'Farms like Mine': A Novel Method in Peer Matching for Agricultural Benchmarking

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Paper prepared for Computers and Electronics in Agriculture

15 July 2019

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Mark Reader would like to thank colleagues from the DEFRA Farm Business Survey and DEFRA Sustainable Intensification Platform, particularly Gavin Huggett from the University of Exeter. Thanks are also due to Rural Business Research; Michael Simmons and Dr Mark Hayes of the Big Data Strategic Research Initiative, University of Cambridge; the StatsLab in the Centre for Mathematical Sciences, University of Cambridge; Rachel J. Lawrence (farmer and former RBU research officer); Dr Belinda Clarke (AgriTech-East); Dr Cesar Revoredo (SRUC); and Dr Liang Wang (Computer Laboratory, University of Cambridge).

Highlights

- In benchmarking, comparing to 'average farms' (or to 'average firms') in high level categories (for example the 'Cereals' farm type) includes many farms with unrelated enterprises.
- This will bias and distort key-performance-indicators, for which benchmarking comparisons are desired.
- So we propose a novel method, which matches (Z-score) on dimensions used to categorise farms.
- And then, calculates results for a 'bespoke farm group' - a uniquely defined comparator group - after the farmer has entered their details.
- This method has potential to be applied across the full range of farm types in the (UK/EU) Farm Business Survey and in a wider range of benchmarking contexts.

Abstract

To find opportunities to improve performance, comparisons between farms are often made using aggregates of standard typologies. Being aggregates, farm types in these typologies contain significant numbers of atypical enterprises and thus average figures do not reflect the farming situations of individual farmers wishing to compare their performance with farms of a 'similar' type. We present a novel method that matches a specific farm against all farms in a survey (drawing upon the Farm Business Survey sample) and then selects the nearest 'bespoke farm group' of matches based on distance (Z-score). We do this across 34 dimensions that capture a wide range of English farm characteristics, including tenure and geographic proximity. Means and other statistics are calculated specifically for that bespoke farm comparator group, or 'peer set'. This generates a uniquely defined comparator for each individual farm that could substantially improve key-performance-indicators, such as unit costs of production, which can be used for benchmarking purposes. This methodology has potential to be applied across the full range of FBS farm types and in a wider range of benchmarking contexts.

Keywords Benchmarking, Survey & administrative datasets, Farm typologies, Peers, Performance

JEL code Micro Analysis of Farm Firms, Farm Households, and Farm Input Markets Q120

INTRODUCTION

Individual farmers face considerable problems when attempting to compare their individual performance with the performance of other farms: every farm is different, with a number of different enterprises, generating a variety of different income streams. However, it is clearly helpful for individual farmers to be able to have some standard against which to judge their performance, in order to identify areas in which they may be underperforming, and thus which aspects of the business could be improved. Benchmarking is an increasingly popular approach in efforts to enable farmers to increase their incomes and levels of productivity (e.g. Camp 1989, Jack 2009, Vitale et al. 2019, Wilson et al. 2005) or to reduce their ecological footprint (e.g. de Olde et al. 2016, de Snoo 2006, Halberg et al. 2005, Mu et al. 2017, Lynch et al. 2018). Currently, farms are usually categorised and compared using typologies that require a minimum level of a particular type of farming (an 'enterprise' such as dairy, or combinations of similar enterprises such as cereal crops). For example, in the European FADN/RICA classification (European Commission 2013), 'Specialist COP' (cereals-oilseeds-pulses, also called 'Cereals Farms' in Britain) are farms that have above a minimum level of cereals, oilseeds and protein crops as measured by 'Standard Output' i.e. the financial share of the different enterprises on the farm. However, the remaining outputs may be very different: two Cereals Farms may meet the threshold to be labelled 'Cereals', but have different enterprises as their remaining output. The result is that each farm type contains significant quantities of 'atypical' enterprises. This is a problem when benchmarking as comparisons are normally made using averages (typically the mean) – atypical enterprises will appear as relatively small amounts (e.g. land area) that are not representative of either the overall sample or the small number of farms that have these atypical enterprises. For example, there were 30 cattle and 69 sheep on the 2017 mean 'General Cropping' farm in England[1]: this will be atypical for most farms of this type, as they will have no livestock, whereas a few may have substantial numbers of animals. The General Cropping farm classification most closely approximates to what is termed a 'mixed farm' i.e. a farm type with a relatively large number of enterprises. However, there is also a tendency to assume that a farm is mixed where there are small numbers within a particular enterprise (to take an extreme example, a farm with cereal crops and a single sheep is not a 'mixed' farm). Many farmers may not even know the type under which their farm falls, or are close to the cut-off point between thresholds for farm types and thus fall within two possible farm type categories.

