Impact of Membership of Dairy Participatory Extension Group on Farm Income: An Application of a Difference-in-Differences Coarsened Exact Matching Approach

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Abstract

This paper evaluates the impact of membership of the dairy Business Development Groups (BDG), a participatory extension programme in Northern Ireland on the gross margin performance of participating farmers relative to non-participants. The study employs a difference-in-differences exact coarsened matching approach and contributes to the literature on the impact of participatory extension programmes on farm income. The results of the analyses showed that membership of dairy BDG has a statistically significant impact on the gross margin of participating farmers. Specifically, the results showed that dairy farmers who are members of the BDGs increased their gross margin by £117 per head respectively compared to farmers that are non-members of the BDGs. The results of the study have practical implications for the design of participatory extension programmes as it provides evidence to inform policy development around the area of participatory extension programmes. It also supports the design of efficient agricultural education and extension systems that incorporates the ideas of the farmers themselves through peer-to-peer learning thereby maximising the economic and social benefits accruable from such programmes.

Key words: Impact assessment; Participatory extension; Conditional difference-in-differences; Matching; Business Development Groups

1.0 Introduction

Effective agricultural extension programmes can increase the productivity of farming households by helping farmers to augment their skills and knowledge as well as embrace new technologies and best practices (Fakayode, Adenuga, Yusuf, & Jegede, 2016; Jack, Adenuga, Ashfield, & Wallace, 2020). However, the extent to which farmers benefit from such extension programmes depends largely on the design of the programme. Agricultural extension service programmes have to be designed with the capacity to improve farm performance and connect emerging research to on-farm practices (Hennessy & Heanue, 2012; King, Fielke, Bayne, Klerkx, & Nettle, 2019; Läpple, Hennessy, & Newman, 2013; Tamini, 2011; Woodhill, 2014). The international literature commonly identifies four major strands of agricultural extension methods namely: linear technology transfer, one-to-one advice, structured education and training, and participatory extension methods (Black, 2000; Esparcia, 2014; King et al., 2019). National advisory programmes around the world have tended to adopt a range and combination of these methods to fulfil their farm-level extension remit.

Northern Ireland as a country has historically delivered extension services on an advisor to farm, one-to-one basis using a top down approach. However, this approach has limitations in terms of the extent of its coverage to farmers and its inability to account for the current, more complex agricultural production environment which requires more responsive and innovative approaches. In a bid to improve economic performance at farm-level through fostering competitiveness of agriculture and ensuring the sustainable management of resources in March 2016, the Northern Ireland College of Agriculture, Food and Rural Enterprise (CAFRE) adopted a new approach to advisory service provision for farmers namely; Business Development Groups (BDG's). The BDG is a knowledge transfer scheme which forms part of a wider programme, the Farm Business Improvement Scheme (FBIS), part funded by the European Union (EU) through Pillar II of the Northern Ireland Rural Development Programme 2014–2020.

The BDG programme employs a group approach aimed at improving the performance of farm businesses through facilitated 'peer-to-peer' learning to encourage the fostering of knowledge capital and knowledge exchange between actors. Farmers participating in the scheme have farm key performance indicators recorded and benchmarked every year to identify areas for potential improvement for the period for which they are members of the BDGs. Participating BDG members maintain an active business development plan, attend training events, and share benchmarking information with other group members. Each farmer also hosts a group training event on their farm during the lifetime of the scheme. Interactions are held under the guidance of a facilitator to bring in new ideas and foster innovation, particularly around the use of new technologies. This gives the farmers improved access to local and expert knowledge, as well as well-functioning social networks that promote rural innovations. The farmers meet formally six to eight times a year, providing them with an opportunity to talk about their own farm business issues, including responses to wider market, policy and technology drivers. The allocation to groups is by main farm enterprise and farm location (Northern Ireland Assembly, 2016).

As with other publicly funded programmes, evaluating the scheme's effectiveness in meeting defined objectives is of pivotal consideration. This is particularly around quantifying the 'value for money' aspect of the scheme while providing robust evidence for future programme developments. Specifically, the objective of this study is to obtain a credible best-estimate of the impact of membership of the dairy Business Development Groups (BDGs) on-farm gross margin using a difference-in-differences coarsened exact matching approach.

