International Journal of Agricultural Economics
2023; 8(6): 305-314
http://www.sciencepublishinggroup.com/j/ijae
doi: 10.11648/j.ijae.20230806.21
ISSN: 2575-3851 (Print); ISSN: 2575-3843 (Online)

The Marginal Effect of Investment in Machinery, Livestock, and Buildings on Irish Agricultural Output and Costs

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To cite this article:

Dilovar Haydarov, Chaosheng Zhang. (2023). The Marginal Effect of Investment in Machinery, Livestock, and Buildings on Irish Agricultural Output and Costs. *International Journal of Agricultural Economics*, *8*(6), 305-314. https://doi.org/10.11648/j.ijae.20230806.21

Received: December 3, 2023; **Accepted**: December 18, 2023; **Published**: December 28, 2023

Abstract: To achieve economically sustainable and profitable farms, farmers must manage various factors that impact farm output and costs. Numerous factors can influence farms' output, including soil quality, environmental conditions, farm size, system, and farmers' experience. This study investigates the impact of investment increases and decreases on farm gross output, direct costs, and overhead costs in Ireland, utilizing the Deep Neural Networks method. The data source for this study is a farm survey of pastoral-based livestock systems from 1996 to 2018. The findings reveal that, on average, Irish farmers ranging from the second gross output decile to the fifth decile will experience an increase in their gross output of 9% to 12.6% if they increase their investment in machinery, livestock, and buildings by 10%. Surprisingly, farmers in the first, ninth, and tenth deciles will experience a decrease in their gross output of 7.7%, 0.05%, and 3.77%, respectively, if investments are increased. This discrepancy may be attributed to the fact that the lowest and highest gross output farms primarily rely on subsidies and have already made substantial investments, respectively, resulting in a lack of positive response to investment increases. As expected, a 10% increase in investments leads to an increase in direct and overhead costs across most deciles, while a decrease in investments results in a decrease in overhead costs across all deciles. The findings of this paper emphasize the significance of farm investments in agricultural output and costs, providing valuable insights for agricultural policymakers and other stakeholders in making research-based decisions.

Keywords: Agricultural Output, Agricultural Costs, Machine Learning, Modelling in Agricultural Economics

1. Introduction

Farm businesses are significantly affected by agricultural output and costs, and scholars have extensively studied the factors that influence these aspects using various methodologies and datasets [1-4]. However, one crucial aspect that remains underexplored in the existing literature is the potential effects of increasing or decreasing investments in farms on output and costs. This research paper aims to address this gap and shed light on the implications of changes in farm investments.

Most previous studies have employed linear models to analyze farm output and costs, lacking built-in validation testing. In contrast, our research paper employs a novel deep learning method to analyze investment variables such as machinery, livestock, and buildings' impact on farm gross output, direct and overhead costs. This approach leads to new findings in the realm of agricultural output, costs, and farm investments.

Understanding the factors that influence farm income [5, 6] due to investments is crucial for farmers seeking to maximize their profits and manage their expenses. Farm profit is determined as the difference between farm output and costs. Knowing these influencing factors can serve as a valuable decision-making tool for farmers and agricultural policymakers. For instance, they may need to consider influencing certain farm variables, such as investment [7] in livestock, buildings, or machinery. Additionally, when farmers have incentives to increase their farm area or make environmentally conscious decisions like reducing machinery usage to decrease pollution, understanding the impact of these changes on farm output and costs becomes crucial [8].

Bokusheva et al. [9] examine the relationship between farm investments and the ratio of sales to capital, revealing that this ratio can significantly influence investment behavior. Carey and Zilberman [10] explore the adoption of irrigation technology as an investment in farms, highlighting that farmers are more likely to invest in modern technologies if the expected future returns outweigh the expected costs. Towne and Rasmussen [11] introduce the concepts of "farm gross product" and "gross investment" and demonstrate investment trends in relation to total farm output since the 19th century.

Weersink and Tauer [12] analyze investment models specific to dairy farms in New York, finding that these farms tend to utilize existing capital for longer periods before making additional investments. Skevas et al. [13] investigate the impact of various farm-related characteristics on investment decisions, identifying factors such as land tenure, liquidity, agricultural support payments, and age as the main drivers of investment likelihood. Hanrahan et al. [14] study the profitability of pasture-based dairy farm systems, revealing that farm size, capital investment in machinery, and buildings per cow significantly affect farm net profit per hectare.

Existing research on the influencing factors of farm income and productivity justifies their methodologies and datasets [15-17]. However, these studies have not expanded their scope to conduct a comprehensive analysis of farm profit using different families of statistical and mathematical techniques, which would provide a broader understanding of the impacting factors. Moreover, the majority of papers in the literature rely on traditional methods, such as linear regression models with a predefined set of explanatory factors, often focusing on specific aspects like livestock well-being, economic effects of subsidies, or environmental impacts of fertilizers, without providing a detailed and comprehensive exploration of the various factors influencing farm profit [18-20].