From the above discussion, it is our contention that comparator groups based on standard typologies are flawed. An improvement would be to have alternative comparator groups that make better use of information contained within available datasets to match farms with similar characteristics. To do this we introduce the innovation of matching to 'farms like mine', where matching is primarily on land use areas and livestock numbers contained in farm survey datasets. We thus demonstrate a novel method for the identification of benchmark performance indicators that can provide more relevant and useful standards for farm management decision-making.

[1] www.farmbusinesssurvey.co.uk/regional/Reports-on-Farming-in-the-Regions-of-England.asp

METHODOLOGY

In the UK, the Farm Business Survey (FBS) has ten 'robust' farm types, where type is determined by an enterprise or combination of enterprises that exceed a threshold of two thirds of total farm output. Outputs are standardised to reflect a 'normal farm in average conditions' (Defra 2018). For example, Dairy Farms are 'holdings on which dairy cows account for more than two thirds of their total Standard Output (SO)'; Cereal Farms are 'holdings on which cereals and combinable crops […] account for more than two thirds of the total SO'. A 'General Cropping' or 'Mixed Farm' is effectively a farm that does not fit into any of the other FBS categories, as no single or defined combination of enterprises meets the two thirds threshold (Defra *ibid*).

As noted in the introduction, the problem for an individual farm manager is that these farm types will probably have different characteristics to his/her farm. To address this problem we use a methodology that is normally used for clustering with smaller number of dimensions (Piegorsch 2015). The method matches farms to all farms in the comparator group (the survey sample) and then selects the nearest neighbours (on Z-score), in 34 dimensions for England. The matching procedure includes almost all characteristic enterprises for farms in England, including tenure (e.g. rented or owner-occupied) and geographic proximity. Means and other statistics are then calculated immediately following the user entering their own farm business data, which then generates the bespoke 'peer set', along with the average data for that peer set[2] - to which the user can then compare their own performance. Peer sets are a minimum of 25 farms in our case (as we have a large sample), or more if the total summed distance is less than one Z-score across the 34 dimensions (in English farming). Euclidean, Mahalanobis, and other distance metrics (including Manhattan Block) (Piegorsch 2015) were also tested in the methodological development stage. The Euclidean method was deemed the optimal, as described below.

Euclidean distances are:

$$d_i = \mathrm{SQRT}(\mathrm{SUM}(\mathbf{X}_{ij}-x_j)^2)$$

$$x_j = (\mathrm{MyFarm}_j-\mathrm{SampleMean}_j)/\mathrm{SampleSD}_j$$

$$\mathbf{X}_{ij} = (\mathbf{Y}_{ij} - \mathrm{SampleMean}_j)/\mathrm{SampleSD}_j$$

Where d_i is a vector of 1-to-n sums of normalised distances, away from each farm in the sample of n farms. $\mathbf{X}_{ij}$ is a matrix of j standardised variables (the 34 dimensions chosen for England) by i, the 1-to-n, farms (the sample n). x_j is a vector of the j standardised variables for 'my farm' (x); $\mathbf{Y}_{ij}$ is the matrix of un-standardised 1-to-n sample, i, values (for each j variables). SD is standard deviation. The peer set is then chosen by selecting 25 farms that have the smallest Euclidean distance or are within one Z-score (across the 34 dimensions for England).

[2] www.benchmarkmyfarm.co.uk

RESULTS:

The 'farms like mine' methodology outlined above generates a bespoke peer comparator data set; hence, results from the approach are specific to the individual farm business data that users enter into the system. The FBS provides a wide range of candidate variables that can be used to generate the bespoke peer set of comparator data. To test the approach, for England we chose 34 dimensions as shown in Table 1.

