THE ROLE OF INNOVATION IN FARM ECONOMIC PERFORMANCE: GENERALISED PROPENSITY SCORE EVIDENCE FROM IRISH DAIRY FARMS

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Abstract

This article assesses the impact of innovation on economic sustainability, specifically focusing on profitability, productivity of land and market orientation. A Generalised Propensity Score method is applied to a representative sample of 342 Irish dairy farms. Our empirical findings reveal that innovation increases economic sustainability, but not necessarily in a linear way. More specifically, small efforts to increase innovation can lead to economic gains of over €200 per hectare. The empirical findings also reveal that innovative farmers can achieve higher economic gains by innovating further. Overall, the findings support the current focus of the Irish extension system on fostering the uptake of innovative technologies and practices in order to achieve sustainable expansion.

Keywords: Sustainability, Innovation, Generalised Propensity Score

JEL codes: Q01; Q12;

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Introduction

Competitiveness and productivity are important aspects of successful dairy farming, especially in the view of the recent elimination of EU milk quotas in 2015. Moving from highly protected and regulated markets towards more open markets will exacerbate existing differences in dairy sector performance across countries, but also among individual farms. It is becoming increasingly obvious in the post quota environment that milk production predominately grows in countries with production advantages (Donnellan et al, 2015), supplied by farmers who can sustain and improve their productivity and manage a profitable enterprise. However, whilst the abolition of milk quotas facilitates opportunities for expansion on many dairy farms, it also poses challenges in terms of economic sustainability as a result of increased investment at farm level within a volatile milk price environment. Furthermore, a concentration and intensification of dairy production also implies increased pressure to minimise undesirable outcomes such as greenhouse gas emissions, water pollution, loss of biodiversity etc. Thus, the concept of sustainability will remain a central element of the debate and efforts to expand dairy production.

Sustainability is commonly defined as the production of crops and livestock for human consumption while simultaneously pursuing environmental, economic and social targets (National Research Council, 2010). Especially in the agricultural sector, it is well recognised that economic performance cannot be seen in isolation, but must be embedded in a sustainability framework (Ryan et al., 2016). In other words, increased economic performance should not be achieved on the expense of the environment.

In this context, innovation is generally seen as an important component of achieving improved productivity growth, sustainable use of resources and resilience to market developments (OECD, 2013), thus continued innovation will play a central role in the sustainable development of the dairy sector. To date, there is very little evidence about how innovation affects economic sustainability at the individual farm level, as the vast majority of existing studies focus on the macro level (see Alston, 2010 for an overview of existing studies).

This article aims to contribute to this lack of knowledge by assessing the impact of innovation on economic sustainability. To this end, we use three economic sustainability indicators: productivity of land, profitability and market orientation (Hennessy et al 2013). We selected these three indicators as they cover important aspects related to the economically sustainable dairy farm systems. The specific indicators chosen relate not just to the returns of cash costs of production (i.e. profitability), but also the productivity of owned factors of production (i.e. productivity of land) which is important in the longer term competitiveness perspective. Furthermore, the market orientation indicator provides a measure of the reliance on direct payments which is important in an ever changing policy environment, one in which future policy direction is unknown.

The aim of this article is to contribute to the empirical evidence on the impact of innovation and economic sustainability at a micro-level. By utilizing data from Irish dairy farms, we assess whether innovation efforts by farmers translate into better economically sustainable farm enterprises. To this end, we use a generalised propensity score (GPS) to measure the impact of innovation on farm economic sustainability.

This article proceeds as follows: the next section introduces background information on the case study with a special focus on the role of agricultural innovation, followed by a review of relevant literature. Section 3 outlines the methodology, while the next section (section 4) describes the data as well as the main indicators used for the analysis. Section 5 presents and discusses the results, while the final section offers some concluding remarks.

Background

EU dairy farmers can expand milk production without quota constraints, for the first time in three decades, since April 2015. To date milk production expansion varies considerably across EU countries, with Ireland being one of the leading countries in terms of dairy production expansion. This can be explained by the fact that Ireland is one of the lowest cost milk producers within the EU based on favourable agronomic and climatic conditions that sustain a mainly grass-based, spring calving milk production system (Dillon et al., 2008). In line with these favourable production conditions, the Irish government announced progressive expansion plans aiming to achieve a 50 percent increase in milk production by 2020, shortly after quota removal was confirmed in 2008 (DAFF, 2010). With an almost 20 percent increase in milk production after the first year of quota removal, expansion of milk production in Ireland is well under-way (CSO, 2017). However, reaching the 50 percent increase in milk production will involve significant further intensification of dairy production methods. It is clear that such ambitious expansion plans pose significant challenges to the individual farmer as well as the entire dairy sector. While there is a general sentiment of farmers to expand their production, for example over 60 percent of farmers stated pre-quota removal that they plan to expand production (Donnellan et al., 2015), concern exists that farmers who do not have an economically viable business will expand production and thus not be able to sustain a profitable business in the long run. It is in this context that the Irish advisory service tries to influence farmers to adopt innovative technologies and farm management practices to foster sustainable milk production (O'Dwyer, 2015).