This research paper conducts a comprehensive examination of the factors influencing farm gross output, focusing on farm investments, utilizing deep neural networks. The choice of this method stems from its unique methodology, allowing for accurate and validated output results. Scholars in the field have established this technique as one of the most reliable for making estimations and projections. By applying this approach, the study aims to assess the measured effect of farm investment variables on farm gross output, direct, and overhead costs, both after a 10% increase and a 10% decrease in investments.

This work contributes to the existing literature by conducting an advanced analysis of the impact of farm investments on farm output, direct, and overhead costs using a relatively novel methodology. It also compares the differences before and after the implementation of investments. The related work section provides an overview of relevant published literature in the field, while the methodology section outlines the reasoning behind the chosen approach. The data section details the Teagasc National Farm Survey panel dataset used in the study, and the results section presents the identified explanatory factors and their effects on farm profit. Finally, the conclusion section offers concluding remarks and reflections on the findings.

2. Methodology and Data

In this section, Deep Neural Networks are initially discussed, followed by an alternative method, the random forest regression model, with its advantages and disadvantages that could potentially be used. Later, the study's utilized data, Teagasc's National Farm Survey, is explained.

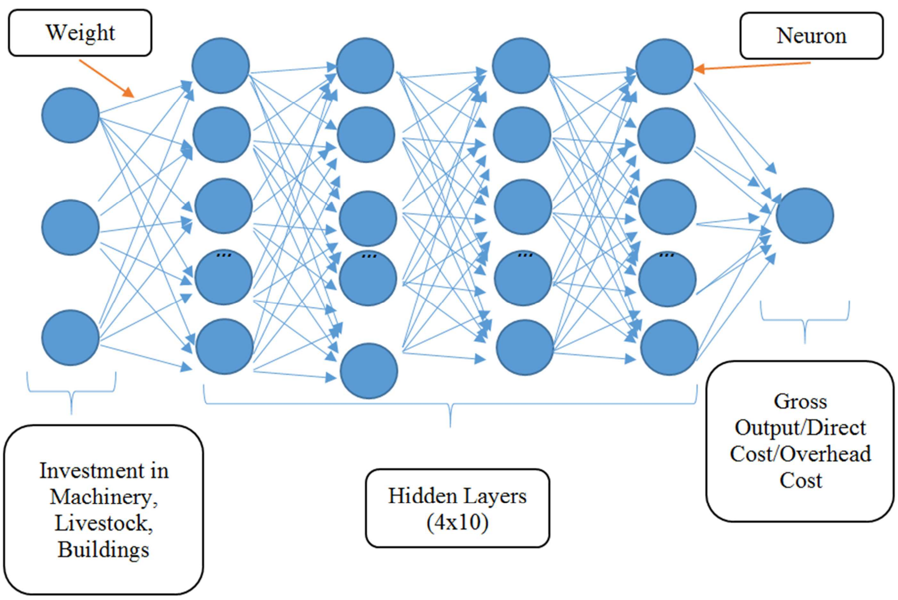

Figure 1. Deep Neural Networks Structure.

2.1. Deep Neural Networks

Deep Neural Networks are a type of artificial neural network architecture characterized by the presence of multiple hidden layers (as depicted in Figure 1). These networks consist of an input layer comprising neurons that take values from predictive or explanatory variables [21-23]. The neurons in the hidden layers calculate their values as a sum of the values from the previous layer (or input values) multiplied by their corresponding weights. The final layer is the output layer, which also contains values estimated by the previous layers' neurons and their respective weights. In Figure 1, four hidden layers with five neurons each are shown, while the input layer has three neurons representing investment in machinery, livestock, and buildings, and the output layer has one neuron representing farm gross output, direct costs, or overhead costs. However, the number of hidden layers and neurons in the input, hidden, and output layers can vary depending on the specific configuration of the deep neural network. In this paper, the deep neural networks used consist of four hidden layers, each containing ten neurons.

Initially, all weights are randomly assigned, and their related neurons are calculated; therefore, predicted outputs can be far from real/true/correct values. In order to reduce errors of weights within deep neural networks, deep neural networks will use the backpropagation technique (equation 1) to reduce errors and adjust weights so that in each iteration of prediction, errors are smaller and predicted values are more accurate.

$$\frac{\partial error}{\partial weight} = \frac{\partial a}{\partial weight} * \frac{\partial b}{\partial a} * \frac{\partial c}{\partial b} * \frac{\partial d}{\partial c} \dots * \frac{\partial error}{\partial z} \quad (1)$$

$\frac{\partial error}{\partial weight}$ is the derivative ration of error to weight (or level of change in errors with respect to weights) and $a, b, c \dots z$ are a chain of neurons from the input layer to the output layer.

