UNIVERSITY OF COPENHAGEN
DEPARTMENT OF FOOD AND RESOURCE ECONOMICS

Master Thesis

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The Effect of a Strategic and Managerial Focus on Productivity among Danish Farmers

- A Factor Analysis and Data Envelopment Analysis Approach

Supervisor: Mette Asmild

Submitted on 31 May 2021

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Title and subtitle:	The Effect of a Strategic and Managerial Focus on Productivity among Danish Farmers - A Factor Analysis and Data Envelopment Analysis Approach
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Abstract

This thesis is an exploratory analysis of the strategic management and leadership in the context of Danish agriculture with a focus on personality traits and management and leadership style by the farm owner and the relationship with farm performance. Data Envelopment Analysis (DEA) is used to measure farm performance as efficiency. Factor Analysis is used to illuminate latent variables within personality traits and management and leadership style. The analysis is based on a survey answered by 107 Danish farmers and the economic data from 40 farmers.

The overall findings are that the variables of management and leadership style are intercorrelated meaning that improving one aspect will improve other parts of management and leadership as well. To improve productivity measured by efficiency, it is important to discuss business issues with other people, in particular advisors and peers, and use software and various operational and management tools. To be a better manager and leader it is important to attend supplementary training and remember to continue to do so. Further, it is important to keep positive regarding both the job as a farmer and the future of farming. If it is not possible to continue to be positive, make changes to the situation by hiring employees or restructuring the production.

Resumé

Dette speciale er en eksplorativ analyse omhandlende strategisk ledelse i dansk landbrug med fokus på bedriftsejerens personlighedstræk, driftsledelse og lederskab i relation til bedriftens resultat. Data Envelopment Analysis (DEA) bliver brugt til at måle bedriftens produktivitet som efficiensscore. Faktoranalyse belyser latente variable i kategorierne personlighedstræk, driftsledelse og lederskab. Analysen er baseret på et spørgeskema med svar fra 107 danske landmænd og økonomisk data fra 40 af disse.

De overordnede resultater er, at variablene i kategorierne om driftsledelse og lederskab er inter-korrelerede. Hvilket betyder, at ved at forbedre et aspekt af driftsledelse og lederskab forbedres andre dele også. Det er vigtigt at diskutere virksomhedsledelse med andre mennesker, særligt rådgivere og ligesindede og bruge software og forskellige drifts- og ledelsesværktøjer. For at blive en bedre driftsleder, er det vigtigt at deltage i efteruddannelse og konferencer og blive ved med dette. Det er vigtigt at forblive positiv både som landmand og i relation til fremtidsperspektivet for landbruget. Hvis det bliver svært at forblive positiv, er det vigtig at ændre forhold ved at ansætte folk eller omstrukturere produktionen.

Preface

This Master Thesis would not have been possible without collaborating with Patriotisk Selskab and them making their members and consultants available for this thesis. The members have kindly answered a survey. The consultants have kindly answered all my questions about the Danish agricultural sector and how to understand an annual report.

A special thank you to Christian Vestager and Thomas Skøtt for being a part of the start-up of the project back in late 2020 and the beginning of 2021. A big thank you to Sarah Lilaa for being available, when I needed guidance and answers to all my questions.

The research question has not been influenced by Patriotisk Selskab in any way. They have made resources and data available for me and in return hoping to get some new knowledge. I hope that they can use some of thoughts about method and results from this thesis in the future business consulting.

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Introduction

Since 4000 B.C. we have permanently been growing plants in specific areas and domesticating animals in Denmark (VKST 2020b). It expanded and developed gradually and in the 1940s and 1950s the number of farms in Denmark were at its highest with more than 200 000 farms where most of them were smallholdings (Kærgård & Dalgaard 2014). Since then, the number of farms has decreased, and the size of the farms have increased. Instead of being a full-time job for a whole family to take care of the farm, it is mostly a part-time job as of 2000 (Kærgård & Dalgaard 2014). We see a high degree of specialization on especially the full-time farms. Even though the number of farms in Denmark decrease, we will continue to have agriculture in Denmark in the future. The global tendencies increase demand for agricultural produce due to the increase in world population and general increase of wealth around the globe (Schou 2019b). The general competitiveness of the Danish agricultural sector is determining for the survival in the increasingly globalized agricultural sector.

In Skøtt (2018) it is stated that the competitiveness of the agricultural sector is largely determined by the manager's ability to apply resources in the best possible way. The demand for creativity and the adaptability increases every year as the regulation and possibilities changes.

A series of articles from SEGES by Mortensen (2017) is published based on the need for more knowledge about business management among farm managers. The aim of the series is to strengthen management competences of the farmers to increase the competitiveness among Danish farmers.

In the book by Skøtt (2018), a quantile analysis of plant breeding in general from 2016 shows that the worst performing quarter of the farms have a negative net yield. The worst performing 10 % of the farms have a negative net yield almost half the size of the positive net yield in the best 10 %. Schou (2019b) presents rate of return for full time farms and the best third does always have a positive and high return compared to the average. The third part doing the worst have negative rate of return which is not sustainable in the long term. In Schou (2019a) the differences in revenue across production types vary greatly. The group of farmers doing the best is doing great and the ones doing the worst are really struggling to keep the farm running.

These representations show the big differences in performance within the agricultural sector of Denmark. There is a big need for knowledge about an alternative way to manage and lead a farm, for the worst performing farms to be able to make changes before they must shut down.

SEGES has together with LandboNord and Patriotisk Selskab initiated a project to find trends and recommendations based on how the best performing farmers are doing (Skøtt 2019). SEGES

(2020) states in their presentation of the findings freely translated into “Top 2 – Learn from the best farmers”, that if the farmers in top 15 % does like the ones in top 2 %, then the overall economic gain would be 6 billion. SEGES (2020) further describe the traits of the farm owners in top 2 %. The farm owners see themselves as CEO on the farm with a focus on business management, the culture on the farm and among the employees. They purely focus on business and earnings.

A headline freely translated into “Management consultancy – is it dangerous?” and the article belonging in the book “Driftsanalyser 2017/2018” from Patriotisk Selskab shows that agricultural consultancies want to enlighten the farm owners about the necessity and possibilities in consultancies regarding the long-term and strategic focus among managers and owners.

In general, when looking at websites for various Danish farmer’s associations, they all provide consultancy regarding strategy and business management (Velas 2020; VKST 2020a; LandboNord 2021; Landbrugsrådgivning Syd 2021). These associations see the need for advising regarding business management in Danish agriculture. But as stated above in the article “Management consultancy – is it dangerous?”, it is still a work in progress making some farmers see that it is necessary to run the farm as a business and not as a family farm, as it has been previously.

The history regarding academic research in the field of strategic business management is limited since the list of research projects seem short. In a publication by Mellerup and Lund (2003) about Balanced Scorecard in dairy farms, which is one of the latest publications regarding a tool used for business management in Danish agriculture. Here, they describe the work regarding consulting about strategic planning and business management in Danish agriculture in the previous 20 years. The first project about strategic planning in Danish agriculture were “Bornholmsprojektet” in the 1980s. This project gave new knowledge about long-term planning and the farmer’s job regarding strategic management and how the consultancies could support this. In the 1990s the project “Langsigtede Bedriftsrådgivning” were conducted and contributed with new experiences and methodologies in the long-term planning. This included knowledge about the need for a specific formulation regarding vision and mission for the farm. In the 1990s another project regarding the consultancy about strategic planning were conducted, where models for development of the strategic competences within the consultancies were developed. Since then, the farmer’s associations have been working with strategic business management, but I have not been able to find more academic research regarding this topic within Denmark. As an example of how the farmer’s associations work with data regarding business management, a short description of the business analysis from Patriotisk Selskab will follow.

Benchmarking by Patriotisk Selskab

In the book from Patriotisk Selskab "Driftsanalyser 2017/2018" (referred to as Skøtt 2018), the consultancy presents the production analysis, which is their benchmarking tool. Skøtt (2018) state that the farmers can compare their own production costs with other similar farms, and thereby focus their effort on parts of the production, where it is most needed, and the trade-off is the highest. The production analysis from Patriotisk Selskab is developed over the last five decades and in the last 12 years in an international collaboration with *agri benchmark* (Skøtt 2018).

In "Driftsanalyser 2017/2018" it is possible to see anonymous results from various farms. Further, the economy of the industry and specific production lines are shown together with previous years and forecasts for the coming two years. One of the characteristics of the production analysis is that they calculate the net yield and the contribution of the production or production line to return on investment. They do take the opportunity cost of the farm owner's own work on the farm into account. The analysis in this thesis does take outset in the method from Patriotisk Selskab by taking the opportunity cost of the farm owners into account as well.

The production analysis is the basis for the general business analysis where it is complemented with comments and numbers for comparison for every farm. The benchmarking in the business analysis is compared to the average of the best half from earlier years in every production line.

The farms are divided into three groups by size of land. The number of animals is not considered in this grouping. Based on the grouping, it is possible to compare the economic performance by size.

Rate of return is a financial performance indicator which Patriotisk Selskab is using in the production analysis (Skøtt 2018). It indicates how big the return on the total value of the assets is. Rate of return is a broadly used financial performance indicator since it makes it possible to compare with the returns on other investments. This gives a perspective on the competitiveness of investments in agricultural production compared to other business sectors (Schou 2019).

Correlation between strategic business management and productivity in agriculture

The focus on strategic business management have been adopted from the general field of business due to increasing demand for documentation by banks and official institutions in the 1970s and 1980s (Christensen et al. 1989). After World War II, the focus on strategy in business increased since businesses were no longer seen as stable environments as it was before the war (Bracker 1980). Over the next 30 years, various authors developed methods and theory in the field of business strategy (Bracker 1980). So, it was at a natural time that the focus on strategic business management and the demand hereof coming from external bodies entered the field of agriculture in Denmark.

Even though various tools and methods have been developed within the Danish agricultural sector to help the farmers have a strategic and long-term focus, it has not explicitly been investigated what the correlation is between the focus on strategic business management and the productivity on the farms in a Danish context.

Various authors present results where there is a correlation between various measures regarding personal traits and the capacity to do strategic business management. A study by Rougoor et al. (1998) presents various studies showing an impact of management capacity by the farmer on farm results. The correlations vary from 7 to 40 %, but the results are hard to compare since the definitions differ across studies. Trip et al. (2002) use a stochastic frontier production function to find a positive association between the efficiency on the farm and the quality of decision, which is divided into four steps in the study. These steps are goal formulation, planning, monitoring and evaluation. The positive association with farm efficiency is especially strong for monitoring and firm evaluation. They find that these steps in decision making is critical on a successful farm. O'leary et al. (2018) focus on the farm manager's personal traits and the potential impact on farm business performance. They find that business goals, the farmer's temper and growth mindset is associated with profitability.

A study by Johansson (2007) investigates personality traits and style of decision-making and its impact on farm efficiency in Swedish dairy farms in a similar way to this study. The efficiency is measured using Data Envelopment Analysis (DEA), and the managerial capacity aspects were collected through a survey on mail. She finds correlation between various of the measures of managerial capacity and farm efficiency.

Multiple of other authors have investigated the importance of managerial capacity and abilities in strategic business management in various agricultural branches around the world: Finnish dairy farms (Mäkinen 2013), Dutch agriculture (de Lauwere 2005), family farm businesses in New Zealand (Nuthall 2006) and farms in Scotland (Willock et al. 1999).

Purpose

This analysis is an exploratory analysis of the strategic management and leadership in the context of Danish agriculture. Data Envelopment Analysis (DEA) and Factor Analysis is used to illuminate two very different aspects of management of agricultural production, to be able to find the relationship between productivity and a farmer's focus on strategic business management and his/her personality traits. DEA illuminates the productivity based on the economic data from the farms in question. The Factor Analysis creates latent factors as variables based on data from a survey, which was created and distributed in 2020 to members of Patriotisk Selskab. A thorough description of this work is found in Schade (2020).

The purpose of this exploratory analysis is to investigate, how personality traits and management and leadership style of the farm owner affect the performance of the farm. Further, this analysis should lead to hands on recommendations regarding how to lead, manage and use tools for management for farm owners/managers and consultants to be able to use in their work in Danish agriculture. The framework of the analysis is described on page 13.

Brief review of structure of the project

This master thesis is divided into two parts. Part 1 presents the overall frame of the project, and the results together with recommendations based on the findings of the project. This part is intended for the farmers and consultants in the Danish agricultural sector. Part 2 describes the theory and methodology of the analysis more thoroughly. In Part 2, the data and data structure are described. Further, DEA is described in theory and the application of it in this project is described as well. The section about DEA is finalised with a part about the results of DEA presenting the efficiency scores. The efficiency scores from DEA represents the productivity based on benchmarking between the farms, which have provided economic data for this project. Part 2 does also contain a section about Factor Analysis in the same composition as the section about DEA. Firstly, the theory and methodology of Factor Analysis is described in general. Thereafter, the methodology is applied on data from the survey. Lastly, the final factors are presented for further application representing the farmer's thoughts and personal traits regarding strategic leadership and management.

To finish the thesis, the method and results are discussed and concluded upon. The conclusion completes Part 1 together with recommendations, and the discussion and future implications completes the entire thesis after Part 2. The description of future implications, recommendations for further research and special issues for further research is important since this thesis is a first in applying DEA and Factor Analysis to describe the link between strategic focus and ability of farm owners in the Danish agricultural sector for inspiration and steppingstone for further knowledge in this field.

Part 1 Executive summary

The broad setting of this project is adopted from the project preparing for this thesis; Schade (2020). The overall connections, which we try to investigate in this project are shown in Figure 1.1. The figure is inspired by a range of papers. They all present models showing structures and relations to describe how personality and leadership style etc. links to the performance on the farm measured in various ways (Nuthall 2009; Rougoor et al. 1998; Willock et al. 1999; Mäkinen 2013; Johansson 2007). These models differ greatly in complexity and the model in Figure 1.1 is designed with the purpose of keeping the relationships and structures simple.

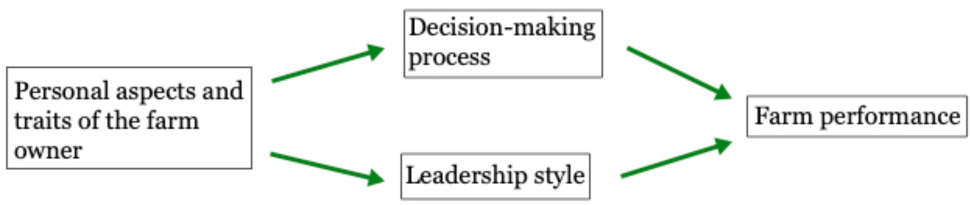

Figure 1.1 From personal aspects and traits to farm performance (Schade 2020)

In the survey, a range of statements were set up for the farm owner to state to what extent he/she agrees with it. These statements describe the farm owner as a person and/or as a leader and manager. These statements illuminate the personal aspects and traits of the farm owner, and the way he/she makes decision and lead on the farm. In this setup it is assumed that the personal aspects and traits determine the decision-making process and the leadership style, which determine the performance on the farm. The performance is the productivity measured as efficiency score in the DEA. We will come back to the DEA model in section 1.1.

The starting point of the model in Figure 1.1 is called *Personal aspects and traits of the farm owner* and contains knowledge about the farmer such as age, education, training, experience, and gender (Schade 2020). It also contains personality traits, which is harder to measure, and this is where the Factor Analysis is needed. This is traits such as attitude, perception, self-perception, challenge management and approachability (Schade 2020).

The *Decision-making process* step covers the management style of the farmer and how he/she uses other people and various tools and methods in the decisions-making process. The *Leadership style* step is included to focus on the quality of the farmer's leadership. This is about how he/she evolves as a manager and about the quality of implementation through planning and personality traits directly relating to leading on a farm and working with a strategy for the farm.

The project preparing for this thesis described in Schade (2020) gave the foundation for the research. 107 answers were collected from the members of Patriotisk Selskab. Of these 46 farmers gave the final permission to investigate their economic data. After looking into the database at Patriotisk Selskab, 42 farmers were left as base for this analysis, since economic data were not available from four farms. Two of these farms were the only respectively poultry or cattle farms. They are excluded from the dataset when doing DEA since they were not directly comparable to other farms. Data from 2015 to 2019 were processed to end up with three inputs and one output for DEA. The data processing is described in section 2.1.

1.1 Data Envelopment Analysis

As a starting point we have rate of return, which is described in the introduction. It is broadly used as a financial performance indicator. It is simple benchmarking per definition since it is "*comparison of production entities*" (Bogetoft & Otto 2011). DEA is modern benchmarking where the amount of each input and output are compared to determine efficiency. Efficiency is "*the use of the fewest inputs (resources) to produce the most outputs*" (Bogetoft & Otto 2011). Here entities are also compared by the efficiency score instead of a financial performance indicator.

A more thorough and technical description of DEA can be found in section 2.2. Here the intuition about the methodology and application in this context is described. A brief presentation of the efficiency scores can be found in this section as a basis for the analysis later in Part 1. A more thorough presentation of the efficiency scores can be found in section 2.2.3.

DEA is a benchmarking tool where it is possible to compare decision making units (DMU) across scale (Bogetoft & Otto 2011). These DMUs should be comparable with the same inputs and outputs. In this context the DMUs are farms. This is plant breeders both organic and conventional and conventional pig breeders.

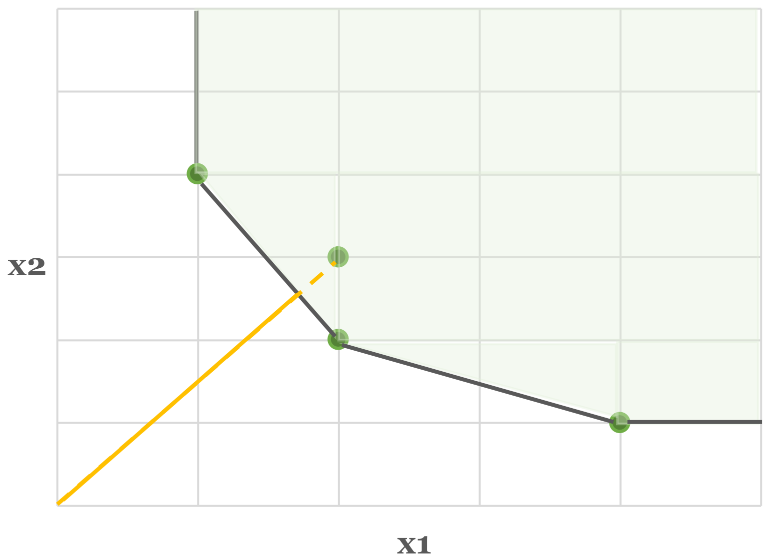

Figure 1.2 Production possibility set, production frontier and projection of inefficient DMU to the production frontier in an input space

The DMUs form a production possibility set (PPS) and with a production frontier. The assumption of PPS is described in section 2.2.2. In Figure 1.2 PPS is the light green area, and the production frontier is the boundary of PPS. The frontier is given by the efficient DMUs and the convex combination of these. The inefficient DMUs are placed in PPS. The efficient DMUs have an efficiency score at 1. The inefficient DMUs have an efficiency score between 0 and 1 depending on the distance to the frontier in the direction of origin as visualised by the yellow solid line and dotted line. The efficiency score is a percentage explaining, that by decreasing the input to that percentage level, the DMU should still be able to produce the same level of output and then be fully efficient. The efficient DMUs are the ones doing the best on the chosen scale, and it is the ones that the inefficient DMUs are compared to. Figure 1.2 is showing the input space in an input-orientated model meaning, that the output level is fixed, and the input level is adjustable. This is also the orientation in the DEA model in this analysis. Further, the model is based on variable returns to scale (VRS), so that the relationship between the inputs and output can vary across scale.

The model is based on economic data from between one to five years depending on the farm. These data are averaged across the available years to limit the year specific variations e.g., in crop rotation and weather conditions. Further, the economic data is summarised in three inputs and one output as shown in Figure 1.3. The inputs and output are thoroughly described in section 2.2.1 and the sub-elements are described in section 2.1.

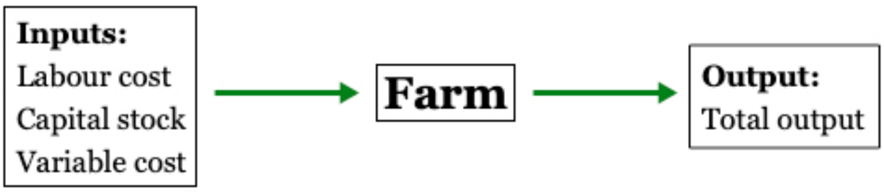

Figure 1.3 Three inputs and one output

Labour cost – This is composed of 50 % of expenses for agricultural machinery centre etc., labour costs from the economic data and estimated payment for the farm owner's work.

The labour cost is a separate input since there is trade-off between the farm owner's own time and hired employees' payment. Further, there is a trade-off between labour cost and both capital stock and variable costs since some of the manual tasks can be automated or substituted to machines or chemicals and therefore contained in variable costs and capital stock.

Capital stock – This is the composed value of assets as an expression for farm size. As already touched upon with more capital stock some things can be produced with less labour.

Variable cost – This is composed of direct costs, indirect costs, lease of land and 50 % of the cost of using agricultural machinery centre etc. These expenses are not directly labour or capital and thereby captures the rest of the input in the production on the farm.

Total output – This is composed of revenue directly from the economic data, leasing of land to others, disconnected EU subsidies and other earnings.

Since all the variables are specified in DKK, the assumption here is, as it is for Aigner & Asmild (2021), that the DMUs should weigh inputs and output equally. Aigner & Asmild (2021) applied the weight restrictions (WR), where it is not possible to weigh an input half than or double as much as another inputs. Here this is applied to labour cost compared to variable cost. The capital stock is a stock, and this is not directly comparable with the two inputs composed of costs. The WR here is scaled to 4 % to be comparable to cost. 4 % is the assumed return on assets by Asmild, Lind & Zobbe (2015) and Asmild (2019). The technicalities of WR are described in section 2.2.2.

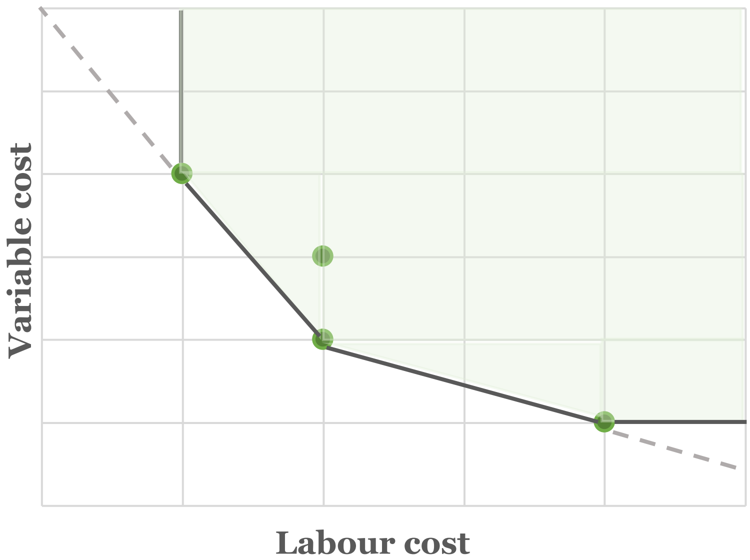

Figure 1.4 Expanded production possibility set with weight restrictions

The mechanics of WR is that PPS is expanded with the given trade-off between the variables. The example in Figure 1.2 has evolved in Figure 1.4 and is now put into the context of this analysis, showing how WR (with minimum half weight and maximum double weight compared to each other) expand PPS in the input space between *Variable cost* and *Labour* cost. We see that the dotted lines have a slope on respectively two and a half as dictated by the WR.

