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Unpacking Total Factor Productivity on Dairy Farms Using Empirical Evidence

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Abstract: This study examines the farm-level factors that influence differences in total factor productivity (TFP) on dairy farms. To this end, a fixed-effects regression approach is applied to panel data for dairy farms obtained from the Farm Accountancy Data Network for Northern Ireland over the period of 2005 to 2016. The findings are largely consistent with existing empirical evidence, showing that herd size, milk yield, stocking density, and share of hired labour have a positive and statistically significant impact on TFP, while labour input per cow, purchased feed input per cow, and share of direct payments in total farm output have a negative and statistically significant impact. The more complex relationships, namely age, education, and investment, have been unpacked using interaction terms and nonlinear approximation. The impact of age is negative, and the drag on productivity grows as age increases. Capital investment and education both have a positive impact on farm-level TFP, as well as on their interaction. Policy recommendations on strategies and best practices to help dairy farms tackle productivity constraints are suggested.

Keywords: agricultural productivity; competitiveness; total factor productivity; farm-level productivity

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1. Introduction

In general, dairy farming faces diverse challenges, including fluctuations in milk prices, climate change effects, regulatory constraints on productive inputs such as fertilisers, and changing policy objectives [1–5]. Improving productivity is widely recognised as a means to address these challenges because it helps farm operators improve resource-use efficiency and consequently farm income; facilitate adaptation of the farm business; and minimise negative environmental impacts [3,4]. Specifically, when productivity increases, dairy farms can produce more output relative to the inputs used, which allows managers to reallocate resources to other economic activities and improve the sustainability of resource use within the farm gate, and therefore improve resilience to price volatility—particularly that of inputs [1,2].

Considering the advantages, many studies have been conducted to measure productivity over time and analyse sources of growth. These studies can be categorised into two groups: those considering the entire agricultural sector, and those related to specific farming enterprises. For example, studies such as Baráth and Fertő [6] and Plastina, et al. [7] estimated productivity growth for the whole agricultural sector in European Union (EU) Member States and the United States, respectively, while studies such as Emvalomatis [3], Keizer and Emvalomatis [8], Moreira and Bravo-Ureta [9], Skevas, et al. [10], and Baležentis and Sun [11] used farm-level data to compute productivity growth estimates and sources of growth with emphasis on specific farming enterprises. These studies identified important sources of growth to include technical progress, technical efficiency change, and scale effects. While the aforementioned studies have focused on the estimation of productivity growth and the identification of sources of growth, only a few have been able to identify the farm and farmer characteristics that influence dairy productivity levels [1]. From a farm-level perspective, understanding these factors is relevant to tackling productivity constraints and identifying strategies to help improve productivity.

The purpose of this study is to examine the farm-level factors that influence differences in total factor productivity (TFP) using data on dairy farms in Northern Ireland. This is motivated by a gap in our knowledge about the complex relationships that exist between farm and farmer characteristics and dairy productivity. We contribute to filling this gap by teasing out how farm and farmer characteristics interact and complement each other in influencing dairy productivity. This is accomplished using interaction terms and nonlinear approximation within a panel fixed-effects modelling framework. Northern Ireland presents a useful case study because there is a good range of dairy farms utilising grass and concentrates in different proportions and operating at different scales. Climactic conditions are well-suited to grass production similar to other regions (such as Ireland, New Zealand, and others). Consequently, the findings from this study are able to inform potential policy approaches to improving productivity in the region and, more widely, within dairy farming.

The remainder of this paper is structured as follows: Section 2 reviews relevant empirical literature, Section 3 presents the data and methodology employed, Section 4 discusses the results of the analysis, and Section 5 concludes the paper.

2. Review of Empirical Studies

Previous empirical studies investigating the link between dairy farm characteristics and productivity tend to consider characteristics that are closely linked to technology, in the direct control of the farm manager, and structural characteristics [12]. Technological progress (e.g., increased soil testing, use of automatic cup removers, artificial insemination, genetics, and improved milking sheds and equipment) is consistently found to be an important driver of productivity improvements in dairy farming [1,13]. The mechanism behind this is understood to be, in part, reducing the labour requirement per cow, therefore opening up greater opportunities to take advantage of economies of scale.