Activation functions are used within deep neural networks to facilitate convergence of neural networks to their optimal weights faster, determine the output values and format, and also impact the accuracy of predicted outputs. Activation functions are located within hidden layers, and they serve to activate or not activate neurons based on specific parameters/criteria. In the case of the sigmoid/logistic function, it compresses/squashes hidden layer neuron values into 0 to +1 values, where closer to +1 value suggests highly likely (activate) and 0 highly unlikely (don't activate). In comparison, the hyperbolic tangent (TanH) activation function has values between -1 to +1 and works better with neurons that have strong negative and strong positive values before conversation into TanH function neurons.

In this paper's analysis, rectified linear unit activation function for hidden layers and linear activation function for the output layer is used. The reasons for utilizing rectified linear unit function are that it is computationally efficient (neural networks converge faster), voids neurons that are not contributing, and the "infinite value range" issue if neurons contribute to the network. Equation 2 provides a simple yet effective equation of rectified linear unit activation function, where it returns either zero value for discontinued (not contributing) neurons or provided original value.

$$\varphi(\tau) = \max(0, \tau) \quad (2)$$

For the output layer, a linear activation function is used in order to keep all values in their given form and not confined to any value range. Equation 3 is a simple equation of linear activation function, where it has infinite positive and negative range.

$$\varphi(\tau) = \tau \quad (3)$$

The analysis of this study is carried output with the help of Python (version 3.7) programming language. And it utilized packages/libraries are Pandas, Numpy, Statsmodels, Sklearn, and Keras. The raw data is also prepared for the analysis in Python language.

One of the alternatives to the deep learning method is the random forest regression method, which was first introduced by Breiman [24], and De'ath and Fabricius [25]. Random forests can be considered as a specific case of the concept of a random element in probability theory, involving a set of root forests with labeled vertices and a uniform probability distribution [26]. Lindner et al. [27] later proposed a new method called random forest regression, which has gained popularity in various disciplines such as machine learning, pattern recognition, data mining, and applied statistics.

Random forests exhibit weak correlations between the solutions of their constituent trees due to the "injection of randomness" at two stages: the bootstrap stage and the random selection of features used in splitting tree nodes [28]. This method has been widely recognized and embraced by both the statistical community and researchers utilizing pattern recognition techniques, becoming one of the most popular methods for classification and non-parametric regression [29]. Its popularity stems from not only its high classification accuracy but also other advantages it offers. However, for the current study, the deep learning networks were preferred due to their relatively advanced model training and testing capabilities, facilitated by their neural network architecture.

2.2. Data - Teagasc National Farm Survey

This paper will utilize data from the Teagasc National Farm Survey (NFS) collected between 1996 and 2018. The survey selects approximately 1000 farms each year based on Central Statistics Office quotas and assigns weights to ensure national representation of the Irish farm population. The survey is voluntary, and farms engaged in pig and poultry systems are excluded. It is part of the EU's Farm Accountancy Data Network (FADN) and serves various purposes, including policy, research, financial analysis, and performance measurement. The farms in the survey are categorized into dairy, cattle rearing, cattle other, sheep, and tillage systems. Due to the limited number of farms, poultry and pig systems are not included in the Teagasc NFS.

The survey collects various key variables, including costs, subsidies, purchases, assets, liabilities, yields, inventories, and sales. Table 1 provides summary statistics for the variables used in this study. Three variables of interest as explanatory factors are investment in machinery, livestock, and buildings. On the other hand, three other variables, namely farm gross output, direct costs, and overhead costs, will be influenced by changes in investments. These variables are presented as unweighted values, as the study aims to focus on the actual surveyed values per farm rather than weighted and nationally representative values.

Farm gross output is defined as total sales minus the purchase of livestock and crops, plus the value of farm produce used in-house, and receipts for hire work and service fees. Farm direct costs encompass costs directly associated with the production of all farm enterprises, such as dairy, cattle, sheep, and tillage. Farm overhead costs are expenses that cannot be directly allocated to a specific farm enterprise or production unit, often referred to as fixed costs.

Investment in machinery refers to the end-of-year valuation of machinery based on the replacement cost methodology. Investment in livestock is defined as the average of the opening and closing valuations of livestock. Lastly, investment in buildings refers to the end-of-year valuation of buildings based on the replacement cost methodology. The study does not consider the effects of public subsidies, climate change, farmers' mental health, different levels of farm asset depreciation, or other factors that can potentially influence both farm output, costs, and investments.