	Efficiency scores
Minimum	0.4329
1st quartile	0.7031
Median	0.8338
Mean	0.8139
3rd quartile	0.9423
Maximum	1.00

Table 1.1 Efficiency scores

The setting of DEA has been described with the inputs and output and the add on of WR, making the model more realistic and it is now possible to calculate efficiency scores. Each farm gets an efficiency score and the 40 efficiency scores from the DEA is summarised in Table 1.1, where we see a variation in the efficiency scores from 0.43 as minimum to 1 as maximum. The efficiency scores are further described in section 2.2.3.

The efficiency scores represent farm performance. It is used to see if there is a relationship between these as an indicator for productivity and the variables representing traits of personality and management and leadership style by the farm owner, and the leadership and management is executed. Some of the variables from the survey can be composed to represent a latent variable, which cannot be measured without this composed structure of various variables. This can give us an insight regarding the farm owner's traits and management style, which were not immediately possible. The method is called Factor Analysis and is explained in the next section.

1.2 Factor Analysis

Factor Analysis is a way to summarise data to get more knowledge than what is immediately possible (Hooper 2012). The method is described in detail and technicalities in section 2.3 where the references are noted as well. Here the overall idea is described to give an understanding of the method. In this analysis the data is clustered into groups with high correlations to explain formative measures, which are latent variables. It is not possible to measure latent variables without the summarized understanding of the variables, which are clustered to represent a latent variable.

Based on the correlations, each variable gets factor loadings for all factors. The factors represent potential latent variables. The factor loadings determine how the variables are grouped. High factor loadings are grouped together as shown in section 2.3.3. An important thing to be aware of when grouping the variables is, that the communality (h^2) should be above 0.2 since this is the part of the variance in the variables that is shared with other variables in the dataset. Further, the variables should not have cross-loadings, meaning that there should not be more than one loading across all factor loadings for a specific variable that is higher the 0.4, since it can be hard to determine to which factor to link the variable then. When being satisfied with the communality values and loadings, it is now possible to construct the factors, each explaining something latent. The factor is made of the factor loadings and the value of the variable as shown here:

$$f_m = a_{1m}x_1 + a_{2m}x_2 + \cdots + a_{Pm}x_P$$

f_m is the factor and $x_1, x_2, \ldots, x_P$is all the variables describing the underlying factor, i.e. the specific value from each farm regarding the specific question in the survey. $a_{1m}, a_{2m}, \ldots, a_{Pm}$ is the factor loadings associated with the variables describing the factor.

As an example, the construct of a factor from this analysis is shown here:

$$f_1 = 0.83 * x_1 + 0.76 * x_2 + 0.74 * x_3 + 0.59 * x_4 + 0.42 * x_5$$

f_1 is the first factor in this analysis and we will come back to the name of this factor. The variables are the following statements from the survey in short titles (the long titles, factors and factor loadings can be found in Appendix 3): x_1 is *Reason for varying economic result*, x_2 is *Financial data is foundation for decisions*, x_3 is *Analyse successfulness*, x_4 is *Compare economic data with earlier years* and x_5 is *Compare budget with initiatives*.

There is no specific method or rules for naming the factors. It is based on experience, knowledge, and previous literature in the field of interest. By looking at the factor loadings showing the importance of a variable for a given factor (higher loading meaning higher importance) and the names of the variables, it should be possible to find similarities and differences leading to a name. The factor in the previous example is named *Financial management and the use of data*.

With Factor Analysis, it is possible to investigate latent variables representing something that was not immediately possible to measure as if it was any other variable with relationships to other variables such as efficiency scores and other variables from a survey as in this analysis.

Description of factors

The factors with the associated variables and the full names of the variables are shown in Table 1.2 and Table 1.3 on the following pages. In the following text, the factors are described to illuminate the meaning of them and how the factor name is connected to the variables. We have nine factors in total and they are split into three groups of variables/factors trying to explain various things about the farm owners and the way they manage a farm and lead people.

The first category is about strategic leadership where the factors are *Financial management and the use of data*, *Strategic and long-term planning*, *Growth orientation*, *Attention trends in society and among consumers* and lastly, *Financial caution*. This category explains decision-making processes, traits in the personality and priorities of the farmer regarding the management of the farm.

Financial management and the use of data captures whether the farm owner use the economic data and experiences on the farm actively in planning the future of the farm. It captures whether the owner is reflective regarding budgeting and finances.

Strategic and long-term planning concerns whether the owner actively focus on strategy and long-term planning and uses strategy and long-term planning as tools in the day-to-day management instead of just getting caught in the immediate challenges.

Growth orientation is about how the owner focus on the growth on the farm, instead of just being satisfied with status quo, and whether the owner believes that growth and specialization is necessary for survival in the long run.

Attention trends in society and among consumers captures how the owner focusses on consumer demand and the trends in society especially regarding environmental conscious and animal welfare, which have been brought more attention to recently.

Financial caution is about how the owner wants to limit the expenses and especially labour cost. One way to do this is by using the family on the farm as much as possible instead of hiring employees.

The next category is personality traits and the owner's perception of agriculture. The factors here are *Attitude towards the future*, *Attitude towards the job* and *Perception of the industry and conditions*.

Attitude towards the future is about how the owner sees the future both regarding his/her own situation as farmer and how the economic results and conditions will be for the Danish agricultural sector in general.

Attitude towards the job captures how the owner works and handles problems, challenges, and opportunities.

Perception of the industry and conditions focusses on how the owner sees him-/herself as a farmer and agriculture as an industry. Further, it is about how the owner thinks other people see this. It is about how he/she finds the job rewarding and whether the industry is profitable and valued. Further, it captures the owner's perception of how policy and political conditions limits the industry as a successful industry, and if it is a determining factor for the performance of his/her farm.

The last category is based on the variables from the survey, which did not fit into factors already described as an attempt to get as much knowledge from the data as possible. The name of this category is miscellaneous and contains the factor *Self-willed*.

Self-willed captures to what extent the owner is self-willed. This covers whether the owner can find it hard to admit that he/she is wrong and finds that the employees are often not good enough for their jobs and the owner must do many things him-/herself. Further, he/she is quite emotional and driven by emotions. He/she find it hard to finish tasks, which can be boring and have difficulties controlling his/her temper when something fails.

Factor	Variables	Factor loading
Financial management and the use of data	I try to find a reason why there is a varying economic result from year to year	0.83
	I use financial data as a foundation for decisions regarding the future	0.76
	When I have implemented a decision, I try to analyse how successful it was	0.74
	I compare economic data with earlier years	0.59
	I compare budget with implemented initiatives and spending	0.42
Strategic and long-term planning	I write down my goals and visions for the future	0.85
	I frequently look at the written plans when I must decide something	0.85
	I have a clear plan for the future of the farm (not necessarily written down)	0.66
	I prioritise to make long term plans instead of just focussing on the challenges on a day-to-day basis	0.57
Growth orientation	A big production size in a good long-term strategy	0.79
	It is a good long-term strategy to become a big and specialised farm	0.67
	Increasing turnover is necessary for success in the long run	0.50
	My farm is bigger and more modern than other farms	0.46
	To keep up with the development in the market faster than others is a good long-term strategy	0.45
Attention to trends in society and among consumers	Environmental conscious breed is a direction that I have chosen	0.66
	To invest in environmentally friendly initiatives or animal welfare is a good investment	0.61
	I am aware of the demand from the consumers	0.52
	My farm shows the way for environmental and animal friendly agriculture	0.51
Financial caution	My farm produces as much as possible with as low expenses as possible	0.71
	I use my own and my family's labour as much as possible	0.54
	I keep my expenses as low as possible	0.48

Table 1.2 Factor descriptions and loadings part 1

Factor	Variables	Factor loading
Attitude towards the future	I expect better living conditions (stable and higher income) for families in agriculture in 10 years	0.93
	I expect better economic results in agriculture in 10 years compared to 2017	0.88
	I expect better economic conditions for agriculture in 10 years	0.69
Attitude towards the job	I confront problems actively	0.86
	When something is not working, I find a solution immediately	0.73
	I often do more than there is expected of me	0.53
	I frequently start new projects	0.42
Perception of the industry and conditions	The economic condition on my farm depends more on agricultural policy than my own decisions	0.66
	It is not rewarding to be a farmer	0.56
	Uncertainties in agricultural policy is a problem for the decision making in the agricultural sector	0.55
	Agriculture is not valued in Denmark	0.45
	Agriculture in Denmark is unprofitable	0.44
	The political conditions are a limiting factor for a successful farm	0.43
Self-willed	I find it hard to admit when I am wrong	0.58
	It is difficult for me to finish work, which do not excite me	0.56
	My employees do often need necessary knowledge and skills to work for me	0.54
	When something goes wrong, I sometimes get infuriated and does not handle the situation in the best way	0.47

Table 1.3 Factor descriptions and loadings part 2

1.3 Effect of personal traits and leadership and management

In this section the purpose is to look for relationships between the starting point of the model *Personal aspects and traits of the farm owner* showed in Figure 1.1 and the two intermediate steps *Decision-making process* and *Leadership style,* to see how the personality of the farm owner potentially affect how the farm owner lead and manages the farm. The data from the survey and the Factor Analysis has been divided into the three parts of the model in Figure 1.1: *Personal aspects and traits of the farm owner, Decision-making process,* and *Leadership style*. The variables from *Personal aspects and traits of the farm owner* joined by the variables *No. of employees and* *hectares* are shown in the columns in Table 1.4, Table 1.5 and Table 1.6 The tables are three parts of the same table. In the rows there are variables from both the categories *Decision-making process* and *Leadership style*.

The correlations are Pearson correlations. The bold correlation coefficients, and the belonging p-values are highlighted if the significance level is 10 % or better. The coefficients close to the 10 % significance boundary (up to 20 %) are highlighted in yellow if the coefficients are discussed as tendencies for a correlation.

Sparring partners

The first five rows in Table 1.4 tells us something about the farm owners' willingness to discuss issues on the farm with other people. We see significant positive correlations between *No. of employees and hectares*, which are indicators of the size of farm, and both *Experience group as sparring partners* (0.44 (0.01), 0.45 (0.00)) and the overall *Values for sparring partners combined* (0.31 (0.05), 0.50 (0.00)). This is an overall summarization of the values of the four variables above the row of the combined variable. Farm owners on bigger farms are also more likely to be talking with advisors and friends about the business compared to farmers on smaller farm, hence the correlations between *No. of hectares* and *Advisors as sparring partners* (0.30 (0.056)) and *Friends as sparring partners* (0.37 (0.02)). There is a tendency towards that the older and more experienced farmers discuss issues on their farm with other people to a lower extent. It is not possible to say whether this is due to the *Age* and *Experience of the farmer* (age and experience are highly correlated (0.77 (0.00)) or if this is a trend from a different time where they were taught about farming and farm management.

It seems like there is a strange trend, since the correlations between *Supplementary training* and the sparring partners variables are negative, and the correlation with the same variables and *Amount of supplementary training* are positive. The variable *Supplementary training* is short for the questions *How long time ago did you attend your most recent supplementary training or conference?* with 1 being most recent and 10 being the furthest away (more than five years ago). With this additional information, it is plausible that the correlation for *Supplementary training* is negative, and the correlation for *Amount of supplementary training* is positive both telling us that if farm owners attend supplementary training, they are more likely to discuss farm issues with others.

Further, we see that farm owners with a negative perception towards the industry is more likely to talk to other people. This can might be an exchange of negative attitude between peers, but we do not know. We also see that farmers with a positive attitude towards the future is less likely to talk to other people about the business on the farm. This might be due to a naïve drive or a secret plan that they do not want to share, but this is just guessing since we do not know the tendencies behind. Lastly, we see that farm owners rating themselves with higher intelligence is more likely to discuss farming with others.

Improvement of management skills

When looking at the variable *Management skills improved in the last five years*, we see a tendency towards that the farmers on bigger farms are more likely to improve their management skills since the correlation between *No. of hectares* and the variable is positive and significant at 10 %.

We see a tendency towards that the older and more experienced farmers get less supplementary training and improve their management skills less, but we cannot say anything about if this is due to a high level of skills or if they just stopped learning and improving. We see that *Amount of supplementary training* have a significant and positive impact on improved management skills. The correlation between *Amount of supplementary training* and respectively age and experience are negative but only at respectively 0.17 and 0.15 significance level, so we cannot conclude anything regarding this relationship.

Further, we see that farm owners rating their intelligence higher is more likely to improve their management skills.

Strategic and long-term planning

For *Strategic and long-term planning,* we see that this is more likely to happen on a bigger farm (*No. of employees*: 0.32 (0.05) and *No. of hectares*: 0.23 (0.13)) where the farmer gets plenty of supplementary training (0.43 (0.01)), have a positive attitude towards both the future (0.32 (0.04)) and the job (0.44 (0.01)) and rate his/her own management skills highly (0.44 (0,00)).

Here we see a surprising correlation with *Experience until 15 years old* (0.29 (0.07)), which is a variable for whether the farm owner thinks that he/she have acquired most of his/her experience in farming before the age of 15. O'leary et al. (2018) find that this is negatively correlated with profitability in Great Britain on the assumption that he/she have almost stopped learning after the age of 15. The assumption here is that strategic and long-term planning is necessary for growth and increasing productivity. This correlation is tending to be contradicting with the conclusion by O'leary et al. (2018). We will look further into the correlation between strategic and long-term planning and productivity in section 1.4.

Growth orientation

For *Growth orientation*, we see almost the same story as for *Strategic and long-term planning*. We see that *Growth orientation* is more likely to happen on a bigger farm (*No. of employees*: 0.56 (0.00) and *No. of hectares*: 0.51 (0.00)) where there is a tendency towards a correlation between *Growth orientation* and *Amount of supplementary training* (0.32 (0.17)). A positive attitude towards the job (0.36 (0.02)) and a high self-rated intelligence (0.33 (0.04)) is also correlated with *Growth orientation*. The causality between *Growth orientation* and size is not clear, and it is not possible to say if it is the size that have made it necessary for the farm owner to focus on growth or if the size have increased with *Growth orientation*.

Attention to trends in society and among consumers

For the factor *Attention to trends in society and among consumers* we see that this tend to be driven by the amount of supplementary training (0.26 (0.11)) and a positive attitude towards the future (0.26 (0.10)) and the job (0.23 (0.16)). Further, we see that self-rated high management skills tend to drive higher *Attention to trends in society and among consumers*.

Financial caution

In regarding to *Financial caution*, we do not find many significant correlations. One is in correlation with *Attitude towards the future* (0.31 (0.05)), which does not tell us much.

Financial management and the use of data

We see based on the correlation between *Financial management and the use of data* that farmers on bigger farms are more likely to use data and manage the finances tight. We cannot say if this is just out of necessity or if this is what have contributed to growth on the farm. Further, we see a correlation between *Financial management and the use of data* and *Amount of supplementary training* (0.33 (0.04)). Here it is also not possible to determine the causality; whether supplementary training made them capable of financial management and use data or if it is out of necessity, that they attend the training. We might see a tendency towards using data if the farm owner has a positive attitude towards the future (0.24 (0.14)). A higher self-rated intelligence (0.25 (0.13)) and management skills (0.33 (0.04)) does also increase the likelihood of using data and managing finances closely.

Supplementary training for employees

As for *Supplementary training for employees*, which is telling us something about how much supplementary training the employees get on average in a year, we see that it is more likely to happen at bigger farms (*No. of employees*: 0.55 (0) and *No. of hectares*: 0.60 (0)). Further, we see that if the farm owner him-/herself is more likely to attend supplementary training, the employees are more likely to get the same opportunity. The variable *Experience until 15 years old* is here associated with less likelihood for the employees to get the opportunity for supplementary training (-0.24 (0.14)). This might indicate that a farmer who thinks he/she has learned most in farming before turning 15 years old, does not think that supplementary training is necessary. Further, if the farm owners have a positive attitude towards his/her job (0.41 (0.01)) and a higher self-rated intelligence (0.26 (0.11)), the employees are more likely to get supplementary training.

Resources for monitoring and management

In general, when looking at the variables for whether the farm owner find it necessary to use computers, software, paper and pen and computers in the machines. We see that farm owners on bigger farms are more likely to use these resources. This is again not telling us anything about whether this is what have made the farm big or if it has been implemented after the farm grew. But we see a significant positive correlation (0.34 (0.03)) between the factor *Growth orientation* and the summarised variable for software and management tools, which can indicate that a personality traits favouring growth leads to more use of resources for monitoring and management. If a farm owner attends supplementary training, he/she is more likely to have these resources on the farm. A positive attitude towards the job and the future increases the likelihood for the farm owner to use resources for monitoring and management. The same tendency is seen for self-rated intelligence (correlated with *Software and management toll summarised*: 0.35 (0.02)) and management skills (correlated with *Software and management toll summarised*: 0.34 (0.03)).

The correlation for *Self-willed* with respectively *Accounting software* (-0.21 (0.19)) and *Management and benchmarking software* (0.40 (0.01)) seems contradicting since accounting is necessary for benchmarking and to be able to improve the performance. It might be a typical character trait for a *Self-willed* farm owner, who can find accounting uninteresting and thereby losing interest in this, while finding ways to improve the farm the benchmarking is something he/she might find interesting.

	No. of employees	No. of hectares	Age	Manage-ment experience in farming	Experi-ence in farming	Supple-mentary training	Amount of supple-mentary training	Experi-ence until 15 years old	Perception of the industry and condi-tions	Attitude towards the future	Attitude towards the job	Intel-ligence	Manage-ment skills	Self-willed
Experience exchange group as sparring partners	**0.44 (0.01)**	**0.45 (0.00)**	-0.01 (0.91)	0.06 (0.73)	-0.16 (0.34)	**-0.4 (0.01)**	**0.43 (0.01)**	-0.18 (0.26)	0.2 (0.22)	**-0.28 (0.08)**	0.17 (0.31)	0.15 (0.37)	0.03 (0.84)	0.19 (0.23)
Family as sparring partners	-0.09 (0.59)	0.21 (0.20)	-0.24 (0.14)	**-0.30 (0.06)**	**-0.35 (0.023)**	**-0.33 (0.04)**	0.14 (0.39)	0.18 (0.26)	0.07 (0.67)	-0.12 (0.44)	**0.24 (0.13)**	**0.31 (0.1)**	0.17 (0.30)	-0.16 (0.32)
Advisors as sparring partners	0.22 (0.17)	**0.30 (0.06)**	0.04 (0.82)	0.05 (0.76)	0.10 (0.55)	-0.19 (0.23)	**0.26 (0.11)**	-0.05 (0.78)	0.16 (0.31)	0.10 (0.56)	0.14 (0.38)	0.10 (0.54)	0.13 (0.43)	-0.17 (0.29)
Friends as sparring partners	0.20 (0.21)	**0.37 (0.02)**	**-0.28 (0.09)**	-0.2 (0.22)	**-0.28 (0.08)**	**-0.25 (0.13)**	0.034 (0.84)	-0.08 (0.61)	**0.27 (0.10)**	**-0.26 (0.10)**	0.10 (0.53)	0.20 (0.21)	-0.08 (0.66)	0.03 (0.85)
Values for sparring partners combined	**0.31 (0.05)**	**0.50 (0.00)**	-0.18 (0.27)	-0.14 (0.41)	**-0.27 (0.09)**	**-0.45 (0.00)**	**0.34 (0.03)**	-0.064 (0.69)	**0.26 (0.11)**	**-0.25 (0.12)**	**0.24 (0.13)**	**0.28 (0.08)**	0.09 (0.60)	0.00 (0.99)
Management skills improved in the last five years	0.12 (0.45)	**0.26 (0.10)**	**-0.46 (0.00)**	**-0.25 (0.11)**	-0.14 (0.40)	-0.18 (0.26)	**0.35 (0.03)**	0.117 (0.47)	**0.27 (0.09)**	0.23 (0.16)	**0.24 (0.13)**	**0.29 (0.08)**	0.19 (0.24)	-0.05 (0.77)

Table 1.4 Pearson correlations between identification, personal traits and aspects and management and leadership traits part 1

	No. of employees	No. of hectares	Age	Management experience in farming	Experience in farming	Supplementary training	Amount of supplementary training	Experience until 15 years old	Perception of the industry and conditions	Attitude towards the future	Attitude towards the job	Intelligence	Management skills	Self-willed
Strategic and long-term planning	**0.32 (0.05)**	0.25 (0.13)	-0.04 (0.82)	-0.01 (0.96)	0.06 (0.70)	-0.12 (0.47)	**0.43 (0.01)**	**0.29 (0.07)**	0.00 (0.98)	**0.34 (0.04)**	**0.44 (0.01)**	0.16 (0.31)	**0.44 (0.00)**	-0.04 (0.81)
Growth orientation	**0.56 (0.00)**	**0.51 (0.00)**	-0.11 (0.52)	-0.07 (0.65)	-0.06 (0.72)	-0.09 (0.59)	0.22 (0.17)	-0.09 (0.57)	-0.05 (0.76)	0.16 (0.32)	**0.36 (0.02)**	**0.33 (0.04)**	0.19 (0.24)	0.24 (0.14)
Attention to trends in society and among consumers	0.20 (0.21)	0.14 (0.40)	0.13 (0.43)	0.19 (0.23)	**0.22 (0.18)**	-0.15 (0.35)	0.26 (0.11)	0.11 (0.52)	-0.06 (0.73)	**0.26 (0.10)**	0.23 (0.16)	-0.03 (0.87)	**0.27 (0.09)**	0.03 (0.85)
Financial caution	-0.07 (0.65)	-0.05 (0.76)	-0.01 (0.97)	-0.00 (0.98)	-0.01 (0.95)	0.14 (0.40)	-0.13 (0.41)	-0.00 (0.98)	-0.17 (0.29)	**0.31 (0.05)**	0.14 (0.40)	0.12 (0.45)	0.21 (0.19)	-0.00 (0.98)
Financial management and the use of data	**0.34 (0.03)**	**0.33 (0.04)**	-0.02 (0.89)	0.04 (0.83)	0.09 (0.57)	-0.2 (0.22)	**0.33 (0.04)**	0.18 (0.27)	0.11 (0.49)	0.24 (0.14)	0.19 (0.25)	0.25 (0.13)	**0.33 (0.04)**	0.03 (0.85)
Supplementary training for employees	**0.55 (0.00)**	**0.60 (0.00)**	-0.01 (0.97)	-0.10 (0.56)	-0.14 (0.38)	**-0.30 (0.06)**	**0.62 (0.00)**	-0.24 (0.14)	0.00 (1.00)	0.08 (0.62)	**0.41 (0.01)**	0.26 (0.11)	0.20 (0.21)	0.02 (0.89)