Sustainability and innovation are also a strong focus of the Irish government that underlines the importance of applying the latest innovation in the agricultural sector in order to improve productivity whilst protecting natural resources (DAFM, 2015). This recommendation is considered timely given the findings from Renwick et al., (2014) where a mixed story was found in terms of the experience of innovation in the Irish agri-food sector. The level of investment in research in the agricultural sector; the proportion of businesses that were innovative and the economic performance of food and drinks manufacturers rated relatively high in a European context. Ireland also rated highly for its general business environment and its investment in research in the agricultural sectors. In contrast, Ireland performed less well in terms of the level of collaboration between businesses, the contribution of new products to business turnover, the growth in productivity within agriculture and the value added from agriculture. An overall 'index of innovativeness' for the Irish agri-food sector found that Ireland lagged well behind market leaders in the EU agri-food sector innovativeness stakes such as Denmark, Finland and the Netherlands.

Whilst Renwick et al. (2014) identified improvements which could be made relating to the experience of innovation, there were positives which must also be highlighted. In particular, the dairy farm sector in Ireland achieved the highest 'index of innovativeness' compared to the other farm sectors, which could be viewed positively given the ambitious growth targets which are laid out for the sector in a post quota environment.

Literature Review

Innovation is seen as the main driver of productivity growth in agriculture (OECD, 2013), and exploring the impact of innovation has attracted considerable interest in the literature. However, to date, efforts have mainly been limited to measuring the national impact of agricultural innovation. As innovation is a complex process, which is hard to measure (Van Galen and Poppe, 2013), it is generally assessed through a set of indicators relating to innovation efforts (i.e. national R&D or extension expenditure), outcomes (i.e. number of patents and publications) and impacts (i.e. total factor productivity (TFP) growth) (OECD, 2013). That is, many studies use proxies to infer innovation impacts on a macro scale.

For example, national expenditure on agricultural R&D, a commonly used indicator for innovation efforts, is generally seen as driving TFP growth and competitiveness in agriculture (Alston, 2010; Alston et al, 2010; Fuglie, 2012).

Kimura and LeThi (2013) take a different approach and use farm performance as indicators of innovation. They conduct a cross country comparison and identify typical characteristics of high and low performing farms. They identified large farm size, younger and better educated farm managers and the use of financial leverage as typical high performer attributes, while higher amounts of agricultural policy payments are associated with low economic performance.

On the micro level, most studies use the adoption of new technologies as proxy for innovation, while few studies use a more comprehensive measure of innovation. For example, Abadi Ghadim and Pannell (1999) use a new crop species as an innovation proxy, while Sauer and Zilberman (2012) regard successful adoption of organic farming as a major technology innovation for dairy farmers. Using one technology as a proxy for innovation may provide a limited representation for innovation, as innovation is more than the adoption of a new technology. Moreover, a farmer may adopt one technology early and thus be classified as innovator, while the same farmer may be slow to adopt a different technology or engage in other innovative activities (Goldsmith and Hofacker, 1991). Hence, relying on one technology as an innovation proxy may provide misleading conclusions.

Other studies use several technologies to proxy for innovation. For example, Mutenje et al (2016) use farm practices and technologies such as maize variety, soil and water conservation to measure innovation among farmers in Malawi and find that adoption of these technologies increases productivity. While Mutenje et al (2016) use a partial productivity measure (i.e. maize output), Karafillis and Papanagiotou (2011) attempt to assess the impact of innovation on TFP at the farm level. Innovation is measured by adoption of ten technologies and each farmer receives a score depending on the number of technologies used. By implementing this measure in their TFP score they find that more innovative farmers have higher TFP scores. The innovation measure used by Karafillis and Papanagiotou (2011) is related to the cross-sectional innovativeness scale often used by psychologists to measure actualised innovativeness (see Im et al, 2003).

While moving from one to several technologies as a proxy for innovation provides a more comprehensive measure, it is still closely linked to the traditional linear or top-down approach of innovation that is now considered overly simplistic (Knickel et al, 2009). That is, until recently, the development and diffusion of agricultural innovations was seen as a linear process involving public sector research and extension organizations, which implicitly assumes that innovation is a product of research (Mofakkarul Islam et al., 2013). A more recent view acknowledges that innovation creation involves the input of various actors that also depends on the social structure of the specific context (Knickel et al., 2009). This implies that agricultural innovation emerges due to exchanges between different actors, such as farmers and extension services, supply chains and economic systems as well as policy and societal environments, which reflect the idea of an Agricultural Innovation System (AIS) (Klerkx et al., 2012). That is, an innovation system can be described as: ‘‘a network of organizations, enterprises, and individuals focused on bringing new products, new processes and new forms of organizations into social and economic use, together with the institutions and policies that affect their behaviour and performance’’ (World Bank, 2006, p. vi–vii). This approach encompasses a much broader view than the linear approach to innovation.