Management and farmer characteristics (e.g., experience, education and training, financial status, and attitude towards risk) are also shown to be important drivers of productivity, with the interpretation that these shape innovative capacity and the adoption of novel technology and practices [1,14,15]. The empirical evidence on how farm manager age impacts productivity indicates it may be sensitive to the regional context. For instance, Kimura and Sauer [1] found evidence of a negative relationship in Estonia and the Netherlands, but no statistically significant relationship in the case of England and Wales, as in Romagnoli, et al. [16] for Italian farms. Work experience and formal education are both linked to greater productivity [17] and a threshold effect, identified by Sauer and Latacz-Lohmann [18], whereby a sufficient level of education is required to reap the productivity gains of investments in innovative technology.

Structural characteristics related to scale and production systems are also found to be important. Farm size is noted in the literature as an important driver of productivity [8,19,20] with the interpretation that this is due to the ability to take advantage of scale in adopting new technology. Intensity of the production system exhibits a more complex relationship. While intensity (stocking density) is related to relatively higher productivity [1,19,21,22], the intensity of purchased feed and labour input use is negative [1,23], indicating that efficiency is still a key driver, regardless of structural advantages.

Much emphasis has also been placed on the effects of farm policies on the productivity of dairy farms. In the EU context, previous studies have found differentiated impacts of policy reforms on productivity. For example, a shift from production-coupled subsidies to a decoupling regime was found to influence productivity positively [24–26], indicating that policies that align farmers’ production decisions with the demands of the market enhance productivity. Also, policies aimed at supporting investments that embody innovations tend to facilitate productivity [27]. In addition, there is evidence that the policy shift that unwound the milk quota system (before it was ended in 2015) was found to have led to an improvement in productivity [1,28,29], while tradability of milk quota was found to reduce allocative inefficiencies and allow resources to flow to more efficient farms [30,31].

Other factors outside the direct control of farmers, including farm location and climatic factors, have also been found to influence dairy productivity. There is a general conclusion in the literature that adverse weather has a negative impact on productivity [7,32,33], explaining that farms, particularly those with high herd stocking density, are susceptible to climate shocks, such as extreme heat and increased temperatures, resulting in lower milk yield. Evidence from Kimura and Sauer [1] and Romagnoli, Giaccio, Mastronardi and Forleo [16] shows that farms located in environmentally disadvantaged areas in Estonia, England, Wales, and Italy are less productive, suggesting that natural conditions could limit productivity improvement.

The empirical literature on farm-level productivity has identified the adoption of improved technologies, management and farmer characteristics, structural factors, farm policies, climate, and land quality as important factors. This paper contributes to the literature by teasing out some of the more complex relationships. This is accomplished by taking advantage of a panel data set to explore the links between farm-level TFP, farm, and farmer characteristics. We test empirically how farm-level characteristics interact and qualify each other with respect to productivity. Specifically, we hypothesise that:

- Farm management practices (such as herd size, milk yield, stocking density, etc.), farmer characteristics (such as age, off-farm activity, and education), land quality, and investment impact productivity independently.
- The impact of investment on productivity will materialise a few years after the expenditure takes place, accommodating a transition period.
- Beyond the independent impact on productivity, when investment is complemented by education, there will be an additional productivity improvement.
- Agricultural-specific education completed more recently will add a positive impact on productivity, due to access to more state-of-the-art and up-to-date industry practices.
- The impact of age will not be linear, such that the marginal impact on productivity will be different within different segments of the age range.

3. Empirical Approach and Data Sources

3.1. Empirical Approach

The main aim of this study is to analyse the factors influencing dairy farm TFP. To achieve this, we applied a panel fixed-effects econometric modelling approach to unbalanced panel data spanning from 2005 to 2016. The advantage of applying the panel fixed-effects approach over other commonly used approaches, such as random-effects modelling and pooled Ordinary Least Square techniques, is that it takes into account unobserved and time-invariant heterogeneity among farms [34,35]. Similar to other studies that employed panel data and modelled farm-level TFP as a function of both observed and unobserved farm and farmer characteristics [1,19], the following empirical model is specified:

$$\ln TFP_{it} = \beta' + \alpha' \ln X_{it} + \varnothing' D_{it} + \delta_i + \psi_t + \varepsilon_{it}, \quad (1)$$

where TFP_{it} represents the natural logarithm of TFP of i dairy farm at year t; X_{it} is a set of continuous variables hypothesised to affect the TFP level of i^{th} dairy farm at year t (these variables include farm size, age, investment, etc.); D_{it} represents a vector of dummy variables (these include education, participation in off-farm activity, and land quality dummies); δ_i denotes the farm fixed-effects, which controls for unobserved farm characteristics which are time-invariant but may influence TFP; ψ_t represents the year fixed-effects, which controls for common shocks in that year such as price volatility or weather; ε_{it} is the idiosyncratic error term; and β', α', and $\varnothing'$ are the parameters to be estimated.