Table 1.5 Pearson correlations between identification, personal traits and aspects and management and leadership traits part 2

	No. of employees	No. of hectares	Age	Management experience in farming	Experience in farming	Supplementary training	Amount of supplementary training	Experience until 15 years old	Perception of the industry and conditions	Attitude towards the future	Attitude towards the job	Intelligence	Management skills	Self-willed
Computers and general software	0.23 (0.15)	**0.35 (0.03)**	-0.10 (0.54)	0.11 (0.52)	0.03 (0.85)	0.06 (0.71)	**0.30 (0.06)**	-0.02 (0.90)	**0.40 (0.01)**	-0.10 (0.56)	0.15 (0.35)	**0.41 (0.01)**	**0.41 (0.01)**	0.09 (0.58)
Accounting software	0.25 (0.12)	0.29 (0.07)	0.05 (0.76)	0.02 (0.89)	0.18 (0.28)	0.02 (0.88)	0.22 (0.18)	0.12 (0.46)	**0.37 (0.02)**	**0.26 (0.10)**	**0.32 (0.04)**	**0.32 (0.05)**	**0.29 (0.07)**	-0.21 (0.19)
Management and benchmarking software	**0.36 (0.02)**	**0.39 (0.01)**	-0.05 (0.76)	-0.02 (0.89)	0.12 (0.47)	-0.21 (0.19)	**0.45 (0.00)**	0.00 (0.99)	-0.10 (0.52)	0.08 (0.65)	**0.29 (0.07)**	0.24 (0.14)	**0.31 (0.05)**	**0.40 (0.01)**
Computers in agricultural machines	0.24 (0.14)	**0.38 (0.02)**	0.03 (0.83)	0.03 (0.87)	0.11 (0.51)	**-0.28 (0.08)**	**0.32 (0.05)**	0.19 (0.25)	**0.29 (0.07)**	0.13 (0.44)	**0.33 (0.04)**	0.19 (0.23)	0.12 (0.45)	0.18 (0.27)
Paper, pen and calculator	0.24 (0.13)	0.17 (0.30)	-0.05 (0.75)	0.03 (0.85)	0.06 (0.72)	**-0.28 (0.08)**	0.25 (0.12)	**0.33 (0.04)**	0.10 (0.55)	**0.37 (0.02)**	0.12 (0.47)	0.12 (0.46)	0.12 (0.48)	0.09 (0.6)
Software and management tools summarised	**0.38 (0.02)**	**0.46 (0.00)**	-0.03 (0.88)	0.04 (0.79)	0.14 (0.38)	-0.22 (0.18)	**0.44 (0.01)**	0.19 (0.25)	**0.30 (0.06)**	0.22 (0.18)	**0.35 (0.02)**	**0.35 (0.03)**	**0.34 (0.03)**	0.16 (0.32)

Table 1.6 Pearson correlations between identification, personal traits and aspects and management and leadership traits part 3

Additional thoughts

There is a range of correlations between *Perception of the industry and conditions* and various variables that I cannot make sense of, since this is a negative perception which in many cases, based on the correlations should increase likelihood for improving management skills and use additional modern aids and resources. This negative perception might just be a general pessimism among the farm owners. It could make sense to investigate this further as a psychologist or similar.

We have looked a little further into how the size of the farm, hence *No. of employees and hectares*, are correlated with personal traits. Noticeable correlations are that supplementary training (*No. of employees* and *Amount of supplementary training* – 0.32 (0.04) and *No. of hectares* and *Supplementary training* (-0.27 (0.10)) and *Amount of supplementary training* (0.31 (0.05)) is positively correlated with the size of the farm, meaning that owners of big farm attend supplementary training. Further, we see that farm owners of big farm tend to have a higher positive attitude towards the job (*No. of employees* (0.30 (0.06) and *No. of hectares* (0.43 (0.006) with *Attitude towards the job*)). It might be better to have employees and people around to discuss the tough decisions with hence being a positive farmer.

Intermediate conclusion

Farmers owning big farms measured in number of employees and hectares have the possibility to pull away from the production and focus on the overall management of the farm. This is clear from the correlations between *No. of employees and hectares* and various other variables from the survey. They are more likely to discuss business issues with other people and focus on strategic and long-term planning. They are more likely to attend supplementary training and improve their management skills continuously. Where we in general also see a positive correlation between attending supplementary training and improving management skills, these farmers are also more likely to offer supplementary training to their employees.

Farmers owning big farms are more likely to have a positive attitude towards both the future and the job. This might be since he/she is not forced to do everything and make all the hard decisions alone. A big farm and the positive attitude towards the job can also lead to more growth orientation in the farm owners' management style.

It is difficult to say whether it is the financial management and use of data actively that contribute to growing the business or if it has been necessary to focus on this to have an overview of the farm after it grew. Further, the bigger farms are more likely to use resources for monitoring and management and here the causality is not completely clear. But we see a positive correlation between *Growth orientation* and the combined variable *Software and management tools summarized* indicating that having this orientation, which can lead to a big farm in the future, can be supported and helped by using resources for monitoring and management. Farmers are more likely to use these resources if he/she attends supplementary training.

Older and more experienced farmers are less likely to discuss issues on the farm with others and he/she is also less likely to attend supplementary training. We do not see a correlation between age and experience relating to farm size. It is not possible to say if it is less experience or farm size that drive the tendency regarding sparring partners and supplementary training.

Now it will be interesting to see the correlations between the variables and factors from the survey and the efficiency scores as a measure for productivity and see whether we can say anything about the correlation between size and especially other indicators in relation to higher productivity.

1.4 Effect of personal traits and management style on farm performance

In this section we investigate the correlations between variables and factors based on the survey and the efficiency scores from the DEA model. Both the variables regarding identification of the farm, *Personal aspects and traits of the farm owner* and the variables regarding *Decision-making process* and *Leadership style* is linked together with efficiency scores to see if there is a relationship between the variables and efficiency scores.

Since the dataset have only 40 DMUs, where 11 of these are pig breeders and 29 are plant breeders, we do not get many significant correlations. The number of significant correlations would most likely have been higher if the number of DMUs had been higher.

As for the previous section, the correlations are Pearson correlations and the bold correlation coefficients and belonging p-values are highlighted, if the significance level is 10 % or better. The coefficients close to the 10 % significance boundary (up to 20 %) are highlighted with yellow.

Identification and personal aspects and traits of the farm owner

When looking at Table 1.7, we do not see any significant difference between the pig and plant breeders using a Wilcoxon rank sum test where the p-value is 0.726. Meaning that it is not just one breeding type that dominate and form the frontier. It is both pig and plant breeders which is a part of the frontier. Secondly, we see that even though we have VRS in the DEA model, we still see that the number of employees and hectares have a significant positive correlation with efficiency scores. Employees and hectares are not direct inputs in the DEA model and is just a part of the cost, due to salaries and value of capital stock in the inputs. This correlation could make us consider whether pig breeders could use inputs better by having more employees and having a bigger area on the farm, which could be used to e.g., grow fodder and spread manure. Both types of breeding could benefit from hiring more people and invest in more land based in the overall model.

	Efficiency scores	Efficiency scores pig breeders	Efficiency scores plant breeders
No. of employees	**0.33 (0.04)**	**0.73 (0.01)**	0.06 (0.76)
No. of hectares	0.25 (0.13)	**0.59 (0.06)**	0.05 (0.78)
Efficiency scores between pig and plant breeders	p-value: 0.73		

Table 1.7 Correlations between identification variables and efficiency scores

In Table 1.8 the last row show that there is no significant difference between the efficiency scores on farms, which is owned by women compared to men. It is a positive tendency, but we cannot conclude anything since the data basis is quite limited. There were only six female farm owners who answered the survey out of 107. The p-value in the last rows is based on six women against 34 men. This might be a distribution between gender, which is quite close to the reality in Danish agriculture, but this is not looked further into.

When looking at the correlations in Table 1.8, we do not see many significant correlations. Based on this dataset, it is not significantly important to be older or have greater experience in farming to manage a farm well. But we see a tendency towards that supplementary training and more of it, increases productivity – remember that *Supplementary training* is inverse meaning that low values is that the farm owners have attended supplementary training most recent.

Further, we only see a significant correlation between efficiency scores for pig breeders and *Attitude toward the job* and an almost significant correlation between *Self-willed* and efficiency scores when both looking at the factor and the self-rated intelligence and management skills. We find that it is important for pig breeders to have a positive attitude towards being a pig breeder, and it might be necessary to be self-willed to be more productive.

	Efficiency scores	Efficiency scores pig breeders	Efficiency scores plant breeders
Age	0.01 (0.96)	-0.08 (0.82)	0.03 (0.86)
Management experience in farming	0.07 (0.69)	0.20 (0.55)	-0.01 (0.95)
Experience in farming	0.09 (0.58)	0.30 (0.37)	-0.01 (0.97)
Supplementary training	-0.11 (0.50)	**-0.69 (0.02)**	0.05 (0.80)
Amount of supplementary training	**0.39 (0.01)**	**0.95 (0.00)**	0.10 (0.61)
Experience until 15 years old	-0.12 (0.47)	-0.06 (0.86)	-0.15 (0.44)
Perception of the industry and conditions	0.014 (0.93)	0.10 (0.77)	-0.05 (0.78)
Attitude towards the future	-0.01 (0.10)	0.02 (0.96)	-0.04 (0.84)
Attitude towards the job	0.17 (0.30)	**0.58 (0.06)**	0.02 (0.90)
Intelligence	-0.15 (0.36)	-0.03 (0.93)	-0.16 (0.40)
Management skills	0.01 (0.98)	-0.06 (0.86)	-0.01 (0.96)
Self-willed	**0.26 (0.11)**	0.26 (0.45)	0.21 (0.27)
Male/female	p-value: 0.92		p-value: 0.68

Table 1.8 Correlations between variables in the personal aspects and traits of the farm owner category and efficiency scores

Decision-making process

In *Decision-making process* where the variables are shown in Table 1.9, we see that it can be beneficial to discuss business on the farm with other people, and that it is worth the time and money to set up systems and use software in the management of the farm.

For the sparring partners categories, it is highly significant and positive to use advisors to discuss business issues. Further, we find a tendency towards that it is beneficial to use experience exchange group for the same. For the pig breeders, a high combined sum of sparring partners tends to be beneficial for the efficiency score on a farm.

	Efficiency scores	Efficiency scores pig breeders	Efficiency scores plant breeders
Experience exchange group as sparring partners	0.22 (0.17)	0.48 (0.14)	0.12 (0.54)
Family as sparring partners	-0.16 (0.34)	-0.01 (0.97)	-0.21 (0.27)
Advisors as sparring partners	**0.33 (0.04)**	**0.71 (0.01)**	0.13 (0.51)
Friends as sparring partners	0.20 (0.21)	0.334 (0.31)	0.19 (0.32)
Values for sparring partners combined	0.18 (0.28)	0.48 (0.13)	0.03 (0.86)
Financial management and the use of data	0.09 (0.57)	0.38 (0.25)	-0.01 (0.96)
Computers and general software	0.14 (0.38)	0.40 (0.22)	0.08 (0.67)
Accounting software	0.07 (0.68)	0.50 (0.12)	-0.10 (0.62)
Management and benchmarking software	**0.36 (0.02)**	**0.82 (0.00)**	0.24 (0.22)
Computers in agricultural machines	**0.29 (0.07)**	**0.68 (0.02)**	0.13 (0.51)
Paper, pen, and calculator	0.03 (0.87)	-0.02 (0.94)	0.05 (0.79)
Software and management tools summarised	**0.29 (0.07)**	**0.76 (0.01)**	0.13 (0.49)
Analysis of financial results (yes/no)	p-v 0.73	p-v 0.91	p-v 0.47

Table 1.9 Correlations between variables in the decision-making process category and efficiency scores

For software and management tools, a high summarised sum of the values from these variables is significantly positively correlated with high efficiency score, meaning that it is important to have and use software and management tools to improve productivity. For the individual variables, we do not see any significant relationship between *Computers and general software* and *Paper, pen, and calculator*, this might be quite broadly used nowadays. As for *Accounting software* we only see a slight tendency towards a positive correlation for the pig breeders. This might also be quite common to use these days. As for *Management and benchmarking software* and *Computers in agricultural machines* the correlation is highly significant and positive both for the overall efficiency scores, and for the efficiency scores only based on the pig breeders. This means that there is an indicator for an increase in use of these resources increase the productivity.

Leadership style

In Table 1.10 showing the correlations between variables and factors based on the survey about *Leadership style* and efficiency scores, we do only see one significant correlation, where there are seven correlations with a p-value between 10 % and 20 %. Based on these we will conclude on tendencies about the correlations and not the correlations as such.

	Efficiency scores	Efficiency scores pig breeders	Efficiency scores plant breeders
Management skills improved in the last five years	-0.12 (0.47)	**0.43 (0.19)**	**-0.35 (0.06)**
Strategic and long-term planning	**0.24 (0.14)**	**0.49 (0.12)**	0.14 (0.47)
Growth orientation	0.18 (0.27)	0.38 (0.25)	0.04 (0.85)
Attention to trends in society and among consumers	0.11 (0.50)	**0.42 (0.20)**	-0.03 (0.86)
Financial caution	0.06 (0.71)	**-0.42 (0.20)**	**0.23 (0.22)**
Supplementary training for employees	0.09 (0.58)	**0.49 (0.12)**	-0.12 (0.53)

Table 1.10 Correlations between variables in the leadership style category and efficiency scores

For *Management skills improved in the last five years* we see a tendency towards a positive correlation with efficiency scores for the pig breeders and a negative correlation for the plant breeders. It is hard to say what lays behind the difference in the two correlations and it is obvious to investigate the difference in future research. We see the same issue for the factor *Financial caution*. Here it is also obvious to investigate how conditions for production and financial possibilities vary between the two production lines, to see if it really is plausible that one production line should be cautious towards spending money and the other should not.

We see a positive tendency towards that *Strategic and long-term planning* have a positive relationship with higher efficiency scores, indicating that focusing on the long-term can increase productivity. This tendency together with the correlation between *Experience until 15 years old* and *Strategic og long-term planning* being positive, could indicate the opposite than found in

Great Britain by O'leary et al. (2018). There are many unknowns, so we do not conclude anything, but it could be interesting to look further into.

Being focused on trends in society and among consumers might increase efficiency scores and thereby productivity for pig breeders based on the positive tendency in the correlation (0.419 (0.199)).

Lastly, we see that there is a tendency towards that supplementary training for employees might improve productivity in pig breeding, indicating that pig breeders should investigate if their employees get enough supplementary training.

Intercorrelations between Decision-making process and Leadership style

Even though we see *Decision-making process* and *Leadership style* as two intermediate steps to farm performance, they are in practice closely interconnected and to get a better understanding of these two sides of management and leadership, it is worth investigating the intercorrelations between the two.

In Table 1.11 the correlations between variables are presented in the same way as all the way through Part 1. In the columns we have variables regarding *Leadership style* and in the rows, we have variables regarding *Decision-making process*. We see many significant and positive correlations between variables divided into the two parts of leadership and management. The point of this small section is not to go through all the correlations in Table 1.11, it is to illustrate that we see clear connections between the two parts. They support each other and that *Management skills improved in the last five years, Strategic and long-term planning, Growth orientation* and *Supplementary training for employees* are closely correlated to using *Software and management tools together* with doing financial management and use data. We also see that the same variables from *Leadership style* are correlated with some of the variables regarding discussing business issues with others. Overall, these correlations show that various aspects of management and leadership are interconnected. The competences, skills and attitudes affect each other back and forth. It is not possible to only look at it, as if it is inside separate elements. It builds upon each other and creates a synergetic effect.

	Management skills improved in the last five years	Strategic and long-term planning	Growth orientation	Attention to trends in society and among consumers	Financial caution	Supple-mentary training for employees
Experience exchange group as sparring partners	0.05 (0.74)	0.24 (0.14)	**0.34 (0.03)**	0.23 (0.16)	-0.15 (0.35)	**0.57 (0.00)**
Family as sparring partners	**0.29 (0.07)**	0.03 (0.86)	0.09 (0.57)	-0.09 (0.60)	0.06 (0.74)	0.17 (0.29)
Advisors as sparring partners	0.23 (0.16)	**0.38 (0.02)**	**0.35 (0.03)**	0.21 (0.19)	0.10 (0.56)	**0.38 (0.02)**
Friends as sparring partners	0.19 (0.25)	0.15 (0.35)	0.13 (0.42)	-0.07 (0.68)	-0.09 (0.59)	0.12 (0.47)
Values for sparring partners combined	0.26 (0.11)	**0.28 (0.08)**	**0.34 (0.03)**	0.11 (0.49)	-0.06 (0.72)	**0.49 (0.00)**
Computers and general software	**0.29 (0.07)**	0.16 (0.32)	**0.31 (0.05)**	0.09 (0.6)	-0.02 (0.91)	**0.27 (0.09)**
Accounting software	**0.45 (0.00)**	**0.42 (0.01)**	0.25 (0.12)	0.21 (0.19)	-0.04 (0.82)	**0.44 (0.00)**
Management and benchmarking software	**0.30 (0.06)**	**0.38 (0.02)**	**0.29 (0.07)**	**0.28 (0.09)**	-0.25 (0.12)	**0.55 (0.00)**
Computers in agricultural machines	0.24 (0.14)	0.30 (0.06)	0.13 (0.43)	0.07 (0.67)	-0.23 (0.15)	**0.35 (0.03)**
Paper, pen, and calculator	**0.31 (0.06)**	**0.52 (0.00)**	**0.29 (0.07)**	**0.54 (0.00)**	**0.29 (0.07)**	0.16 (0.33)
Software and management tools summarized	**0.44 (0.00)**	**0.51 (0.00)**	**0.34 (0.03)**	**0.32 (0.04)**	-0.09 (0.58)	**0.51 (0.00)**
Financial management and the use of data	**0.40 (0.01)**	**0.61 (0.00)**	**0.36 (0.02)**	0.22 (0.18)	0.16 (0.34)	**0.34 (0.04)**

Table 1.11 Intercorrelations between Decision-making process and Leadership style

Intermediate conclusion

In the correlations where the efficiency score is the main character, we find various useful correlations. It is not significantly better to be older and have more experience in relation to productivity. We see that there is a tendency towards an increase in efficiency score for farm owners frequently attending supplementary training. The same tendency is seen in the correlation between a higher amount of supplementary training and productivity. Further, we see a correlation between using sparring partners and higher productivity. This is especially the case for experience exchange groups and advisors as sparring partners. These trends indicate that it is important to be open towards new knowledge and discussion, about business management with others.

We both see a positive relationship between using *Software and management tools* and a focus on S*trategic and long-term planning* in relation to the productivity, meaning that using available tools both for dealing with issues here and now and in the longer perspective is important for increasing productivity. We do not see any significant relationship between efficiency score and the factor *Financial management of the use of data,* which might indicate, that the use of software and computers in agricultural machines and long-term planning contribute to an overview of the operations and optimization of the operations and not the overall financial management.

Lastly, we find a significant and positive relationship between *No. of employees and hectares*. Since the DEA model is VRS, it is not an expression for economies of scales. It is an expression for that on the specific scale more of the inputs regarding employees and hectares compared to other inputs could be higher. Farmers might put too much trust into capital stock such as buildings and machines instead of e.g., hiring more people and buy more land to produce fodder oneself as an example.

1.5 Overall conclusion and recommendations

The discussion and future implications of this analysis is found after Part 2 on page 65-69.

The conclusion here is based on the assumptions about relationships and causality from Figure 1.1. Here the first step *Personal aspects and traits of the farm owner* determines both how the farmer leads and manages the farm in the two steps: *Decision-making process* and *Leadership style*. They both contribute to the farm performance in either a good or bad way depending on the execution by the farm owner. To conclude upon what gives a high productivity, a range of recommendations is given to both farmers and consultants in this section.

When focussing on the *Decision-making process* as a part of what gives high farm performance, it is important to discuss business issues with other people and use software and various management and operations tools e.g., management and benchmarking software and computers in agricultural machines.

As sparring partners, it is important to use experience exchange groups and advisors from farm associations since both types are professionals, who can give a new perspective on farming as a business. To continue to be motivated regarding sparring partners, it is important to attend supplementary training and conferences, which we can see increase the likelihood of using sparring partners to a greater extent. We further see, that as experience in farming increase, the tendency towards using sparring partners decrease. We do not see a significant relationship between experience as a farmer and productivity. Even though you might be the most experienced in the room, you are most likely able to learn something from the less experienced or someone from "outside" after all.

Focusing on continuing to use software and management tools, it is important to keep updated by attending supplementary training and conferences and keep a positive mindset regarding both the job as a farmer and the future for Danish agriculture. We see a correlation between these personality traits and likelihood of using software and management tools. It might be easier to see possibilities in these tools when being positive and have the most recent knowledge available.

As for *Leadership style* we see a tendency towards that *Strategic and long-term planning* increases productivity. The variables from *Personal aspects and traits of the farm owner,* which contribute to a higher degree of *Strategic and long-term planning* is the *No. of employees and hectares*. It might be easier to focus on the long-term planning if the farm is bigger, and if is possible for the farm owner get further away from the day-to-day operations. Further, it is important to be positive both regarding the job as a farmer and the future of Danish agriculture.

We find a synergetic effect between the variables with *Decision-making process* and *Leadership style,* where we see positive correlations between *Management skills improved in the last five years, Strategic and long-term planning, Growth orientation* and *Supplementary training for employees* (all within *Leadership style)* and *Software and management tools* together with *Financial management and the use of data* and *Sparring partners* (all within *Decision-making process).* All the significant correlation are all positive when investigating the correlation between variables in *Leadership style* with *Decision-making process*. More variables are being affected when one variable increase. Therefore, it is important to focus on how to lead and manage as a farm owner due to the synergetic effect between the variables, where it can easily increase productivity in multiple ways when assessing one part of leadership and management.

In short: To be a better manager and leader, attend supplementary training and remember to continue to do so – no matter age and experience level. Remember to continue to discuss business issues with others, also no matter age and experience. Keep positive regarding both the job as a farmer and the future of farming. If you start to get negative about your job or Danish agriculture in general, find a way to be able to hire people or restructure the production to make it more bearable to do the job as a farm manager. The rest will come with an open mind, and it is important to act in agreement with what is described in this conclusion and not just talk or think about it.

