Technology gaps and leaps in the sustainable development of English cereal and general cropping farms

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Abstract

Identifying and assessing technology gaps and technology leaps observed in the agricultural productivity change analysis is of paramount importance since it enables the identification of a set of effects that influence the way that inputs are transformed into outputs and resources are allocated between diversified farm activities. Previous studies have ignored the importance of heterogeneity between different farming systems and their characteristics and have also failed to account for the different rates of technology absorption with respect to an unrestricted universal production frontier considering simultaneous generation of main products and by-products. Furthermore, the technology leaps defined as varying rates of technology absorption over time with respect to the unrestricted universal production frontier may lead to miss-specified local production functions and biased efficiency and productivity change estimates. The analysis focused on the regional variation of the production environment, farm specialisation and level of engagement as constraints to productivity gains. By considering two different levels of endogenous and exogenous heterogeneity in the production environment, the analysis used data from the Farm Business Survey of English arable farms for the years 2005-2013 and employed the parametric stochastic meta-frontier analysis to measure sustainable productivity change as producers engage into agricultural and diversified activities as alternative sources of income. The model approaches simultaneous value-adding generation processes to reveal the relationship between change in producers' endowments and productivity gains in a network application under uncertainty.

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Keywords: technology gaps, technology leaps, meta-frontier analysis, productivity change

1 Introduction

Sustainable intensification prevailing the agricultural policy agenda has grown over concerns on how change is reinforced and realised in terms of rural development. The agrarian transition involves the optimisation of farm management practices, balancing consumer preferences, identifying sectoral heterogeneity and finally optimising the utilisation of inputs (Garnett et al. 2013). This in a broader sense refers to improving the allocation of resources with minimum impact to the environmental and social output which may be considered as by-products of agricultural production. While productivity analysis has been proven to be very effective in identifying proxy factors as sources of "observed inefficiency", its theoretical grounds shared with production theory reveal a refracted perspective on the actual goals of sustainable intensification (Loos et al. 2014). Sustainable intensification components may well provide scenarios of sectoral sensitivity in maximising sustainable outputs with references to utility theory and welfare models. However, risk and uncertainty will remain the main conditions under which producers make decisions on their expected agricultural output and the use of inputs. Under this perspective, producers' benefit from sustainable intensification would be latent effects on production due to gains in biodiversity and appropriate use of potentially detrimental inputs. An outcome oriented approach to efficiency that dominates the literature of environmental performance indicators but raises doubts on its policy reforming power (Mahon et al. 2017). The environmental economics literature contributed by considering focusing on farming systems instead, separating the effects inclusively for different levels of analysis and introducing investment behaviour and risk profiles to analyse change (Janssen and van Ittersum 2007). None the less, sustainability goals still manifest reforms that target regional deficiencies thus resulting in a complex remit of contradicting and counterbalancing regulation and deregulation under monetary incentives (Evans, Morris, and Winter 2002). The conceptual revision of Sustainable Intensification is recognised as a requirement to ensure it purpose has been fulfilled (Cook, Silici, and Adolph 2015).

Agricultural policy in the UK has been based on the concepts of food security and development through expansion. Sustainable development has long extended the applicability of the concept of "prosperity through growth" in all sectors to ensure conformity between human interaction, farming activities and the environment (Kirwan and Maye 2013). Insufficiently, though, it requires restructuring that will allow the sector to advance beyond the scope of a goal-driven or counterbalancing proactivity over the challenges. Instead it would require producers to realise their farm specific competencies, reorient on their intrinsic and regional heterogeneity and maximise the potential benefit from their farming activities. Increasing demand has been urging the change of farm holdings to more productive formations, while policy changes attempt to ease transition by augmenting returns towards the farm (Bailey, Lang, and Schoen 2016). More specifically, modern utilitarian ethics have narrowed the field of economic assessment and benchmarking to the concept of quantifying productivity and identifying its drivers (Tilman et al. 2011).

By introducing the notions of efficiency and sustainability as restrictive iterations to agrarian change, we observe production analyses focusing on weak and strong sustainable performance, positive and negative outputs, where adaptation is motivated by concerns to avoid damage (Costanza et al. 2016). Even when sectoral heterogeneity or inequality has been realised, a growth driven productivist and post-productivist approach to sustainable development has been preponderantly mandating agricultural policy reforms (Wilson, Harper, and Darling 2013). Benchmarking and marginalising lapses, regional and qualitative assessment have been introduced based to redirect growth diffusion perceived as betterment for the communities (Barnes et al. 2010). In terms of sustainability focus is around the ecosystem "loss" such as the degradation of natural resources in air, soil, water quality, the effects of climate change, the resilience of crops to pests and diseases and the market oriented increase in demand for more and of higher quality agricultural produce. Without rejecting the concept of sustainable intensification considered by policy-makers and reformers, a revision may be introduced to relocate the dynamic processes that define an agricultural system and its deficiencies, providing complement approach to benchmarking. Based on the visions, in the UK agriculture has evolved into a sector of the economy where improvement is marginal, the needs are global and the challenges are local. Sustainable intensification calls for a holistic view of optimising production based on market conditions and risk management that would align all stakeholders to minimum waste or loss in a coordinated manner (Kirwan and Maye 2013).

This analysis is based on the intuition that social and environmental output cannot enter the decisional path of farmers as outputs, but instead as observed by-products of production (Ahmadi et al. 2015). Furthermore, uncertainty and risk define specific decisional patterns based on which the expected output is conceived and they define how resources such as agricultural land, production practices and labour are allocated a priori (Monjardino et al. 2015). Production defines the process of transforming inputs into outputs and their accompanying by-products which under the influence of inefficiency drivers receive achieve relative suboptimal returns. The main interest, however, is to approach and visualise the heterogeneity present in a sample of English arable farms that limits their attainable levels of performance. Sustainable intensification in the current context would require the disentanglement of agricultural policy from efficiency performance and its re-orientation towards stabilising technological progress (expansion of the universal frontier) by controlling or compensating for the true factors of uncertainty and risk that limit the technological capacity of producers. The contribution of this analysis is two-folded. It is updating contemporary literature on the productivity of

English arable farms. Also, it provides an insight to systematic differences due to heterogeneity by controlling for their variability at the farm level which would be necessary for a targeted future agricultural policy.

2 Theoretical Framework

2.1 Sustainable Intensification as policy direction and productivity change in British arable farms

Sustainability assessment frameworks approximate sustainable performance through stages at farm-level operations moving from an unsustainable state, to shallow sustainability and eventually to deep improvement (Bell and Morse 2008). Substantially these approaches describe the gradual transition of agricultural farms from initial stages of profit-oriented production towards a more efficient operation. Moreover, the consideration of environmental security factors that are closely related to the availability of resources and the improved management in the long-run, is contributing to a process of learning by experience (S. B. Hill and MacRae 1996). Although these 'stages of sustainability' describe the actual management strategies and the performance of agricultural farms in terms of intervention, it is inevitable to supress the introduction of sustainable trade-offs between stakeholders. As commented by Rankin, Gray, and Boehlje (2011), improvement through stages indicated that strong managerial decisions have greater effect than exogenous factors such as competition or government regulations on the farm business. This are the farm business specific marginal gains for the conversion of agricultural farms to more sustainable farming businesses. The frequent practice of noting trade-offs and compensatory schemes for production must be treated cautiously as, spill over effects are present and can be disguised as inefficiency. Understanding the internal output, by-products and abatement technologies related mechanisms, provides more accurate estimation. To consider all aspects of sustainable farming we must assume that sustainable farms are operating stochastically independently and there are no conflicts in resource inputs. Analysis must be defined in a continuum of level (time and space scale) for latent effects unique to every production period, and the accumulated effect of prior performance (learning-by-doing or underperformance) to be revealed. Agricultural production intensification follows a pathway that poses risks of ineffectiveness and inefficiency (Garnett et al. 2013). The main core of Sustainable Intensification (SI) incorporates the increase or maintenance of agricultural yields while reducing the negative environmental impacts (Ahmadi et al. 2015) (Chaplin-Kramer et al. 2015). This form of intensification takes place under terms of undiscriminating policies that may restrict or favour specific farm types over others (Garnett et al. 2013). Thus, farm sustainability is defined as the optimal response to the system of production functions, given the future expectations and based on previous measurable experiences (Janssen and van Ittersum 2007).