We specify three models based on Equation (1). The first (Model 1) tests for the effect of investment per cow within the year the investment was made (that is, at time t). The second (Model 2) tests for the effect of investments made three years previously, by lagging investment (t-3). Comparing Model 1 and 2 allows us to test whether the initial impact of new capital is lower than the future impact, once installation, training, and adjustments to management have been completed [18]. The choice to lag investment by three years is informed by previous studies, as in Sauer and Latacz-Lohmann [18], and our data structure. Also, three years provide a long enough period to allow for a transitional period while limiting the reduction in sample size. Model 3 retains the lag for investment and adds in additional variables. To test our hypotheses that the impact of investment will be stronger when combined with specialist education and that more recent education may be more influential, we include interaction terms. To test our hypothesis that age will be nonlinear, a transformation of age is also included.

The dependent variable, TFP_{it}, measures how efficiently a farm transforms material and factor inputs into outputs that year. TFP is calculated as the ratio of total outputs to total inputs. Measuring TFP requires indices sensitive to assumption around the aggregation of output and input components, which influence the resulting TFP metric due to the different underlying assumptions around the production function [1]. Common TFP indices include Laspeyres and Paasche indices [36] although these are being replaced by the Törnqvist–Theil and Fisher indices, due to their relative strength meeting 'axiomatic' and 'economic' tests [37]. However, a relevant weakness of the Törnqvist–Theil index is the difficulty of handling sparse data with many zero values [12], which is a feature of the data set being used. Considering the above, this paper uses the Fisher index to obtain farm-specific TFP expressed as a ratio of a Fisher output index to a Fisher input index. These intermediate indices are calculated by weighting quantities with prices to obtain a 'value,' providing a common unit to then obtain the ratio of outputs to inputs. Both prices and quantities are taken from the data set whenever possible, but in some cases, price is not available, and so a price (or relative price from an index) is sourced from the UK Office of National Statistics. Milk, livestock, crops, and other outputs are weighted by their respective prices to obtain a Fisher output index, while labour, capital, land, materials, and services are weighted to calculate a Fisher input index. To ensure that the farm-specific TFP can be compared over time and across farms, we adjusted the Fisher index using the Eltetö–Köves–Szulc (EKS) formula developed by Eltetö and Köves [38,39]. The TFP index calculated is relative to a specific 'base' dairy farm and year. For any farm-year observation, the 'index gives the relative difference in TFP between that and the base observation' (Sheng & Chancellor 2019, p. 197). See Zhao, Sheng and Gray [12] for a detailed explanation of the methodology on how the inputs and outputs are aggregated.

Our analysis incorporates a vector of independent variables, hypothesised to affect farm TFP levels independently or in combination. These variables are classified into four main groups. The first is farm operator characteristics, and these include age of farmer, education, and farmer's participation in off-farm activity. The second category includes variables related to farm management practices, and these include farm size, milk yield, stocking density, purchased feed per cow, labour input per cow, and hired labour share. The third is investment and technology, and this includes net investment per cow. The fourth category is land quality, and this includes the location of farms in severely disadvantaged areas, disadvantaged areas, and lowland areas. The fifth category is the subsidy variable, and this includes the share of direct payments in total output (the denominator of the 'subsidy/total output' variable includes direct payments, that is, 'total output' contains direct payments).

3.2. Data Sources

The data set used is the Northern Ireland Farm Business Survey (FBS). This is collected annually through the Statistics and Analytical Services Branch of the Department of Agricultural, Environment and Rural Affairs (DAERA) as part of the EU Farm Accountancy Data Network (FADN). The farms are part of a panel constructed to be representative of the main farm types above a minimum size threshold of 0.5 Standard Labour Requirement (SLR). As almost all dairy farms in Northern Ireland are greater than 0.5 SLR in size, the sample is representative of the population. Farms are selected at random, and farmers approach to join the panel—however, participation is voluntary. Farm accounts information was received for 325 farms (all types) in the 2019–2020 accounting year, of which 69% had been in the panel for more than 10 years. The survey collects information on production, socio-demographic, and financial variables—for example, input and output costs, total subsidy received, taxes, investments, farm size, farmer age, etc. For the purpose of this study, we consider the time period spanning from 2005 to 2016. Dairy farms are defined as farms with at least two-thirds of total output from milk. In total, there are 1343 observations with close to 40% of the farms present each year over the entire time period.