Part 2 **Technical issues and methodology**

In this second part all the technicalities regarding the analysis are presented. This part covers information about how data have been collected and how it has been accumulated. Further, the theory and technicalities regarding Data Envelopment Analysis and Factor Analysis are described. The results from the Data Envelopment Analysis and Factor Analysis are also described here. They are applied in Part 1.

2.1 Data

The survey from the project preparing for this thesis was sent to all members of Patriotisk Selskab (approximately 800 farmers) within the first months of 2020. This led to 107 answers, where 42 farms were left for further investigation due to data limitations. 27 are conventional plant breeders. 2 are organic plant breeders. 11 are pig breeders. One is a poultry breeder, and one is a cattle breeder. 40 farms are left for the productivity analysis, since the poultry and pig breeder are excluded, since they are the only one in their category of production.

The general trends in the answers to the survey found with the Factor Analysis will be investigated based on all the 107 answers. When the findings within the answers are linked with the economic data from the specific farms with a correlation analysis. The analysis is conducted on the 40 plant and pig breeders we base the economic analysis on.

The economic data is based on tax reports, annual reports, and business analyses from Patriotisk Selskab. They are not always directly comparable due to different divisions of the economics, but on this aggregated level, it is reasonably comparable.

The business analysis is a tool that has been developed over many years by Patriotisk Selskab. It is the base for the benchmarking Patriotisk Selskab uses in their consultant work. The data is from 2015 to 2019. For some farms it has not been possible to get data from all years. This is due to e.g., change of owner or changes to membership to Patriotisk Selskab within the period. As many years as possible have been included in the data for each farm. An average of the included years from each farm is the basis of this analysis.

The average across years is necessary when considering weather changes, varying prices, and crop rotations. The changes in prices of crops and animals can affect the revenue greatly. Lastly, the crops on farmer's land rotate so that the nutritive content is suitable for the preferred crops. This means that some years the land is used for less profitable crops than other years. The average is then most representative since the yearly fluctuations both down and ups are balanced.

Farm type:

The farm type is defined by the farmer in the survey, where they had to state their primary type of production. Several of them are not completely specialised and they may both have animal and plant breeding. This specialisation may also have changed over the period of investigation. But the type of production is stated by the farmer when answering the survey in the beginning of 2020, so this indicates what the farmer identifies him-/herself and the farm as.

The type of breed in this analysis is conventional plant breeders, organic plant breeders, pig breeders, poultry breeders and cattle breeders.

Revenue:

The revenue from the agricultural production.

Direct costs:

Direct costs are the cost, which is directly tied to the production of agricultural products e.g., plant protection measures, fertilizers, seeds, and fodder.

Indirect costs:

Indirect costs are maintenance and operational costs of machines and buildings such as energy, minor acquisitions, and other expenses. Expenses for using agricultural machinery centre and insurance. Tax for buildings and labour costs are excluded here since this is captured.

Agricultural machinery centre etc.:

These are the costs of using the service from an agricultural machinery centre and freight service etc. These are tasks that could be completed by own employees if the farm had the manpower and machines to do so. There is a trade-off between internal and external services here. It is often used when the usual staff must be supplement with more labour and machines are needed especially in the harvest period for plant breeding.

Based on annual reports from 2019 from 10 randomly selected agricultural machinery centres based on Zealand, Fyn, and the southern half of Jutland, it is estimated that approx. 50 % of the costs on agricultural machinery centres is labour costs. See an overview of a summary of the annual reports and proportions of labour cost in Appendix 1. Costs regarding financing is considered. This considered, half of these expenses to agricultural machinery centre etc. is considered staff costs and the other half is considered as indirect costs since this is an opportunity cost to not having the staff and machinery in house. Even though it might not be possible for all farmers to buy or lend money to all the needed machinery and hire all the necessary staff, the assumption about the substitution effect between the internal and external services is needed to keep the model simple.

Labour costs:

Labour costs is the costs of having people employed at the farm. Here it is summarised for all employees. If there are employees where the farmer gets financial support for having hired them, then this income is simply just subtracted from the total labour costs. The salary of the farm owner is not included here.

Lease of land:

The lease of land can both be positive and negative. It has only been possible to get the summarised specification, where there is both land that the farmer lease from others and land which the farmer leases to others is summarised. If the summarised lease of land is negative, it is an input i.e., a cost, meaning that the farmer leases land from others. If it is positive, it is an output i.e., earnings, meaning that the farmers leases land to others and has an income from this.

Other earnings:

Other earnings are earnings from other production lines than the primary ones. It can be earnings from renting out houses, earnings from having a piece of land for hunting or something so far away from farming as earnings from having windmill operations.

Disconnected EU subsidies:

Where the disconnected EU subsidies is stated in the economic data, it is stated in this category. This is considered as revenue from the farm and is therefore output in the DEA model. This will be further described later in this thesis.

Assets:

The combined value of assets is included as an expression for the capital stock and the size of the farm.

Income from other work:

The income from work away from the farm is included to be able to assess whether the farmer has a job outside the work on the farm. Further, whether this is a part time job as a supplement for the income on the farm or if it is a full-time job and the work on the farm is a secondary occupation.

Estimated payment for the farm owner’s work:

The payment, which the farmer gets from the farm is largely dependent on the result and can vary greatly. It is often not directly related to the value of work, which the farmer puts into the farm. If the farmer did not do the job him-/herself, it would be necessary to hire an operations manager. The assumption here is that the opportunity cost of a farmer’s work is the price of hiring an operations manager. This is how Patriotisk Selskab estimate payment to the farm owner (Lilaa, 2021). The hourly wage is 250 DKK in a full-time position, which is 1924 hours a year. Based on this, the estimated yearly wage to the farm owner is 481 000 DKK.

This is applied under a few conditions. The total labour cost should be lower than 481 000 DKK. Based on the assumption that if the labour cost is lower than the price for an operations manager, then there is no employee to do that job and the job of an owner/operations manager is done by the owner.

Another condition for applying the estimated 481 000 DKK in payment to the farm owner is, that the owner’s income from work outside the farm should be lower than 150 000 DKK. If so, he only works part time outside the farm, and he/she has the time available to do work as manager on the farm. Here is the assumption that he does an owner/operations manager full time, and the secondary occupation is a “spare time” job. If the owner’s income from work outside the farm is lower than 150 000 DKK, the full 481 000 DKK is the cost of the owner’s work on the farm.

It is just one of the two above mentioned conditions that should be fulfilled for the wages of 481 000 DKK to the farm owner to be applied.

This is calculated for each of the available years for every farm since the work situation on the farm and for the farm owner can change from year to year. These estimations are averaged on the available years as it is the case for all the other economic data as well.

2.2 Data Envelopment Analysis

To be able to investigate the relationship between the productivity based on economic data and personal traits and view on and use of strategic leadership based on the survey various methodologies have been used in the project. These methods are Data Envelopment Analysis (DEA) and Factor Analysis. Both Exploratory Factor Analysis and DEA will be presented based on theory, and how it is applied in this project. Firstly, the focus will be on DEA.

As already stated, the focus in this thesis is primarily on both the conventional and organic plant breeders together with the pig breeders. All these farmers are combined in a common benchmarking model DEA. The model assumes variable returns to scale (VRS) since the assumption in agriculture is that the returns vary across scale. VRS is further described on page 46. This makes it possible to combine plant and pig breeders in one DEA model because they are placed in different areas of the production possibility set (PPS). The groups do not have a significant impact on each other's efficiency scores determined by a Wilcoxon rank sum test in section 2.2.3, so they can easily be combined into a combined model.

2.2.1 The benchmarking model

DEA let us examine the efficiency of the farms. Here meaning how well the farm turns the input into output. The efficiency is determined by comparison to other similar farms. To be able to determine the efficiency, it is necessary to group the inputs and outputs. In the following model there is three inputs and one output, which is the base for DEA in this analysis.

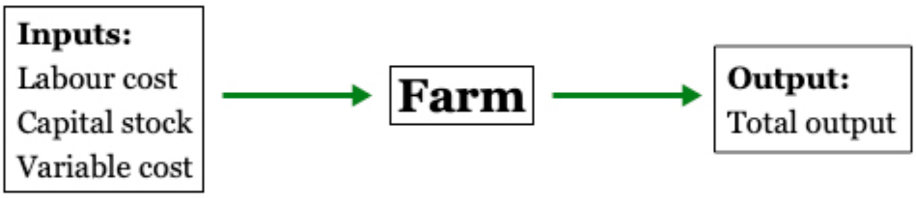

Figure 2.1 The benchmarking model

Inputs

Labour cost – This is composed of 50 % of agricultural machinery centre etc. as described on page 41. Labour costs from the economic data described on page 42 and estimated payment for the farm owner's work as described on page 43.

It has been necessary to group labour cost by itself, since there is a trade-off between the farmer owner's own time spend on the farm and the cost of the labour hired to do the job that the owner should have been doing. To know more about the underlying assumptions within the variable within the input Labour cost, see section 2.1.

Capital stock – This is the composed value of assets described on page 43. This input is a term for the farm size and the machinery, which is available for making input into output. The assumption here is that with a bigger capital stock, it is easier and thereby also cheaper to transform input to output. It is therefore necessary to take the capital stock into account as well.

Variable cost – This is composed of direct costs and indirect costs as described on page 41. Further, it contains lease of land as described on page 42 and 50 % of the cost of using agricultural machinery centre etc. described on page 41.

This is all the inputs/costs on a farm which is not directly linked to labour and capital to be able to capture the rest of the inputs on a farm. Here we also have half of the cost of using agricultural machinery centre etc. under the assumption that most of the cost on such a centre is for maintenance, fuel (50 % combined) and labour (50 %).

This might not be completely true and some of the expenses on an agricultural machinery centre is also financing and should therefore be included in capital stock as the value of the capital stock and not the expenses to having it financed. A more thorough distinction between the elements within the cost of using agricultural machinery centre etc. for further division of the cost between the input categories is out of scope of this project. Even though it could be interesting to look further into.

Output

Total output – This is composed of revenue directly from the economic data as described on page 41, leasing of land to others as described on page 42, disconnected EU subsidies also described on page 42 and other earnings described on page 42 as well.

In this analysis we are not interested in the composition of output just the size of it, and therefore it is just summarised and used as a combined output.

2.2.2 Theory of Data Envelopment Analysis

Shortly defined by Bogetoft & Otto (2011), Data Envelopment Analysis (DEA) is a mathematical programming method which estimate a best practice production frontier and evaluates the efficiency for different decision-making units (DMUs) relative to the estimated frontier. DMUs are entities which transform inputs into outputs. In this case the DMUs are farms.

Assumptions:

- *Observed DMUs are possible* (Thanasoulis 2011)

This means that both all DMUs have a production which is possible. For the application of DEA in this case, it means that there is no noise and outliers to consider and that all the points in Figure 2.2 are included in the analysis. Figure 2.2 show the assumptions described here and how DEA works graphically.

- *Free disposability of input and output* (Bogetoft & Otto 2011)

This means that DMUs can increase the level of inputs and outputs. Inefficient DMUs can produce less output with the same amount input. This assumption partly creates the production possibility set as shown in Figure 2.2 by the solid line forming an almost staircase shape. Every point below this line is inefficient and a possible production.

- *Convexity* (Bogetoft & Otto 2011):

Convexity is a fundamental assumption in DEA. Convexity means, that any combination of the observed DMUs is feasible. This extends the production possibility set, since all points between efficient DMUs are also with in the production possibility set. This is shown in Figure 2.2 by the potted lines between the efficient DMUs on the production possibility frontier.

- *The production possibility set is the smallest set*, which ensures that the above-mentioned assumptions are fulfilled and containing all DMUs (Thanasoulis 2001). The efficient DMUs form the frontier of the production possibility set.

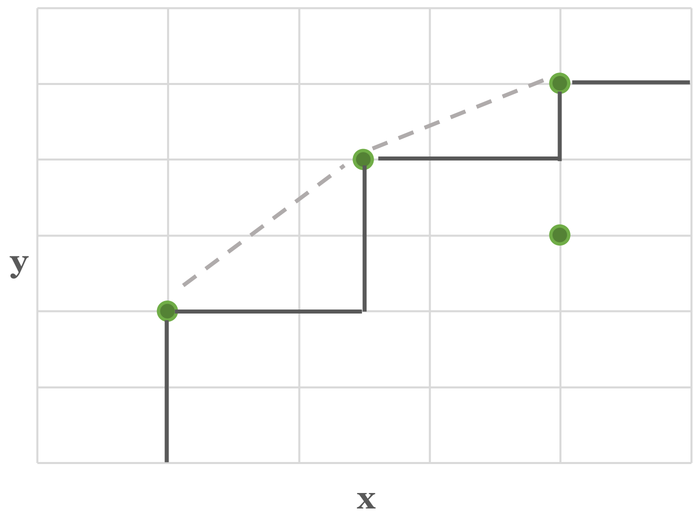

Figure 2.2 Free disposability and convexity

The model in this thesis is an input orientated model with variable returns to scale (VRS). This means that farms minimize the inputs (costs) given a fixed output (revenue). The return varies across scale since one big assumption about farming is economies of scale. Further the model includes both pig and plant breeders in the same model.

These two types have different relations between the inputs and output, so to be able to limit the impact on each other's efficiency scores between these two groups, it is necessary to use VRS.

The multiplier and envelopment scape – mathematically

In this section the combined model is expressed mathematically as a LP problem with inspiration from Bogetoft & Otto (2011). This is showing the primal minimization problem in envelopment space and the dual maximization problem in multiplier space. These two problems lead to the same result (Bogetoft & Otto 2011).

Envelopment space

Generally, the primal formulation in the envelopment space is most widely used in the literature (Bogetoft & Otto 2011).

Input orientated VRS DEA model

- Consider K observed farms (DMU's), k=1, ... ,40.
- x_i^k is amount of input i (Labour cost, Capital stock, Variable cost) which is used by farm k to produce y_j^k (total output).
- λ^k is the convex weights of the efficient DMUs, which is used in the convex combination, where each farm is projected on the frontier of the production possibility set.
- x^0 and y^0 is input and output vector of the specific DMU, which is under observation.

$$Eff\ (x^0, y^0) = \theta^{0*} = \ Min\ \theta$$

Subject to

$$\sum\nolimits_{k=1}^{K} \lambda^k x_i^k \leq \theta x_i^0, i = Labour\ cost, Capital\ stock, Variable\ cost$$

$$\sum\nolimits_{k=1}^{K} \lambda^k y_j^k \leq y_j^0, j = Total\ output$$

$$\sum \lambda^k = 1, k = 1, \dots, 40$$

θ is the efficiency score for DMU°. The interpretation of θ is that it is the percentage of DMU°'s inputs that is necessary to produce the current output of the DMU. An efficiency score at 0.75 means that a farm should only use 75 % of each input to produce its current amount of output to be efficient.

Multiplier space

The dual formulation to the primal formulation in the envelopment space is presented in the multiplier space. This dual formulation is like a pricing problem, where the weights work instead of prices, which we do not know. The weights become priorities of each variable instead of prices (Bogetoft & Otto 2011). In the multiplier space, the idea is to maximize the benefit and cost ratio as if it is a cost-benefit analysis, here being the input and output ratio (Bogetoft & Otto 2011). The maximizing of the production ratio is subject to the condition that no DMU have a ratio higher than one with the set weights. The focus is here on determining the appropriate weights to the inputs and output to get the best possible efficiency score.

- The model includes i inputs, i=1, ..., 3, and j outputs, j=1.
- u_i^k is the weights for input i belonging to DMU k.
- $u_i x_i^k$ is the virtuals for input i belonging to DMU k. Virtuals being the product of the level of the specific input and the belonging weight.
- v_j^k is the weights for output j belonging to DMU k.
- $v_j y_j^k$ is the virtuals for output j belonging to DMU k.

$$Max\ \frac{\sum_{j=1}^{J} v_j y_j^0 + \varepsilon}{\sum_{i=1}^{I} u_i x_i^0}$$

Subject to

$$\frac{\sum_{j=1}^{J} v_j y_j^{\mathrm{k}} + \varepsilon}{\sum_{i=1}^{I} u_i x_i^{\mathrm{k}}} \leq 1\ for\ all\ k = 1, \dots, 40$$

$$u_i^k, v_j^k \geq 0$$

$$u_1, u_2, u_3, v_1 \geq 0$$

ε relates to the scale properties and is the cost of only having convex combinations available. It would be zero, if the scale would have been constant (Bogetoft & Otto 2011).

The dual formulation can be rewritten as:

$$\theta^* = \max \sum\nolimits_{j=1}^{J} v_j y_j^k + \varepsilon$$

Subject to

$$\sum\nolimits_{j=1}^{I} v_j y_j^k + \varepsilon - \sum\nolimits_{j=1}^{I} u_i x_i^k \leq 0\ for\ all\ k = 1, \dots, 40$$

$$\sum_{j=1}^{I} u_i x_i^0 = 1$$

$$u_1, u_2, u_3, v_1 \geq 0$$

Weight restrictions

As explained in the section about multiplier space, the setup in the DEA model is to put weights on the inputs and outputs, so that each DMU maximizes the efficiency score meaning that the weights on the various inputs and outputs can vary greatly between DMUs. In this project the data is based on economic data which is all stated in Danish kroner (DKK). The underlying assumption for the efficiency measured when measuring all in the same unit (DKK) is that the DMUs weigh their inputs and outputs equally. This is the same setting and assumption with the same unit as DKK for all variables presented in Aigner & Asmild (2021) where they applied weight restrictions (WR) so that the inputs and outputs could only weigh the double and half compared to each other. These WR are also applied here just with a twist. Since one of the inputs are capital stock and not costs, this input is not directly comparable to the other inputs and the WR between this input and the other must be scaled. Both in Asmild, Lind & Zobbe (2015) and Asmild (2019) they use 4 % return on assets as capital cost, which is comparable to the two other inputs being labour cost and variable cost. This gives us the following relative WR between the three inputs:

$$0.5 < \frac{u_{Labour\ cost}}{u_{Variable\ cost}} < 2$$

$$0.5 * 0.04 < \frac{u_{Labour\ cost}}{u_{Capital\ stock}} < 2 * 0.04$$

$$\Updownarrow$$

$$0.02 < \frac{u_{Labour\ cost}}{u_{Capital\ stock}} < 0.08$$

To implement these into the DEA model, the weight restrictions are presented in the multiplier space as conditions so that the DMUs are limited under these conditions when choosing the optimal weights:

$$\theta^* = \max \sum_{j=1}^{J} v_j y_j^k + \varepsilon$$

Subject to

$$\sum_{j=1}^{J} v_j y_j^k + \varepsilon - \sum_{i=1}^{I} u_i x_i^k \leq 0 \; for\ all\ k = 1, \ldots, 40$$

$$\sum_{i=1}^{I} u_i x_i^0 = 1$$

$$0.5u_{Variable\ cost} - u_{Labour\ cost} < 0$$

$$-2u_{Variable\ cost} + u_{Labour\ cost} < 0$$

$$0.02u_{Capital\ stock} - u_{Labour\ cost} < 0$$

$$-0.08u_{Capital\ stock} + u_{Labour\ cost} < 0$$

$$u_1, u_2, u_3, v_1 \geq 0$$

2.2.3 Results of Data Envelopment Analysis

The result of the DEA is the efficiency score for each farm. A summary of the efficiency scores is found in Table 2.1. Here the minimum efficiency scores are shown together with the 1st quartile, median, mean, 3rd quartile, maximum and number of NA's. The number of NA's and the background of this will not be described any further since it is not relevant for the following analysis. There is summary of efficiency scores for DEA models both with and without WR. Where we see a wider spread in the efficiency scores for the DEA models with WR. DEA is both conducted in two separate models - one for pig breeders and one for plant breeders and in one where both the pig and plant breeders are compared to each other. To be able to compare the separate frontiers, where pig breeders are compared to pig breeders and plant breeders are compared to plant breeders, with a common frontier, the efficiency scores from the two separate models are combined in the first and third column. In the second and fourth column efficiency scores from all farms with a common frontier are shown. When comparing the efficiency scores in the separate models and the common model, the 1st quartile, median and mean are all lower in the common model both with and without WR. The summary of the efficiency scores will always show lower numbers when introducing more DMUs and WR to a model.

The p-value at 0.3138 from a Wilcoxon rank sum test show that the differences are not significant between the two model types with WR, as already stated in the introduction to section 2.2.

We continue the analysis with the common frontier with WR, since WR is most practical and realistic as stated in section 2.2.2 about weight restrictions. Further, we continue with the common frontier since the efficiency scores are not significantly different from the separate frontiers meaning that efficiency scores are not noticeably influenced by the other type of breeding. The application of the efficiency scores can be found in Part 1.

	Separate frontiers without WR	Common frontier without WR	Separate frontiers with WR	Common frontier with WR
Minimum	0.4947	0.4947	0.4329	0.4329
1st quartile	0.8720	0.8113	0.7249	0.7031
Median	0.9738	0.9165	0.8681	0.8338
Mean	0.9120	0.8840	0.8442	0.8146
3rd quartile	1.00	1.00	1.00	0.9423
Maximum	1.00	1.00	1.00	1.00
No. of NA's	-	-	1	-
			Wilcoxon rank sum test: p-value = 0.3138	

Table 2.1 Efficiency scores

2.3 Exploratory Factor Analysis

Factor Analysis is generally used to summarize data to better understand patterns within a dataset by examining intercorrelations between specific items within the dataset (Hooper 2012). This method clusters items/variables with high correlation into groups (Yong & Pearce 2013). The groups represent latent variables such as personal traits or concepts describing attitudes, which cannot be measured. Figure 2.3 shows two different types of latent variables described by Schwartz & Ash (2008). In combination a group of items in a dataset can either represent a reflective measure or form a formative measure. A reflective measure exists without the items as indicators. A farmer's ability of farm management exists both with and without indicators to make ability measurable. Therefore, ability of farm management is a reflective measure.

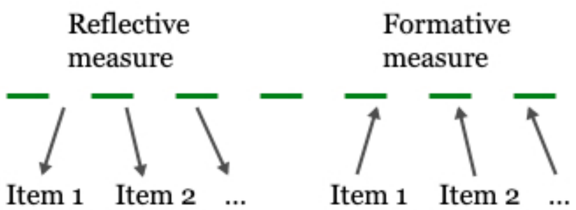

Figure 2.3 Reflective and formative measure

Contrary, a formative measure is composed of specific items and does not exist as a concept without the indicators. These are concepts such as socio-economic status, which is measured by education level, income, type of occupation and where a person resides (Schwartz and Ash 2008).

The analysis in this project will focus on reflective measures. The Factor Analysis is a method to get the weights between the variables when representing the latent construct.

Exploratory Factor Analysis is used to explore a dataset by investigating the nature of it (Yong and Pearce 2013). The method is typically used to make new scales and metrics. With Exploratory Factor Analysis, it is possible to find the best grouping of variables by analysing which variables correlate based on factor loading, communalities and Cronbach's alpha (Schwartz and Ash 2008).