Attempts to observe patterns of agricultural productivity in the UK, recognise regions and farm types as a main parameter of discrepancy in their performance over time. As a sector-wide analysis, performance is varying between farm types both in absolute terms as well as their rate of change in technology absorption (Hadley 2006). This is the result of some specific well-performers that raise the bar towards more efficient production. Based on the results reported by Hadley (2006) this improvement over time was observed in arable production between cereal and general cropping farms with the later ones presenting a better rate. However, the gap between average efficiency and productivity change suggests that there are factors preventing a balanced change within each farm type, making narrowing down the scope of productivity analysis necessary. Productivity and technical efficiency change contextualise performance to the level of success in adjusting production size and matching resource requirements to maximise output and minimise waste. In highly intensified and regulated farming systems such as in the UK (Barnes and Revoredo-Giha 2011), optimising size of operations and restructuring provided improved productivity and economic efficiency gains (Firbank et al. 2013). This required shifting main production to arable cropping instead of livestock and dairy (for mixed farms). Also, it revealed significant differences in changes of their returns, by-products and contribution to biodiversity per hectare utilised for each type of production. Sustainability at its core environmental component, presents observed a priori trade-offs meaning that intensification came at a cost. With respect to the drivers of technical efficiency change in the UK Barnes et al. (2010) considered size, income, subsidies and contracting (farm characteristics), tenanted land, age and education of the farmer and policy indicators as shifters of technological progress. Furthermore, specific farm management practices were included in the efficiency driving part i.e. farm specialisation, debt gearing, subsidies over gross margins ratio, paid over unpaid labour. For the period 1989-2008 apart from the regional differences[1], specialisation and gearing, the other attributes were significant drivers of efficiency change in arable farms.

This analysis extends current literature by reorienting focus on the inherent performance variability of producers. Furthermore, it considers an inextricable factor that dictates farmer's investment endowments; the income of the farmers. This corresponds to the Total Income from Farming or Farming Income (imputed unpaid labour to family members) (Berkeley Hill 2012) which is considered to be linked to agricultural policy both in terms of supporting rural employment and development but also in improving the welfare of rural communities and ensuring supply of agricultural produce. Also, consideration of the off-farm income dependency is added to existing literature as a factor influencing productivity lags. By treating farmers' decisional variability as defining factor of heterogeneity, we are partially exposing those that are more vulnerable to shifts in productivity and we conclude on the degree farmers' objective gains are well represented in their performance in terms of economic efficiency (profitability). Furthermore, we may provide if group-specific gaps and technical economic efficiency gains are attributed to lower or higher income returns to the farmer rather than regional differences.

2.2 Farmer's endowments and resource use under Sustainable Intensification

Although significant as a resource in the planning phase, land productivity in the UK is presented as stagnant over time (Rounsevell et al. 2003). This is contrasting the performance of labour as a resource as production intensification provides the advantages of economies of scale, farm size and progressive technology advancements to substitute for manual labour (Horrocks et al. 2014). The inelastic returns of land may be assumed to be deteriorating due to the systematic effects of production intensification and the aggregation of detrimental input effects (soil quality and fertility). With respect to these remarks, change in the productivity of such resources can be either an outcome of technology absorption or technology change or lagged by-product effects. Resources such as land and labour present a qualitative link to ecosystem services and social output through their use both as resources and technological factors that accumulate inefficiency if wasted. Also, they act as linkage between the economic objectives (income security) of the farmer and their management practices (Peh et al. 2014). They served as the medium of policy intervention through the distribution of subsidies, set-aside regulations, cropping practices or agri-environmental scheme requirements (Walker et al. 2007) (Merckx et al. 2009) (Angus et al. 2009). They remain into focus as future policies target sustainable rural development. According to Westbury et al. (2011) arable farms present improved environmental performance compared to other types of farms which is likely more related to the use of land and subject to weather conditions and soil quality. The findings suggest that farmers' decisions such as intensity and proper use are responsible for their environmental performance with respect to the production environment, which is only partially influenced by the regional characteristics. Policies such as agri-environmental schemes need to be specific on the conditions which farmers are exposed to and in context to their management practices such as intensity of production (Mauchline et al. 2012). A more in-depth analysis of the differences in the use of land with respect to farming behaviour as a response to the production environment in England is provided by Rounsevell et al. (2003). As reported, the patterns of risk aversion and profit maximising behaviour are being spatially projected through the allocation of land between farming activities. As discussed, their results present spatial distribution of land use patterns between "neighbours" which is however subject to their attitude towards risk and

[1] England & Wales, Scotland, and Northern Ireland

future returns of their investment even if market effects such as price variation and competition are eliminated. Risk aversion is expressed throughout the crop and therefore land planning period (Townsend, Ramsden, and Wilson 2016). For the years under analysis the available rural payments that related to the use of land and ecosystem services were aiming at enhancing uncropped area quality and mitigate use of detrimental inputs (Holland et al. 2015). However, any intervention that aims to enhance sustainable performance through increases in the environmental output, should provide sufficient gains that would compensate for the change in productivity (Horrocks et al. 2014). The trade-offs between a sustainable output and a productivity oriented strategy cannot be approximated effectively, however, the process under which these netputs are realised over time can be optimised through their joint assessment.

In terms of policy, removing direct payments to farmers that well served as a supplement to income support and redirecting resources evenly to balance the distribution of rural income and environmentally sustainable rural development has dominated case scenarios. In the UK due to the intensity and spatial distribution of farm types, land availability is not expected to dramatically change the use of resources or such an effect would be marginal (Renwick et al. 2013). The effectiveness of distributed support schemes as a medium to retain the relatively more productive and profitable producers in the market is subject to factors such as demographic characteristics, management practices and farm's resilience or exposure (Posthumus et al. 2015). These, as mentioned already, require a holistic approach to the assessment of the choices taken at the farm-level, while the policy interventions may marginally influence productivity and profitability change (through gain or loss) and its sustained improvement. Structural changes that would provide a productivity boost universally are less likely to exist in highly intensified and less support dependent farming systems. As discussed by Renwick et al. (2013) the aims of policy intervention e.g. greening of the farming activity, should be clearly formatted and applied to producers that face analogous production environment and express similar attitudes towards their economic, environmental and social output. On those terms, effective policy intervention requires a deeper understanding of the response process to structural changes in the sector that varies significantly even within regions. Here we consider an indirect approach to producers' behaviour, risk and investment by positioning every farmer in the sample in a constrained technological frontier based on the similarity of their investment endowments and use of inputs and resources. The producers are allocated based on the levels of time variability. The dissimilarity feature in the production behaviour as a mixture of environment characteristics, investment choices and performance is captured in synthetic factors of uncertainty.