All variables in monetary values are deflated using appropriate price indices obtained from the UK Office of National Statistics. The descriptions of the variables believed to influence productivity are presented in Table 1.

Table 1. Variable descriptions and hypothesised signs.

Variable	Description	Hypothesised Signs
Farm management practices		
Herd size	Number of dairy cows	+
Milk yield	Total milk yield per cow (litres per cow)	+
Stocking density	Stocking density (cow equivalents per hectare)	+
Purchased feed	Purchased feed per cow (£ per cow)	-
Labour input	Labour input per cow (hour)	-
Hired labour share	Share of hired labour in total labour (%)	+
Farmer characteristics		
Age	Age of operator (years)	+/−
Education	=1 if farmer has qualifications of at least A level or college level 0	+
Off-farm	=1 if farmer participates in off-farm activity	+/−
Investment level		
Net investment per cow	Net investment per cow (£/cow)	−
Land quality		
SDAs	=1 if farm is located in severely disadvantaged areas (SDAs)	−
DAs	=1 if farm is located in disadvantaged areas (DAs)	−
Subsidy		
Subsidy share	Share of payments in total output (%)	+/−

4. Results and Discussion

4.1. Summary Statistics by Productivity Class

The summary statistics including mean and standard deviation values of the entire sample are reported in Table 2. Over the period from 2005 to 2016, the average herd size, milk yield, and stocking density of the overall sample are 97, 6139 litres/cow, and 1.91 cow equivalents per hectare, respectively. The average annual work hours per cow is 68, with 2.7% of labour use being hired. On average, dairy farmers are 56 years old, with close to a quarter of them engaging in off-farm activity and less than half (about 36%) with at least college- or A-level qualifications. The majority of farms (about 73%) are located in Less Favoured Areas (LFAs) (those classified as naturally constrained—encompassing both the SDA and DA farms) and have about 11% share of total farm output from subsidy. In addition, farms have an average capital investment of £362/cow over 11 years.

To generalise differences in farm and farmer characteristics by productivity class, dairy farms are classed into three TFP groups using k-means cluster analysis. This clustering technique involves a non-hierarchical, iterative procedure that divides farms into k-groups by reducing Euclidean distances among them [40]. It ensures that farms within a cluster are as similar in characteristics as possible but different from farms in another cluster. Univariate clustering was carried out using TFP to categorise farms into three groups, with the number of groups specified a priori. Studies, including Shrestha, et al. [41] and Shrestha, et al. [42], employed a similar approach to cluster Irish dairy farms with similar characteristics into groups. See Tan, Steinbach and Kumar [40] for a detailed description of this analytical approach.

Table 2. Characteristics of Farmers and Farms Disaggregated by Productivity Class.

Variable	Productivity Class			All Farms
	Low	Middle	High	
TFP score	64.47 [9.20]	89.21 [7.06]	115.20 [11.28]	86.79 [20.36]
Herd size	55.37 [32.79]	98.42 [65.50]	158.85 [90.3]	97.42 [73.89]
Milk yield	5334.29 [1178.79]	6262.31 [1187.38]	7094.65 [1301.07]	6139.45 [1369.82]
Stocking density	1.64 [0.48]	1.96 [0.43]	2.22 [0.44]	1.91 [0.49]
Purchased feed	540.32 [264.74]	565.29 [236.63]	619.24 [279.71]	568.78 [257.6]
Labour input per cow	100.29 [44.47]	60.18 [22.64]	40.68 [13.54]	68.04 [38.00]
Hired labour share	1.50 [6.84]	2.39 [9.81]	6.04 [13.19]	2.72 [9.21]
Age	56.38 [12.90]	54.43 [12.96]	57.99 [12.33]	56.01 [12.83]
Education	0.33 [0.47]	0.35 [0.47]	0.44 [0.49]	0.36 [0.48]
Off-farm	0.31 [0.46]	0.28 [0.45]	0.24 [0.43]	0.27 [0.44]
Net investment	366.13 [571.09]	369.20 [628.83]	340.64 [697.03]	362.05 [625.98]
SDAs	0.53 [0.49]	0.39 [0.48]	0.32 [0.46]	0.42 [0.49]
DAs	0.22 [0.41]	0.34 [0.47]	0.32 [0.46]	0.30 [0.45]
Subsidy share	13.42 [7.21]	10.13 [5.26]	8.55 [4.07]	10.85 [6.05]
Number of observations	437	617	289	1343

Source: authors' computation based on FBS 2005–2016.