Theory of Factor Analysis

To better understand the dynamics behind the model of Factor Analysis, the focus is here on the mathematical approach towards Factor Analysis inspired by Yong & Pearce (2013).

The starting point is a certain number of variables (x_1, x_2, ..., x_P) and a certain number of underlying factors (f_1, f_2, ..., f_M). x_p denotes the variables in the underlying factors. The relationship between the variables and factors are represented by a linear relationship, which is a fundamental assumption to this method:

$$x_p = a_{p1}f_1 + a_{p2}f_2 + \cdots + a_{pM} + e_p$$

The factor loadings for each variable are represented by $a_{p1}, a_{p2}, \ldots, a_{pM}$. e_p is the error term in the linear regression. The factor loadings determine how important a variable is to the specific latent factor. Higher loading means more importance to the factor. These factor loadings are basically the weights in a basic regression, and they show the strength of the correlation between variable and underlying factor. All the correlation coefficients in the function above is determined using matrix algebra for all variables and possible factors. In general, a Factor Analysis is computed using a correlation matrix with correlations between all variables. In the matrix all the diagonal is 1 since it is the correlation within itself. In Factor Analysis, the diagonal elements are replaced with the communality estimates (h^2), which is the estimated proportion of variance in a variable which is free from error variance. It is the shared variance with the other variables in the analysis. h^2 is the summation of the squared correlations of a specific variable with all factors. It is given by the following equation:

$$h_p^2 = a_{p1}^2 + a_{p2}^2 + \cdots + a_{pM}$$

A general rule is that the variables with low communalities are excluded from the analysis. The limit is 0.2 since this means that 80 % of the variance in a variable is unique and this does not fit with the purpose of Factor Analysis, which is to explain variance through common latent factors.

The fundamental idea of Factor Analysis is shown in this equation:

$$R_{m\times m} - U^2_{m\times m} = F_{m\times p}$$

$R_{m\times m}$ is the correlation matrix and $U^2_{m\times m}$ is the diagonal matrix of unique variance for each variable. Subtracting the unique variance from the correlation matrix leaves the common factor loadings represented by $F_{m\times p}$. The common factor loadings are found by determining the eigenvalues. The equation from above describes which variable is a combination of which factors.

2.3.1 Requirements of Factor Analysis

Generally, it is necessary to have univariate and multivariate normality within the data to perform a Factor Analysis (Yong & Pearce 2013). This is not the case for the data subject for this analysis since the variables are measured on a Likert scale with 5 points. Hooper (2012) states that this is usually not disastrous. There are several choices for factor extraction and by using the Principal Axis Factor method (PA), we can use data, which does not fulfil the multivariate normality assumption (Yong & Pearce 2013). The idea behind PA is that all variables belong to the first factor and during the extraction of this factor, a matrix of residuals is calculated as well. Factors are extracted until the variance in the correlation matrix is large enough.

There are various opinions about the minimum size of datasets suitable for Factor Analysis (Yong & Pearce 2013; Hooper 2012). According to both Yong & Pearce (2013) and Hooper (2012) the suggested size is at least 300 observation and the more the better since this diminish the error in the analysis. As few as 100 observations can be enough if the number of variables is limited (Hooper). Yong & Pearce (2013) suggest at least 5 to 10 observations for each variable.

Since this study is explorative and investigating a new topic at least in a Danish context, it has not been possible to limit the number of variables enough. It should be limited to between 10 to 20 variables to be sufficient with 107 observations which is the data size in the Factor Analysis here. It has been necessary to ask various questions to find trends and a starting point for a Factor Analysis regarding viewpoints among Danish farm owners regarding leadership and strategic management. The survey was split into various topics in the design, so it has been possible to divide the variables into various groups based on the topics from the survey on which the Factor Analysis was performed to decrease the number of variables in consideration to a level closer to the desired level between 10 to 20 variables.

In the end all the factors created from the survey were combined to check, if the division held across all, and this did not show big changes, so the factors were carried onto further analysis. With small samples the correlations are less reliable (Hooper 2012), and this was clear in the Factor

Analysis since many correlations were not sufficient to be included in the analysis and many variables were excluded in the Factor Analysis.

2.3.2 Steps in the Factor Analysis

As already described, a central element in Factor Analysis is correlations. One of the first assessments to make before doing a Factor Analysis is checking whether there is a base for doing a Factor Analysis. To do this, the correlation matrix for all variables is investigated to see whether there are correlations bigger than 0.3 since this suggests sufficient relationship between the variables (Yong & Pearce 2013). This should not be the case for all correlations, but a fair amount of them should be bigger than 0.3.

Next up is to check the factorability with the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and the Bartlett's Test of Sphericity (Hooper 2012). KMO is described by Kaiser & Rice (1974). It assesses whether the correlation matrix is suited for Factor Analysis and whether the variables are connected in a psychometrically matter (Dziuban & Shirkey 1974). KMO takes on a value between 0 and 1. The following division show how the factorability is based on KMO:

In the 0.90s	marvellous
In the 0.80s	meritorious
In the 0.70s	middling
In the 0.60s	mediocre
In the 0.50s	miserable
Below 0.50s	unacceptable

Kaiser & Rice (1974) states further that 0.50 is the borderline for acceptability.

The Bartlett's Test of Sphericity is computed by this formula (Dziuban & Shirkey 1974):

$$-[(N-1)\frac{1}{6}(2P+5)Log_e|R|$$

Where N is the sample size, P is the number of variables and $|R|$ is the determinant of the correlation matrix. The test compares the determinant of the correlation matrix to the determinant of an identity matrix (Zygmont & Smith 2014), which is a matrix where all the off-diagonal elements are zero. Hence, the variables are correlated, and it is appropriate to use Factor Analysis. The null hypothesis is that the two matrices are the same so rejecting the null hypothesis (low p-value) means that they are different from each other (Zygmont & Smith 2014). Having checked for factorability, it is now time to start the Factor Analysis.

The next step is to determine the number of factors to extract (Hooper 2012). It is important to find the correct number of factors to extract. Too many factors can lead to too much error variance present and too few might leave out some of the common variance (Yong and Pearce 2013). The purpose of the Factor Analysis is to capture the common variance. Here it is necessary to use an exploratory approach. Again, it is necessary to take multiple things into account. In 1960 when Kaiser introduced the electronic computers to Factor Analysis, he presented the criterion that the eigenvalue for a factor should be greater than one when including another factor in a Factor Analysis. Yong & Pearce (2013) state that it has been argued that Kaiser's criterion can lead to overestimation in number of factors. Another application of eigenvalues in determining the number of factors is the Scree plot presented by Cattell as shown in Figure 2.4 (Hooper 2012). In the scree plot the x-axis represent the number of factors and the y-axis represent the eigenvalue. The point of inflexion, an obvious break in the line also known as the elbow, determines the number of factors. Here it is the number of factors above the point of inflexion that should be included in the analysis.

Figure 2.4 Example of Scree plot

Lastly, the level of cumulative variance among all factors should be investigated. Hooper (2012) state that 60 % of cumulative variance is commonly accepted in social sciences. It is a balance between these three criteria; Kaiser's criterion, point of inflexion on the Scree plot and minimum 60 % of cumulative variance together with empirical knowledge in the field being investigated.

Third step is to create the factors. Generally, there should be at least three variables to construct a factor (Yong & Pearce 2013). If the correlation between the variables is higher than 0.7, it might be plausible for empirical reasons to combine the two variables to one factor (Yong & Pearce 2013). A critical assumption is that variables should be unidimensional, meaning that it should only load on one factor (Hooper 2012). If the variables have cross-loadings, they are not unidimensional. A cross-loading is if variable have loadings higher than 0.4 for multiple factors (Hooper 2012). These are excluded from the Factor Analysis. Further, another criterion for exclusion of variables is when the communality h^2 is below 0.2 meaning that less than the variance within a variable is common with the other variables. This is already explained on page 17.

To be able to interpret the factors, it is important to do factor rotation (Yong & Pearce 2013). The goal of factor rotation is to get a simple but optimal structure by having each variable load on as few factors as possible and at the same time maximize the number of high loadings from each variable.

There are two types of rotation: orthogonal and oblique (Yong & Pearce 2013). Oblique rotation is more complex than the orthogonal rotation. Oblique rotation will not be described further since the orthogonal rotation is the method which will be used in this analysis. The orthogonal rotation is described by Yong & Pearce (2013) as when the factors are rotated 90 degrees from each other and that the factor are uncorrelated. This causes clearer differentiation between factor loadings and makes them easier to interpret. Within the category of orthogonal rotation, there are several techniques to use. Varimax is the most common technique since it minimizes the number of variables with the extremely high loadings and makes small factor loadings even smaller (Yong & Pearce 2013). It makes it easier to identify factors. A more thorough description of factor rotation is out of scope of this thesis.

To find the final number of factors, the final variables to include in the analysis and factor loadings from the variables, it might be necessary to go back and forth between step two and three until the final set of variables and factors with factor loadings can be named and used for further analysis. Just before beginning the last step of the analysis, it is important to test for reliability of the factors meaning how much random error is found (Hooper 2012). Reliability is measured by Cronbach's alpha which is a measure of internal consistency (Drost 2011). It ranges from 0 to 1. Higher value indicates a higher level of consistency/reliability. Hooper (2012) suggests a lower limit of alpha values at 0.7 to ensure a satisfying level of reliability. The length of the scale increases the alpha value (Drost 2011). Since the scales in this Factor Analysis a 5-item test, the alpha values are lower than e.g., a 7-item test (Drost 2011). So, it is important to also take the factor loadings into account as well (Hooper 2012).

The last step is naming and constructing the factors. This is described by Hooper (2012) as "black art" with no specific rules. Here it is important to look at the specific factor loadings and the variables within a factor to determine what the latent factor is based on. The variables with the highest factor loadings should be most determining for the name of the latent factor. Here it is also important to apply the empirical knowledge and previous findings within the field of investigation.

Now we move on to construct the factors. If any of the factor loadings are negative, it is important to invert them (Hooper 2012). This makes the factor loadings positive and gives the correct effect to the factor. The factor is made of the factor loadings and the value of the variable:

$$f_m = a_{1m}x_1 + a_{2m}x_2 + \cdots + a_{Pm}x_P$$

f_m is the specific factor and $x_1, x_2, \dots, x_P$is all the variables describing the underlying factor. $a_{1m}, a_{2m}, \dots, a_{Pm}$ is the factor loadings associated with the variables describing the specific factor. With this construct, it is possible to continue the analysis with the factors as if they were variables themselves. In the next section the Factor Analysis and results thereof is described.

2.3.3 Results of the Factor Analysis

The Factor Analysis is based on all 107 answers to the survey where only a part of these answers came from farmers that also gave permission to get insight in their economic data. This is 79 conventional plant breeders, 4 organic plant breeders, 19 pig breeders, 2 poultry breeders and 3 cattle breeders.

It has not been possible to do polychoric correlations, which is the most correct correlations for Likert scales variables, with either the EFA.dimensions package or the psych package in R. It is out of scope of this thesis to code it manually. The Pearson's correlations are then used as base for the analysis.

In the Factor Analysis, the data is split into three categories one about strategic leadership and another about personality traits. The last category is based on the variables that did not fit into the factors in the two other categories. This is done to see if there were any correlations and factors to construct with these variables to give more knowledge than if they were just left out.

Strategic leadership

The first group of variables I will focus on is regarding Strategic leadership, where there are 35 variables, which potentially could construct factors based on the survey. There is several of correlations in the correlation matrix, which is above 0.3. So, there is a potential for a Factor Analysis. The KMO is 0.68 and the Bartlett test is significant (0.00), which also supports the potential for a Factor Analysis.

By looking at the Scree plot, Eigenvalues, and cumulative variance for Strategic leadership in Appendix 2, there is no clear picture of how many factors to construct. Based on the empirical foundation of the survey from where the variables are based, we set the number of factors to six. We will move on to check the communality (h^2) of the variables. By removing variables in multiple steps based on the changes in communality and cross-loadings, we end up with the following 21 variables, five factors and the factor loadings shown in Table 2.2 and Table 2.3. The full names of the variables can be found in Appendix 3.

Table 2.2 and Table 2.3 show five factors with 3 to 5 variables to construct the latent factors. The bold factor loading indicate the highest loading for that specific variable and this also indicates which latent factor it is partly explaining. The variables are sorted in the factors and with decreasing factor loadings so that the one in top is the variable with the highest factor loading for the given factor. The rows represent five different factors: *Financial management and the use of* *data, Strategic and long-term planning, Growth orientation, Attention to trends in society and among consumers,* and finally *Financial caution*. The last two rows show the communality (h^2)

	Financial management and the use of data	Strategic and long-term planning	Growth orienta-tion	Attention to trends in society and among consumers	Financial caution	h^2	u^2
Reason for varying economic results	**0.83**	0.19	0.16	0.20	0.07	0.80	0.20
Financial data is foundation for decisions	**0.76**	0.28	0.05	0.11	0.20	0.71	0.29
Analyse successfulness	**0.74**	0.15	0.04	0.11	0.09	0.60	0.40
Compare economic data with earlier years	**0.59**	0.17	0.26	0.04	0.13	0.46	0.54
Compare budget with initiatives	**0.42**	0.32	0.22	0.22	-0.18	0.41	0.59
Write down goals and visions	0.19	**0.85**	0.14	0.06	-0.10	0.79	0.21
Look at written plan for decision making	0.21	**0.85**	-0.07	0.06	-0.12	0.79	0.21
Plan for the future	0.15	**0.66**	0.00	0.02	0.16	0.48	0.52
Prioritise long term plans	0.19	**0.57**	0.12	0.21	0.02	0.42	0.58
Big production long term strategy	0.10	-0.01	**0.79**	0.07	0.15	0.66	0.34
Specialised long-term strategy	0.09	0.07	**0.67**	0.00	-0.12	0.47	0.53
Increasing turnover	0.06	-0.10	**0.50**	0.23	0.17	0.35	0.65
Farm is bigger and more modern	0.15	0.23	**0.46**	0.13	-0.02	0.30	0.70
Keep up with the market	0.11	0.07	**0.45**	0.24	0.26	0.34	0.66

Table 2.2 Factor overview regarding strategic leadership part 1

and the opposite, which is the unique variance. This is the part of the variance that the variable does not share with any other variables in the data.

With a KMO on 0.76 which is middling based on the division on page 54. The Bartlett test is significant (0.00). The new group of 21 variables is factorable. Further, the group of factors are considered reliable with a Cronbach's alpha at 0.83 and 0.78 as lower bound and 0.87 as upper bound in a 95 % confidence interval.

The Scree plot in Figure 2.5 and the eigenvalues and cumulative variance in Table 2.4 show in general that the number of factors chosen is appropriate. The Scree plot have a point of inflexion at six meaning that we should include five factors. The eigenvalues are also above 1 until the 6th factor indicating that five factors are the appropriate number. The cumulative variance is not 0.6 which is the desired level. But we see a clear decrease in extra added variance by the 6th factor indicating that another factor does not contribute with a lot of new knowledge of latency. Overall, we have here five factors which can give us a better insight to different aspects of the strategic leadership and the traits of the farm owners regarding this. An application of the factors and a more thorough description of the factors can be found in Part 1.

	Financial management and the use of data	Strategic and long-term planning	Growth orienta-tion	Attention to trends in society and among consumers	Financial caution	h^2	u^2
Environmental conscious	0.13	0.14	0.27	**0.66**	-0.02	0.54	0.46
Environmentally friendly and animal welfare	0.04	-0.03	0.33	**0.61**	0.01	0.49	0.51
Demand from consumers	0.20	0.09	-0.08	**0.52**	-0.17	0.35	0.65
Environmental and animal friendly agriculture	0.10	0.19	0.09	**0.51**	0.25	0.38	0.62
Big production and low expenses	0.11	0.06	0.28	0.08	**0.71**	0.61	0.39
Labour of myself and my family	0.02	0.02	-0.11	-0.20	**0.54**	0.35	0.65
Low expenses	0.22	-0.14	0.11	0.16	**0.48**	0.33	0.67

Table 2.3 Factor overview regarding strategic leadership part 2

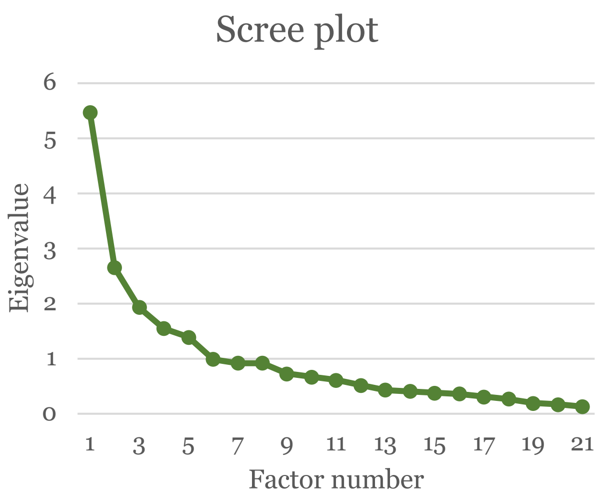

Figure 2.5 Final Scree plot for strategic leadership

Factor	Eigen-value	Cumulative variance
1	5.47	0.13
2	2.65	0.25
3	1.93	0.36
4	1.55	0.44
5	1.39	0.51
6	0.99	0.54

Table 2.4 Final eigenvalues and cumulative variance for strategic leadership

Personality traits

Next category up for investigation of factors is category with personality traits based on 21 variables. Here we have correlations above 0.3 again and a KMO 0.6 which is mediocre and a significant Bartlett test (0.00) both indicating that we can do Factor Analysis. Here the Scree plot, Eigenvalues, and cumulative variance in Appendix 2 show no clear picture again. Based on the structure from the survey, we start by making four factors. Here the procedure is same as it was for the strategic leadership, where variables are excluded based on communality and cross-loadings. The final three factors and factor loadings are based on 13 variables which have a fair level of communality without cross-loadings. Some of the variables have a negative correlation, so “Not valued” and “Not rewarding to be a farmer” have been inverted to have the right impact on the factor.

KMO has increased a bit to 0.66 and the Bartlett test is still significant (0.00) after narrowing down the field of variables. The reliability is not as convincing as before with Cronbach’s alpha at 0.63 and a lower bound at 0.53 and upper bound at 0.74 in a 95 % confidence interval. We choose to move on with the factors anyway due to the low number of items on the Likert scales in the variables and the low number of observations.

By looking at the Scree plot in Figure 2.6, we now have clear point of inflexion at the 4^{th} factor meaning that we should have 3 factors. Again, we find the same answer by looking at the eigenvalues in Table 2.6 where the fourth factor have an eigenvalue below 1. For the cumulative variance also shown in Table 2.6, it is not quite high enough with 0.44, but we will make it work anyway.

Table 2.5 show the three factors, 13 variables and factor loadings. The latent factors have between three to six variables to describe it. The 3 factors have been named: *Attitude toward the future*, *Attitude toward the job* and *Perception of the industry and conditions*. The loadings from the variables associated with the given factor is marked with bold. The bold loadings are the highest loadings from each variable. The criteria with communality on at least 0.2 are not fully fulfilled here since, there is multiple variables with values just around the limit. The three variables around the limit vary from 0.19-0.21, so it is hard to argue for exclusion of the one on 0.19 and not the one on the limit and the one just above. Therefore, they are all left in the Factor Analysis since they have reasonable factor loadings and clear loadings on one specific factor, hence no cross-loadings. An application of the factors and a more thorough description of the factors can be found in Part 1.

	Attitude towards the future	Attitude towards the job	Perception of the industry and conditions	h^2	u^2
Better living conditions in 10 years	**0.93**	0.08	-0.08	0.88	0.12
Economic results in 10 years	**0.88**	-0.04	0.04	0.78	0.22
Economic conditions in 10 years	**0.69**	-0.05	0.05	0.48	0.53
Problems	-0.01	**0.86**	-0.06	0.74	0.26
Solutions	0.05	**0.73**	0.02	0.54	0.46
Does often more than requested	-0.02	**0.53**	0.09	0.29	0.71
New projects	-0.03	**0.42**	0.10	0.19	0.81
Agricultural policy v. own decisions	0.17	0	**0.66**	0.47	0.55
Not rewarding to be a farmer	-0.1	-0.06	**0.56**	0.33	0.67
Uncertainties in agricultural policy	0	0.20	**0.55**	0.34	0.66
Not valued	-0.21	0.09	**0.45**	0.25	0.75
Unprofitable	0.10	-0.05	**0.44**	0.21	0.79
Political conditions	0.01	0.12	**0.43**	0.20	0.80

Table 2.5 Factor overview regarding personality traits

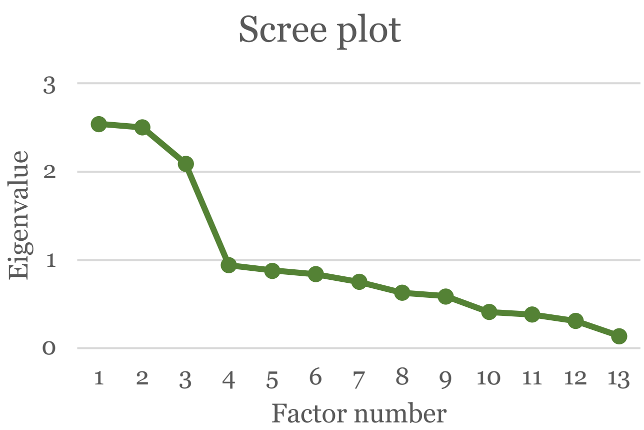

Figure 2.6 Final Scree plot for personality traits

Factor	Eigen-value	Cumulative variance
1	2.54	0.17
2	2.50	0.31
3	2.09	0.44
4	0.94	0.50

Table 2.6 Final eigenvalues and cumulative variance for personality traits

Miscellaneous

Lastly, we have the miscellaneous category, which is created by the variables not suited for factors in the strategic leadership and personality traits categories to make sure that we do not exclude potentially important knowledge about the farm owners. The KMO is 0.55 and the Bartlett test is significant (0.00) meaning that there is a slight potential in doing a Factor Analysis. The scree plot, eigenvalues, and cumulative variances in Appendix 2 does not show anything specific about number of factors in the dataset with 23 variables. As in the two previous categories, variables are excluded based on communality and cross-loadings. After excluding variables in multiple steps, we end up having four variables left describing one latent factor called Self-willed. The KMO have increased to 0.62 and the Bartlett test is still significant (0.00) suggesting that it is fair to do a Factor Analysis. The reliability is not great with Cronbach's alpha at 0.61 and a lower bound at 0.49 and upper bound at 0.73 in a 95 % confidence interval. As with *Personal traits*, we choose to move on with the factor anyway due to the low number of items on the Likert scales in the variables and the low number of observations.

