

### 5.3 Discussing policy implications

In summary, out results suggest that farmers improve their production technology by employing more innovations, while also all farmers become more efficient with increasing levels of innovativeness. This finding is similar to previous studies (e.g. DeLay et al. 2022; Dinar et al. 2007; McFadden et al. 2022), who also found innovation to affect productivity through technology and efficiency effects. The effect of innovation on farmers' scale effect, which are mixed at different levels of innovativeness, is a result not shown before in SFA using cross-sectional data. In particular, if farmers switch from group one to group two, the positive technology effect will be partly offset by the negative scale effect. Farms experience a positive scale effect when they switch from group two to three. This effect indicates that the effect of innovation to farm-level productivity is non-linear, favouring larger farms, through the scale effect.

Hence, policies should target to reduce the unequal gains of innovation to productivity among farmers, securing the economic viability of small farms. For instance, future regulations may target to mitigate methane emissions, which may entail limiting herd sizes (Bradfield et al. 2020). However, such a policy policy may put further pressure on the Irish dairy sector. Alternatively, the promotion of innovations to less innovative, smaller farmers (i.e. Group 1), should be coupled with policies that will assist them to operate closer to the optimal scale of production. This can be achieved with better allocation of resources across farmers. For instance, if smaller farmers face financial constraints that prevent them from investing in capital, then institutional arrangements such as capital outsourcing or the introduction of machinery rings could secure better access for those farmers to capital services (Möhring and Finger 2022; Sheng and Chancellor 2019).

## 6 Conclusions

The recent EU Common Agricultural Policy (CAP) and Farm to Fork Strategy (FFS) aim to foster a more competitive and sustainable way of farming. For this aim, these policy documents (among others) aim to promote the role of the AIS for fostering innovation at the farm level in a demand-driven fashion. In this way, innovations will be tailored at the farm level, enabling producers to expand production volume without necessarily increasing the use of environmentally harmful (fertilisers, pesticides etc.) or scarce inputs (e.g. labour or land). This is particularly important for ensuring that the EU dairy sector will be more competitive and sustainable in a post quota era, given the particular constraints it faces (i.e. most farms are family farms, operating in constrained land) and its arising environmental pressures (e.g. GHG emissions, nutrient run-off).

This paper proposes a methodology for assessing whether the impact of innovation on productivity is in line the Sustainable Intensification (SI) vision, using stochastic frontier analysis (SFA). Specifically, we extend Karafillis and Papanagiotou (2011) to assess the contribution of innovation (as measured by an innovation index in order to capture various components of the AIS) on the production technology, efficiency and scale and to aggregate these into a single total factor productivity (TFP) index. In contrast to all previous SFA cross-sectional studies, this paper models directly the dependence of the productivity components on the level of innovativeness at the farm level. The main advantage of our approach is that it builds a simple framework that takes into account the scale effect on crosssectional productivity differences. Moreover, the proposed method avoids splitting the sample and allows capturing the simultaneous impact of several innovation variables. The latter is useful given that most innovation variables may be measured in binary form, which could possibly result in collinearity.

Therefore, our study extends the previous literature in two ways. First, from a policy perspective it focuses on multiple specific AIS actors, in line with the vision of CAP and FFS, instead of focusing on a single one such as FAS (Parikoglou et al. 2022b). Therefore, our study can be considered as complementary to Parikoglou et al. (2022b), who examined the impact of FAS on TFP growth. In this paper, (given data limitations that prevent us from expanding the analysis into a panel analysis) we assess cross-sectional TFP differences and its components due to innovations promoted with the overall contribution of Irish AIS. Second, from a methodological perspective, while TFP growth decompositions are not informative regarding the initial level of farmers' productivity; this study provides a way to measure productivity differentials due to discrepancies in innovativeness across farmers at a specific point of time. The proposed methodology could be a useful framework when evaluating the impact of AIS or a single AIS actor on other indicators related to sustainability (see for example Elmiger et al. 2023; Kelly et al. 2013).

Future research could focus on examining the contribution of each input to the scale effect, and in turn to TFP, in order to provide more tailored policy recommendations. This framework could be also expanded using panel data (if data availability allows), accounting for unobserved heterogeneity; and building an appropriate framework that would accommodate the fact that some of the variables used in the innovation index are not observed over time. In a panel-data setting, the contribution of materials and of innovation on TFP growth through scale could be better accounted for. It would be also interesting to expand the analysis to account for possible bi-directional causality between efficiency and innovation. In particular, farmers may innovate and become more efficient, but the opposite could be true, in which case farmers innovate based on their inefficiency level. In such a framework, either less innovative farmers innovate more to improve their efficiency, or they do not innovate, as they expect the new technology to be a source of higher inefficiency, due to adjustment costs.