The clustering exercise resulted in three dairy farm productivity classes: low-productivity (average TFP level of 64.47; range of 33.80 to 76.78; 437 farms), middle-productivity (average TFP level of 89.21; range of 76.94 to 102.18; 617 farms), and high-productivity (average TFP level of 115.20; range of 102.24 to 160.02; 289 farms). Table 2 also presents mean and standard deviation of farm characteristics disaggregated by the three productivity categories between 2005 and 2016. Productivity in the high-productivity group is, on average, 1.8 times higher than the low-productivity group. The TFP of the middle-productivity group is about 1.2 times higher than the low-productivity group.

Farm and farmer characteristics vary across high-productivity, middle-productivity and low-productivity farms. For instance, farms classed as high-productivity have larger herds, realise higher milk yield, use more purchased feeds, and use less labour than those classed as low- and middle-productivity. In addition, the high-productivity farms rely more on hired labour for production, and 44% of their operators have at least college-level or A-level educations, which compares to 33% in the low-productivity farms. There appears to be no large difference between the ages of operators. Low-productivity dairy farm operators, on average, tend to participate more in off-farm activities, and a higher proportion of these farms are located in LFAs and have a higher proportion of income from direct subsidy payments. In general, the summary statistics have shown that farm and farmer characteristics vary across the three productivity clusters. The observed differences were tested statistically based on regression analysis reported in Table 3.

Table 3. Estimation Results of the Factors Influencing Farm TFP Level.

Dependent Variable: Farm-Level TFP	Model 1 (Contains 1-In Year Investment)	Model 2 (Contains Lagged Investment)	Model 3 (Extended Model with Interaction Terms)
Herd size	0.078 ***	0.196 ***	0.197 ***
	[0.025]	[0.045]	[0.041]
Milk yield	0.516 ***	0.544 ***	0.541 ***
	[0.028]	[0.055]	[0.056]
Stocking density	0.073 ***	0.101 ***	0.108 ***
	[0.024]	[0.036]	[0.036]
Purchased feed per cow	−0.068 ***	−0.087 ***	−0.092 ***
	[0.017]	[0.024]	[0.024]
Labour input per cow	−0.337 ***	−0.134 ***	−0.123 ***
	[0.024]	[0.034]	[0.031]
Hired labour share	0.114 *	−0.066	−0.077
	[0.061]	[0.075]	[0.071]
Age	0.086	0.138	3.082 ***
	[0.060]	[0.135]	[1.172]
Age squared			−0.396 **
			[0.152]
Education—A levels, Agric. college or above	0.030 *	0.052 **	0.784 ***
	[0.017]	[0.025]	[0.270]
Age * Education—A levels, Agric. college or above			−0.199 ***
			[0.075]
Off-farm	−0.008	−0.022	−0.019
	[0.013]	[0.020]	[0.019]
Net investment per cow	−0.065 ***		
	[0.005]		
Net investment per cow *(3-year lagged)*		0.012 **	0.015 ***
		[0.003]	[0.005]
Net investment per cow *(3-year lagged)* * Education—A levels, Agric. college or above			0.059 *
			[0.032]
SDAs	−0.012	−0.052	−0.006
	[0.033]	[0.035]	[0.007]
Das	−0.033	−0.014	−0.020
	[0.022]	[0.022]	[0.023]
Subsidy share	−0.093	−0.181 **	−0.164 **
	[0.057]	[0.076]	[0.077]
Constant	1.200 ***	−0.662	−6.078 ***
	[0.352]	[0.508]	[2.35]
Year Fixed-Effects	Yes	Yes	Yes
Farm Fixed-Effects	Yes	Yes	Yes
Number of Observations	1343	866	866
Number of farms	169	137	137
R-Squared	0.747	0.668	0.690
F-statistics	79.880 ***	53.130 ***	52.77 ***

Note: Robust standard errors are in parentheses; *, **, and *** represent statistical significance at $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. Source: authors' computation based on FBS 2005–2016.