3 Analytical framework

3.1 Technology gaps and leaps in productivity analysis – The concept of Meta-frontier analysis

Efficiency benchmarking assumes deviation from the expected outcome is a result of heterogeneity between the peers and the inefficiency drivers. To obtain consistent estimates of the efficiency and therefore an unbiased measurement of productivity change it is important to identify the factors that influence a systematic lagged adoption of technology (Bravo-Ureta 2014). The outcome of any systematically applied effects is referred to as a technology gap that reveals significant variation or no variation over time. In agriculture, these are commonly considered as attributes of the production environment such as of climate, landscape and soil quality zones usually captured by regional classification of producers and are econometrically treated as a form of cross-sectional dependence analysed in a spatial context for spill over effects (Bai, Econometrica, and Jul 2009) (Chou, Chuang, and Shao 2014). Battese, Prasada Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) consider a deterministic meta-frontier approach employing mathematical programming to create the group-frontiers. While, Huang, Huang, and Liu (2014) suggest a two-step parametric approach that provides statistical inference and improved identification of sources of variation between groups yielding improved estimates of technical efficiency. Kounetas, Mourtos, & Tsekouras, (2009) discuss the matter of false-heterogeneity of the technology gaps because of input scale rather than actual technological differences between the groups.

Other attempts to capture the time scope distortion caused by its presence include dynamic or stochastic multivariate analyses that proxy unobserved unobservable common factors (Hove, Touna Mama, and Tchana Tchana 2015) (Lambarraa, Stefanou, and Gil 2016). In highly intensified farming systems where technology advancement is strongly marginal, variation originating from these sources is assumed to be limited. However, these production systems are still vulnerable to decisional capabilities and management efficiency. Their production environment may be further decomposed into systematic effects of equally predictable or unpredictable objective conditions and risk or uncertainty in production. Market effects may also be treated as drivers of this form of heterogeneity-patterns with the most prevalent being proximity to population density centres, Less Favoured Areas or highly competitive markets in the sector. Production and efficiency analysis has been extended to comply with the genuine savings theory, defining between-groups technology gaps, as the producers' response to the production environment that forms a natural state of operation. The second level heterogeneity refers to variation in production intensity, specialisation or diversification of farming systems. In the presence of untreated sources of heterogeneity stochastic frontier analysis yields biased estimates of efficiency and intercept terms complicating the inferential power of the results (Castellacci and Natera 2016). As Huang, Huang, and Liu (2014) suggest, an extended two-stage parametric stochastic frontier will tackle the limitations through the addition of stochastic components to the group-frontier restricted production functions.

3.2 Multiple Factor Analysis on panel data to cluster farmers based on production variability and clustering on the factors

Little significance has been attributed to the theoretical basis of the modelling of the meta-frontier with, either defining constrained technology through a frontier analysis on pooled data, or over clusters in a supervised (response) approach that does not implement features of uncertainty or pattern recognition. In this analysis, the primer position of the producers with respect to the meta-frontier analysis will represent the production environment that separates the effects of constraints upon accessing the assumed universal technology available. This classification will use data structure to proxy the aggregate effect of economies of scale, scope, financial exposure, technological gearing and characteristics that relate to the structure of the management choices. The joint analysis of farm management practices and structure assumes that all those variables influence the performance of the farms in a multi-dimensional (multivariate) context. Therefore, we are interested in eradicating the commonalities in their global projection, extract those that are significantly distinct and thus trigger heterogeneity. Multiple Factor Analysis treats data jointly by forming factors to which active variables are contributing. This is achieved by implementing a principle component analysis and a correspondence analysis in a unified setting to maintain observation structure and project it on their factorial representation (Husson, Josse, and Pagès 2010). The second step involves hierarchical clustering which is performed in an analogous way to the Hierarchical Clustering on Principle Components (PCA). Classification of producers is performed based on their prevailing characteristics as variables are linked together into themes of interest and a specified measure of similarity (proximity).

Exploratory analysis on the data revealed significant variability between producers and the production environment with no patterns in the regional distribution. Categorical and continuous variables were extracted from the Farm Business Survey for the period 2005-2013 focusing mainly on structural characteristics (Farm type, form, tenure type, main region (GOR), income (Farm Business Income, diversified output), financial exposure (loans, Insurance costs as risk factor), technological gearing (machinery structure, repairs and equipment evaluation, contractors work, resource requirements (area farmed/UAA, Annual Work Units), External support (subsidies and agri-environmental payments), fixed costs, capital investment. Based on the literature farmers' reliance to farm business income leads to intensified production thus increasing their exposure to external shocks such as weather, production inefficiency and market fluctuations. (Alston, Martin, and Pardey 2012). Technology-intensive activities as main source of income resources are less elastic to market effects and change. Structure and higher level of mechanisation is assumed to represent a highly elastic supply unless this comes at the expense of higher levels of dependence such as leased and contract work.

The time oriented factor analysis extends the Multiple Factor Analysis for structuring censoring profiles across the time dimension. The aim is to classify producers in distinct groups that all members of each group present similar values in their characteristics across time (Lê, Josse, and Husson 2008). In other words, the time effects on observed characteristics of the production environment that had been varying in an analogous way. After grouping is completed a description based on the prevailing variables (characteristics) follows. Nine groups were created each one corresponding to a year in the panel sample (for years 2005-2013). The groups contained variables observed at one time and were standardised. This weighting process allows us to represent variability over time between individuals (dimensions) and a correlation between the variables (factor components). The contributions of each group capture the relative boost or downgrade in performance caused by observed values that resulted in an influence on the inertia of the individuals' cloud formation represented and is equal to the sum of variances of the variables of this group over total variance. By treating the data this way to perform the Multiple Factor Analysis, time trend is using cross-sectional variability to reveal dissimilarities. This creates a universal scale for measuring time variation true effects and projecting them on a reduced dimensional plane. Hierarchical clustering on factor components is used to identify groups of similar observations. As part of the exploratory analysis, an attempt was made to first treat data in a mixed processing framework. The framework is described as Multiple Factor Analysis for the analysis of continuous and categorical data were input factors are treated equally between groups (Bai and Ng 2008). Classification of producers was completed based on their prevailing characteristics with respect to the contribution of the later to the factorial dimensions previously constructed, thus the structure of the data was maintained and projected to reveal the dominating variables with respect to the year-groups defined. The software that was used for the Multiple Factor analysis and HCPC FactoMineR (Lê, Josse, and Husson 2008) and factoextra[2] for data visualizations.

3.3 Meta-frontier

For the construction of the meta-frontier and the constrained frontiers we consider the flexibility of the econometric implementation of Battese, Prasada Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) by Henningsen and Kumbhakar (2008) and Henningsen et al. (2015).We assume a universal technological frontier as described by the production possibilities set in a short run profit function. All input and output values have been deflated using the latest Agricultural Price Index provided by DEFRA [3] Farmers laying on the frontier are efficient while those that are positioned under the frontier are presenting inefficiency. The theoretical background of the parametric meta-frontier productivity analysis considers sub-groups of producers that due to factors influencing their technology absorption ability (other than inefficiency and noise) are restricted or locally constrained frontiers. In this analysis, we consider the economic efficiency of the farmers in realising the profit generating ability of a sample of English arable farms. In the short run this approximates the production function in a Cobb-Douglas specification. The analytical process approaches the technology gap ratio for each of the groups specified through the Multiple Factor Analysis. This is the discounting aggregate effect that reveals the relationship between the global technology and each of the restricted technologies. The construction and exploration of technology gap ratios allows us to identify the sources of inefficiency (farmer based or production environment based), their relative magnitude and the characteristics of lower or higher performers. Furthermore, conclusions may be raised upon the characteristics of the farmers in each group. Due to the current exploratory characterisation of the groups and their formation

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[2] Alboukadel Kassambara and Fabian Mundt (2017). factoextra: Extract and Visualize the Results of Multivariate Data Analyses. R package version 1.0.4. http://www.sthda.com/english/rpkgs/factoextra

[3] https://www.gov.uk/government/collections/agricultural-price-indices

based on the variability of their endowments and returns we may conclude stability of the technological change observed in the sample.