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## 7 Appendix A

We use the *K*-means algorithm that was proposed by Hartigan and Wong (1979). The algorithm allocates N observations to *K* clusters, by minimizing their squared Euclidean distance to the cluster mean. The algorithm is an iterative process of two steps:



Fig. 1 Within-cluster sum of squares vs number of clusters)

- 1. for each cluster, the total within cluster variance is minimized, obtaining the means of the cluster assignment.
- 2. given the estimated means of the clusters, the distance of each of the observation is minimized by allocating each unit to the nearest cluster mean.

We employ the K-means algorithm to build four Kmeans models, assuming three, four, five and six innovation groups in each one. Then, we need to choose whether the Kmeans with three, four, five or six groups explain the data better. The simplest method that can be used to choose the number of clusters is with a scree plot. This is presented in Fig. 1: on the y-axis is the within clusters sum of squares (WCSS) is of each of the four k-means models, and the number of clusters on the x-axis. The scree plot indicates that the WCSS decreases when more clusters are considered. The point that the WCSS starts decreasing in a linear fashion (i.e. when additional clusters are not associated with lower WCSS) indicates the number of clusters that fit our data better (Woods and Edwards 2007). In our case this is three clusters, although already the decrease in WCSS when switching from two clusters to three is quite smaller, compared to increasing from one to two clusters. In general, the scree plot is quite often criticised for being subjective and restrictive in its interpretation, because the primary objective is to guide the choice of clusters between two or three options (Woods and Edwards 2007).

To corroborate then the choice of three clusters we use further the "jump method" proposed by Sugar and Gareth (2003). According to this method, the choice of the clusters can be motivated by finding the maximum  $\hat{d}_{K}^{-Y} - \hat{d}_{K-1}^{-Y}$ , where *d* is the "distortion", i.e. the distance between each observation and cluster centroid. Sugar and Gareth (2003) proposes Y = 1 or Y = 2/3. In the former case we found the jump from one to two clusters to be 0.1425, and from two to three clusters to be 0.2042. In the latter case, the jump from one to two clusters was calculated to be 0.199, and 0.206 from two to three clusters. Hence, the results suggest that we should choose three clusters. 
 Table 6 Posterior means (and standard deviations)

Parameter	Mean (St. dev.)	Parameter	Mean (St. dev.)
Constant	-0.155 (0.258)	$I \cdot \log y_2$	-0.032 (0.056)
log K	-0.258 (0.035)	$I \cdot \log K$	0.221 (0.081)
$\log L$	0.062 (0.040)	$I \cdot \log L$	-0.272 (0.085)
$\log A$	-0.155 (0.042)	$I \cdot \log A$	-0.181 (0.083)
$\log M$	-0.531 (0.042)	$I \cdot \log M$	0.025 (0.191)
$\log y_2$	-0.527 (0.042)	constant (ineff effect)	2.120 (0.204)
$\log y_2 \cdot \log y_2$	-0.527 (0.042)	I (ineff effect)	0.726 (0.371)
Ι	-0.016 (0.040)		

Table 7 Differences in TFP and its components (%) with respect to FAS  $% \left( \mathcal{F}_{A}^{\prime}\right) =\left( \mathcal{F}_{A}^{\prime}\right) \left( \mathcal{F}_{$ 

Groups	Technology	Efficiency	Scale	TFP difference
FAS group vs non- FAS group	2.059	0.052	0.904	3.017

## 8 Appendix B

We first consider a model that does not take into account the potential endogeneity of innovation. Thus, we ignore eq. (7) and we estimate only the parameters in eq. (6) and decompose TFP differences with respect to I. We present the results in Tables 4 and 5. The results show that when accounting for possible endogeneity, then the effect of I on the technology becomes much larger. As it follows, the TFP differences between innovation groups become larger, which are explained by technology effects. The overall picture of the results remains the same as in the main part of the manuscript: farmers experience a negative scale effect, when switch from group 1 to group 2.