4.2. Regression Analysis of Farm-Level Productivity

The results of the panel fixed-effects regression are reported in Table 3. Model 1 (with no lag on investment) and Model 2 (with a three-year lag on investment) show that the estimated coefficients for all the variables have the same signs but different levels of significance, except for the net investment per cow variable. Model 3 maintains the lag on investment and includes a transformation of age to try to capture a nonlinear relationship and interaction effect amongst age, education, and investment. The results of all three models are provided in Table 3.

The results show that herd size is consistently positive and statistically significant across all the models. This is consistent with previous empirical studies [8,19,43,44]. The results also show that milk yield is positive and statistically significant, supporting the finding of Ali, et al. [45] that dairy farms adopting improved genetic materials attain higher productivity. Our analysis also shows stocking density as positive and significant, consistent with Reinsch, Loza, Malisch, Vogeler, Kluß, Loges and Taube [22] and Kimura and Sauer [1], finding that dairy farms operating intensive systems tend to be relatively more productive. The intensity of the purchased feed input variable is negative and significant after controlling for other factors (note that, contrary to the results of the econometric analysis, the productivity class analysis based on mean comparison shows that high-productivity farms use more purchased feeds. This difference in findings shows that comparing averages across productivity classes does not always reveal the relationship to TFP, therefore justifying the need for econometric analysis). Potentially diminishing marginal returns to purchased feedstuffs set in for some farmers, at which point, higher feed input will not enhance productivity, but may boost profits if used to generate a short-run yield response to high milk prices. This result also supports previous findings that better utilization of grassland combined with optimal use of concentrate inputs (e.g., precision feeding of relatively expensive feeds) improves productivity [46] and could also support profitability by improving the efficiency of a relatively expensive input.

Labour-intensity per cow has a significant and negative impact on productivity, as expected. It is important to note that the measurement of labour in farming is complex given the usual family-business nature of the enterprise. Therefore, the interpretation of results in relation to labour-intensity should be treated with caution. In Model 1, hired labour share was found to be positive and significant. This result further points to the relevance of scale in influencing productivity, as noted by Kimura and Sauer [1], and Sipiläinen [47]. Participation in off-farm activities has a negative sign but is not statistically significant. Dairy farmers engaged in off-farm activities are optimising available time by allocating between the farm and other enterprises. The negative sign indicates that they may be choosing to run a less intensive unit to maximise overall economic welfare.

Past studies have reported differing findings on the impact of age on the productivity of dairy farms. For example, Sheng and Chancellor [19] reported a positive relationship between age and farm-level TFP in Australia, whereas Kimura and Sauer [1] found a negative relationship for Estonian dairy farms but could not ascertain any significant relationship for dairy farms in England and Wales. This is not surprising given the nature of many farm businesses as family enterprises—with input from several individuals across generations shaping management decisions. In Models 1 and 2, age is linear, and the results show a positive, but not statistically significant, relationship. When age as well as age-squared (quadratic form) are included in Model 3, age is positive and significant, and age-squared is negative and significant. To illustrate the nonlinear relationship between age and TFP, the predictive margins graph was constructed (see Figure 1). The predictive margins graph plots the response of TFP when age is allowed to vary from 19 years to 84 years, and other remaining variables in the model are fixed at their mean values (margins are statistics estimated from prediction of the already-fitted model at fixed values of one/more explanatory variable(s) and averaging over other explanatory variables). The graph shows that the average effect of age is negative and that the negative impact increases in magnitude as farmers get older.

The education variable is binary, indicating a post-secondary qualification (advanced levels, agricultural college, and university), and has a positive and statistically significant estimated coefficient across all the models. This reinforces the wider literature indicating that additional years in education have a positive impact on farm management performance [18,19,48] (preferably, dummy variables for each of the education qualification categories should have been used, but the number of observations is few, and hence the amalgamated education variable—'A levels, agricultural college or above' was used in the main analysis. The majority of the observations within the amalgamated variable has an agriculture college qualification). However, as with age, estimating the true impact of education is complicated due to the family-business management structure, in which the farm owner and practical manager may not be one and the same. The interaction of age and education in Model 3 is negative, suggesting that both the level of education, as well as how recently it has been completed, may influence TFP.