The estimation process for the technology gap ratios (TGR) that discounts the Technical Efficiency estimates based on their relative position and with respect to the global frontier. This theoretical approach in an econometric framework is discussed by Huang, Huang, and Liu (2014) in a two-step estimation of partial sub-frontiers and their partial meta-frontier:

$$lny_{git} = lnf_t^g(x_{git}) + v_{git} - u_{git}\ ; \qquad i = 1, 2, \ldots N_g,\ \ t = 1, 2, \ldots, T,$$

for g groups and t periods

$$\varepsilon_{git} = v_{git} - u_{git}\ ;$$

$$v_{git} \approx N\left(0,\ \sigma_v^{g2}\right);\ \ u_{git} \approx N^+\left(\mu^g(Z_{git}), \sigma_u^{g2}(Z_{git})\right),$$

for z environmental exogenous group-specific variables, where $\sigma_u^{g2}(Z_{git})$ captures the production uncertainty

$$ln\hat{f}_t^g(x_{git}) = ln\ f_t^g(x_{git}) + v_{git}^M - u_{git}^M\ ,$$

as the stochastic farmer-specific estimate of the meta-frontier that envelopes all individual groups' frontiers

$$\widehat{MTE}_{it}^g \equiv \frac{y_{git}}{f_t^g(x_{git})\, e^{v_{git}}} = \widehat{TGR}_{it}^g \times \widehat{TE}_{it}^g \leq 1$$

MTE_{git} is the firm-specific technical efficiency discounted due to its group membership effect with a statistical noise component. In particular,

$$lny_{git} = \beta_{g0} + \sum_k \beta_\kappa z_{git} + \sum_h \beta_h p_{hgit} + \sum_m \beta_m lnx_{mit} + \beta_g time + v_{it} - u_{it} + v_{git} - u_{git}\ ;$$

$$lny_{it} = \sum_m \beta_m lnx_{mit} + \sum_h \beta_h\, p_{pit} + v_{it} - u_{it}\ ;$$

4 Data description

4.1 Multiple factor analysis variables

The objective of the Multivariate Factor Analysis is to create distinct classes of arable farmers based on their production planning characteristics. These would proxy their differences in accessing the universal technology and achieving the maximum feasible production for given inputs. The characteristics (loadings) can be common to the groups or unique. The selection criterion implemented the uncertainty factor by considering the dissimilarities between farmers' performance over time. Thus, farmers are classified in groups based on the level of variability between years or in other words based on their observed performance in maintaining similar values in all variables considered over time. This in the technological stability context is defined by the notion of technology gap ratio in efficiency analysis. The efficiency analysis that followed aimed at signifying high-risk and low-risk behaviour in terms of technical and technological change. Through the estimation of the group-frontiers we may identify the differences due to their planning patterns and approach their relative distance with respect to the global unconstrained technological frontier. Furthermore, we may identify the group-dominant producers in terms of risk behaviour. Due to the small period and the approach to risk by reducing the time dimension through reorientation of the data by the effects of each period, long-term and short-term influences are treated with a time trend in the production frontiers. The time-varying price effects have been eliminated and we assumed inputs reported as expenditure entail quality differences in their value.

For the clustering process, we take advantage of the flexibility of MFA in comparing groups of individuals each associated a group of variables. Each observation (farmer) is attributed to an indicator referred to as partial individual (Pagès 2015). The indicators are associated with a group of variables which is constitutes a partial cloud. All clouds compose the global cloud which is used as a mean based on its characteristics. Representation is revealing both directions and magnitudes. Comparisons of the clouds are done in terms of their relative similarity in their components.

The criteria used to define the was the joint performance over time were focused on technological capabilities of the farms:

- Farm business income
- Technological gearing
- Investment
- Financial exposure
- External support dependency
- Land utilisation

4.2 Stochastic frontier model variables

Table 1. Variables for the short-run production function, their units and definitions

Variable	Unit of measure	Definition
Output quantity for agriculture per area farmed		
Agricultural gross margin	£/ha	Agricultural gross margin per ha of area farmed
Input quantities for agriculture per area farmed		
Seeds	£/ha	Seeds expenditure per area farmed
Fertiliser	£/ha	Fertiliser expenditure per area farmed
Crop-protection	£/ha	Crop-protection expenditure per area farmed
Energy	£/ha	Energy and fuel expenditure per area farmed

Variable	Unit of measure	Definition
Efficiency heterogeneity		
Farm type	Binomial	Mainly cereal 1, otherwise 0
Tenure form	Categorical	Tenanted, Owner occupied
Efficiency drivers		
Education	Ordinal	Farmer’s highest educational attainment
Diversified output ratio	Ratio	Diversified output over Farm Business Output
Size	Ordinal	Small, medium, large
Contract work ratio	£/ha	Contract costs over area farmed
Total grassland ratio	£/ha	Grassland area/ha of area farmed
Tenanted land ratio	Ratio	Tenanted land over total area farmed

Off-farm income ratio	Farmer spouse off-farm income over farm business income ratio

4.3 Descriptive statistics for the efficiency estimates

Table 2. Descriptive characteristics for Group 1 production function per hectare of total arable crops area

Group 1		mean	sd	skew
Output	Agricultural Gross Margin	1192.42	839.1	1.81
Inputs	Fertiliser	181.15	96.8	0.21
	Seeds	128.12	160.71	2.63
	Crop-protection	165.18	56.11	0.91
	Energy	156.68	100.21	1.18
Inefficiency drivers	Diversified output ratio	0.03	0.05	1.59
	Contract cost ratio	38.45	41.5	1.97
	Grassland ratio	0.07	0.1	1.32
	Tenanted area ratio	0.34	0.31	0.66
	Off-farm income ratio	0.05	0.38	7.79
	Debt ratio	0.55	0.81	2.12
	Support ratio	47.79	40.01	1.48

Group 2		mean	sd	skew
Output	Agricultural Gross Margin	778.15	534.37	1.56
Inputs	Fertiliser	178.18	107.02	0.62
	Seeds	82.10	63.72	3.02
	Crop-protection	147.91	62.51	1.89
	Energy	23.80	26.86	3.53
Inefficiency drivers	Diversified output ratio	0.05	0.10	3.32
	Contract cost ratio	71.31	99.31	2.74
	Grassland ratio	0.01	0.11	1.10
	Tenanted area ratio	0.40	0.42	0.37
	Off-farm income ratio	0.62	5.09	9.24
	Debt ratio	0.22	0.50	3.08
	Support ratio	31.47	39.19	3.43

5 Analysis

The inferential strength of Multivariate Factor Analysis relies on the association of producers to each set of variables. Thus, proximity of the producers that would otherwise be defined as distance (Manhattan), gains a structural representation with respect to the sets. Proximity between theme sets of variables is subject to joint proximity of producers per each set. Therefore, sample structure is defining variable sets weights and therefore factors' magnitude and orientation. In Figure 1 we observe the distances between the groups of variables that correspond to the nine years of the period of the analysis.