Table 1. *Summary Statistics of Variables.*

	Investment in Machinery	Investment in Livestock	Investment in Buildings	Farm Gross Output	Farm Direct Costs	Farm Overhead Costs
count	24611.00	24611.00	24611.00	24611.00	24611.00	24611.00
mean	32521.49	66675.09	42734.21	89493.94	31983.03	28339.65
std	46604.44	65797.65	60540.29	99424.31	44263.75	33552.11
min	0.00	0.00	-1431.06	0.00	0.00	-9508.39
max	1007385.00	836415.00	2049920.00	3339889.00	2676570.00	672717.00

3. Results

In this section of the paper, the validation of the deep learning model for the three dependent variables, namely farm gross output, direct costs, and overhead costs, is initially presented. This is followed by the results of the impact of increasing or decreasing investments in machinery, livestock, and buildings on our three target variables.

Tables 2-4 display the level of association between investment in machinery, livestock, and buildings with farm gross output, direct costs, and overhead costs, respectively. It is observed that investment in machinery and livestock shows a relatively high association with farm gross output compared to investment in buildings. For every one euro increase in machinery and livestock investments, farm gross output increases by 0.72 euros and 0.69 euros, respectively. However, with a one-euro investment in machinery, farm direct costs only increase by 0.17 euros, while in the case of livestock and buildings investments, they lead to direct costs increasing by 0.28 euros and 0.25 euros, respectively. Furthermore, if a farmer invests one euro in machinery, livestock, and buildings, they should expect overhead costs to increase by 0.39 euros, 0.13 euros, and 0.13 euros, respectively. These statistically significant correlation coefficients demonstrate a strong basis to estimate the impact of investment increase and investment decrease on farm output and costs using machine learning technique.

Table 2. *Association of investment factors with farm gross output.*

	Coefficient	Standard error	T-value	P-value
Constant	3613.43	417.11	8.66	0.00
Investment in Machinery	0.72	0.01	92.07	0.00
Investment in Livestock	0.69	0.01	105.23	0.00
Investment in Buildings	0.38	0.01	54.57	0.00
R-squared	0.79			
F-statistic	30620			
Prob. (F-statistic)	0			
Log-Likelihood	-298990			
AIC	598000			

Table 3. *Association of investment factors with farm direct costs.*

	Coefficient	Standard error	T-value	P-value
Constant	-2843.42	232.43	-12.23	0.00
Investment in Machinery	0.17	0.00	38.14	0.00
Investment in Livestock	0.28	0.00	77.28	0.00
Investment in Buildings	0.25	0.00	63.38	0.00
R-squared	0.67			

	Coefficient	Standard error	T-value	P-value
F-statistic	16580			
Prob. (F-statistic)	0			
Log-Likelihood	-284600			
AIC	569200			

Table 4. *Association of investment factors with farm overhead costs.*

	Coefficient	Standard error	T-value	P-value
Constant	1227.46	136.24	9.01	0.00
Investment in Machinery	0.39	0.00	152.41	0.00
Investment in Livestock	0.13	0.00	61.56	0.00
Investment in Buildings	0.13	0.00	57.65	0.00
R-squared	0.80			
F-statistic	33240			
Prob. (F-statistic)	0			
Log-Likelihood	-271450			
AIC	542900			

3.1. Validation of the Accuracy of the Model

Figure 2 displays the validation accuracy of our deep learning model, with farm gross output, farm direct costs, and farm overhead costs represented from right to left. The term "actual" refers to the actual data samples, while "testing estimation" indicates the deep learning model's estimated values for testing purposes. For example, 89,753.46€ represents the actual average farm gross output, while 84,772.27€ is the deep learning model's average estimation of farm gross output.

The overall accuracy is calculated to be approximately 94.12%, resulting in a mean absolute difference of -4,981.19€ for farm gross output. For farm direct costs, the overall accuracy is 90.87%, with a mean absolute difference of -2,682.36€, and for farm overhead costs, it is 95.42% with a mean absolute difference of -1,245.24€. In other words, the estimated farm gross output is, on average, 94.12% close to the actual farm gross output, while the closeness to farm direct and overhead costs is 90.87% and 95.42%, respectively. This estimation closeness is relatively good compared to the literature on machine learning models [30, 31] and general modelling field.