This study contributes to the existing literature by analysing the impact of membership of a participatory extension programme on farm gross margin. In conducting our analysis, we take advantage of both the longitudinal nature of the FBIS dataset and the Northern Ireland Farm Business Survey (NBS) to estimate the impact of membership of the BDG programme on-farm economic performance making use of the conditional difference-in-differences coarsened exact matching approach which previously has had limited application in the agricultural extension and education evaluation literature. The results of the study will provide evidence to inform policy development around the area of participatory extension programmes.

The remaining sections of this paper are organised as follows: Section 2 describes the methodology employed in the study. Section 3 explains the nature of the data used and describes the characteristics of the BDG groups. The results and discussion are presented in Section 4 and finally, Section 5 concludes the paper.

2.0 Methodology

The methodology employed in this study addresses the problem of endogeneity by combining the non-parametric coarsened matching (CEM) estimator with a difference-in-differences analytical technique to facilitate obtaining a credible estimate of the impact of BDG membership on farm gross margin performance in a non-experimental context. The methodology is able to account for selection on observables and to control for unobservable time-invariant farm heterogeneity (Love, Javorcik, & Brucal, 2017; Wardani, Baryshnikova, & Jayawardana, 2022).

2.1 Estimation Strategy

An ideal way to estimate the causal impact is to conduct randomized controlled trials which ensure the exposure to "treatment" (being a member of the dairy BDG group) is exogenous to the potential outcome (i.e., farm gross margin performance)(Heckman, Ichimura, & Todd, 1997). However, random assignment of members into group is not feasible for this study because the decision to join or not to join a BDG group may be inherently related to observed and/or unobserved factors resulting in selection bias (Adenuga, Jack, Ashfield, & Wallace, 2021; Chen, Guo, & Shangguan, 2022). To address this challenge, this study employs the difference-in-differences coarsened exact matching approach (Iacus, King, & Porro, 2012, 2019).

Our estimation strategy follows the framework developed by Rubin (1974). Taking Y_i^1 as the income of a farmer who joined the BDG programme and Y_i^0 as the income of the farmer if he or she had not joined the BDG programme. The overall policy impact of membership of the BDG programme can be identified as the average treatment effect on the treated units. This can be obtained as the difference in farm income (ΔY) between income of farmers in the BDG programme (Y_i^1) and income of the farmers had they not joined the BDG programme (Y_i^0)

$$\Delta Y = \frac{1}{N_1}\sum_i \Delta Y_i \qquad (1)$$

Where $\Delta Y_i = Y_i^1 - Y_i^0$

Y_i^1 and Y_i^0 as already defined, represents the income of the farmer *i* if he or she is in a BDG group (D =1) and if not in the BDG group (D = 0) respectively while N_1 is the number of farmers in the BDG group under consideration. However, Y_i^0 cannot be observed directly from the data for the farmers in the BDG programme (Counterfactual outcome). To estimate the average treatment effect of membership of the BDG group, the unobservable counterfactual outcome will have to be replaced by a proxy that can be measured. This can be achieved by any of two ways available in the literature. The first is to explore the situation of the farmers before and after they join the BDG programme and the other is to identify a control group consisting of farmers who are not members of the BDG programme based on the crucial “parallel trend assumption”. However, given that the farm business entity might be subjected to changes in the policy environment or could improve productivity over the observation period, the before-and-after identifying assumption in itself might result in biased impact estimates (Adenuga et al., 2021; Buscha, Maurel, Page, & Speckesser, 2012; Udagawa, Hodge, & Reader, 2014). On the other hand, the farmers who are members of the BDG programme and those that are not members are likely to differ in their characteristics which might influence their farm economic performance. As a result, the mean of the outcome variable of non-members of BDG programme is not sufficient to identify the counterfactual. This fundamental evaluation problem can be minimized through the application of the “conditional difference-in-differences” methodology employed in this study assuming that the parallel trend assumption holds. Although there are no specific way to determine if the assumption is true, its plausibility can be visually assessed by plotting the income trajectories of the treatment and control group for the pre-treatment period (Gebel & Voßemer, 2014). However, in the absence of pre-treatment data, recent studies have employed the “conditional difference-in-differences” methodology in order to make the parallel trend assumption more plausible by combining matching approaches with difference-in-differences (DiD) analytical technique (Adenuga et al., 2021; Gebel & Voßemer, 2014; Iacus et al., 2012). The conditional difference-in-differences approach allows for the balancing of the treatment and control groups with respect to the observed characteristics