For the interpretation, we observe the data based on their profiles (group association). Based on the graph years 2005 and 2006, 2010 and 2013 are very similar in terms of the size effect (Dimension 1) which accounts for 51.28% of the inertia. The greatest difference on this axis is presented between years 2006 and 2008 while for Dimension 2 which accounts for 9.48% of the inertia we have significant distances between 2012 and 2008. In the graph of partial axes, we observe the size effect and the relationships between components of the factors (of the partial axes). We see that there is significant relationship between the factor loadings and the two dimensions.

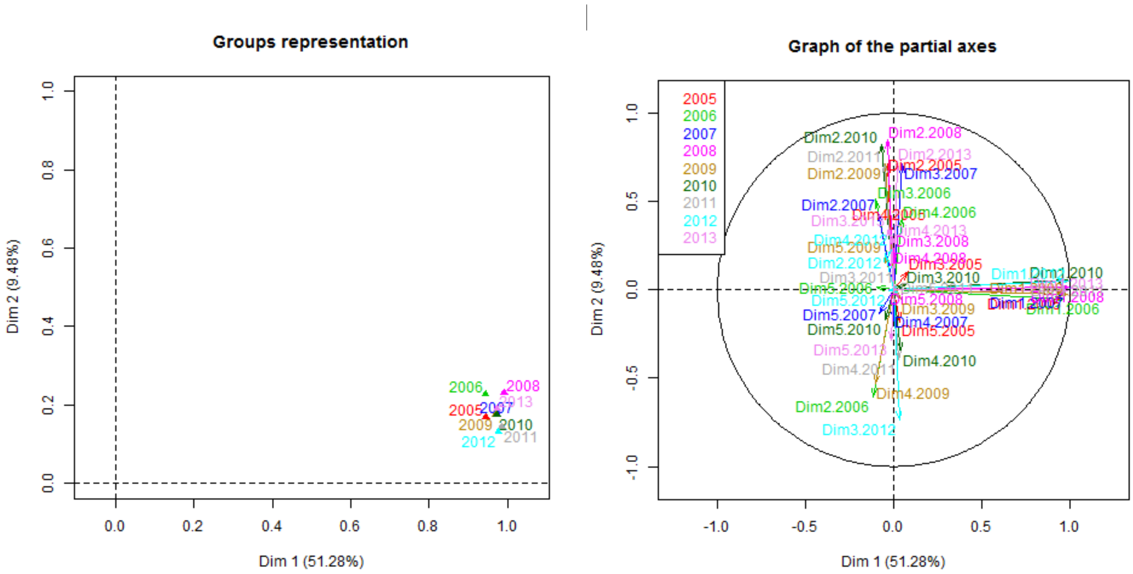

Figure 1. Time representation in a low two-dimensional view

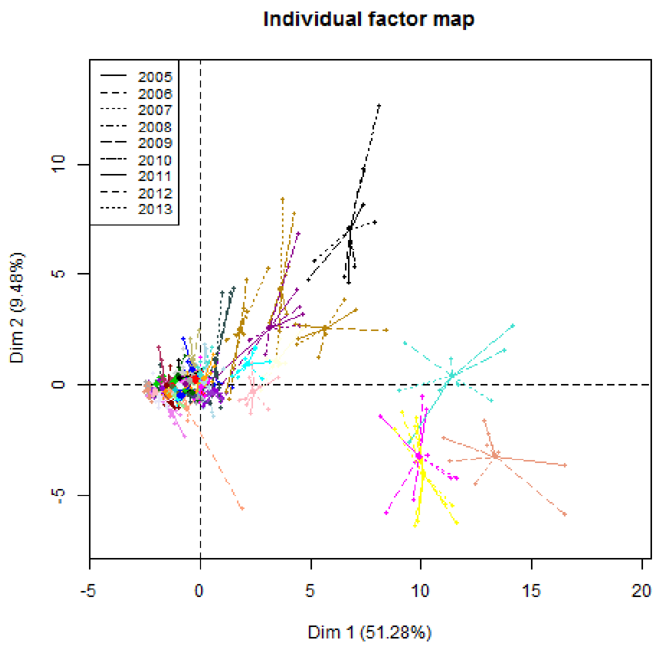

Figure 2. Individuals factor map

Figure 2 illustrates the individual factors (indicators) to which each farmer is contributing on the low dimensional two-axis representation. Which provides an easy to understand representation of their time-oriented performance. We observe some differences but most farmers are located within a close position around the origin. The ones being located far from the origin are indicative of outliers. While the producers are represented in simple two-axes, their relative position and structure is maintained and we may observe it with respect to the other dimensions (Figure 3).

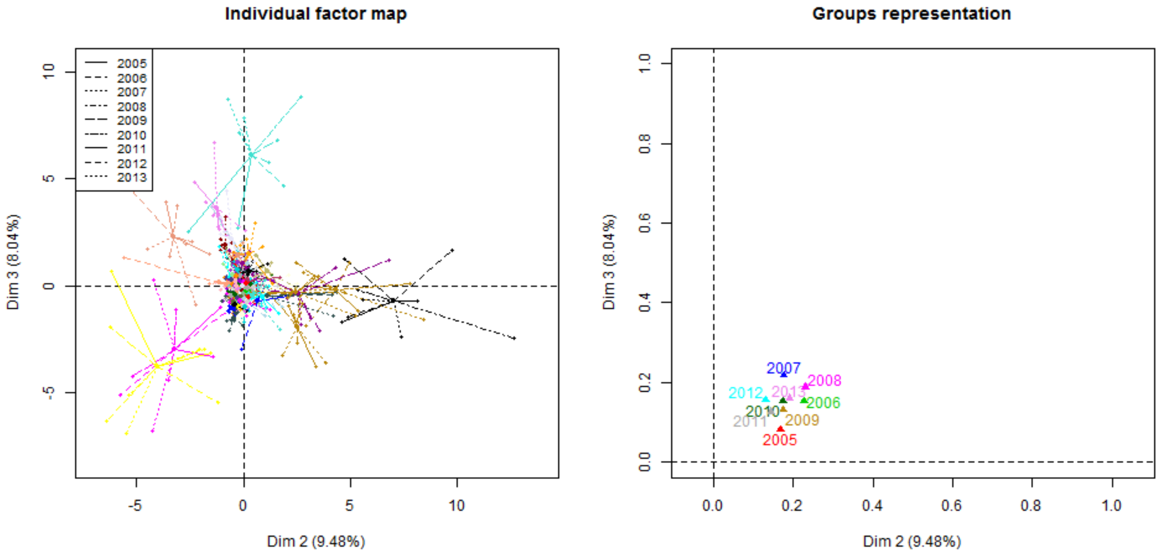

Figure 3. Structure representation over Dimensions 2 and 3

Most of the partial individuals are correlated to Dim 1. This dimension is mainly described by technological engagement set of variables. (i.e. MACHINERY, CONTRACT COSTS, INSURANCE COSTS). The second dimension (Dim.2) is highly correlated with labour and land intensity. Dimension 2 is described from high loans and capital introduction. The axes representation follows the same structure of the Principal Component Analysis. Axis for Dimension 1 captures those farmers that reported either high or low values on all variables. In terms of interpretation we would consider it as a size-effect of time variability (groups within and between inertia). A clearer representation of the farms with respect to the axes based on their group-variable associations can be viewed in Figure 4. Based on the correlation circle we observe the relationship between the component-variables of each group year. Almost all variables are well represented (distance from the origin). Based on the different colours and the location of the farmers to the 2nd and 4th quadrant the individual factor map we observe years 2011, 2012 and 2013 being of very high or low variability for most of the farmers, while for years 2007, 2008 and 2005 their effects are associated to the Dimension 2.