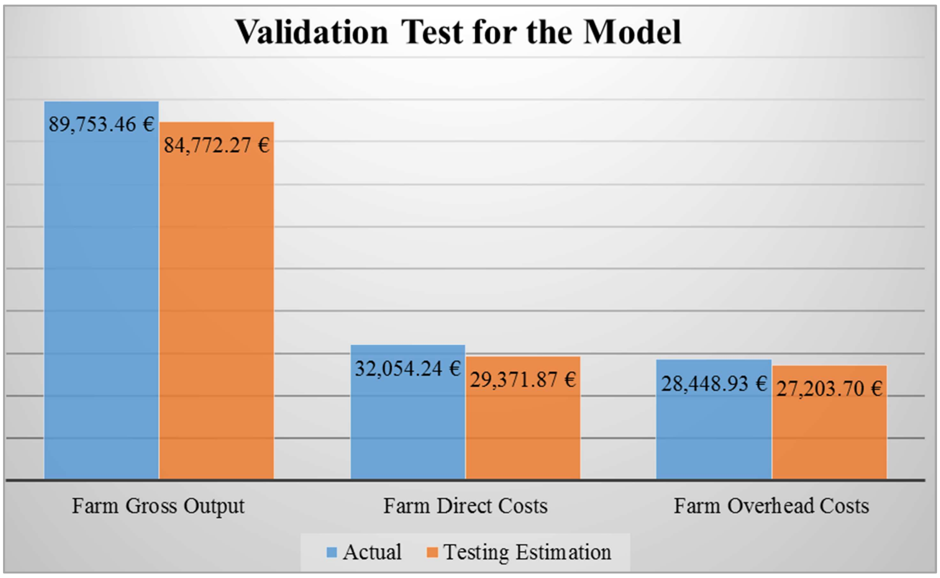

Figure 2. *The validation of the accuracy of the Deep Learning Model.*

3.2. A Comparison of an Increase and Decrease in Investments

Table 5 presents a comparison of the actual farm gross output values from Deep Neural Networks with values after a 10% increase and 10% decrease in investments in machinery, livestock, and buildings. The table includes information on counts, means, standard deviations, minimum and maximum percentiles, as well as quartiles (25th, 50th, and 75th percentiles).

After a 10% increase in investments, farm gross output showed an increase of 12.85%, 9.28%, and 1.83% in the 25th, 50th, and 75th percentiles of the farm gross output range, respectively. However, for the top quartile (75% to 100%) of the farm gross output range, the gross output decreased significantly by 61.42%.

Conversely, after a 10% decrease in investments, farm gross output also declined by 3.30%, 6.19%, 12.69%, and 65.85% in the bottom first to fourth quartiles of the farm gross output range. The mean impact of a 10% increase in investments on farm gross output was 1.35%, while a 10% decrease led to a substantial decrease of -13.14% in farm gross output.

Table 5. *Actual farm gross output comparison with 10% increased and 10% decreased values.*

	Actual Farm Gross Output	10% Increased Farm Gross Output	Percentage Change (%) of Increase	10% Decreased Farm Gross Output	Percentage Change (%) of Decrease
count	24611	24611		24611	
mean	89493.94	90699.47	1.35%	77738.32	-13.14%
std	99424.31	91503.90	-7.97%	78472.32	-21.07%
min	0.00	2.25		2.30	
25%	27058.53	30536.14	12.85%	26166.65	-3.30%
50%	56362.13	61591.29	9.28%	52872.50	-6.19%
75%	116447.50	118573.90	1.83%	101669.40	-12.69%
max	3339889.00	1288400.00	-61.42%	1140662.00	-65.85%

Table 6 provides a comparison of the actual farm direct costs values with values after a 10% increase and 10% decrease in investments in machinery, livestock, and buildings. The table presents counts, means, standard deviations, minimum and maximum percentiles, as well as quartiles (25th, 50th, and 75th percentiles). Following a 10% increase in investments, farm direct costs saw an increase of 47.85%, 27.34%, and 10.67% in the 25th, 50th, and 75th percentiles of the farm direct costs range, respectively. However, for the top 75% to 100% range of farm direct costs, a 10% increase in investments resulted in a substantial decrease of 78.28% in direct costs.

Conversely, after a 10% decrease in investments, farm direct costs also decreased by 6.06%, 18.49%, and 82.81% in the second to fourth quartiles of the farm direct costs range. Surprisingly, the bottom 25% farm direct costs percentile increased by 9.07% after a 10% decrease in investments. The average effect of a 10% increase in investments on farm direct costs was 7.49%, while a 10% decrease led to a significant decrease of -20.71% in farm direct costs.

Table 6. *Actual farm direct costs comparison with 10% increased and 10% decreased values.*

	Actual Farm Direct Costs	10% Increased Farm Direct Costs	Percentage Change (%) of Increase	10% Decreased Farm Direct Costs	Percentage Change (%) of Decrease
count	24611	24611		24611	
mean	31983.03	34377.66	7.49%	25358.56	-20.71%
std	44263.75	34793.17	-21.40%	25764.90	-41.79%
min	0.00	-0.52		-0.04	
25%	7861.91	11624.14	47.85%	8574.72	9.07%
50%	18361.50	23381.29	27.34%	17248.71	-6.06%
75%	40575.71	44905.10	10.67%	33072.51	-18.49%
max	2676570.00	581424.19	-78.28%	460135.13	-82.81%

Table 7 presents a comparison of the actual and estimated values after a 10% increase or 10% decrease in investments in machinery, livestock, and buildings, focusing on the count, mean, standard deviation, minimum, 25th, 50th, 75th, and maximum farm overhead cost percentiles. With a 10% increase in investments, farm overhead costs experienced slight increases of 2.27%, 2.57%, and 3.48% in the 25th, 50th, and 75th farm overhead cost percentiles, respectively. However, for the top quartile (75% to 100%) of the farm overhead cost range, a 10% increase in investments resulted in a notable decrease of 43.96% in overhead costs. On the other hand, after a 10% decrease in investments, farm overhead costs declined by 18.32%, 18.31%, 18.19%, and 50.09% for the first to fourth farm overhead cost quartiles. The average impact of a 10% increase and 10% decrease in investment on farm overhead costs was -1.39% and -21.89%, respectively.