2.2 Conditional Difference-in-Differences Coarsened Exact Matching Approach

The “conditional difference-in-differences” methodology combines a matching approach with DiD analysis to obtain credible estimate of the causal effect of BDG membership on farmers’ income. The approach is attractive because it is able to control for time-invariant unobserved heterogeneities and at the same time reduce selection bias that arise with simple comparisons (Bertoni, Curzi, Aletti, & Olper, 2020; Heckman et al., 1997; Pufahl & Weiss, 2009; Smith & Todd, 2005; Udagawa et al., 2014). Previous study has shown that heterogeneities in the distribution of covariates between groups can lead to a bias in estimating the treatment effect (Rubin, 1974). Selection bias is alleviated when a treatment unit is matched individually with control units that are as similar as possible in observable characteristics that are critical to programme participation and to the subsequent outcome. The DiD approach estimates the treatment effect by the change in outcome variable between the members and non-members of the BDG programme based on the matched datasets (Dehejia & Wahba, 2002; Heckman et al., 1997; Imbens & Wooldridge, 2009; Smith & Todd, 2005). Smith and Todd (2005) in their study found the conditional DiD methodology to perform much better than cross-sectional methods in cases where participants and non-participants are drawn from different samples.

Suppose subscript *t* represents the time of enrolment into the programme while subscript *k* denotes the time period after the programme starts with $k \geq 0$ and farm *j* belongs to the control (i.e. non-members of the BDG programme) group, while X is the set of observable characteristics on which the members and non-members of the BDG groups are matched. The conditional DiD estimator can be defined as presented in equation 2. The treatment indicator in the DiD setting requires absence of any intervention in the baseline for either group (Villa, 2016).

$$\Delta Y = \left(Y_{i,t+k}^{1} - Y_{i,t-1}^{0} \mid D = 1, X\right) - \left(Y_{j,t+k}^{0} - Y_{j,t-1}^{0} \mid D = 0, X\right) \quad (2)$$

Where $Y_{i,t+k}^{1}$ is the outcome (farm gross margin) for a farmer after joining the BDG and $Y_{i,t-1}^{0}$ is the outcome before joining the BDG while $Y_{j,t+k}^{0}$ and $Y_{j,t-1}^{0}$ represents the outcome for the control group after and before joining the BDG programme respectively. In our model our base year (*t-1*) is 2015. This is the year preceding the setting up of the BDG groups in 2016 (t) and our evaluation period is three years after farmers have joined the BDG groups (*t+3*). A positive (negative) ΔY indicates an increase (decrease) in farm gross margin for the treated farms (BDG members) in comparison with the control farms (non-BDG members).

2.3. Matching Procedure

Matching is a nonparametric method of controlling for some of or all the confounding factors of pretreatment control variables in observational data (Blackwell, Iacus, King, & Porro, 2020).The aim is to reduce the observable differences, or, the imbalance between the two groups as much as possible in the absence of random assignment such that the empirical distributions of the covariates (X) in the groups are more similar (Blackwell et al., 2020; Iacus et al., 2019; Stuart et al., 2014).