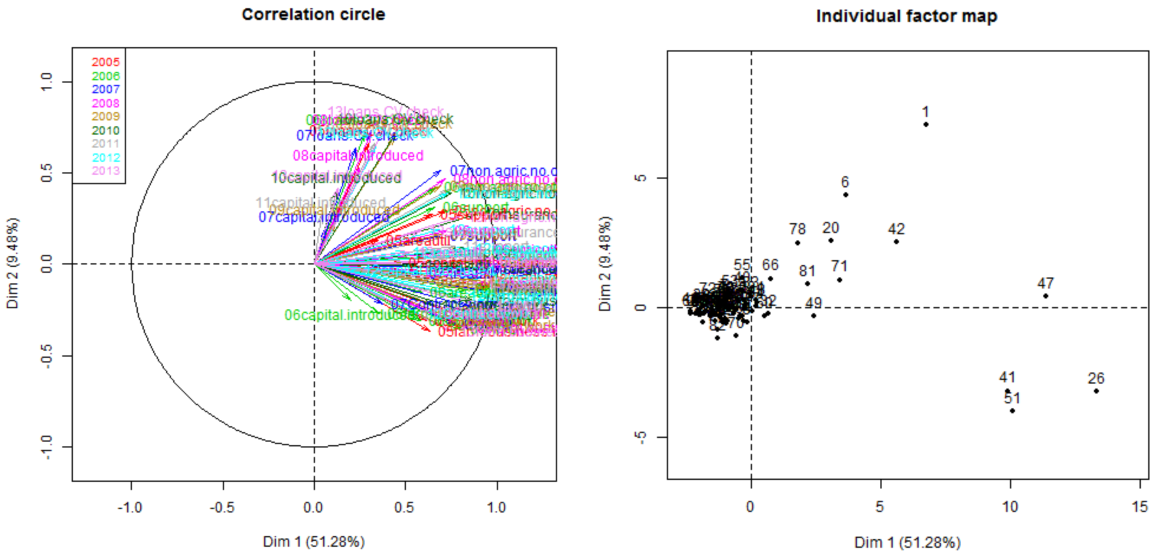

Figure 4. Correlation circle and farm representation

For the first 5 dimensions the eigenvalues and the percentage of total variance explained is approximately 77%.

Table 3. Percentage of variance for the first five dimensions

Eigenvalues	Dimensions				
	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5
Variance	8.73	1.61	1.36	0.83	0.60
% of var.	51.28	9.48	8.03	4.90	3.54
Cumulative % of var.	51.28	60.76	68.80	73.70	77.24

After observing the factor loadings, their correlations and the contribution to the first two dimensions as well as the graphical illustration of the data cloud we employed the Hierarchical Clustering process on the principal components to define groups of the producers and their planning profiles. Based on the inertia gain we identified four clusters each one defined by either higher, lower or mixed variability between components of the factors. To construct the hierarchical tree we define the distance or dissimilarity between the groups of individuals. The v-test reveals whether the dimension or the factor component is underrepresented or over represented in the cluster, being negative or positive respectively and revealing its significance based on the absolute value.

- Cluster 1 based on the results is underrepresented by all factor components relative to the rest. However, the most dissimilar characteristics factor components are insurance expenditure (excluding labour and buildings), machinery evaluation, agricultural fixed costs. Furthermore, farm business income is very underrepresented as well. In other words, we would relatively conclude that this group is technologically inferior compared to the other groups.
- Cluster 2 is overrepresented by loans, capital introduced and high farm business income for certain years. This group presents high debt and investment on machinery.

- Cluster 3 is overrepresented by loans, capital introduced and high non-agricultural fixed costs insurance costs support. Also, area utilisation is introduced as a characteristic compared to the rest.
- Cluster 4 is overrepresented by high labour requirements, machinery evaluation and farm business income factors. Agricultural fixed costs, machinery and area utilisation.
- The extended results allow for the consolidation of the data into two basic groups. Group 1 which resembles a technologically disadvantaged group and a second one that reveals signs of intensification increased expenditure on machinery and increased utilisation of resources.

The dissimilarities revealed are a result of the between and within group inertia of the partial individuals (factor components that comprise the sample).

Table 4. Cluster composition with respect to dimensions of the MFA[4]

	v.test	Mean in category	Overall mean	sd in category	Overall sd	p.value
Cluster 1						
Dim.10	2.67	0.08	0.00	0.35	0.56	0.01
Dim.2	-2.44	-0.17	0.00	0.35	1.27	0.01
Dim.1	-6.75	-1.11	0.00	0.65	2.95	0.00
Cluster 2						
Dim.18	3.35	0.30	0.00	0.40	0.28	0.00
Dim.13	3.16	0.43	0.00	0.89	0.43	0.00
Dim.27	-2.12	-0.10	0.00	0.25	0.14	0.03
Dim.8	-2.14	-0.44	0.00	0.54	0.64	0.03
Dim.22	-2.57	-0.17	0.00	0.34	0.21	0.01
Dim.10	-3.09	-0.55	0.00	0.75	0.56	0.00
Cluster 3						
Dim.2	6.81	3.78	0.00	1.76	1.27	0.00
Dim.1	3.27	4.21	0.00	1.78	2.95	0.00
Dim.9	2.19	0.59	0.00	1.38	0.61	0.03
Cluster 4						
Dim.1	7.72	11.20	0.00	1.36	2.95	0.00
Dim.2	-4.06	-2.54	0.00	1.72	1.27	0.00

[4] The overall mean represents the global cloud average. Partial clouds are regarded as categories

Table 5. Cluster representation on the first two fimensions of the Multiple Factor Analysis

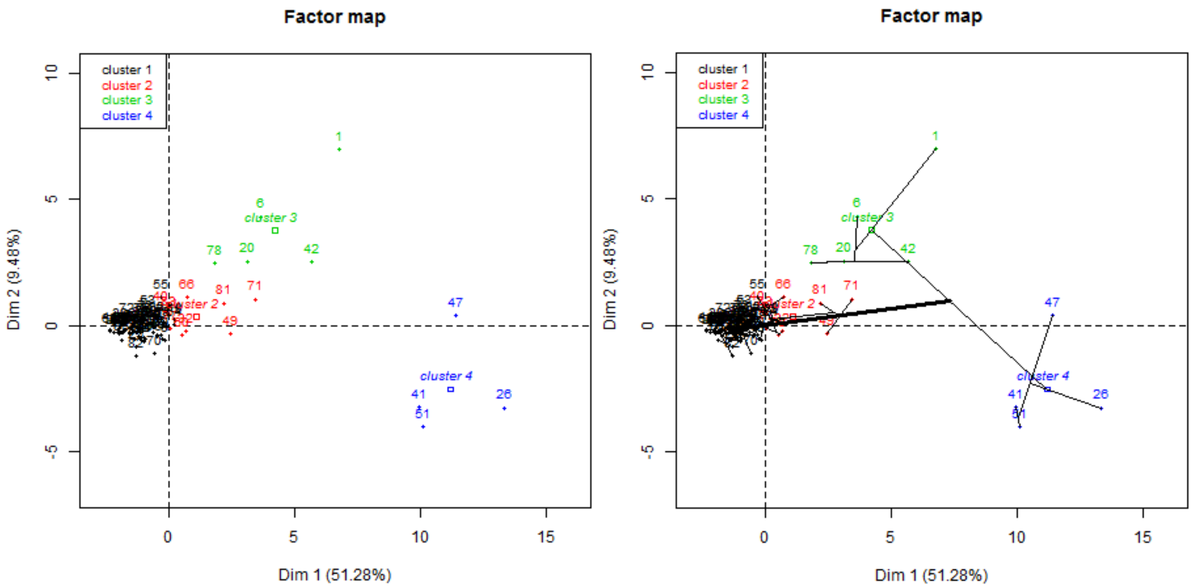

Figure 5. Cluster representation on the factor map and the cluster means

The last step is the Stochastic Frontier Analysis that accounts for time variant farm specific technical efficiency and technology change. The model based on the G. E. Battese and Coelli (1995) implementation for R[5].