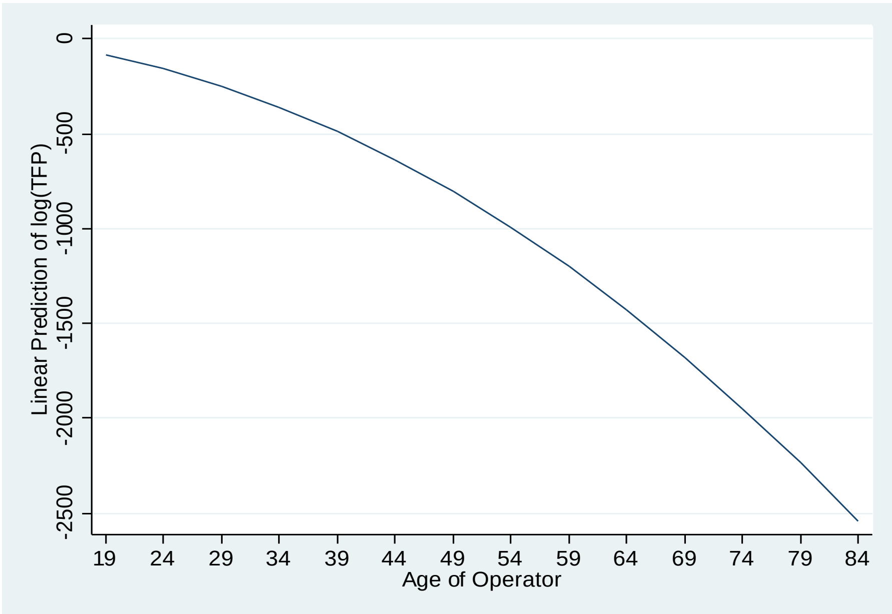

Figure 1. Predictive margins graph showing nonlinear relationship between age and Total Factor Productivity. Source: authors' computation based on FBS 2005–2016.

In Model 1, net investment has a negative impact on productivity. This may reflect the irregular nature of farm investments, with farmers responding opportunistically to short-term increases in farm-gate milk price movements. For example, when milk price increases above the long-term average, dairy farmers may increase their level of investment to expand output, thereby resulting in a short-term negative impact from investment on productivity until system changes are operating efficiently and benefits are fully realised. When lagged to accommodate a transition period (Model 2), the relationship between investment and productivity is positive. This suggests that the impact of capital investments is not immediate, and the coefficient reflects a long-term impact of investment. Kimura and Sauer [1] also found that the short-term impact of investment on dairy productivity was negative across the Netherlands, Estonia, and England and Wales. Sauer and Latacz-Lohmann [18] determined that capital investment requires two years to realise productivity gains for dairy farms in Germany. When lagged, net investment interacts with education (Model 3), indicating education has a complementary effect, consistent with other findings (Sauer and Latacz-Lohmann [18]).

Consistent with expectations, being located in an LFA is associated with lower TFP, but this is statistically insignificant. This suggests that natural conditions could be a constraint for productivity [49], but the fact that it is not significant suggests that, potentially, a relatively low-input, low-output system on such land can be productive. Dairy farms in LFAs are typically smaller and more likely to be part-time, therefore the more conventional pathways to increasing productivity via scale/technology are not appropriate, and instead low-input strategies may be more applicable. The share of payments in total farm output is negative and significant in Models 2 and 3. As direct payments have not increased in real terms for many years, this could suggest that specialist dairy farms that are highly reliant on direct payments are less productive as market revenues have grown more slowly than the average. However, the phenomenon may also reflect structural differences linked to the establishment of subsidy values at the farm level which were based on historic production. Farms with significant beef production tended to have higher baseline subsidies than specialist dairy farms. So, while the overall result is in line with the previous finding that specialised dairy farms (compared to mixed farming activities) are more productive [24], some caution is needed in interpretation as structural differences are unlikely to be the only factor involved.

We tested two additional hypotheses. Note that the additional analyses are based on Model 2. First, we tested whether education (a college qualification that specialises in agricultural training) would have a positive impact on TFP. This was done by replacing the general 'Education' variable with an 'Agriculture college' dummy variable (operators with agricultural college qualification take a value of 1, and 0 if otherwise) as presented in Model 2a of Table A1 in Appendix A. The results show that agricultural college has a positive and significant effect on productivity. Secondly, we tested whether the relationship between the 'Proportion of income as direct payments' variable and TFP is sensitive to the level of farm specialisation proxied by the share of milk in farm outputs (as shown in Model 2b of Table A1 of Appendix A). After controlling for level of specialisation, the subsidy variable still retains its negative sign and level of significance.