In this study, we employed the Coarsened Exact Matching (CEM) approach combined with a DiD estimator. The CEM is in a class of matching methods called Monotonic Imbalance Bounding (MIB)(Blackwell et al., 2020). It involves pre-processing data by coarsening variables, implementing one-to-one exact matching, and reducing multivariate imbalance measures (Blackwell, Iacus, King, & Porro, 2009; Blackwell et al., 2020; Iacus et al., 2012, 2019). The CEM compared to other matching approaches in the estimation of causal inferences reduces the imbalances between the treated and control units *ex-ante*, rather than having to discover it *ex-post*, thus, giving room for a more precise matching of participating units with their counterfactuals and eliminating the need for a separate procedure to restrict data to common empirical support as is the case with propensity score matching (PSM) (Bertoni et al., 2020; Blackwell et al., 2020; Wardani et al., 2022). The PSM approach although widely used, requires the user to set the size of the matching solution ex ante, and then check for balance ex post which can be sometimes labourious with no guarantee of it reducing the imbalance between the treatment and control groups (Blackwell et al., 2020; Iacus et al., 2012, 2019). Furthermore, it is preferable to other matching procedures (i.e., PSM) in terms of processing more efficiently and reducing model dependence, variance and bias (Bertoni et al., 2020).

In making use of the CEM approach, a set of covariates on which matching is to be done are identified after which they are coarsened into different strata, either according to user choice, or automatically through the CEM algorithm (Iacus et al., 2012, 2019; Wardani et al., 2022). This results in the creation of a unique stratum for each observation (Bertoni et al., 2020). CEM automatically considers only data within a coarsened stratum, where treated and control units are present, while the unmatched observations are pruned. The higher the coarsening (the higher the number of strata), the lower will be the number of matches provided by the CEM, as well as the lower will be the imbalance (Bertoni et al., 2020; Iacus et al., 2012, 2019).

3.0 Data and Descriptive Statistics

The study analysis used data obtained from the CAFRE Farm Business Improvement Scheme (FBIS) – Longitudinal Study benchmarking data and the Farm Business Survey (FBS) data. While data for the members of the BDG group was obtained from the FBIS benchmarking data collected annually from the members of the BDG programme (treatment group), data for non-members was obtained from the farm business survey (FBS) data collected by the Department of Agriculture, Environment and Rural Affairs (DAERA), Statistics and Analytical Services Branch (Adenuga, Davis, Hutchinson, Patton, & Donnellan, 2020). The benchmarking and FBS data contain detailed information regarding the financial position of the farm businesses, and they are compiled using comparable accounting standards. The economic performance of the farmers in respect of their membership of the BDG groups was compared on the basis of gross margin per head. The gross margin is estimated by subtracting the total variable costs from gross farm revenue.

An overview of the farm characteristics of the dairy BDG group stratified by treatment status is presented in Table 1. The results of the analysis showed a statistically significant difference in farm characteristics between dairy farmers participating in the BDG programme and the non-participants. For example, it can be observed that farmers in the BDGs have larger land areas, larger herd size, are younger and are the more profitable farmers. The higher profitability of the dairy BDG farmers may be associated with the fact that farmers who join participatory extension programmes are more motivated to improve farm-level profitability and are therefore more likely to adopt new technologies and best farm management practices (Hennessy & Heanue, 2012). Previous studies in the literature, for example Davis et al. (2012) and (Läpple et al., 2013) also found initial differences between participants and non-participants of participatory extension programmes.

Table 1. Descriptive statistics on characteristics of the BDG and Non BDG Farmers, 2015

Variables	Unit	BDG farmers		Non BDG farmers		Mean difference
		Mean	SD	Mean	SD	
Dairy Group		N=159		N=48		
Land area	Hectares	55.1	30.7	42.8	24.3	12.2**
Age of farmer	Years	44.9	11.8	54.7	12.8	-9.8***
Size of herd	Cow numbers	120.6	66.9	85.7	50,7	34.9***
Gross margin	£/cow	646.1	206.4	490.7	194.7	155.4***
Milk yield	Litres per cow	7646.1	1323.3	6366.1	1495.3	1279.9***

Double, and triple asterisks (**, ***) indicate significance at the 5%, and 1% level, respectively.