Table 1. Variables chosen for peer-matching of farms in England

Land Use (hectares):	***Livestock (average head over year):***
winter wheat area	*other male cattle 1 to 2years*
winter barley area	*other female cattle 1 to 2years*
spring barley area	*other male cattle over2years*
other cereals area	*heifers*
oilseeds area	*dairy cows*
peas beans area	*beef cows*
potatoes area	*ewes*
sugar beet area	*other sheep*
other arable crops area	
fodder crops area	*breeding sows**
fallow area	*store pigs**
uncropped area	*broilers**
temporary grass area	*laying flock**
permanent grass area	*growing pullets**
sole rough grazing principle area	
top fruit area	
outdoor vegetable area	
Other characteristic variables:	*organic area fully* (ha)*
	Easting (metres, OGS grid)†
	Northing (metres, OGS grid)†
	Tenanted area (percentage)

In Table 1, note that * represents double weighting (of the Z-score) within the Euclidean-based optimisation approach, while † refers to weighting at 0.6. These alternative weightings were adopted following extensive testing of the approach in order to appropriately capture and represent enterprises that occur less frequently within the test dataset for England. The corollary to this is the lower weighting attributed to geographical dimensions. Farms that are geographically far away will be matched very closely on all other dimensions and farms that are in close proximity may diverge more in other dimensions. However, note that the closest matches will be chosen in all cases, ensuring that, where farms match on both enterprise mix and close geographical proximity, these will always be chosen with the bespoke peer set in preference to farms with close enterprise mix matches, that are geographically far from the individual farm business (as entered by the user of the system). The simplest distance metric (namely Euclidean), on Z-scores (of farms with the enterprise only), was found to be superior to others, in terms of closer peer sets (by inspection).

As an example, in the putative farm in Table 2 (below), the coefficient of variation (SD/MEAN), of farm income per farm, was reduced by 27% points (or 1/6) for the FBS2016 peer match set (n=28, <1 Z-score away) compared to the CEREALS farm type sample (n=353)

Table 2. Putative Suffolk, upland, arable farm (as matched for calculation of Farm Income)

Winter wheat area (ha)	70
Winter barley area	20
Oilseeds area	30
Temporary grass area	2
Permanent grass area	4
Uncropped area	5
TENANTED_PCT (%)	45
EASTING (m)	565000
NORTHING (m)	215000

{ - all other variables match on 0 - }

DISCUSSION AND CONCLUSIONS:

This paper has demonstrated a new approach to benchmarking. While this has been applied to farms, there is no reason in principle why it should not be applied in benchmarking in other sectors (e.g. Camp 1989, ten Raa 2009), from survey or administrative datasets.

However, the need for benchmarking in agriculture is clear for a range of reasons. The rate of productivity increase in the UK is low (Baráth and Fertő 2017). Allowing for uncontrollable farm diversity due to environmental factors - such as altitude, soil type and weather - it is clear from the FBS that performance varies considerably between similar farms. Political developments such as Brexit (Ward 2019) and a potentially more stringent financial environment gives an added urgency to the need to increase farm productivity and incomes, through techniques such as Benchmarking.

'Farms like mine' i.e. matched to closest-peers gives a better framework for comparison precisely because the peer set is closer - in scale and mix of enterprises, tenure, proximity and so forth - to 'my farm' than to the broader industry aggregate farm types. It will also be perceived as closer by farm managers and thus will make benchmarking more attractive as a management technique. Key-performance indicators such as cost per litre of milk or per tonne of wheat become more meaningful because the comparison is made to a more relevant set than is the case for comparisons with standard farm type groupings.

These improvements are reflected in the reduced dispersion and systematic bias in benchmarking values, e.g. in the reduction in variability of the Farm Income indicator above.

Matching leads to groupings that feature farms that do not include features found in the aggregate farm type categories: from other regions (which differ in climate, soils and markets); from other sizes and scales of operation; and, as we know, from the presence of atypical enterprises. The improved matching is also likely to manifest itself in management effects: 'farms like mine' are more likely to have more in common from a management-decision-making perspective.

In the case of General Cropping farms in particular, average figures, from farms with a large range of enterprises, will compromise the usefulness of benchmark comparisons with farmers' own farms. By contrast, with 'farms like mine', these peer sets of more similar farms (as outlined using the approach described here) provide more relevant comparisons.

Options for future development would be: i) selection of different variables for matching, ii) doing more to understand farmers' objectives, and developing matching around those objectives (be they climate, ecosystem, farm-income, or economic - e.g. Total Factor Productivity), iii) systematic analysis of the weighting criteria for the different variables; iv) more extensive and systematic testing of comparisons (for dispersion, bias, and presence/absence of extraneous enterprises) from 'peer-sets' against 'industry-aggregates'; and v) finding new technologies or enterprises that might be added in particular circumstances - and then extending matching to encompass these alongside or instead of the 34 dimensions we use for England.

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COMPETING INTERESTS

Declarations of interest: none.