Both the scree plot in Figure 2.7 and eigenvalues in Table 2.8 suggest one factor and the cumulative variance on 0.29 in Table 2.8 for one factor is low, but as with the category personality traits we will make it work anyway.

In Table 2.7 we see the four variables which describe the latent factor Self-willed. The communality levels are generally not high, but they are above the limit of 0.2. Since we end up with one factor, we do not have to take cross-loadings into account, but in the process of creating with factor, where we started with four factors, the cross-loadings have been considered along the way to make sure, that we are left with variables that explain the same latent factor. An application of the factors and a more thorough description of the factors can be found in Part 1.

	Self-willed	h^2	u^2
Admit mistakes	**0.58**	0.34	0.66
Infuriated	**0.56**	0.31	0.69
Do not finish	**0.54**	0.29	0.71
Employees need knowledge and skills	**0.47**	0.22	0.78

Table 2.7 Factor overview regarding miscellaneous

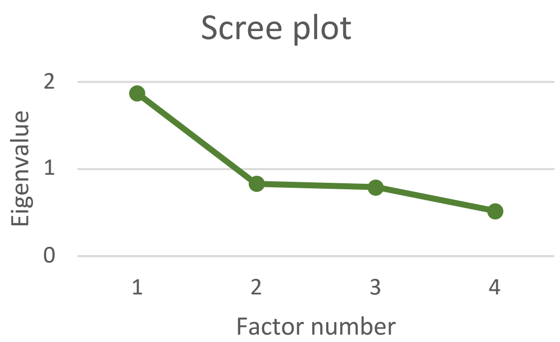

Figure 2.7 Final Scree plot for miscellaneous

Factor	Eigen-value	Cumulative variance
1	1.87	0.29
2	0.83	0.52
3	0.79	NA
4	0.52	NA

Table 2.8 Final eigenvalues and cumulative variance for miscellaneous

Quality assurance of the factors

To do an extra check of the constructed factors, all the variables were combined in one dataset, and another Factor Analysis were conducted with nine factors, which is the combined number of factors. The KMO is at 0.65 and the Bartlett test is significant (0.00) suggesting factorability. In Figure 2.8 showing the scree plot we see a point of inflexion at the 10th factor meaning that the nine factors are plausible. Heading over to Table 2.9, it is at the 13th factor that the eigenvalue drops below 1 and the cumulative variance hits 0.60 suggesting respectively 12 and 13 factors. Even though some evidence points in another direction in the overall data, we will still check how the variables divide themselves into factors, how the loadings are both in regarding absolute size and cross-loadings. We will of course also check the communality as always.

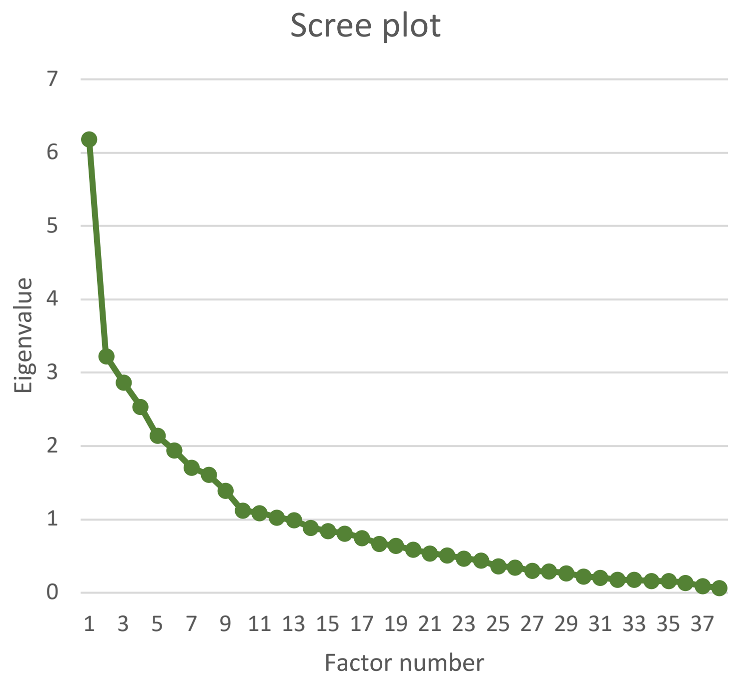

Figure 2.8 Scree plot of quality assurance analysis

Factor	Eigen-value	Cumulative variance
1	6.18	0.08
2	3.23	0.15
3	2.87	0.22
4	2.54	0.28
5	2.14	0.33
6	1.94	0.38
7	1.71	0.43
8	1.61	0.47
9	1.39	0.51
10	1.12	0.54
11	1.09	0.56
12	1.03	0.58
13	0.99	0.60
14	0.89	0.62

Table 2.9 Eigenvalues and cumulative variances for quality assurance analysis

All the communality values are above 0.20, which is a great start. When looking at the factor loadings, the picture is generally the same as for the factors split into three categories. Some factor loadings increase, some decrease and one variable would have been excluded based cross-loadings if the factors were based on an overall dataset. One variable has the highest factor loading on a new factor compared to the categorical separated data, but this variable has loadings, which is very close to cross-loadings and could have been considered excluded if the analysis were based on this data frame. Generally, an overall dataset does not change the picture tremendously, so we will continue working with the set factors and factor loadings based on the categorical separated data. The picture tends to be clearer with fewer variables since the more observations per variable is better as explained in section 2.3.1.

As a last quality check a reliability check with Cronbach's alpha is conducted. The test result is 0.78 with a lower bound of 0.72 and an upper bound of 0.84 in a 95 % confidence interval. The factors created here passes the reliability test especially considering the Likert scale with 5 items, which is short, and the increasing length increases the likelihood of a high reliability.

Discussion

This thesis is an explorative study based on various studies from all over the world in countries with familiar agricultural sectors to Denmark. This study is unique in the sense that it applies DEA for determining the rate of productivity and uses Factor Analysis to give the possibility to enlighten something immediately latent about personal traits and management and leadership style. Based on the study, there is plenty of aspects to dive deeper into and challenge to assess by increasing the dataset or restructuring the survey. Another obvious improvement is to qualify the questions in the survey further and supplementing them with new questions based on the changes to the structure when creating the factors in this thesis. This is described further in the following section about further implications.

An immediate discussion point and an obvious way to improve this study is with a bigger dataset. It would have been easier to see trends and patterns in a bigger dataset. This have been the biggest issue both when creating factors, determining productivity with DEA, and doing the correlation analysis between the two. All correlations are analysed separately. It has not been possible to create regressions to get a clearer picture of the numerical and specific effect from the various variables in determining productivity as it is visualised in Figure 1.1. It could have given a clearer picture of the relationship with a regression analysis, since many of the variables affect each other, as we saw when looking into the intercorrelations between the variables in the *Decision-making process* and *Leadership style*. There is no guarantee that the regressions would have made the picture clearer, since it is plausible that in practice it all together adds up to a synergetic effect. Thereby it would not have been easier or even possible to separate the effect since it is not *ceteris paribus*. They might all add up to create that typical example for a synergetic effect where 2+2=5, meaning that various variables and factors add up to more than they would have done if they just appeared separately.

For the correlation analysis between the factors and the efficiency scores, we only see one significant correlation in relation to efficiency scores for pig breeders. We see some tendencies (meaning significance level between 10 and 20 %) for three factors mostly relating to efficiency scores for pig breeders. This is not the desired level of correlations between the factors and the efficiency scores. This can also be ascribed to the low number of DMUs, since the low number can both blur the picture when creating the factors, determining the efficiency scores, and analysing the correlation as already touched upon earlier. It all adds up to make the picture unclear.

The focus of the survey has been to get knowledge about the farm owners. This might be misleading if he/she is not the overall manager of the farmer since another farm manager is hired to lead and manage the overall operations and direction. The assumption has been that the owner is involved in some way even though a manager is hired. It has not been clear from the economic data to see if this assumption is plausible or not.

Some questions from the survey were not applied in this analysis. One question about education type/level were not applied. It did not make sense to split up the answers or rank the types of education in any way, since the types of education and supplementary education did not have a clear grading. It was a design error, when designing the survey. It is necessary to think the application of a question through when framing it. Further, the questions about professional experience and management experience outside of farming where also framed in a way that gave strange answers where the answers here and with the experience in farming did not add up to age or compared to each other. Some farmers have multiple occupations at the same time, and the occupations can vary greatly across their lifetime. It might not be as linear as it was thought to be at the time of designing the survey. These variables from the survey were not brought into this analysis. Lastly, a question regarding thoughts about future profit on the farm with the possibility to write text as answer, did not make sense when the answers were analyzed. There were too many variations to how the question was answered to compare them. It has also been excluded from the analysis. If it would have been possible to use these variables the conclusion might have differed in some way. These questions could have led to further insight into the perception, experience, and education of the farmer, and how this is correlated between management and leadership style and lastly, how it could be linked to farm performance. But luckily many variables were left for further analysis. Throughout the Factor Analysis many variables were excluded when creating the factors. This is what typically happens when creating factors, especially when applying it in a slightly new context. These variables could also have contributed to be slightly different conclusion in another setting.

The DEA model were based on the average economic data of up to five years, depending on what was available for the specific farm. It was important to take more than one year into account since there is many external factors that agriculture is dependent on which vary from year to year. This is factors such as animal health, plants conditions, weather, prices, and crop rotation, which can both influence all farms or the specific farm. It could have made sense to look at the changes of the economic data over time and relate this to the traits regarding personality, management, and leadership. A way to consider both the fluctuations between the years and determine the change over time, is to use a window analysis. Here the data is averaged over multiple years and for the subsequent period. The “block” of years to include is moved one to include one new year and exclude the oldest year. Another aspect to consider, when including data over multiple years is, that the focus of the farm can change over a five-year period. As an example, it is possible to change the production from animal to plants or the other way around. The farmers were the determining factor to how the farm was classified when they were asked in the survey. The answer could have been another if they were asked five years before where the oldest data is based. This is not something, that have been considered in this analysis.

The DEA model here assumes VRS where an assumption of constant returns to scale (CRS) could have made sense, since the farms should work on the optimal scale and thereby the compared to the optimal scale. The VRS here should be seen as a precautionary principle, and that it is not possible for all farmers to easily scale their farm, hence it would not be a good advice to give them. The purpose of the analysis here is to see what can be changed to increase the farm performance on the given scale of the farm. If the goal of this thesis would have been purely benchmarking, it might have made sense to assume CRS.

The application of benchmarking and DEA here is a presentation of, how it can be used regarding "softer" management topics, which is not directly related to economic performance, and how the performance can be affect directly. This is an important notion of the correlations and the influence of the variables and factors regarding personality, management, and leadership. They do not affect the efficiency score and the farm performance directly. The personality traits and management and leadership style affect the circumstances on the farm, and how the inputs are converted into output, meaning how the input and output mix is on the specific farm which then change the efficiency score. It is not enough to make changes to the thought about how to lead and manage the farm. It is important to make changes to the actions by the farmer, among employees and within the operations of the farm.

The original idea with this analysis from the project preparing for this thesis had a focus on how and to what extent the farm owners work with strategic management and leadership. Secondly, the idea was to investigate the correlations with personality traits and productivity with a hypothesis that a focus on strategic management and leadership increase productivity. Here the focus has been on the relationships between the steps in the model in Figure 1.1 more than within the elements representing either *Personal aspects and traits of the farmer, Decision-making process, Leadership* or *Farm performance*. This determine how traits and management and leadership style can change productivity more than on what level the farmers and farms, which the data is based on, are.

Even though there are many limitations to this analysis, it is a good first step in getting empirical evidence about the relationship between traits in personality and management and leadership style of the farm owner with the productivity as farm performance in a Danish context. There are plenty of issues to improve and look further into. But this thesis has illuminated some of the importance of the focus on managing a farm as a business, as it is generally accepted. There is plenty of work to be continued, but this thesis gives tangible recommendations to the farm owners and consultancies.

Future implications

As an exploratory study investigating the relationship between personality traits and management and leadership style of the farm owners and the productivity on the various farms, there are plenty of issues to dive further into both regarding framework of this analysis, the method, and findings.

It might be insightful to have a psychological angle and perform qualitative interviews based on psychological theory to get further knowledge about the relationship between the personality traits, and both the leadership and management style and the farm performance.

As already described multiple times in this thesis, it would be insightful to conduct this analysis or one similar on a bigger dataset that might only focus on one production type to be completely sure that the DMUs are comparable. This will lead to more incisive factors and correlation if it is based on this setup, when supplemented by the experiences from here both regarding what to do and what not to do. If trying to collect more data, the survey can easily be improved based on the structures and finding described in this thesis.

Some specific variables to investigate further is the self-rated variables regarding intelligence and management skills to see if the self-rated variables are the same as if it is measured by an objective test. Further, it is possible to investigate if the differences between the self-rated variables and the test scores can tell us anything about the leadership and management style by the farm owner and secondly the farm performance.

Another variable to look further into is *Experience until 15 years old* where we get a tendency towards the opposite, compared to the finding by O'leary et al. (2018) as described on page 23. Here the further research should concern if it is possible to get a significant correlation between the efficiency scores and variables to either falsify or verify the earlier findings from Great Britain in a Danish context.

As mentioned in the discussion, a farm owner and a farm manager have broadly been seen as the same person is this thesis, expect for under a few conditions. It could be insightful to look further into the ownership and management of the farms in question to see if there are tendencies relating to how the farm is owned and managed, and more so use this as a basis for the survey to find the proper farmer to answer the survey, which should the one that makes to decisions and manages the farm.

To look further into the effect of employees both farmers and farm managers, and the relationship with both the attitude of the farm owner and the productivity of the farm. It could be interesting to follow some farms in progress towards hiring people and investigate the scores in both the two attitude factors and efficiency scores and how this might change when hiring employees so that the farm owner should not do everything alone. Historically, it is possible to look at the changes of the efficiency scores based on the annual economic data and compare this to the change in employees through time. This should most likely be based on ten years or more and on farms that have had the same ownership in that period.

As for the setup of the economic data, a rather big issue was how to split *Agricultural machinery centre etc.* into labour cost and variable cost. The split ended up being 50 % to each cost input in the DEA model based on the economic data from various agricultural machinery centres shown in Appendix 1. It would be insightful to investigate this split further for future DEA models used for benchmarking in Danish agriculture.

As mentioned on page 34 a further investigation into the correlation between both *Management skills improved in the last five years* and *Financial caution* with the efficiency scores for both pig breeders and plant breeders could be interesting, since correlations for plant breeders are negative and positive for the pig breeders. Three out of four of the correlations are only at tendency level (significance around 20 %), so to increase the dataset is an obvious starting point for a more thorough analysis of this relationship.

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Appendix 1 Labour cost in agricultural machinery centres

Name	Region	Year	Labour cost	Depreciation	Other operational cost	Other financial cost	% of labour cost in total cost
Assenbølle Maskinstation	Fyn	2019	123653	355151	0	92030	22%
Bülows Maskinstation	Sjælland	2019	288147	1113397	110834	428046	15%
Jejsing Maskinstation	Sydjylland	2019	1939958	1431449	0	350615	52%
Henne Maskinstation	Vestjylland	2019	1095291	349991	0	121867	70%
Gangergårdens Maskinstation	Sjælland	2019	9631547	5496833	0	458145	62%
Hjadstrup Maskinstation	Fyn	2019	2401504	1346417	0	88318	63%
Niemanns Maskinstation	Sjælland	2019	1880826	1379080	0	501716	50%
J.J. Maskinstation	Falster	2019	3283095	778707	0	43152	80%
Gammelskov Maskinstation	Sydjylland	2019	177016	172942	0	17751	48%
Stolbrolykke Maskinstation	Als	2019	2335852	1384376	0	211784	59%
Average							**52%**

Table A1.1 Labour cost in agricultural machinery centres

Appendix 2 Scree plot, eigenvalues, and cumulative variance

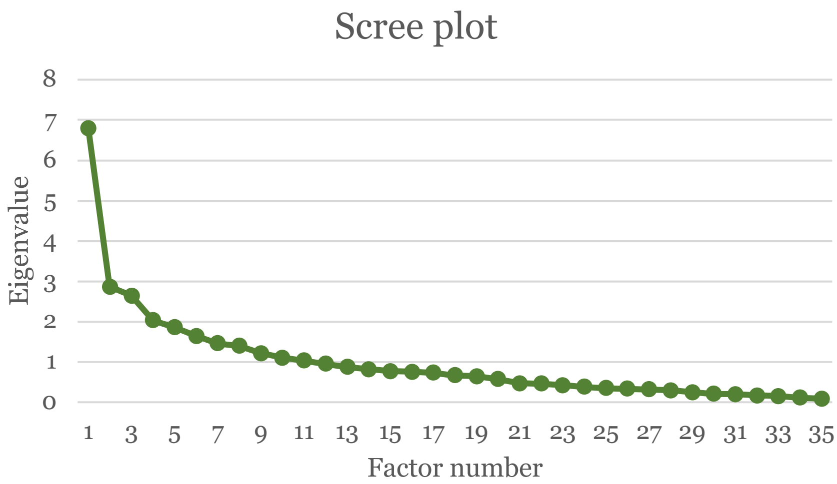

Figure A2.1 Introductory Scree plot regarding factors in the Strategic leadership category

Factor	Eigen-value	Cumulative variance
1	6.79	0.09
2	2.86	0.17
3	2.64	0.23
4	2.03	0.28
5	1.86	0.31
6	1.64	0.35
7	1.46	0.39
8	1.40	0.43
9	1.21	0.46
10	1.10	0.50
11	1.03	0.53
12	0.95	0.57
13	0.87	0.59
14	0.82	0.62

Table A2.1 Introductory eigenvalues and cumulative variance regarding factors in the Strategic leadership category

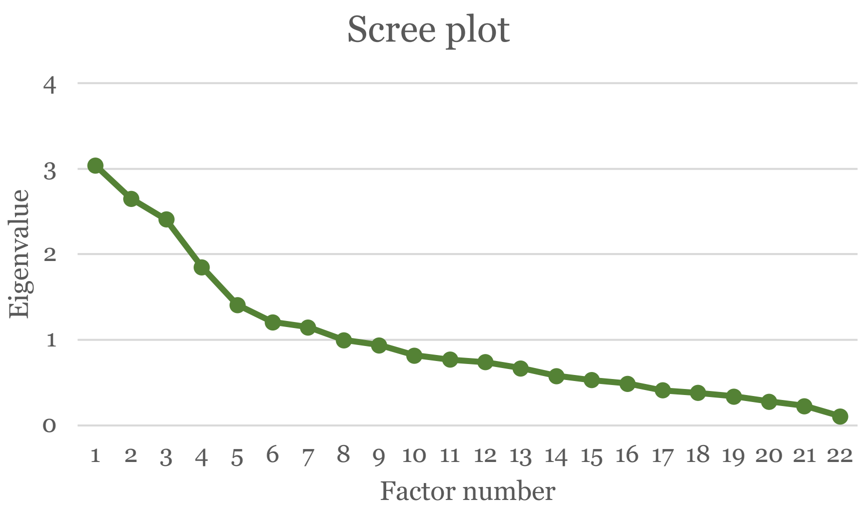

Figure A2.2 Introductory Scree plot regarding factors in the Personality traits category

Factor	Eigen-value	Cumulative variance
1	3.04	0.11
2	2.65	0.20
3	2.41	0.29
4	1.85	0.35
5	1.41	0.39

Table A2.2 Introductory eigenvalues and cumulative variance regarding factors in the Personality traits category

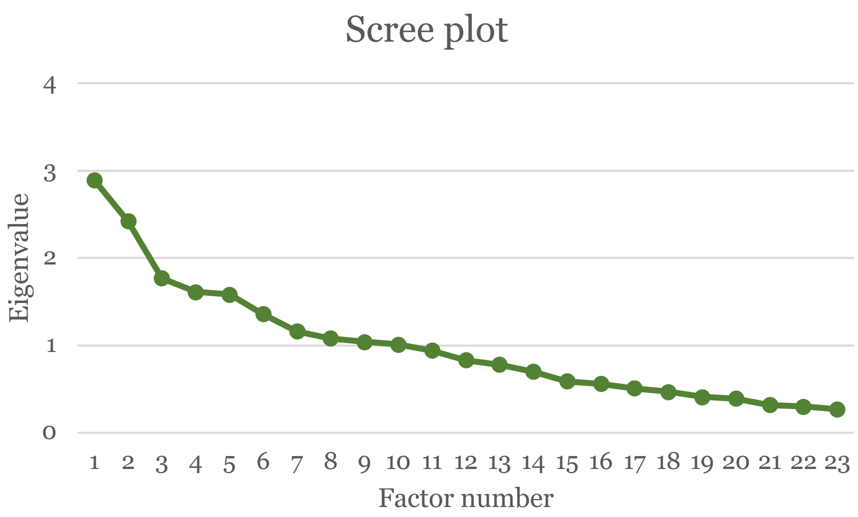

Figure A2.3 Introductory Scree plot regarding factors in the Miscellaneous category

Factor	Eigen-value	Cumulative variance
1	2.89	0.07
2	2.42	0.15
3	1.77	0.21
4	1.61	0.26
5	1.58	0.31

Table A2.3 Introductory eigenvalues and cumulative variance regarding factors in the Miscellaneous category

Appendix 3 Full text of variables in Factor Analysis

Factor	Short name	Full name	Factor loadings
Financial management and the use of data	Reason for varying economic result	I try to find a reason why there is a varying economic result from year to year	0.83
	Financial data is foundation for decisions	I use financial data as a foundation for decisions regarding the future	0.76
	Analyse successfulness	When I have implemented a decision, I try to analyse how successful it was	0.74
	Compare economic data with earlier years	I compare economic data with earlier years	0.59
	Compare budget with initiatives	I compare budget with implemented initiatives and spending	0.42
Strategic and long-term planning	Write down goals and visions	I write down my goals and visions for the future	0.85
	Look at written plan for decision making	I frequently look at the written plans when I must decide	0.85
	Plan for the future	I have a clear plan for the future of the farm (not necessarily written down)	0.66
	Prioritise long term plans	I prioritise to make long term plans instead of just focussing on the challenges on a day-to-day basis	0.57
Growth orientation	Big production long term strategy	A big production size is a good long-term strategy	0.79
	Specialised long-term strategy	It is a good long-term strategy to become a big and specialised farm	0.67
	Increasing turnover	Increasing turnover is necessary for success in the long run	0.50
	Farm is bigger and more modern	My farm is bigger and more modern than other farms	0.46
	Keep up with the market	To keep up with the development in the market faster than others is a good long-term strategy	0.45

Attention to trends in society and among consumers	Environmental conscious	Environmental conscious breed is a direction that I have chosen	0.66
	Environmentally friendly and animal welfare	To invest in environmentally friendly initiatives or animal welfare is a good investment	0.61
	Demand from consumers	I am aware of the demand from the consumers	0.52
	Environmental and animal friendly agriculture	My farm shows the way for environmental and animal friendly agriculture	0.51
Financial caution	Big production and low expenses	My farm produces as much as possible with as low expenses as possible	0.71
	Labour of myself and my family	I use my own and my family's labour as much as possible	0.54
	Low expenses	I keep my expenses as low as possible	0.48