While psychologists have developed quite comprehensive measures of innovativeness, such as innate or domain specific innovativeness (Goldsmith and Hofacker, 1991), few studies in agricultural economics have used more comprehensive measures of innovation. Ariza et al (2014), for example, create an innovation matrix that uses sub-sector specific technologies, also taking frequency and advancement of technologies into account. VanGalen and Poppe (2013) explored innovation in the agri-food business sector where farmers were classified as innovators if they introduced innovative changes in products or production processes that were new to Dutch agriculture. They report that three per cent of Dutch farmers were innovators in 2010. Finally, Läpple et al (2015) developed an innovation index for Irish agriculture that combines innovation adoption, acquisition of knowledge and continuous innovation. However, the aforementioned studies do not go on to assess the impact of innovation on farm performance. Hence, this article attempts to fill this gap by estimating the effect of innovation on economic performance, utilising a generalised propensity score methods that allows assessing heterogeneous effects of different innovation levels on farm performance.

Methodology

As previously mentioned, the objective of this study is to measure the impact of innovation on farm economic sustainability. Innovation efforts depend on the farmer's ability and motivation hence it is likely that innovative farmers are different to less innovative farmers (see Imbens and Wooldridge, 2009). Ability and motivation of the farmer also lead to different farm performances, regardless of innovation efforts. This suggests that isolating the impact of innovation is complicated, as farmers choose (i.e. self-select) to innovate. In other words, "better" farmers may be more innovative and also achieve higher economic performance on their farms. Thus, solely attributing higher economic performance to innovation efforts would most likely overestimate the effect of innovation. Hence, differences between more and less innovative farmers require disentangling the causal effect of innovation on economic sustainability from the selection effect based on observed differences between innovative and less innovative farmers (see Pufahl and Weiss, 2009).

Traits such as ability and motivation are generally not fully (if at all) observed and are thus captured in the error term, causing endogeneity issues. This implies that "normal" regression techniques would be biased and methods that account for self-selection and endogeneity are needed. Common methods (for cross-sectional data) used in the absence of experimental data are the endogenous switching regression model that first accounts for self-selection and then models the outcome conditional on the treatment (see for example Di Falco et al 2011; Fuglie and Bosch, 1996; Läpple et al 2013) or binary propensity score matching (see for example Ali and Abdulai, 2010; Kassie et al., 2010; Läpple et al 2015). While all methods have their advantages and disadvantages, they are best suited for binary treatments. Another possibility is the use of instrumental variable techniques, which however hinges on the availability of an exogenous instrument.[1]

In the absence of a suitable instrument and given that our innovation measure is a continuous score, using a binary estimation technique would be inefficient. Hence, in order to overcome self-selection and endogeneity issues, we use a generalized propensity score (GPS) method following Hirano and Imbens (2004). The GPS is an extension of the binary treatment propensity score method (Rosenbein and Rubin, 1983). However, in contrast to the binary propensity score, the GPS method allows estimation of average and marginal outcomes that correspond to different innovation levels. That is, the GPS does not only provide an average

[1] We explored this option, but the absence of a suitable instrument rendered this approach as not applicable for our data set.

innovation effect on economic sustainability, but it allows estimation of economic effects of different innovation levels.

Similar to the binary propensity score method, it is assumed that, conditional on observable characteristics, innovation efforts can be considered as random. Hence, the first step in the empirical process is to estimate the conditional distribution of innovation given covariates (see equation 1). Treatment is assumed to be normally distributed conditional on covariates. Due to the absence of a normal distribution, we transform our innovation variable and normality is tested by a Kolmogorov-Smirnov test (Bia and Mattei, 2008).

$$g(T_i)|X_i \sim N\{h(\beta X_i), \sigma^2\} \tag{1}$$

where $g(T_i)$ is a a zero skewness log transformation of innovation (T_i), X_i is a vector of covariates for each famer i supposed to simultaneously affect treatment and outcome (Caliendo and Kopeinig, 2008), $h(\beta X_i)$ is a function of covariates with linear terms, which depends on a vector of parameters β. The parameters β and σ^2 are estimated by maximum likelihood.

Next the GPS ($\hat{R}_i$) is estimated as:

$$\hat{R}_\iota = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\{-\frac{1}{2\hat{\sigma}^2}\{g(T_i) - h(\hat{\beta}X_i)\} \tag{2}$$

where $\hat{\sigma}^2$ and $\hat{\beta}$ are the estimated parameters from equation 1 (Bia and Mattei, 2008). Similar to the binary treatment propensity score method, the balancing property of the propensity score needs to be satisfied (Rosenbaum and Rubin, 1983). To this end, the innovation index is divided into k intervals, with $k = 4$. The four intervals were chosen to have an approximately equal number of observations in each category. Within each interval the median innovation index is calculated and the representative GPS is computed for each observation i. The values of the GPS for each of the four intervals are divided in *j* blocks, with $j = 5$. Within each interval *j* the mean difference of each covariate that is in the same innovation interval k and observations that are in the same GPS interval j, but in another innovation interval k is calculated. The differences in means are then combined by using a weighted average based on the number of observations in each of the *j* GPS intervals. A t-test is performed for each covariate, which indicates if the mean of the covariate is different to the combined means of the covariate from other k intervals but the same *j* interval (see Bia and

Mattei, 2008 and Hirano and Imbens, 2004). Differences in means should be eliminated or significantly reduced in order to overcome selection bias.