5. Conclusions

Productivity is essential to improving and sustaining international competitiveness. In light of the numerous challenges, gaining a better understanding of productivity at the farm-level can help develop strategies to improve individual farm, regional, and national performance. In this study, we analyse the factors influencing farm-level TFP for dairy farms. The first step of the analysis involves the use of a nonparametric approach to measuring farm-specific TFP based on an unbalanced panel of enhanced FADN data for the period of 2005–2016. Subsequently, a panel fixed-effects regression analysis that controls for observed and time-invariant unobserved differences among farms was used to investigate the factors influencing TFP.

Our findings show that herd size and stocking density have a positive impact on productivity, but purchased feed input per cow tends to have a negative impact. This result is consistent with the interpretation that purchased feeds may be increased to drive yields in the short-term in response to prices, but that there is a diminishing return with less and less benefit as more feed is used. The analysis also shows that more productive farms have a lower intensity of labour input per cow, a finding that is consistent with the benefits observed from capital investment via the substitution of labour with capital. These results suggest that policy strategies aimed at efficient management of inputs are key for dairy farms to becoming more productive. This may involve optimising labour input as part of the labour, capital, and land resource mix. For example, adoption of precision-feeding systems, use of sensor systems, and robotic milking in larger herds could be effective management options.

The finding that the impact of farmer age on productivity is negative, and increases in magnitude with age, touches on the complex issue of evolving career objectives, retirement, and farm succession. Age impacts are compounded by the interaction with educational attainment at the time of entry into the profession and subsequent engagement with continuing professional development. At face value, more recent training is more strongly related to higher productivity growth, but for family farms in particular, the influence of different generations on productivity growth is difficult to unravel. However, in all cases, policies that facilitate orderly farm succession or facilitate land mobility when succession is not an option, can be expected to enhance productivity when contrasted with an alternative laissez-faire approach.

Findings from this study also show that capital investment is a significant factor in improving productivity although this impact may be delayed. Making the correct investment decision is therefore a key component in sustaining productivity growth and suggests that expert advice and support are needed—given the increasing scale of investment required and technological complexity of the choices involved. In this respect, our findings also highlight the role of education in the relationship between investment in innovative technology and productivity. The findings reveal that innovative dairy technologies require a sufficient level of complementary education to trigger an increase in productivity at farm-level.

As we have been able to establish, the important role of education as a standalone variable, as well as its interactions with other variables—age and capital investments in facilitating productivity, initiatives that foster positive attitudes towards training and qualifications should be encouraged and barriers (e.g., time and cost) to uptake of agricultural training and education should be addressed [50].

Our study is not without limitations. First, the data available are limited to the years 2005–2016. Future research may consider more recent years as the data become available to the research team. Secondly, the productivity estimation in this study only considers marketable outputs and inputs, not environmental factors external to the market. Future studies may include incorporating indicators such as greenhouse gases, nitrogen and phosphorus surplus into TFP, and subsequently explore the interactions and trade-offs associated with productivity changes in the dairy farming sector.

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Appendix A

Table A1. Supplementary Analyses.

Variables	Model 2a (Contains Lagged Investment and Includes Only Agric. College)	Model 2b (Contains Lagged Investment and Controls for Specialisation)
Number of dairy cows	0.196 ***	0.247 ***
Milk yield	0.542 ***	0.662 ***
Stocking density	0.103 ***	0.098 ***
Purchased feed per cow	−0.086 ***	−0.101 ***
Labour input per cow	−0.135 ***	−0.150 ***
Hired labour share	−0.065	−0.054
Age	0.127	0.115
Education—A levels, Agric. college or above		0.048 **

Table A1. *Cont.*

Variables	Model 2a (Contains Lagged Investment and Includes Only Agric. College)	Model 2b (Contains Lagged Investment and Controls for Specialisation)
Education—Agric. college only	0.047 **	
Net investment per cow *(3-year lagged)*	0.011 **	0.012 **
Share of payments in farm outputs	−0.180 **	−0.147 **
Share of milk in farm outputs (specialisation proxy)		0.420 ***
Off-farm participation ratio		−0.022
Severely disadvantaged area	−0.052	0.042
Disadvantaged area	−0.014	0.011
Observations	866	866
Number of farms	137	137

Note: ** and *** represent statistical significance at $p < 0.05$ and $p < 0.01$, respectively. Only coefficients are reported. Source: authors' computation based on FBS 2005–2016.

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