For the variant farm-specific inefficiency model that does not account for heterogeneity but includes a trend the reported inefficiencies are:

	2005	2006	2007	2008	2009	2010	2011	2012	2013	Time
Group 1	0.68	0.67	0.65	0.64	0.62	0.61	0.60	0.58	0.57	-5.5% sign.
Group 2	0.44	0.55	0.65	0.74	0.81	0.86	0.90	0.92	0.95	-3% non-sign
Global	0.70	0.69	0.68	0.67	0.66	0.64	0.63	0.62	0.61	9% sign

All coefficients except seed expenditure and energy consumption were not statistically significant. Fertiliser presented a negative coefficient that may be interpreted as elasticity for the change in the agricultural profitability per ha of arable production. Group 2 clearly includes an increasing mean efficiency. For the case of Group 1 we have 5.5% regress. At all models the performance of the Group 1 was inflating the mean efficiency and the technological change effect was further enhanced (negatively).

Other specifications considered an Efficiency Effects frontier with farm and tenancy type variables that may be responsible for various levels of inefficiency and technology change. The results presented that these two variables of heterogeneity in the production function were valid only for the group. This is consistent with the previous results from the MFA since Cluster 2 was treated as a highly intensified productive group of farmers. Among the other variables, rurality and education of the farmer were not statistically significant but with positive coefficient for general cropping farm type but negative for tenanted land use group 1. For the global general cropping farms presented better profit performance.

[5] Tim Coelli and Arne Henningsen (2017). frontier: Stochastic Frontier Analysis. R package version 1.1-2. https://CRAN.R-Project.org/package=frontier.

Inefficiency determinants were added to explain the efficiency levels. Group 1 inefficiency drivers reported as significant were diversified output ratio, contract cost ratio, increased size, tenancy ratio, grassland and off-farm income. For the second group higher levels of education, diversified output ratio, increased size and off-farm income had positive coefficients and are statistically significant. As it is observed also in Figure 6 Group 1 is inflating global technical efficiency estimates based on the characteristics of the farms.

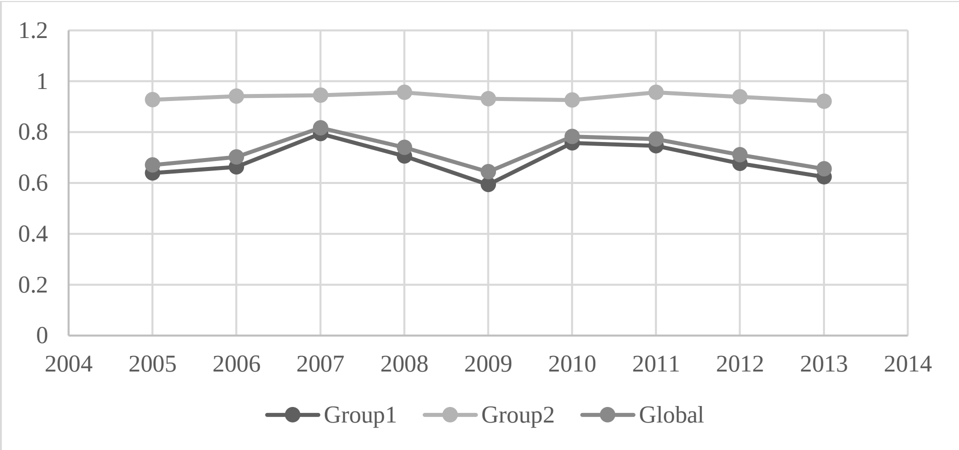

Figure 6. Group and global mean efficiencies for the period 2005-2013

6 Discussion

This paper provided an outline on the literature of technological change and a data driven representation of how heterogeneity present in a sample influences technical efficiency estimates and possibly technological progress or regress. Several approaches to the concept of meta-frontier have been developed based either on a deterministic approach or on a stochastic two-stage estimation and calibration of efficiency estimates. More in-depth analysis is required to understand how technology is realised by producers based on their profit maximising or cost minimising behaviour, their planning approaches and responses to market insecurity and uncertainty. Future work will include an attempt to capture how the technological frontier (unconstrained production frontier) is changing based on the performance of the producers, estimate the Meta-Frontier Technology ratios and capture patterns in the dominant producers by either approaching efficiency at a local optimum or defining technological change in the form of leaps (between groups). With respect to the methodology employed Multiple Factor Analysis was proved to be a flexible tool in dealing with high-dimensional datasets and effectively defining groups based on joint dissimilarity criteria. It can be further extended to account for the time varying effects of the factor components modelled as Dynamic Factor Analysis.

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8 Appendix

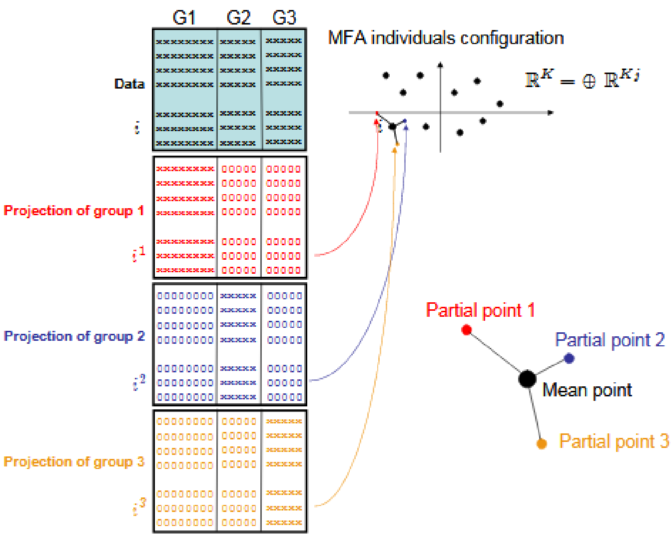

Figure 7. Representation of individuals by groups and their projection in the two-dimensional plane[6]

[6] Adopted from http://juliejosse.com/wp-content/uploads/2016/01/MFA_staf2015.pdf