4.0 Results and Discussion

4.1 Quality of the Matching

The quality of matching for the observations was assessed on the basis of the covariate imbalance reduction. The age of the farmer and herd size were the covariates included in the CEM for matching. Due to data limitations, we were not able to include more variables in the matching especially because of the small sample size as including more variables reduces the sample size further. Moreover, only those farmers who were in the BDG over the three year period (2016 to 2019) were included in our analyses. The results of the level of covariates inbalance L1, pre- and post-match of the sample are presented in Table 2. The first column, labelled L1, reports the L1 measure, which is computed separately for both covariates (which of course does not include interactions). The second column in the table of unidimensional measures, labelled "mean difference", reports the difference in means. Total matched sample among the treatment was 146 with 13 observations dropped and the total matched sample among controls was 42 with 6 observations dropped. The L1 statistic varies from 0 to 1 and represents a comprehensive measure of global imbalance (Iacus et al., 2012). Perfect global balance is indicated by L1 = 0, and larger values indicate larger imbalance between the groups, with a maximum of L1 = 1, which indicates a complete separation. It is based on the L1 difference between the multidimensional histogram of all pretreatment covariates in the treated group and the same in the control group. The results show a reduction in multivariate and univariate inmbalances for each of the covariates included in our analysis. Specifically, the matching shows that the overall multivariate imbalance reduces from 0.425 before matching to 0.371 after coarsened exact matching with decrease in univariate imbalance also observed for the individual covariates.

Table 2. CEM weighted balance report before and after matching

Matching variable	Before matching		After matching	
	L1	Mean difference	L1	Mean difference
Age	0.286	-9.848	0.191	-2.414
Herd size	0.224	34.96	0.076	4.28
Overall	**0.425**		**0.371**	

4.2 Impact of Membership of BDG Programme on Farm Gross Margin

The results of the analysis using the conditional difference-in-differences approach to examine the impact of membership of the BDG groups on gross margin performance shows that membership of the dairy BDG group has a positive and statistically significant (significant at 10%; standard error = 64.399 and t-value of 1.81) impact on farm gross margin performance. The results showed that farmers who are members of the dairy BDG group increased their gross margin per cow by £116.6 compared to dairy farmers that are not members of the BDG programme. This result is similar to that obtained by Läpple et al. (2013) in which they found a positive and statistically significant impact of membership of dairy discussion groups on farm gross margins in Ireland. It may be concluded that participation in the BDG programme exposes the farmers to a wide variety of information and, thus, enhances farm operations, which helps raise financial performance. Our study result also supports findings from similar research by Cawley et al. (2018) and Davis et al. (2012) conducted on the impact of participatory extension programmes on farm income, indicating that membership of participatory extension groups has a significant effect on members' farm profitability. Given the current climate in which farmers are faced with a rapidly changing environment, education and training in the form of participatory extension programme has the potential to help them understand how and what information to acquire; to make better use of information, and to become innovators and early adopters of new technologies. This will consequently lead to an increase in farm income.

5.0 Conclusion

In this study, we analysed the impact of membership of the dairy BDG on farm income in Northern Ireland by employing the conditional difference-in-differences coarsened exact matching approach. This study provides a unique application of the conditional difference-indifferences analytical technique and also contributes to the literature on the impact of participatory extension programmes on farm income. Our use of CEM reduces model dependence and ensure that the study findings represent an empirical picture of the data. The study result has practical implications for the design of participatory extension programmes as it provides robust evidence to inform policy development around the area of participatory extension programmes. It also supports the design of efficient agricultural education and extension systems that incorporates the ideas of the farmers themselves through peer-to-peer learning thereby maximising the economic and social benefits accruable from such programmes.

In the interpretation of the study results, however, it should be noted that the conditional DiD methodology employed in this study is implemented on the assumption that the model contains the 'appropriate' (observable) covariates that may influence the programme effect before and after matching. However, unobservable covariates may result in different trends between the treatment and control groups, which could bias the results obtained. Also, the use of the DID approach assumes there is a common trend for the two groups before the introduction of the BDG programme. . It is assumed in this study that there are no interference (spill overs) between members and non-members of the BDGs such that each farmer's treatment status has no effect on the potential outcomes of other farmers and that treatment is homogeneous across the BDG groups (Stable Unit Treatment Value Assumption (or SUTVA). It is important to point out that this is an ongoing programme and further analysis on the impact of the scheme as well as participants views on the challenges and how to improve the BDG programme will still be conducted at the end of the programme.

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