We also analyze the data using a binary variable as an indicator of innovativeness, instead of the innovation index. This variable assumes the value of one if a farmer contacted FAS during the year for which the data are available. We note that contact with FAS is the main component of the Irish AIS. Below we present the stochastic frontier results (Table 6) and the TFP differences (Table 7) between farmers who contacted FAS and those who did not.

Apparently, the key difference between using the FAS and the innovation index is evident in the role of the scale effect in TFP differences. Now, we find that if farmers switched from not contacting FAS to contacting FAS, they would experience an increase in TFP due to the scale effect. One explanation for this difference is that the innovation index can capture more accurately any differences regarding the employed level of technologies at the farm level, i.e. the effect of using more complementary innovations. Therefore, taking into account additional innovations that can be considered complementary to FAS innovations is not only

Variable	Mean	Z-score (Chain 1)	Z-score (Chain 2)	Z-score (Chain 3)		
Constant	-0.120*	1.61	0.36	-0.55		
log K	-0.274*	-0.18	-0.84	0.84		
$\log L$	0.146*	-2.26	-0.29	-0.88		
$\log A$	-0.016*	1.26	1.60	0.12		
$\log M$	-0.746*	-0.39	-1.41	-0.67		
$\log y_2$	0.319*	-1.13	-1.48	-0.51		
$\log y_2 \cdot \log y_2$	0.119*	-1.05	0.51	1.43		
$I_2$	-0.014	-1.48	-0.41	0.83		
$I_3$	0.004	-0.83	0.95	5.45		
$I_2 \cdot \log K$	-0.014	0.97	0.89	-0.15		
$I_2 \cdot \log L$	-0.045	3.01	0.09	0.48		
$I_2 \cdot \log A$	-0.096*	-1.68	-2.05	-0.62		
$I_2 \cdot \log M$	0.122*	0.18	1.11	-0.09		
$I_2 \cdot \log y_2$	0.036*	0.69	0.13	0.97		
$I_3 \cdot \log K$	0.036	-0.30	1.60	-1.18		
$I_3 \cdot \log L$	-0.105*	2.67	0.60	1.56		
$I_3 \cdot \log A$	-0.051*	-1.38	-2.12	0.32		
$I_3 \cdot \log M$	-0.076*	0.70	1.50	-0.08		
$I_2 \cdot \log y_2$	0.004	0.97	0.66	-0.48		
Inefficiency effects						
Constant	1.907*	1.35	0.30	-0.79		
$I_2$	0.020	-1.50	-0.40	1.01		
I <sub>3</sub>	1.024*	-0.40	0.54	3.45		

Table 8 Posterior means of parameters and Z-scores for each chain

\*The corresponding 95% credible interval does not contain zero

important from a methodological perspective, but also from a policy context: European Common Agricultural Policy and Farm to Form strategy also suggest the development of well functioning AIS in each EU member state that will result in promoting a more innovative and in turn more productive and sustainable way of farming.

Lastly, we estimate a model that captures the effect of innovation on the technology via the inclusion of sets of a dummy variables. Specifically, there are two binary variables  $I_2,I_3$ , that indicate whether a farmer is assigned to the second and third innovation group, and the interaction

Table 9 Differences in TFP andits components (%)

Groups	Technology	Efficiency	Scale	TFP difference
Group 1 - Group 2	1.08	0.2	0.59	1.68
Group 2 - Group 3	0.90	0.0	0.85	1.76
Average	0.99	0.0	0.72	1.72

effects with inputs and other output. Group one is the reference group. Farmers were assigned to the three innovation groups, based on the *K*-means clustering method.

We encountered convergence issues when running the MCMC procedure described in the main body of text. Hence, we altered out sampling scheme as follows: we ran three Markov chains, with each one contributing 12,000 sample to the pool of draws from the posterior distribution and used a thinning of 10 (120,000 were produced by each chain but only one in 10 were kept) to reduce the effects of autocorrelation in the draws. Furthermore, in each chain, there was a burn-in phase of 120,000 iterations. Nevertheless, the convergence issues persisted. Specifically, we use the Z-statistic as a convergence diagnostic for each parameter and each chain (Geweke 1991). The Z-statistic is the difference between the first 10% of the draws and the last 50%, divided by the asymptotic standard error. When the Z-statistic is smaller in absolute value than 1.96, then we cannot reject the hypothesis of convergence. The results are reported in Table 8 and the TFP differences in Table 9. In each chain, there is at least one parameter for which the Z-statistic is larger than 1.96, which indicates that convergence was not successful.

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