Table A3.1 Names on variables in the Strategic leadership category

Factor	Short name	Full name	Factor loadings
Attitude toward the future	Better living conditions in 10 years	I expect better living conditions (stable and higher income) for families in agriculture in 10 years	0.93
	Economic results in 10 years	I expect better economic results in agriculture in 10 years compared to 2017	0.88
	Economic conditions in 10 years	I expect better economic conditions for agriculture in 10 years	0.69
Attitude toward the job	Problems	I confront problems actively	0.86
	Solutions	When something is not working, I find a solution immediately	0.73
	Does often more than requested	I often do more than there is expected of me	0.53
	New projects	I frequently start new projects	0.42
Perception of the industry and conditions	Agricultural policy v. own decisions	The economic condition on my farm depends more on agricultural policy than my own decisions	0.66
	Not rewarding to be a farmer	It is not rewarding to be a farmer	0.56
	Uncertainties in agricultural policy	Uncertainties in agricultural policy is a problem for the decision making in the agricultural sector	0.55
	Not valued	Agriculture is not valued in Denmark	0.45
	Unprofitable	Agriculture in Denmark is unprofitable	0.44
	Political conditions	The political conditions are a limiting factor for a successful farm	0.43

Table A3.2 Names on variables in the Personality traits category

Factor	Short name	Full name	Factor loadings
Self-willed	Admit mistakes	I find it hard to admit when I am wrong	0.58
	Infuriated	When something goes wrong, I sometimes get infuriated and does not handle the situation in the best way	0.56
	Do not finish	It is difficult for me to finish work, which do not excite me	0.54
	Employees need knowledge and skills	My employees do often need necessary knowledge and skills to work for me	0.47

Table A3.3 Names on variables in the Miscellaneous category

Appendix 4 R-script DEA and data processing

```
rm(list=ls())
options(scipen=999)
library(readxl)
library(Benchmarking)
library(dplyr)
library(Hmisc)
library(writexl)
Data <- read_excel("/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Data/Regnskabsdata/Benchmarking data.xlsx")
Data<- data.frame(Data)

#====================================#
#### Walk through and conversion of direct costs ####
#====================================#
Data$Pos_Markbrug_omkostninger <- (-Data$Markbrug_omkostninger)
summary(Data$Pos_Markbrug_omkostninger)
Data$Kundenummer[Data$Pos_Markbrug_omkostninger==0] #689
Data$Årstal[Data$Pos_Markbrug_omkostninger==0] #2017

#======================================#
#### Walk through and conversion of indirect costs ####
#=====================================#
Data$Pos_Kontante_kapacitetsomkostninger <- (-Data$Kontante_kapacitetsomkostninger)
summary(Data$Pos_Kontante_kapacitetsomkostninger)

#================================#
#### Walk through and conversion of AMC ####
#================================#
Data$Pos_Maskinstation_mv <- (-Data$Maskinstation_mv)
summary(Data$Pos_Maskinstation_mv)
Data$Kundenummer[Data$Pos_Maskinstation_mv==0]
unique(Data$Kundenummer[Data$Pos_Maskinstation_mv==0])

#======================================#
#### Walk through and conversion of labour costs ####
#======================================#
Data$Pos_Lønomkostninger <- (-Data$Lønomkostninger)
summary(Data$Pos_Lønomkostninger)

#====================================#
#### Create lease of land variables (input/output) ####
#====================================#
# If lease of land is positive, it is output and if lease of land is negative, it is input
i <- 1
Data$Forpagtning_input<-0
Data$Forpagtning_output<-0
for (i in 1:dim(Data)[1])
{
 if (Data$Forpagtning[i]>0)
 {
   Data$Forpagtning_output[i]<-Data$Forpagtning[i]
 }  else {
   Data$Forpagtning_input[i]<-(-Data$Forpagtning[i])
 }
}

# Check (Y)
length(Data$Kundenummer[Data$Forpagtning_output>0])+
 length(Data$Kundenummer[Data$Forpagtning_output==0]) #184
length(Data$Kundenummer[Data$Forpagtning_input>0])+
 length(Data$Kundenummer[Data$Forpagtning_input==0]) #184

Data$Løn <- as.numeric(Data$Løn)

# Remove poultry and cattle
Dea_data <- Data[-c(which(Data$Bedriftstype=="Fjerkræ"),which(Data$Bedriftstype=="Kvægbrug")),]

#==================#
#### Standard payment ####
#==================#
Driftslederløn <- 250*1924
```

```
Dea_data$Løn_fra_virksomhed <- 0
Dea_data$Løn_fra_virksomhed[which(Dea_data$Pos_Lønomkostninger<Driftslederløn|Dea_data$Løn<150000)] <- Driftslederløn

#================================#
#### Create dataset of average across years ####
#================================#
Kundenummer <- unique(Data$Kundenummer)

Gennemsnitsdata <- data.frame(cbind(Kundenummer))
Gennemsnitsdata$Bedriftstype <- 0

#=============================#
#### Put data into the average dataset ####
#=============================#
i <- 1
for(i in 1:dim(Gennemsnitsdata)[1])
{
 z <- Gennemsnitsdata$Kundenummer[i]
 x <- (Data$Bedriftstype[Data$Kundenummer==z])
 Gennemsnitsdata$Bedriftstype[i] <- x[1]
}

colnames(Data)
# Create columns for average data
Gennemsnitsdata$Bruttoudbytte <- 0
Gennemsnitsdata$Forpagtning <- 0
Gennemsnitsdata$Anden_indtjening <- 0
Gennemsnitsdata$Afkoblet_EU_støtte_mv <- 0
Gennemsnitsdata$Årets_resultat <- 0
Gennemsnitsdata$Aktiver <- 0
Gennemsnitsdata$Driftsresultat <- 0
Gennemsnitsdata$Pos_Markbrug_omkostninger <- 0
Gennemsnitsdata$Pos_Kontante_kapacitetsomkostninger <- 0
Gennemsnitsdata$Pos_Maskinstation_mv <- 0
Gennemsnitsdata$Pos_Lønomkostninger <- 0
Gennemsnitsdata$Forpagtning_input <- 0
Gennemsnitsdata$Forpagtning_output <- 0

# Calculate average numbers from economic data
# For all
a <- 1
i <- 1
c <- 0

Elementer <- c("Bruttoudbytte", "Forpagtning", "Anden_indtjening", "Afkoblet_EU_støtte_mv", "Årets_resultat",
"Aktiver","Driftsresultat", "Pos_Markbrug_omkostninger", "Pos_Kontante_kapacitetsomkostninger", "Pos_Maskinstation_mv",
"Pos_Lønomkostninger", "Forpagtning_input", "Forpagtning_output")

for (a in 1:length(Elementer))
{
 y <- noquote(Elementer[a])
 c <- 0
 for (i in 1:dim(Gennemsnitsdata)[1])
 {
  z <- Gennemsnitsdata$Kundenummer[i]
  q <- Data[y]
  w <- as.numeric(which(Data$Kundenummer==z))
  x <- mean(q[w,])
  c <- c(c,x)
 }
 Gennemsnitsdata[y] <- c[-1]
}

# Remove poultry and cattle
 Dea_Gennemsnitsdata <- Gennemsnitsdata[-
c(which(Gennemsnitsdata$Bedriftstype=="Fjerkræ"),which(Gennemsnitsdata$Bedriftstype=="Kvægbrug")),]

 y <- Dea_Gennemsnitsdata$Output


# Create average payment from farm based on Dea_data
i <- 1
c <- 0
```

```
Dea_Gennemsnitsdata$Løn_fra_virksomhed <- 0

for (i in 1:dim(Dea_Gennemsnitsdata)[1])
{
  z <- Dea_Gennemsnitsdata$Kundenummer[i]
  q <- Dea_data$Løn_fra_virksomhed
  w <- as.numeric(which(Dea_data$Kundenummer==z))
  x <- mean(q[w])
  c <- 0
  c <- c(c,x)
  Dea_Gennemsnitsdata$Løn_fra_virksomhed[i] <- c[-1]
}

#=============================================================#
#### Avg data: DEA model with standard payment and 50 % AMC in labour costs ####
#=============================================================#
Dea_Gennemsnitsdata$Løn_DEA_input_est_ejerløn_50_maskin <- Dea_Gennemsnitsdata$Pos_Lønomkostninger +
Dea_Gennemsnitsdata$Pos_Maskinstation_mv*1/2 + Dea_Gennemsnitsdata$Løn_fra_virksomhed
Dea_Gennemsnitsdata$Variable_omkostninger <- Dea_Gennemsnitsdata$Pos_Markbrug_omkostninger +
Dea_Gennemsnitsdata$Pos_Kontante_kapacitetsomkostninger +
  Dea_Gennemsnitsdata$Pos_Maskinstation_mv*1/2 + Dea_Gennemsnitsdata$Forpagtning_input
Dea_Gennemsnitsdata$Kapital <- Dea_Gennemsnitsdata$Aktiver
Dea_Gennemsnitsdata$Output <- Dea_Gennemsnitsdata$Bruttoudbytte + Dea_Gennemsnitsdata$Forpagtning_output +
Dea_Gennemsnitsdata$Anden_indtjening + Dea_Gennemsnitsdata$Afkoblet_EU_støtte_mv
x_med_est_ejerløn <- (cbind(Dea_Gennemsnitsdata$Løn_DEA_input_est_ejerløn_50_maskin,
Dea_Gennemsnitsdata$Variable_omkostninger, Dea_Gennemsnitsdata$Kapital))
y <- Dea_Gennemsnitsdata$Output
e <- dea(x_med_est_ejerløn, y, RTS="VRS", ORIENTATION = "in")
Dea_Gennemsnitsdata$Efficiens_med_est_ejerløn_50_maskin <- eff(e)
summary(Dea_Gennemsnitsdata$Efficiens_med_est_ejerløn_50_maskin)

#==================================================#
#### Split data into two DEA models - one for pig and one for plants ####
#==================================================#
Gns_svin <- subset(Dea_Gennemsnitsdata,Bedriftstype=="Svinebrug")
x <- (cbind(Gns_svin$Løn_DEA_input_est_ejerløn_50_maskin,Gns_svin$Variable_omkostninger,Gns_svin$Kapital))
y <- Gns_svin$Output

e <- dea(x, y, RTS="VRS", ORIENTATION = "in")
eff(e)
Gns_svin$Kundenummer[which(eff(e)==1)]
Gns_svin$Efficiens_svin <- eff(e)

summary(Gns_svin$Efficiens_svin)
eff_svin <- data.frame(cbind(Gns_svin$Kundenummer,Gns_svin$Efficiens_med_est_ejerløn_50_maskin,Gns_svin$Efficiens_svin))

Gns_planter <- subset(Dea_Gennemsnitsdata,Bedriftstype!="Svinebrug")
x <- (cbind(Gns_planter$Løn_DEA_input_est_ejerløn_50_maskin,Gns_planter$Variable_omkostninger,Gns_planter$Kapital))
y <- Gns_planter$Output

e <- dea(x, y, RTS="VRS", ORIENTATION = "in")
eff(e)
Gns_planter$Kundenummer[which(eff(e)==1)]
Gns_planter$Efficiens_planter <- eff(e)

summary(Gns_planter$Efficiens_planter)

eff_planter <- data.frame(cbind(Gns_planter$Kundenummer,Gns_planter$Efficiens_med_est_ejerløn_50_maskin,
Gns_planter$Efficiens_planter))
eff_forskel <- data.frame(rbind(eff_svin,eff_planter))

colnames(eff_forskel)
names(eff_forskel)[names(eff_forskel)=="X1"] <- "Kundenummer"
names(eff_forskel)[names(eff_forskel)=="X2"] <- "Efficiens_samlet"
names(eff_forskel)[names(eff_forskel)=="X3"] <- "Efficiens_opdelt"
colnames(eff_forskel)

summary(eff_forskel$Efficiens_samlet)
summary(eff_forskel$Efficiens_opdelt)

wilcox.test(eff_forskel$Efficiens_samlet,eff_forskel$Efficiens_opdelt) #p-værdi 0,3085
cor.test(eff_forskel$Efficiens_samlet,eff_forskel$Efficiens_opdelt, method="spearman")
```

```
#==========================#
#### DEA with weight restrictions ####
#==========================#
x_med_est_ejerløn <- (cbind(Dea_Gennemsnitsdata$Løn_DEA_input_est_ejerløn_50_maskin,
Dea_Gennemsnitsdata$Variable_omkostninger,Dea_Gennemsnitsdata$Kapital))
y <- Dea_Gennemsnitsdata$Output
e <- dea(x_med_est_ejerløn, y, RTS="VRS", ORIENTATION = "in", DUAL=TRUE)
summary(eff(e))

e$lambda
Dea_Gennemsnitsdata$eff <- eff(e)
Dea_Gennemsnitsdata$ux <- e$ux
e$vy

virtuals <- cbind(Dea_Gennemsnitsdata$Kundenummer,Dea_Gennemsnitsdata$Bedriftstype,Dea_Gennemsnitsdata$ux,
Dea_Gennemsnitsdata$eff,Dea_Gennemsnitsdata$efficiensscorer_vægte )

WR1<- c(0.5,2)
WR2<- c(0.5*0.04,2*0.04)
WRdual<-rbind(WR1,WR2)

e_weight <- dea.dual(x_med_est_ejerløn, y, RTS="vrs", ORIENTATION = "in", DUAL=WRdual)
eff(e_weight)
summary(eff(e_weight))
Dea_Gennemsnitsdata$efficiensscorer_vægte <- eff(e_weight)

U <- e_weight$u
V <- e_weight$v
U*x_med_est_ejerløn
V*y

# scaled capital stock
x_est_løn_reskal_kapital <-
(cbind(Dea_Gennemsnitsdata$Løn_DEA_input_est_ejerløn_50_maskin,Dea_Gennemsnitsdata$Variable_omkostninger,Dea_Genne
msnitsdata$Kapital*0.04))
y <- Dea_Gennemsnitsdata$Output
e_reskal <- dea(x_est_løn_reskal_kapital, y, RTS="VRS", ORIENTATION = "in", DUAL=TRUE)
summary(eff(e_reskal)) # The same as without scaling - super!

WR1<- c(0.5,2)
WR2<- c(0.5,2)
WRdual<-rbind(WR1,WR2)

e_weight_reskal <- dea.dual(x_est_løn_reskal_kapital, y, RTS="vrs", ORIENTATION = "in", DUAL=WRdual)
eff(e_weight_reskal)
summary(eff(e_weight_reskal)) # The same as scaling directly in WR

WR1<- c(0.5,2)
WR2<- c(0.5*0.04,2*0.04)
WRdual<-rbind(WR1,WR2)

Gns_svin <- subset(Dea_Gennemsnitsdata,Bedriftstype=="Svinebrug")
x <- (cbind(Gns_svin$Løn_DEA_input_est_ejerløn_50_maskin,Gns_svin$Variable_omkostninger,Gns_svin$Kapital))
y <- Gns_svin$Output

e_reskal <- dea.dual(x, y, RTS="VRS", ORIENTATION = "in", DUAL=WRdual)
eff(e_reskal)
Gns_svin$Kundenummer[which(eff(e_reskal)==1)]
Gns_svin$Efficiens_svin <- eff(e_reskal)
summary(Gns_svin$Efficiens_svin)

eff_svin_reskal <- data.frame(cbind(Gns_svin$Kundenummer,Gns_svin$efficiensscorer_vægte,Gns_svin$Efficiens_svin))

Gns_planter <- subset(Dea_Gennemsnitsdata,Bedriftstype!="Svinebrug")
x <- (cbind(Gns_planter$Løn_DEA_input_est_ejerløn_50_maskin,Gns_planter$Variable_omkostninger,Gns_planter$Kapital))
y <- Gns_planter$Output

e_reskal <- dea.dual(x, y, RTS="VRS", ORIENTATION = "in", DUAL=WRdual)
eff(e_reskal)
Gns_planter$Kundenummer[which(eff(e_reskal)==1)]
Gns_planter$Efficiens_planter <- eff(e_reskal)
summary(Gns_planter$Efficiens_planter)
```

```
eff_planter_reskal <-
data.frame(cbind(Gns_planter$Kundenummer,Gns_planter$efficiensscorer_vægte,Gns_planter$Efficiens_planter))

eff_forskel_reskal <- data.frame(rbind(eff_svin_reskal,eff_planter_reskal))

colnames(eff_forskel_reskal)
names(eff_forskel_reskal)[names(eff_forskel_reskal)=="X1"] <- "Kundenummer"
names(eff_forskel_reskal)[names(eff_forskel_reskal)=="X2"] <- "Efficiens_samlet"
names(eff_forskel_reskal)[names(eff_forskel_reskal)=="X3"] <- "Efficiens_opdelt"
colnames(eff_forskel_reskal)

opdelt <- cbind(eff_forskel_reskal,eff_forskel)
summary(eff_forskel_reskal$Efficiens_samlet)
summary(eff_forskel_reskal$Efficiens_opdelt)

wilcox.test(eff_forskel_reskal$Efficiens_samlet,eff_forskel_reskal$Efficiens_opdelt) #p-værdi 0,3138
cor.test(eff_forskel$Efficiens_samlet,eff_forskel$Efficiens_opdelt, method="spearman") #p-værdi 0,0000

#=============#
#### Summary ####
#=============#
efficiensscorer <- data.frame(cbind("Kundenummer"=Dea_Gennemsnitsdata$Kundenummer,
"Bedriftstype"=Dea_Gennemsnitsdata$Bedriftstype,"Efficiensscorer"=Dea_Gennemsnitsdata$Efficiens_med_est_ejerløn_50_maskin,
"Efficiensscorer_vægte"=Dea_Gennemsnitsdata$efficiensscorer_vægte))

eff_forskel <-  eff_forskel[order(eff_forskel$Kundenummer,decreasing = FALSE),]
eff_forskel_reskal <-  eff_forskel_reskal[order(eff_forskel_reskal$Kundenummer,decreasing = FALSE),]
efficiensscorer <- cbind(efficiensscorer,"Efficiensscorer_opdelt"=eff_forskel$Efficiens_opdelt,
"Efficiensscorer_opdelt_vægte"=eff_forskel_reskal$Efficiens_opdelt)

write_xlsx(efficiensscorer,
        "/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Data/Efficiensscorer.xlsx")
```