In the second step, the conditional expectation of the economic performance (Y_i) given innovation level (T_i) and GPS score (R_i) is estimated using a flexible function of T_i and R_i. Specifically, we estimate the following model with an OLS estimator

$$\varphi\{E(Y_i|T_i, R_i)\} = \psi(T_i, R_i; \alpha) = \alpha_1 + \alpha_2 T_i + \alpha_3 T_i^2 + \alpha_4 T_i^3 + \alpha_5 R_i + \alpha_6 R_i T_i \tag{3}$$

Where α is a vector of parameter estimates and R_i controls for endogeneity and selection bias (Michalek et al, 2014). The estimates from this regression do not have a direct interpretation, but are used in the calculation of the so called dose-response function (Hirano and Imbens, 2004).

The last step implies estimating the dose-response function, i.e. the average potential outcome for each innovation level, as follows:

$$E\{\hat{Y}(t)\} = \frac{1}{N}\sum_{i=1}^{N} \hat{\beta}\{t, \hat{r}(t, X_i)\} = \frac{1}{N}\sum_{i=1}^{N} \varphi^{-1}\,[\hat{\psi}\{t, \hat{r}(t, X_i); \hat{\alpha}]\tag{4}$$

where $\hat{\alpha}$ is the vector of the estimated parameters in the previous step. The average potential outcome for each innovation level from 0 to 1 in o.1 steps is estimated. In addition to the average dose-response function $E[Y_i(t)]$, we also compute the derivate dose-response function, also known as treatment effects function, as $[Y_i(t+1) - Y_i(\mathrm{t})]$. Finally, we calculate standard errors for the dose-response and treatment effects functions via bootstrapping with 100 iterations (Bia and Mattei, 2008).

Data and Descriptive Statistics

The main data source used is Irish FADN data for 2012 (Hennessy et al., 2013). Irish FADN data are collected through the Irish National Farm Survey (NFS). The NFS was established in 1972 and has been published on an annual basis since. Overall, a statistically representative random sample of approximately 900 farms is surveyed representing a farming population of approximately 80,000. The data is collected through a series of face to face interviews by professional farm recorders. Farms are classified into farming systems based on the dominant enterprise which is calculated on a standard gross output basis. The NFS collects data on all prominent farm systems in Ireland, and for the purposes of this analysis we restrict our sample to dairy farms (i.e. specialized dairying and dairying other). While these farms are specialized in dairy production, there is typically a significant alternative enterprise also operating on the farm. The sample used for this analysis comprises of 342 dairy farms.

As previously mentioned, we are interested in the effect of innovation effort on farm economic sustainability. With respect to innovation, this is measured for each farm based on an innovation index developed by Läpple et al. (2015). The innovation index is a composite index that consists of three components of innovation relating to *innovation adoption*, *acquisition of knowledge* and *continuous innovation* (e.g., Spielman and Birner, 2008; Knickel et al., 2009; OECD, 2013). In relation to innovation adoption, the following technologies and farm practices are included: financial analysis tool, information and communications technology usage, soil testing, re-seeding and milk recording. Each of these technologies were assessed by six knowledge transfer and innovation experts and assigned weights in relation to their level of innovativeness and perceived effort of implementation. Acquisition of knowledge, the second indicator, is represented by whether or not the farmer has consulted advisory services for non-scheme related matters, i.e. any advice that is not targeted towards participation in any agricultural policy measures. Whether or not a farmer has renewed some machinery in the past year is used as a proxy for the continuous innovation indicator.

The three indicators were then given expert weights to reflect their relative importance for innovation. As expected, innovation adoption was judged by the experts as the most important component of innovation and assigned a weight of 0.45, followed by acquisition of knowledge with 0.40 and the lowest weight was assigned to the continuous innovation indicator with 0.15. The final agricultural innovation index takes values between zero and one, with larger values indicating greater levels of innovation. Overall the average innovation score in our sample of dairy farms was 0.63, with a standard deviation of 0.28.

While we acknowledge that this is not a perfect measure of agricultural innovation, we do believe that the measure goes far beyond previously used measures (e.g., Ariza et al., 2013; Karafillis and Papanagiotou, 2011) by attempting to capture and reflect the complexity of agricultural innovation frequently discussed in the literature (VanGalen and Poppe, 2013; Ariza et al 2013; OECD, 2103).

In relation to farm economic performance, we use three economic indicators, which are seen as important measures to capture economic sustainability (Hennessy et al 2013). While sustainability is mainly associated with the environment, other dimensions of sustainability become increasingly important. Moreover, Hennessy et al (2013) argue that environmental sustainability by itself is not sufficient if the farm cannot survive from an economic perspective. As previously mentioned, we assess the impact of innovativeness on *productivity of land*, which is measured as gross output per hectare and is seen as a measure of efficiency. *Profitability* which is market based gross margin per hectare and implies that subsidies are taken out of the measure and *market orientation* which is the output derived from the market in percentage terms.