Table 7. *Actual farm overhead costs comparison with 10% increased and 10% decreased values.*

	Actual Farm Overhead Costs	10% Increased Farm Overhead Costs	Percentage Change (%) of Increase	10% Decreased Farm Overhead Costs	Percentage Change (%) of Decrease
count	24611	24611		24611	
mean	28339.65	27945.51	-1.39%	22137.36	-21.89%
std	33552.11	29592.13	-11.80%	23497.90	-29.97%
min	-9508.39	2.34		2.06	
25%	8680.80	8877.90	2.27%	7090.44	-18.32%
50%	17809.40	18266.48	2.57%	14549.37	-18.31%
75%	35295.76	36524.43	3.48%	28875.99	-18.19%
max	672717.00	376962.72	-43.96%	335757.00	-50.09%

Figure 3 illustrates the change in farm gross output after a 10% increase or a 10% decrease in investments in machinery, livestock, and buildings. Compared to the actual data with no increase or decrease, farm gross output increased across the second to eighth gross output deciles, ranging from 1.96% to 12.59%. Conversely, the first, ninth, and tenth deciles experienced a decline in farm gross output with a 10% increase in investments. On the other hand, a 10% decrease in investments resulted in a decrease in farm gross output across all ten gross output deciles, ranging from 3.46% to 20.95%.

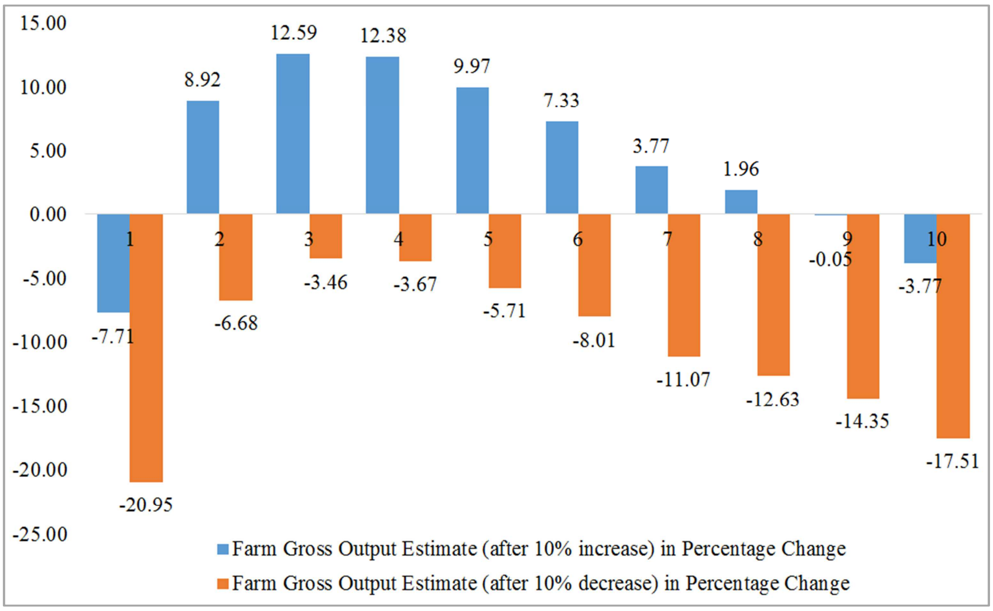

Figure 3. *Farm gross output change after 10% increase and decrease in investments.*

Figure 4 displays the change in farm direct costs after a 10% increase and a 10% decrease in investments in machinery, livestock, and buildings. Following a 10% increase in investments, farm direct costs also increased across the first to ninth direct costs deciles, ranging from 5.04% to 49.45%, compared to the actual data with no increase or decrease. However, the tenth farm direct costs decile experienced a decline of 7.55% with a 10% increase in investments. On the other hand, a 10% decrease in investments resulted in a decrease in the first and fifth to tenth farm direct costs deciles, ranging from 1.87% to 31.69%, while the second to fourth farm direct costs deciles increased.