Table 6. Within inertia for the individual farmers. MFA results

	Dim.1	Dim.2	Dim.3	Dim.4	Dim.5
1	5.11	13.48	4.46	14.87	6.62
2	0.14	0.11	0.16	0.23	0.21
3	0.3	0.12	0.17	0.14	0.13
4	0.29	0.1	0.13	0.33	0.05
5	0.24	0.13	0.1	0.21	0.1
6	0.54	10.95	2.53	1.85	2.74
7	0.1	0.41	0.28	0.47	0.03
8	0.15	0.08	0.11	0.1	0.05
9	0.08	0.04	0.11	0.23	0.41
10	0.71	0.16	0.18	0.29	0.14
11	0.18	0.09	0.14	0.61	0.27
12	0.05	0.04	0.18	0.39	0.42
13	0.05	0.03	0.35	0.1	0.16
14	0.02	0.05	0.05	0.16	0.39
15	0.03	0.03	0.05	0.25	0.43
16	0.04	0.03	0.06	0.15	0.25
17	0.04	0.08	0.24	0.17	0.17
18	0.23	2.65	8.6	0.82	0.23
19	0.23	0.03	0.34	0.18	0.27
20	14.46	9.41	3.34	2.8	4.17
21	0.19	0.03	0.16	0.17	0.39
22	0.03	0.03	0.46	0.13	0.09
23	0.43	0.09	0.38	0.26	0.35
24	0.07	0.13	0.1	0.26	0.23
25	0.16	0.07	0.7	0.55	0.03
26	15.69	2.91	6.5	14.13	24.29
27	0.65	0.18	0.33	0.4	0.45
28	0.02	0.02	0.04	0.17	0.38
29	0.05	0.02	0.11	0.16	0.14
30	0.67	0.43	0.14	0.14	0.1
31	0.26	0.02	0.53	0.24	0.06
32	0.4	1.04	0.42	0.3	0.18
33	0.1	0.04	0.19	0.1	0.14
34	0.05	0.03	0.04	0.14	0.16
35	0.15	0.05	0.14	0.22	0.2
36	0.03	0.18	0.07	0.09	0.14
37	0.14	0.07	0.33	0.64	0.26
38	0.1	0.1	0.04	0.08	0.44
39	0.11	0.1	0.18	0.24	0.39
40	2.71	0.79	1.81	4.01	2.24
41	5.37	6.08	11.68	6.8	4.63

42	8.07	1.07	4.09	2.09	0.58
43	0.04	0.04	0.07	0.47	0.27
44	0.04	0.08	0.1	0.29	0.38
45	0.15	0.11	1.2	0.54	0.09
46	0.4	0.08	0.9	1.06	0.78
47	15.89	4.51	11.86	14.67	13.35
48	0.17	0.18	0.24	0.6	0.03
49	1.27	1.03	0.81	0.37	0.46
50	0.1	0.17	0.57	0.22	0.05
51	4.14	9.27	11.99	6.15	10.28
52	0.41	0.15	0.83	0.38	0.09
53	0.28	0.57	0.4	0.42	0.29
54	0.58	0.44	0.4	1	0.02
55	0.18	0.9	0.91	0.67	0.18
56	0.81	0.24	0.34	0.42	0.18
57	0.23	0.06	0.74	0.47	0.15
58	0.1	0.05	0.12	0.08	0.11
59	0.19	0.03	2.27	0.51	0.2
60	0.67	0.19	0.89	1.09	0.11
61	0.03	0.23	0.07	0.3	0.21
62	0.06	0.14	0.17	0.54	0.2
63	0.4	0.21	0.31	0.09	0.15
64	0.5	0.08	0.11	0.35	0.07
65	0.27	0.09	0.23	0.13	0.11
66	1.26	10.01	0.3	0.13	1.25
67	0.22	0.04	0.49	0.13	0.2
68	0.07	0.05	0.16	0.15	0.18
69	0.09	0.07	0.19	1.03	0.23
70	3.89	5.22	0.43	0.52	8.25
71	1.44	1.26	0.46	1.05	1.2
72	1.25	1.05	0.48	1.94	2.37
73	0.66	0.31	0.24	0.27	0.44
74	0.26	0.23	0.38	0.15	0.13
75	0.39	0.05	0.06	0.14	0.13
76	0.05	0.04	0.06	0.81	0.27
77	0.22	0.69	0.26	0.2	0.24
78	1.5	7.21	0.66	1.28	2
79	0.12	0.06	0.09	0.3	0.07
80	0.14	0.03	0.26	0.09	0.11
81	1.31	0.51	0.77	1.22	1.1
82	0.57	0.75	4.07	1.63	0.18
83	0.35	1.02	0.93	0.5	0.13
84	0.59	0.53	1.39	0.51	0.06
85	0.05	0.03	0.09	0.4	0.38
86	0.21	0.49	2.66	1.02	0.21

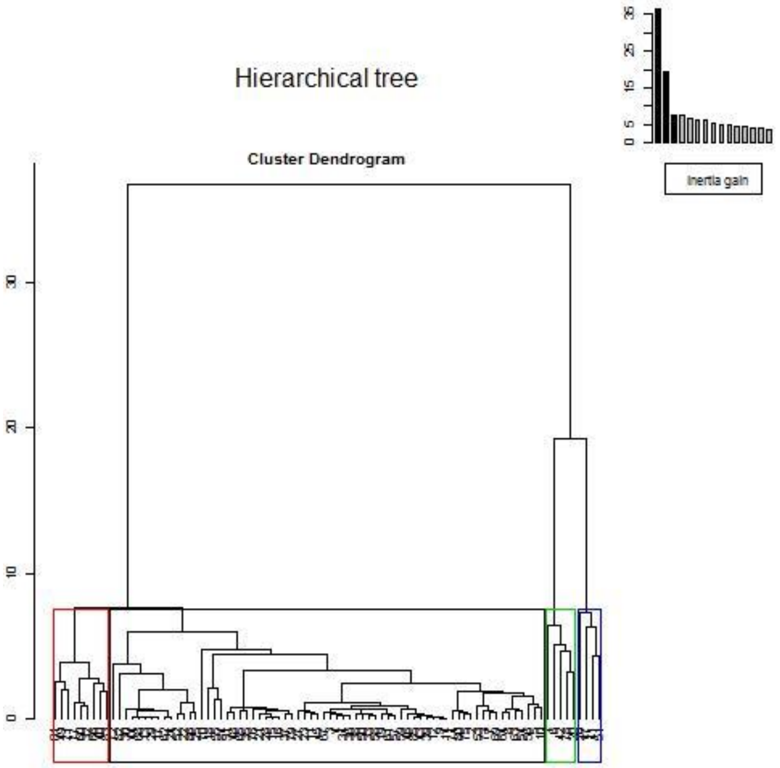

Figure 8. Hierarchical tree on the components of the factor analysis. Farmers that belong to the same branch or to its lower hierarchy presented greater similarity

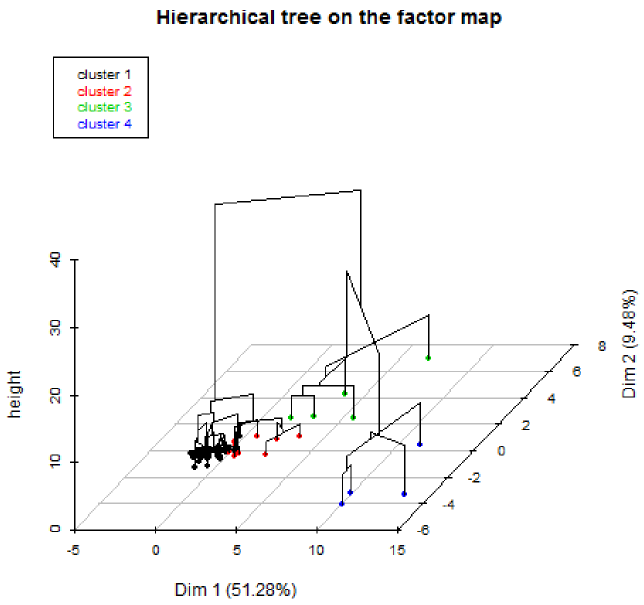

Figure 9. 3-dimensional representation of the clusters