Turning our focus back to innovation, by dividing farms into four innovator groups, we can see that economic performance differs quite remarkably among farms with different levels of innovativeness (see Table 1). For example, a farmer with low levels of innovativeness (group 1) has an on average € 1,000 lower productivity per hectare than an innovative farmer (group 4). The market orientation indicator shows that innovative farmers (group 4) are 5 percent less reliant on subsidies than their less innovative counterparts (group 1).

Table 1: Economic Performance by Level of Innovativeness

	All farms	Group 1	Group 2	Group 3	Group 4
Innovation level		[0; 0.42)	[0.42; 0.7)	[0.7; 0.85)	[0.85; 1)
Economic Performance					
Profitability (€/ha)	1,351.71	1,053.77	1,304.07	1,389.23	1,654.99
	(603.10)	(581.30)	(599.21)	(546.27)	(536.20)
Productivity of land (€/ha)	2,915.89	2,477.49	2,817.36	2,875.03	3,488.00
	(1,040,20)	(971.90)	(1,050.65)	(913.68)	(983.84)
Market orientation (%)	84.31	82.19	83.07	84.96	87.03
	(7.49)	(10.99)	(7.10)	(4.74)	(4.50)
Observations (n)	342	83	89	85	85

Means and standard deviations in parentheses

In relation to covariates to estimate the GPS, only variables that simultaneously affect innovativeness and economic performance are included (Caliendo and Kopeinig, 2008). Summary statistics for the full sample and divided by level of innovativeness are displayed in Table 2. We include farm size (UAA) and farm intensity (dairy livestock units per hectare) as farm characteristics that are commonly used to explain innovation or economic performance (Läpple et al 2015). Similar to the economic performance indicators, we observe differences between more and less innovative farms. That is, more innovative farms are generally larger and more intensively stocked. In addition, we control for managerial ability by the inclusion of two proxy variables: we use somatic cell count (SCC), which is a measure of milk quality and a lower value indicates better dairy herd management skills (Dillon et al., 2015). The average of all farms in the sample is 222, which is slightly above a recommended value of 200 (Teagasc 2015b). However, more innovative farmers (group 4) have, with a SCC value of 187, significantly lower cell counts than less innovative farmers (group 1) who on average have SCC values of 264. The statistical significance of this difference is confirmed by a t-test (t=-5.53). In addition, we use feed conversion, which measures the amount of milk produced per kg concentrates fed. A higher number indicates better managerial ability. The sample average is 5.7 kg milk per kg concentrates fed. In terms of farmer characteristics, we include age, agricultural education and number of children. Younger and better educated farmers are generally believed to be more innovative (Feder et al 1984), which our data also confirms. Finally, we also account for regional variables, as Läpple et al (2015) found considerable differences in innovativeness across regions and differences in economic performance among dairy farms are evident across Ireland (Hennessy et al., 2013).

Table 2: Summary Statistics of Covariates for GPS estimation

	All farms	Group 1	Group 2	Group 3	Group 4
Innovation level		[0; 0.42)	[0.42; 0.7)	[0.7; 0.85)	[0.85; 1)
Covariates to estimate GPS					
UAA in hectares	64.69 (33.97)	51.80 (30.45)	59.66 (33.42)	72.03 (35.48)	75.19 (31.51)
Dairy livestock units/hectares	1.85 (0.47)	1.72 (0.50)	1.83 (0.45)	1.84 (0.44)	2.02 (0.46)
Somatic cell count (in 1,000)	222.56 (90.84)	264.71 (110.16)	227.39 (98.27)	210.99 (65.33)	187.89 (64.34)
Feed conversion	5.73 (3.12)	5.23 (2.19)	5.77 (4.44)	5.98 (2.85)	5.94 (2.35)
Age of main farm holder	52.87 (10.51)	56.59 (10.30)	52.27 (10.44)	52.51 (9.82)	50.31 (10.65)
Agricultural education	0.73	0.53	0.73	0.79	0.88
Number of children	1.35 (1.49)	1.14 (1.46)	1.03 (1.36)	1.71 (1.74)	1.51 (1.27)
Farms located in north west (%)	22.22 (1)	20.48	25.84	21.17	20.48
Farms located in south west (%)	21.34 (2)	21.68	23.59	27.06	21.69
Farms located in east (%)	25.73	18.07	29.21	23.52	18.07
Farms located in south (%)	30.70 (4)	39.75	21.35	28.23	39.76

Results and Discussion

The GPS method allows estimating heterogeneous and incremental effects of innovation efforts on economic performance. As previously explained, the GPS has to be estimated first in order to control for selection bias. That is, the conditional probability of innovation effort given covariates is estimated by maximum likelihood. The results suggest that the conditional distribution of innovation effort is clearly explained by the selected covariates. Six out of ten included covariates have a significant impact on innovation effort at least at 10 percent level.