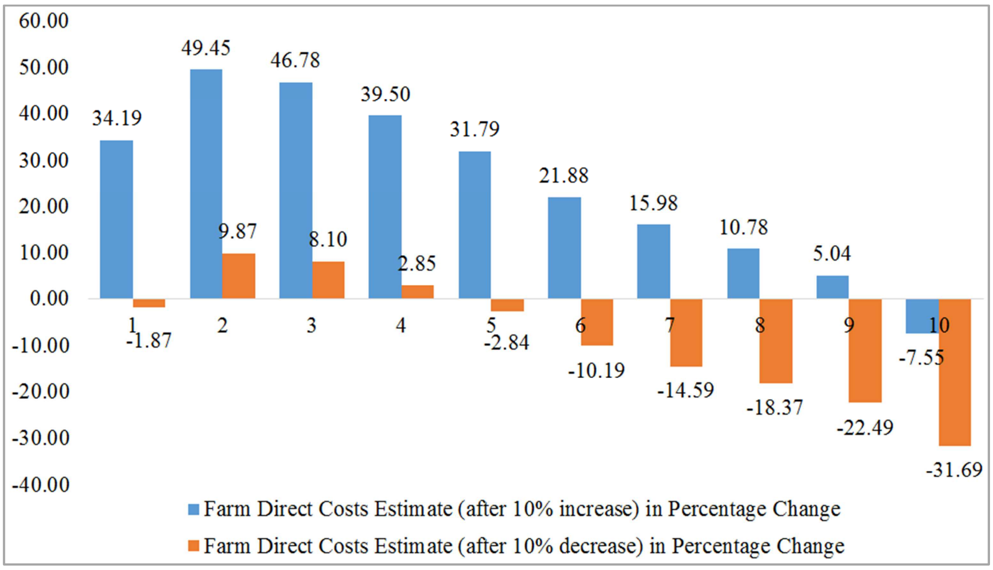

Figure 4. *Farm direct costs change after 10% increase and decrease in investments.*

Figure 5 depicts the change in farm overhead costs after a 10% increase and a 10% decrease in investments in machinery, livestock, and buildings. With a 10% increase in investments, farm overhead costs increased from the third to ninth overhead costs deciles, ranging from 1.55% to 3.32%, when compared to the actual data with no increase or decrease. However, the first (4.74%), second (0.12%), and tenth (7.36%) overhead costs deciles experienced a decline in farm overhead costs with a 10% increase in investments. On the other hand, after a 10% decrease in investments, a decrease in all ten overhead cost deciles, ranging from 18.25% to 26.65%, was observed.

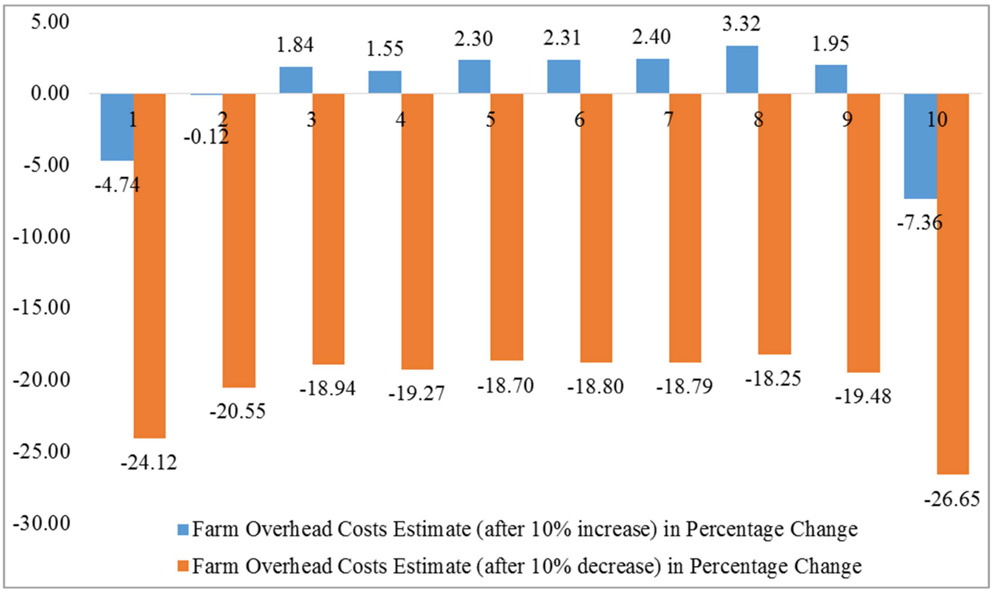

Figure 5. *Farm overhead costs change after 10% increase and decrease in investments.*

Relatively recent developments in the field of analytical methodologies, such as machine learning, have enabled a new and expanded analysis of the explanatory factors influencing farm gross output, farm direct costs, and farm overhead costs. These findings contribute to a deeper understanding of the role of investments in farm gross output, as well as direct and overhead costs.