Next, in order to use the GPS to estimate the impact of innovation on economic performance (i.e. dose-response function) balancing of the included covariates needs to be assessed. Thus, we divided innovation level into four intervals that contain roughly equal numbers of observations (see row 2 and 3 in Table A2). For all covariates that are used to calculate the GPS, we tested whether the unadjusted means in one of the intervals was different from the combined means of the remaining intervals using t-tests. 14 out of 44 t-statistics are greater than 1.96, for the unadjusted means. As one would expect, larger differences exist between the most innovative group (interval (0.85, 1]) and the least innovative group (interval (0, 0.42]). The GPS adjusted statistics show that the covariates are well balanced, with only 2 out of 44 being significant at the 5 percent level (see Table A1 for details).

The results of the estimated dose (innovation) response (economic sustainability) and the corresponding treatment effects function are presented in Table 3 and Figures 1 to 3. The standard errors and confidence intervals of the dose-response and treatment effects function were estimated via bootstrapping and are included in the figures as lower and upper bounds.

Beginning with profitability, Figure 1 (left) indicates that profitability increases with higher innovation levels, but not in a linear way. For example, we observe that profitability increases from no innovation (0) to low innovation levels of 0.2. Profitability then decreases slightly for innovation levels between 0.2 and 0.5, while profitability then increases rapidly for higher innovation levels, before slightly levelling off at high innovation efforts of approximately 0.9. Column 2 and 3 in Table 3 show the corresponding numbers of the effect of innovation on profitability. More specifically, the estimates reveal that overall a higher level of innovation is associated with higher profits, for example a farmer who makes no effort to innovate (value of 0) has a potential profitability outcome of €1,161, while in contrast a highly innovative farmer (value of 1) has a potential profitability outcome of €1,580. The average causal effect for farmers moving from a low level of innovation, i.e. 0.2 to a high level (0.9) is €215 per hectare.

We also report the derivatives of the dose-response function (treatment effects function), which can be interpreted as the change in profitability due to the increase in innovation effort by 0.1. On the right panel of Figure 1, we can see that the effect of increasing innovation varies considerably from low to high innovation efforts. While extra profitability gains from innovation improvements even falls below 0 between innovation levels of 0.2 to 0.4 it is important to recognise that these levels are not statistically different from zero (lower and upper bounds are below and above zero). However, at higher innovation levels, farmers clearly benefit from increasing innovation efforts. For example, a change in innovation effort from 0.7 to 0.8 is associated with an extra € 126 profit per hectare. The results are graphically displayed in Figure 1 (right panel).

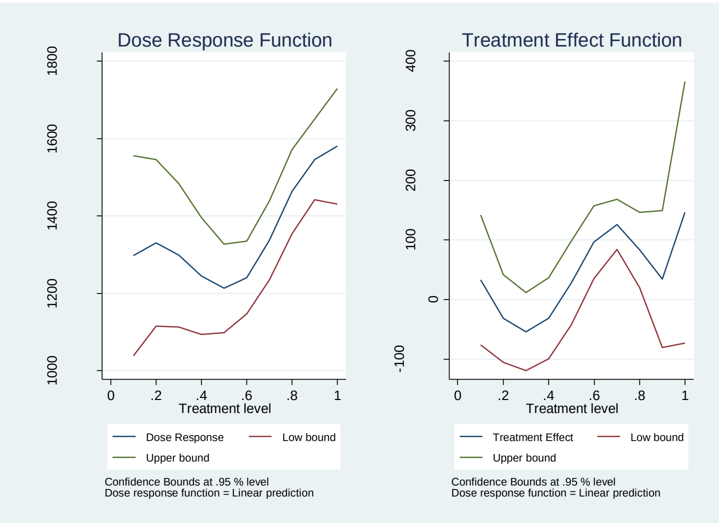

Figure 1: Average and Marginal Effect of Innovativeness on Profitability

Our second economic indicator, productivity of land, shows a very similar pattern to profitability. By focusing on the left panel of Figure 2, we observe that productivity increases as a response to increased innovation efforts, i.e. moving between values of 0 to 0.2, then declines with an increasing innovation effort, but increases rapidly then as a response to innovation efforts above 0.5. Columns 4 and 5 in Table 3 show the corresponding figures, which reveal that a farmer who is not innovative (score 0) achieves an average of € 2,727 compared to € 3,306 for a farmer who is very innovative (score 1).

The marginal effects (right panel of Figure 2) fluctuate from over € 200 to less than €-119, per extra 0.1 increase in innovation effort. However, only higher innovation efforts bring significant effects for productivity increase (see column 5, Table 3), for example increasing innovation effort from 0.7 to 0.8 increases productivity by €217 per hectare.

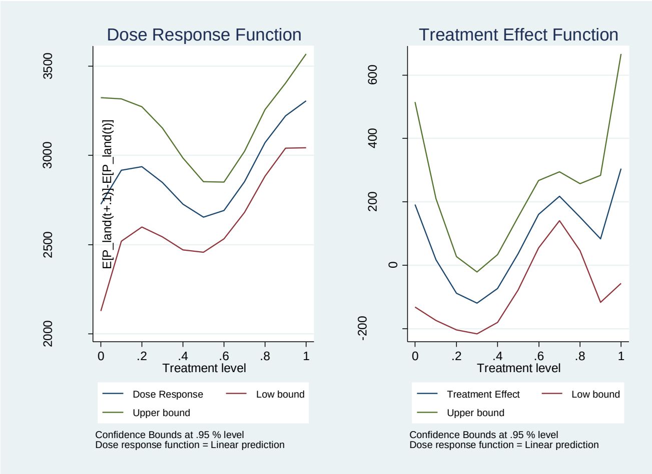

Figure 2: Average and Marginal Effects of Innovativeness on Productivity of Land

Our last indicator, market orientation, provides insight into dependence on subsidies. The dose-response function reveals that low levels of innovation (between 0 and 0.4) result in quite similar market orientation scores. However, once innovation scores move above 0.4, market orientation improves rapidly as a result of innovation effort, but levelling off once high levels are achieved. For example, a farmer with no innovation efforts (score 0) has an average market orientation of 83 percent, while a very innovative farmers (score 1) achieves a market orientation of 86 percent (see Column 6, Table 3). In relation to marginal effects, a 0.1 increase in innovation efforts (from 0.6 to 0.7 and 0.7 to 0.8) leads to an almost 1 percent increase in market orientation.

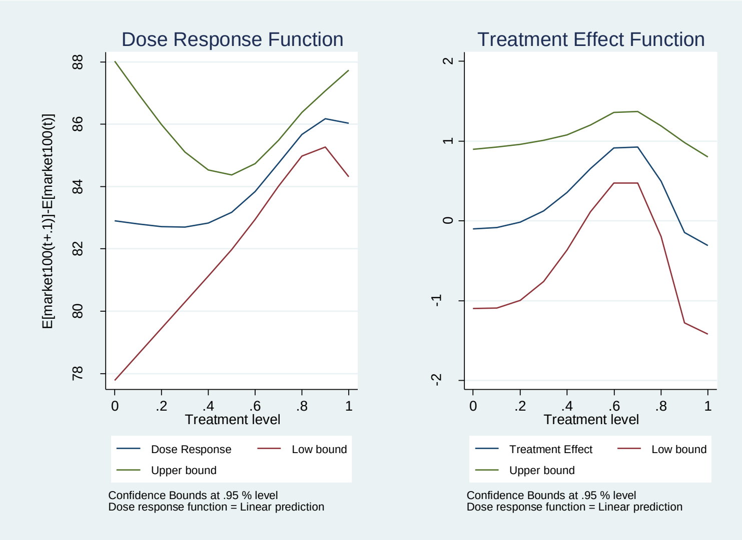

Figure 3: Average and Marginal Effects of Innovativeness on Market orientation

Table 3: Average and Marginal Effect of Innovation on Economic Performance

	Profitability			Productivity of Land			Market Orientation		
Innovation level	Average effect	Marginal effect	(SE)	Average effect	Marginal effect	(SE)	Average effect	Marginal effect	(SE)
0	1,161.37	136.07	(98.97)	2,726.82	191.38	(165.05)	82.90	-0.10	(0.51)
0.1	1,297.43	33.14	(55.64)	2,918.20	17.95	(98.19)	82.80	-0.08	(0.51)
0.2	1,330.57	-31.82	(37.61)	2,936.15	-88.30	(59.08)	82.72	-0.02	(0.50)
0.3	1,298.75	-54.01	(33.49)	2,847.85	-119.45	(49.84)	82.70	0.12	(0.45)
0.4	1,244.74	-31.56	(34.86)	2,728.40	-73.00	(54.65)	82.82	0.36	(0.37)
0.5	1,213.18	27.60	(35.77)	2,655.40	36.45	(58.87)	83.18	**0.66**	**(0.28)*** **
0.6	1,240.77	**96.21**	**(31.30)*** **	2,691.85	**161.01**	**54.46)*** **	83.84	**0.92**	**(0.23)*** **
0.7	1,336.98	**126.08**	**(21.52)*** **	2,852.86	**217.91**	**(39.49)*** **	84.76	**0.92**	**(0.23)*** **
0.8	1,463.06	**83.14**	**(32.35)*** **	3,070.77	**151.66**	**(54.16)*** **	85.68	0.50	(0.35)
0.9	1,546.20	34.16	(58.55)	3,222.43	83.65	(102.16)	86.18	-0.15	(0.58)
1	1,580.36	146.43	(111.97)	3,306.08	304.60	(184.77)	86.03	-0.31	(0.57)

As a final step of our analysis, we explore how much a typical farmer in each innovation group would gain from being more innovative. To this end, we estimate the gains for three typical farmers from innovator groups 1 to 3 and assume they increase their current innovation efforts to a score of 0.9. Typical characteristics for the farmer types can be found in Table 2[2]. For example, Farmer A, a typical farmer from innovation group 1, has a farm size of 52 hectares with a stocking density of 1.72 dairy cows per hectare, is 56 years of age, has completed agricultural education and the farm is located in the south region. We predicted expected innovation and economic sustainability with OLS estimation. The change in economic sustainability is then calculated based on a change from the predicted innovation level (i.e. 0.5) to a high level (0.9) based on the treatment effects in Table 3.