4. Discussion

Understanding the impact of farm investments on farm gross output and costs is crucial for farmers and agricultural policymakers to maintain the economic viability of farms. Given the global importance of food security and recent increases in food prices, it has become even more critical for farmers to closely monitor output and costs while ensuring overall farm profitability. As demonstrated in this study, farm investments do influence farm output and costs, but the magnitude of this influence varies depending on the size of farm output and costs. It is also supported by a study [32] that found that farm investments increase production.

It was observed that increasing investments in machinery, livestock, and buildings resulted in increased farm gross output for most gross output deciles, except for the lowest and highest gross output farms. Higher gross output increases were particularly noticeable around the third and fourth deciles. Conversely, decreasing investments led to a decrease in farm gross output across all output deciles. A related research investigated that limited investment amounts lead to elevated expenses and diminished production efficiency, culminating in an agricultural production system that lacks competitiveness [33].

Regarding farm direct costs, increasing investments led to an increase of more than five percent in all direct cost deciles, except for the top tenth decile. However, decreasing investments only affected certain direct cost deciles. For farm overhead costs, an investment increase in machinery, livestock, and buildings resulted in slight increases, ranging up to about three percent in overhead cost deciles, while simultaneously decreasing costs in the bottom first, second, and top tenth overhead deciles. Conversely, an investment decrease led to a decrease of approximately twenty percent in most overhead cost deciles. Another study found that substantial spending on investments, often backed by loans, leads to heightened expenses. However, study's every farm category that undertook these investments witnessed an improvement in the cost-effectiveness of specific inputs [34]. Mogues et al. [35] mention that governmental financial measures, like subsidies or taxes, are frequently employed to incentivize alterations in production behavior by modifying the production cost or the revenue and profit derived from production encountered by the individual or entity involved. The new findings of this paper provide valuable insights for farmers and farm decision-makers in better understanding and managing agricultural investment factors related to farm gross output and costs. Findings also show that based on the size of farm output and costs farms will respond differently to investments.

5. Conclusion

The performance of farm enterprises is substantially influenced by agricultural output and costs, and extensively examined by scholars using diverse methods and data. Yet, an overlooked area in current literature pertains to the potential impacts of altering investments on farm output and costs. This paper seeks to bridge this gap by exploring the consequences of fluctuating farm investments, aiming to provide insight into their implications.

Previous literature studies often used linear models to scrutinize farm output and costs, lacking inherent validation testing. In contrast, our research employs a relatively innovative deep learning technique to examine how investment variables—such as machinery, livestock, and buildings—affect farm gross output, direct costs, and overhead costs. This approach yields fresh insights into the literature of agricultural output, costs, and farm investments.

Understanding the factors that impact farm income due to investments holds immense importance for farmers aiming to optimize profits and manage expenses. Farm profit, derived from the disparity between farm output and costs, hinges on these factors. Familiarity with these influential elements can serve as a valuable tool for farmers and agricultural policymakers when making informed decisions.

The findings demonstrate the impact of altering investments in machinery, livestock, and buildings on farm gross output, direct costs, and overhead costs. A 10% increase in investments led to increased farm gross output across mid-range deciles, while the highest and lowest deciles saw decreased output. Meanwhile, a 10% decrease in investments resulted in decreased farm gross output across all deciles.

Following a 10% increase in investments, farm direct costs increased across most cost deciles but decreased in the highest cost decile. Conversely, a 10% decrease in investments led to decreased costs in most deciles with increases in the mid-range deciles. Regarding overhead costs, a 10% increase in investments led to increased costs in several mid-range deciles, but decreased costs in the highest, lowest, and second deciles. Conversely, a 10% decrease in investments resulted in decreased overhead costs across all deciles.

Future research could explore the nuanced impact of varying investment distribution among machinery, livestock, and buildings on farm output and costs. Examining the interaction effects between different types of investments and their influence on specific sectors of agricultural production could provide a more comprehensive understanding of optimizing investment strategies.

Additionally, investigating the long-term implications of investment changes on farm sustainability and economic resilience could be beneficial. Understanding how these changes affect ecological sustainability, resource management, and the adaptive capacity of farms in different regions or contexts would offer valuable insights for sustainable agricultural practices.

Finally, exploring the potential role of government policies or incentives, such is farm subsidies, in influencing investment decisions and their subsequent effects on farm output, costs, and overall agricultural systems could be an area of interest for future research. Understanding how policy interventions can support or hinder investment dynamics within the agricultural sector would be beneficial for policymakers and stakeholders aiming to optimize farm performance and long-term sustainability.

Data Availability

To access the data used to support the findings of this study, Teagasc - the Agriculture and Food Development Authority should be contacted at https://www.teagasc.ie/rural-economy/rural-economy/national-farm-survey/.

Acknowledgments

The authors would like to acknowledge the support of the Teagasc Walsh Fellowship Programme. The corresponding author is currently at the Urban Institute. This paper’s preliminary work was put online as a preprint at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4331322, which was later deleted.

Conflicts of Interest

The authors declared no conflict of interests.

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