Table 4: Economic Performance Gains for Different Farmer Types

	Farmer A (Group 1)	Farmer B (Group 2)	Farmer C (Group 3)
Predicted innovation level	0.53	0.65	0.67
Farm size	51.80	59.66	72.03
Predicted profitability (€/ha)	1,154	1,438	1,374
Δ profitability (€/ha)	+325	+257	+238
Δ profitability (€/farm)	16,823	15,352	17,149
Predicted productivity (€/ha)	2,632	3,050	2,843
Δ productivity (€/ha)	556	450	417
Δ productivity (€/farm)	28,808	26,851	30,100
Predicted market orientation	83.69	82.70	84.74
Δ market orientation	2.80	1.88	1.70

Our simulation exercise shows that Farmer A would get an extra €325 per hectare in profit, which implies €16,900 additional profit per farm, when increasing innovation effort to a high level of 0.9. Farmer B, with an average farm size of 60 hectares, would gain an extra €257 profit per hectare, or €15,420 on a whole farm basis. The largest gains from improving innovativeness on a farm a basis would be made by farmer C, which is driven by a considerably larger farm size. For example, farmer C's enterprise is €30,100 more productive by improving innovativeness from 0.67 to 0.9. Overall, these results illustrate that increasing innovativeness brings significant economic gains to all farmer types. Moreover, improving

[2] In order to calculate the typical farmer, we took the mean for all continuous variables, the median for binary and the region with the highest proportion of farmers of that group.

relatively high level of innovativeness even further (i.e. from 0.7 to 0.9) still brings significant economic gains.

Conclusions

The 2015 elimination of EU milk production quotas is inducing major restructuring of the agricultural sector. In regions with a comparative advantage for milk production, such as Ireland, concentration and intensification of dairy production is well underway. This also implies increased pressure on exciting resources and the environment. Sustainability will remain a central element of the efforts to expand dairy production. That is, a sustainable expansion path hinges on continuous adoption of innovative technologies and farm practices.

In this article we have investigated the impact of innovation on economic sustainability, specifically focusing on profitability, productivity of land and market orientation. To this end, we applied a Generalised Propensity Score (GPS) method to a representative sample of Irish dairy farms. Our empirical findings reveal that innovation increases economic sustainability of farms, but not necessarily in a linear way. However, small efforts to increase innovation can lead to economic gains of over €200 per hectare. Moreover, our results also reveal that innovative farmers can achieve higher economic gains by innovating further. These findings could be considered important from a future policy planning perspective when sustainability credentials will become increasingly important. Results have shown that given a finite set of resources improvements in innovation can positively contribute to economic performance.

Ireland's extension system has a strong focus on technology transfer of innovative farm practices and technologies in order to foster a sustainable expansion of the dairy sector. Our findings confirm the success of this path to enhance economic performance through innovation.

In order to achieve sustainable growth of the dairy sector, expansion should happen in an environmentally sensitive manner. How environmental implications of milk production are influenced by innovation efforts also need to be addressed. This provides important avenues for future research.

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Appendix

Table A 1: Balance of Covariates before and after GPS Adjustment

Variable	Unadjusted				Adjusted			
Interval	[0,0.42]	(0.42,0.7]	(0.7,0.85]	(0.85,1]	[0,0.42]	(0.42,0.7]	(0.7,0.85]	(0.85,1]
n	83	89	85	85	83	89	85	85
UAA	***4.06***	1.63	*2.31*	***-3.34***	1.23	0.49	-1.53	-1.59
LU/ha	***3.04***	0.58	0.23	***-3.88***	-0.38	-0.37	0.70	-1.30
SCC	***-5.03***	-0.58	1.35	***4.15***	-0.22	-0.51	0.75	0.99
Feed	1.69	0.12	-0.84	0.71	0.97	-0.71	-0.56	0.02
Age	***3.78***	0.62	0.46	***2.60***	-0.11	1.20	-0.43	0.10
Agr Educ	***4.99***	0.09	-1.31	***-3.63***	0.02	-0.58	-0.52	-0.64
Children	1.45	***2.35***	***-2.64***	-1.19	-0.79	***1.99***	-1.69	0.14
Reg1	0.44	-0.95	0.27	0.26	0.18	-0.97	0.47	0.50
Reg2	-0.09	-0.6	-1.48	***2.19***	0.23	-0.59	-0.81	-0.07
Reg3	1.83	-0.87	0.53	-1.47	0.43	-1.28	1.07	-0.77
Reg4	***-2.06***	***2.23***	0.57	-0.78	-0.79	***2.71***	-0.71	0.29