Appendix 5 R-script Factor Analysis and data processing

```
rm(list=ls())
options(scipen=999)
library(plyr)
library(dplyr)
library(readxl)
library(corrgram)
library(polycor)
library(EFA.dimensions)
library(psych)
library(writexl)
library(MVN)
Data <- read_excel("Dropbox/Universitet/Speciale/Data/Spørgeskemadata/Spørgeskemadata.xlsx")

#===========================#
#### Create dataset with numbers ####
#===========================#
Data_tal <- data.frame("Base"=cbind(1:107))
Data_tal$Kundenummer <- Data$Kundenummer
Data_tal$Base <- NULL

Data_tal$DEA_analyse <- Data$DEA_analyse
Data_tal$Samtykke <- Data$Samtykke
Data_tal$Bedriftstype <- Data$Produktionstype

Data_tal$Ansatte <- Data$Ansatte
Data_tal$Ansatte <- revalue(Data_tal$Ansatte, c("1-2"=1,"3-5"=2,"6-10"=3,"Flere end 10"=4))
Data_tal$Ansatte <- as.numeric(Data_tal$Ansatte)

Data_tal$Hektar <- Data$Hektar
Data_tal$Hektar <- revalue(Data_tal$Hektar, c("Færre end 100"=1,"101-200"=2,"201-300"=3,"301-400"=4,"401-500"=5,"501-
600"=6,"601-700"=7,"701-800"=8,"801-900"=9, "901-1.000"=10,"Flere end 1.000"=11))
Data_tal$Hektar <- as.numeric(Data_tal$Hektar)

Data_tal$Køn <- Data$Køn

Data_tal$Alder <- Data$Alder
Data_tal$Alder <- revalue(Data_tal$Alder, c("Under 30"=1,"30-40"=2,"41-55"=3,"56-70"=4,"Over 70"=5))
Data_tal$Alder <- as.numeric(Data_tal$Alder)

Data_tal$Uddannelsesniveau <- Data$Uddannelsesniveau
table(Data$Uddannelsesniveau)

Data_tal$Ledelseserfaring_landbrug <- Data$Ledelseserfaring_landbrug
Data_tal$Ledelseserfaring_landbrug <- revalue(Data_tal$Ledelseserfaring_landbrug, c("Op til 2 år"=1,"3-4 år"=2,"5-7 år"=3,"8-9
år"=4,"10-13 år"=5, "14-20 år"=6,"Mere end 20 år"=7))
Data_tal$Ledelseserfaring_landbrug <- as.numeric(Data_tal$Ledelseserfaring_landbrug)

Data_tal$Erfaring_landbrug <- Data$Erfaring_landbrug
Data_tal$Erfaring_landbrug <- revalue(Data_tal$Erfaring_landbrug, c("Op til 2 år"=1,"3-4 år"=2,"5-7 år"=3,"8-9 år"=4,"10-13
år"=5,"14-20 år"=6, "21-30 år"=7,"31-40 år"=8,"Mere end 40 år"=9))
Data_tal$Erfaring_landbrug <- as.numeric(Data_tal$Erfaring_landbrug)

Data_tal$Ledelseserfaring_ikkelandbrug <- Data$Ledelseserfaring_ikkelandbrug
Data_tal$Ledelseserfaring_ikkelandbrug <- revalue(Data_tal$Ledelseserfaring_ikkelandbrug, c("Ingen"=0,"Op til 2 år"=1,"3-4
år"=2,"5-7 år"=3, "8-9 år"=4,"10-13 år"=5,"14-20 år"=6,"Mere end 20 år"=7))
Data_tal$Ledelseserfaring_ikkelandbrug <- as.numeric(Data_tal$Ledelseserfaring_ikkelandbrug)

Data_tal$Erfaring_ikkelandbrug <- Data$Erfaring_ikkelandbrug
Data_tal$Erfaring_ikkelandbrug <- revalue(Data_tal$Erfaring_ikkelandbrug, c("Ingen"=0,"Op til 2 år"=1,"3-4 år"=2,"5-7 år"=3,
                                          "8-9 år"=4,"10-13 år"=5,"14-20 år"=6,"21-30 år"=7,"31-40 år"=8,"Mere end 40 år"=9))
Data_tal$Erfaring_ikkelandbrug <- as.numeric(Data_tal$Erfaring_ikkelandbrug)

Data_tal$Efteruddannelse <- Data$Efteruddannelse
Data_tal$Efteruddannelse <- revalue(Data_tal$Efteruddannelse, c("Indenfor den seneste måned"=1,"Indenfor det seneste halve
år"=2,"Indenfor det seneste år"=3,"Indenfor de seneste 2 år"=4,"Indenfor de seneste 3 år"=5,"Indenfor de seneste 5 år"=6, "Mere end 5
år siden"=7))
Data_tal$Efteruddannelse <- as.numeric(Data_tal$Efteruddannelse)

Data_tal$Mængde_efteruddannelse <- Data$Mængde_efteruddannelse
Data_tal$Mængde_efteruddannelse <- revalue(Data_tal$Mængde_efteruddannelse, c("Op til 2 dage"=1,"3-5 dage"=2,"6-10
dage"=3,"11-15 dage"=4,"16-20 dage"=5, "Flere end 20 dage"=6))
```

```
Data_tal$Mængde_efteruddannelse <- as.numeric(Data_tal$Mængde_efteruddannelse)

Data_tal$Erfaring_op_til_15_år <- Data$Erfaring_op_til_15_år
Data_tal$Erfaring_op_til_15_år <- revalue(Data_tal$Erfaring_op_til_15_år, c("I meget lav grad"=1,"I lav grad"=2,"I nogen grad"=3,"I
høj grad"=4, "I meget høj grad"=5))
Data_tal$Erfaring_op_til_15_år <- as.numeric(Data_tal$Erfaring_op_til_15_år)

enig_uenig <- data.frame(cbind(subset(Data[17:38]),subset(Data[46:74]),subset(Data[82:87])))
(38-16)+(74-45)+(87-81) #57
enig_uenig_colnames <- colnames(enig_uenig)

Data_tal[,enig_uenig_colnames] <- Data[,enig_uenig_colnames]
i <- 1
y <- enig_uenig_colnames
for (i in 1:length(enig_uenig_colnames))
{
 z <- y[i]
 Data_tal[z] <- revalue(Data_tal[[z]],c("Helt uenig"=1,"Uenig"=2,"Hverken/eller"=3,"Enig"=4,"Helt enig"=5))
}

i <- 1
for (i in 1:length(enig_uenig_colnames))
{
 z <- y[i]
 Data_tal[z] <- as.numeric(Data_tal[[z]])
}

Data_tal$Intelligens <- Data$Intelligens
Data_tal$Intelligens <- revalue(Data_tal$Intelligens, c("Intelligens under gennemsnittet"=1,"Gennemsnitlig intelligent"=2,"Rimelig
intelligent"=3, "Høj intelligens"=4))
Data_tal$Intelligens <- as.numeric(Data_tal$Intelligens)

Data_tal$Ledelsesegenskaber <- Data$Ledelsesegenskaber
Data_tal$Ledelsesegenskaber <- revalue(Data_tal$Ledelsesegenskaber, c("10 (Højest)"=10))
Data_tal$Ledelsesegenskaber <- revalue(Data_tal$Ledelsesegenskaber, c("-"=NULL))
Data_tal$Ledelsesegenskaber <- as.numeric(Data_tal$Ledelsesegenskaber)

høj_lav_grad <- subset(Data[41:44])
høj_lav_grad_colnames <- colnames(høj_lav_grad)

Data_tal[,høj_lav_grad_colnames] <- Data[,høj_lav_grad_colnames]
i <- 1
y <- høj_lav_grad_colnames
for (i in 1:length(høj_lav_grad_colnames))
{
 z <- y[i]
 Data_tal[z] <- revalue(Data_tal[[z]],c("I meget lav grad"=1,"I lav grad"=2,"I nogen grad"=3,"I høj grad"=4,"I meget høj grad"=5))
}

i <- 1
for (i in 1:length(høj_lav_grad_colnames))
{
 z <- y[i]
 Data_tal[z] <- as.numeric(Data_tal[[z]])
}

Data_tal$Ledelsesegenskaber_forbedret_5_år <- Data$Ledelsesegenskaber_forbedret_5_år
Data_tal$Ledelsesegenskaber_forbedret_5_år <- revalue(Data_tal$Ledelsesegenskaber_forbedret_5_år,
                                        c("Meget forværret"=1, "Forværret"=2, "Ingen ændring"=3, "En vis grad"=4, "I høj grad"=5))
Data_tal$Ledelsesegenskaber_forbedret_5_år <- as.numeric(Data_tal$Ledelsesegenskaber_forbedret_5_år)

Værktøjer <- subset(Data[75:79])
Værktøjer_colnames <- colnames(Værktøjer)

Data_tal[,Værktøjer_colnames] <- Data[,Værktøjer_colnames]
i <- 1
y <- Værktøjer_colnames
for (i in 1:length(Værktøjer_colnames))
{
 z <- y[i]
 Data_tal[z] <- revalue(Data_tal[[z]],c("Slet ikke"=0,"I begrænset omfang"=1,"I nogen grad"=2,"I høj grad"=3,"I meget høj grad"=4))
}
```

```
i <- 1
for (i in 1:length(Værktøjer_colnames))
{
  z <- y[i]
  Data_tal[z] <- as.numeric(Data_tal[[z]])
}

Data_tal$Analyse_regnskabstal <- Data$Analyse_regnskabstal

Data_tal$Overskud_ændring <- Data$Overskud_ændring

Data_tal$Ansatte_efteruddannelse <- Data$Ansatte_efteruddannelse
Data_tal$Ansatte_efteruddannelse <- revalue(Data_tal$Ansatte_efteruddannelse, c("0 dage"=0, "1-2 dage"=1, "3-4 dage"=2, "5-7 dage"=3, "8-10 dage"=4, "Flere end 10 dage"=5))
Data_tal$Ansatte_efteruddannelse <- as.numeric(Data_tal$Ansatte_efteruddannelse)

str(Data_tal)

Data_baggrund <- data.frame(cbind(Data_tal[1:13],Data_tal[86:88]))
Data_faktor <- data.frame(cbind(Data_tal[10:85],Data_tal[88]))
Ny_data_faktor <- na.omit(Data_faktor)
str(Data_faktor)

#==========================#
#### Management and leadership ####
#==========================#
which(colnames(Ny_data_faktor)=="Store_investeringer_fremtid") # 30
which(colnames(Ny_data_faktor)=="Regnskabstal_fremtidige_beslutninger") #58
which(colnames(Ny_data_faktor)=="Medarbejdere_mangler_viden") # 59
which(colnames(Ny_data_faktor)=="Overbevise_andre") # 64

Ledelse <- data.frame(Ny_data_faktor[30:64])

cor(Ledelse)
FACTORABILITY(Ledelse) # KMO 0.68
SCREE_PLOT(Ledelse)
summary(Ledelse)

fa(Ledelse, nfactors=6, fm="pa", rotate="varimax")

which(colnames(Ledelse)=="Medarbejdere_mangler_viden") #
which(colnames(Ledelse)=="Ophidset") # 31
which(colnames(Ledelse)=="Klippe") # 32
Ledelse <- Ledelse[-c(30:32)]

fa(Ledelse, nfactors=6, rotate="varimax", fm="pa")

which(colnames(Ledelse)=="Andre_lytter_argumenter") # 32
which(colnames(Ledelse)=="Overbevise_andre") # 32

Ledelse <- Ledelse[-c(30:32)]
SCREE_PLOT(Ledelse)

fa(Ledelse, nfactors=6, rotate="varimax", fm="pa")

# Remove variables with cross loadings
which(colnames(Ledelse)=="Teknologisk_udvikling") # 2
which(colnames(Ledelse)=="Prioriterer_opgaver") # 24

Ledelse <- Ledelse[-c(2,24)]

fa(Ledelse, nfactors=5, rotate="varimax", fm="pa")

which(colnames(Ledelse)=="Samarbejde_kollegaer") #13

Ledelse <- Ledelse[-c(13)]

fa(Ledelse, nfactors=6, rotate="varimax", fm="pa")

which(colnames(Ledelse)=="Ambitiøse_investeringer") #8

Ledelse <- Ledelse[-c(8)]
```

```
fa(Ledelse, nfactors=6, rotate="varimax", fm="pa")

which(colnames(Ledelse)=="Store_investeringer_fremtid") #1
which(colnames(Ledelse)=="Låne_kapital") #2

Ledelse <- Ledelse[-c(1,2)]

fa(Ledelse, nfactors=5, rotate="varimax", fm="pa")

which(colnames(Ledelse)=="Høje_udbyttetal") # 5
which(colnames(Ledelse)=="Lovgivning_tendenser") # 9

Ledelse <- Ledelse[-c(5,9)]

fa(Ledelse, nfactors=5, rotate="varimax", fm="pa") # Finally!!!!!
FACTORABILITY(Ledelse) # KMO 0.76
SCREE_PLOT(Ledelse)
summary(Ledelse)
alpha(Ledelse)

#==================#
#### Personality traits ####
#=================#
which(colnames(Ny_data_faktor)=="Virksomhedsleder") # 8
which(colnames(Ny_data_faktor)=="Landbrugspolitik_mod_egne_beslutninger") # 29
which(colnames(Ny_data_faktor)=="Indrømme_fejl")
summary(Ny_data_faktor[21])
Personlighedstræk <- data.frame(Ny_data_faktor[8:29])
str(Personlighedstræk)

cor(Personlighedstræk)
FACTORABILITY(Personlighedstræk) # KMO 0.6
SCREE_PLOT(Personlighedstræk)

fa(Personlighedstræk,nfactors=4,rotate="varimax",fm="pa")

# remove stolthed h^2 0.132, indrømme_fejl h^2 0.102, naturgivende_forhold h^2 0.170
which(colnames(Personlighedstræk)=="Stolthed") # 3
which(colnames(Personlighedstræk)=="Indrømme_fejl") # 14
which(colnames(Personlighedstræk)=="Naturgivende_forhold") # 20
Personlighedstræk <- Personlighedstræk[-c(3,14,20)]

FACTORABILITY(Personlighedstræk) # KMO 0,62

fa(Personlighedstræk,nfactors=4,rotate="varimax",fm="pa")

# remove Ikke_afslutter h^2 0.140, Succes_lokalområdet h^2 0.052
which(colnames(Personlighedstræk)=="Ikke_afslutter") # 13
which(colnames(Personlighedstræk)=="Succes_lokalområdet") # 17
Personlighedstræk <- Personlighedstræk[-c(13,17)]

FACTORABILITY(Personlighedstræk) # KMO 0.63

fa(Personlighedstræk,nfactors=4,rotate="varimax",fm="pa")

# remove succes_virksomheder h^2 0,16
which(colnames(Personlighedstræk)=="Succes_virksomheder") # 15
Personlighedstræk <- Personlighedstræk[-c(15)]

FACTORABILITY(Personlighedstræk) # KMO 0.63
SCREE_PLOT(Personlighedstræk)

fa(Personlighedstræk,nfactors=4,rotate="varimax",fm="pa")

# Remove Arbejder_for_meget grundet due to cross loadings
which(colnames(Personlighedstræk)=="Arbejder_for_meget") # 13
Personlighedstræk <- Personlighedstræk[-c(13)]

FACTORABILITY(Personlighedstræk) # KMO 0.63
SCREE_PLOT(Personlighedstræk)

fa(Personlighedstræk,nfactors=4,rotate="varimax",fm="pa")
```

```
which(colnames(Personlighedstræk)=="Virksomhedsleder") # 1
which(colnames(Personlighedstræk)=="Landbrug_ledes_virksomhed") # 2
Personlighedstræk <- Personlighedstræk[-c(1,2)]

fa(Personlighedstræk,nfactors=3,rotate="varimax",fm="pa")

# Inverse Værdsat og Givende
max(Personlighedstræk$Værdsat)
max(Personlighedstræk$Givende)

Personlighedstræk$Ikke_værdsat <- max(Personlighedstræk$Værdsat)-Personlighedstræk$Værdsat+1
Personlighedstræk$Ikke_givende <- max(Personlighedstræk$Givende)-Personlighedstræk$Givende+1

# Use ikke-værdsat and ikke-givende in stead of værdsat og givende
which(colnames(Personlighedstræk)=="Værdsat") # 1
which(colnames(Personlighedstræk)=="Givende") # 2
Personlighedstræk <- Personlighedstræk[-c(1,2)]

fa(Personlighedstræk,nfactors=3,rotate="varimax",fm="pa")

SCREE_PLOT(Personlighedstræk)
FACTORABILITY(Personlighedstræk)
alpha(Personlighedstræk

#==========================#
#### Factor Analysis with the rest ####
#==========================#
which(colnames(Ny_data_faktor)=="Virksomhedsleder") # 8
which(colnames(Ny_data_faktor)=="Landbrug_ledes_virksomhed") # 9
which(colnames(Ny_data_faktor)=="Stolthed") # 10
which(colnames(Ny_data_faktor)=="Indrømme_fejl") # 21
which(colnames(Ny_data_faktor)=="Ikke_afslutter") # 22
which(colnames(Ny_data_faktor)=="Arbejder_for_meget") # 23
which(colnames(Ny_data_faktor)=="Succes_virksomheder") # 25
which(colnames(Ny_data_faktor)=="Succes_lokalområdet") # 26
which(colnames(Ny_data_faktor)=="Naturgivende_forhold") # 27
which(colnames(Ny_data_faktor)=="Store_investeringer_fremtid") # 30
which(colnames(Ny_data_faktor)=="Teknologisk_udvikling") # 31
which(colnames(Ny_data_faktor)=="Låne_kapital") # 32
which(colnames(Ny_data_faktor)=="Høje_udbyttetal") # 37
which(colnames(Ny_data_faktor)=="Ambitiøse_investeringer") # 38
which(colnames(Ny_data_faktor)=="Lovgivning_tendenser") # 42
which(colnames(Ny_data_faktor)=="Samarbejde_kollegaer") # 43
which(colnames(Ny_data_faktor)=="Prioriterer_opgaver") # 53

Resten <- Ny_data_faktor[c(8:10,21:23,25:27,30:32,37,38,42,43,53,59:64)]
cor(Resten)

FACTORABILITY(Resten)
SCREE_PLOT(Resten)

fa(Resten,nfactors=4,rotate="varimax",fm="pa")

which(colnames(Resten)=="Virksomhedsleder") # 1
which(colnames(Resten)=="Stolthed") # 3
which(colnames(Resten)=="Succes_virksomheder") # 7
which(colnames(Resten)=="Succes_lokalområdet") # 8
which(colnames(Resten)=="Beslutninger_negative") # 22

Resten <- Resten[-c(1,3,7,8,22)]

FACTORABILITY(Resten)
SCREE_PLOT(Resten)

fa(Resten,nfactors=4,rotate="varimax",fm="pa")

which(colnames(Resten)=="Landbrug_ledes_virksomhed") # 1

Resten <- Resten[-c(1)]

fa(Resten,nfactors=4,rotate="varimax",fm="pa")

which(colnames(Resten)=="Arbejder_for_meget") # 3
```

```
Resten <- Resten[-c(3)]

fa(Resten,nfactors=4,rotate="varimax",fm="pa")

which(colnames(Resten)=="Høje_udbyttetal") # 7
Resten <- Resten[-c(7)]

fa(Resten,nfactors=4,rotate="varimax",fm="pa")

which(colnames(Resten)=="Naturgivende_forhold") # 3
Resten <- Resten[-c(3)]

fa(Resten,nfactors=4,rotate="varimax",fm="pa")

# Lovgivning_tendenser fjernes crossloading
which(colnames(Resten)=="Lovgivning_tendenser") # 7
Resten <- Resten[-c(7)]

fa(Resten,nfactors=4,rotate="varimax",fm="pa")

# Ambitiøse_investeringer removed due to cross loading and low h^2
which(colnames(Resten)=="Ambitiøse_investeringer") # 6
Resten <- Resten[-c(6)]
SCREE_PLOT(Resten)
fa(Resten,nfactors=3,rotate="varimax",fm="pa")

which(colnames(Resten)=="Prioriterer_opgaver") # 6
Resten <- Resten[-c(6)]

fa(Resten,nfactors=3,rotate="varimax",fm="pa")

which(colnames(Resten)=="Overbevise_andre") # 10
Resten <- Resten[-c(10)]

fa(Resten,nfactors=2,rotate="varimax",fm="pa")

which(colnames(Resten)=="Store_investeringer_fremtid") # 3
Resten <- Resten[-c(3)]

fa(Resten,nfactors=2,rotate="varimax",fm="pa")

which(colnames(Resten)=="Låne_kapital") # 4
Resten <- Resten[-c(4)]

fa(Resten,nfactors=2,rotate="varimax",fm="pa")

which(colnames(Resten)=="Teknologisk_udvikling") # 3
Resten <- Resten[-c(3)]

fa(Resten,nfactors=2,rotate="varimax",fm="pa")

which(colnames(Resten)=="Klippe") # 6
Resten <- Resten[-c(6)]

fa(Resten,nfactors=2,rotate="varimax",fm="pa")

which(colnames(Resten)=="Prioriterer_opgaver") # 3
which(colnames(Resten)=="Overbevise_andre") # 6
Resten <- Resten[-c(3,6)]

fa(Resten,nfactors=1,rotate="varimax",fm="pa")

FACTORABILITY(Resten)
SCREE_PLOT(Resten)
alpha(Resten)

Alle <- cbind(Resten,Personlighedstræk,Ledelse)
FACTORABILITY(Alle)
SCREE_PLOT(Alle)

mvn(Alle)

fa(Alle,nfactors=9,rotate="varimax",fm="pa")
```

```
FACTORABILITY(Alle)
SCREE_PLOT(Alle)
alpha(Alle)

which(colnames(Data)=="Erfaring_op_til_15_år") # 16
which(colnames(Data)=="Intelligens") # 39
which(colnames(Data)=="Ledelsesegenskaber_forbedret_5_år") # 45
which(colnames(Data)=="Værktøjer") # 75
which(colnames(Data)=="Overskud_ændring") # 81
which(colnames(Data)=="Ansatte_efteruddannelse") # 88
Data_spørgeskema <- Data[c(1:16,39:45,75:81,88)]

#================#
#### Create factors ####
#================#
Data_spørgeskema$Attitude_fremtiden <- 0.93*Data_faktor$Bedre_levevilkår_10_år+
  0.88*Data_faktor$Økonomiske_resultater_10_år+0.69*Data_faktor$Økonomiske_rammevilkår_10_år

Data_spørgeskema$Indstilling_arbejdet <- 0.86*Data_faktor$Problemer+0.73*Data_faktor$Løsning+
  0.53*Data_faktor$Gør_ofte_mere+0.42*Data_faktor$Nye_projekter

Data_spørgeskema$Opfattelse_erhvervet_rammevilkår <-
  0.66*Data_faktor$Landbrugspolitik_mod_egne_beslutninger+0.56*(5-Data_faktor$Givende+1)+
  0.55*Data_faktor$Usikkerhed_landbrugspolitik+0.45*(5-Data_faktor$Værdsat+1)+
  0.44*Data_faktor$Landbrug_ulønsomt+0.43*Data_faktor$Politiske_rammevilkår

Data_spørgeskema$Økonomistyring_data <- 0.83*Data_faktor$Årsag_økonomisk_resultat+
  0.76*Data_faktor$Regnskabstal_fremtidige_beslutninger+0.74*Data_faktor$Beslutning_succesfuld+
  0.59*Data_faktor$Sammenligner_regnskabstal_år+0.42*Data_faktor$Budget_realiseret

Data_spørgeskema$Langsigtet_planlægning <- 0.85*Data_faktor$Nedskrevet_mål_visioner+
  0.85*Data_faktor$Forholder_nedskrevne_planer+0.66*Data_faktor$Plan_fremtiden+
  0.57*Data_faktor$Prioritet_langsigtede_planer

Data_spørgeskema$Vækst_orientering <- 0.79*Data_faktor$Stor_produktion_langsigtet_strategi+
  0.67*Data_faktor$Langsigtet_strategi_specialiseret+0.5*Data_faktor$Stigende_omsætning+
  0.46*Data_faktor$Større_moderne+0.45*Data_faktor$Udviklingen_markedet

Data_spørgeskema$Samfund_forbruger <- 0.66*Data_faktor$Miljøbevidst+
  0.61*Data_faktor$Miljøtiltag_dyrevelfærd+0.52*Data_faktor$Forbrugernes_efterspørgsel+
  0.51*Data_faktor$Miljø_dyrevenligt_landbrug

Data_spørgeskema$Finansiel_tilbageholdenhed <- 0.71*Data_faktor$Produktion_lave_omkostninger+
  0.54*Data_faktor$Arbejdskraft_mig_selv_familie+0.48*Data_faktor$Lave_omkostninger

Data_spørgeskema$Resten <- 0.58*Data_faktor$Indrømme_fejl+0.54*Data_faktor$Ikke_afslutter+
  0.47*Data_faktor$Medarbejdere_mangler_viden+0.56*Data_faktor$Ophidset

write_xlsx(Data_spørgeskema,
        "/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Data/Data_spørgeskema.xlsx")
write_xlsx(Data_faktor,
        "/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Data/Data_faktor.xlsx")
write_xlsx(Data_baggrund,
        "/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Data/Data_baggrund.xlsx")
```

Appendix 6 R-script findings

```
rm(list=ls())
options(scipen=999)
library(readxl)
library(plyr)
library(dplyr)
library(psych)
library(writexl)

Efficiensscorer <- read_excel("/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Data/Efficiensscorer_rigtig.xlsx")
Data_baggrund <- data.frame(read_excel("/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Data/Data_baggrund.xlsx"))
Data_spørgeskema <-
data.frame(read_excel("/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Data/Data_spørgeskema.xlsx"))

#================#
### Preparing data ####
#================#
Efficiensscorer$Efficiensscorer <- as.numeric(Efficiensscorer$Efficiensscorer)
Efficiensscorer$Efficiensscorer_vægte <- as.numeric(Efficiensscorer$Efficiensscorer_vægte)
Efficiensscorer$Efficiensscorer_opdelt <- as.numeric(Efficiensscorer$Efficiensscorer_opdelt)
Efficiensscorer$Efficiensscorer_opdelt_vægte <- as.numeric(Efficiensscorer$Efficiensscorer_opdelt_vægte)

Data_baggrund_eff <- Data_baggrund %>% filter(Kundenummer %in% Efficiensscorer$Kundenummer)
Data_spørgeskema_eff <- Data_spørgeskema %>% filter(Kundenummer %in% Efficiensscorer$Kundenummer)
str(Data_baggrund_eff)
str(Data_spørgeskema_eff)
str(Efficiensscorer)

Data_baggrund_eff <- Data_baggrund_eff[order(Data_baggrund_eff$Kundenummer,decreasing = FALSE),]
Data_spørgeskema_eff <-  Data_spørgeskema_eff[order(Data_spørgeskema_eff$Kundenummer,decreasing = FALSE),]

Data <- cbind(Efficiensscorer[1:6])

Data$Ansatte <- Data$Ansatte
Data$Ansatte <- revalue(Data_spørgeskema_eff$Ansatte, c("1-2"=1,"3-5"=2,"6-10"=3,"Flere end 10"=4))
Data$Ansatte <- as.numeric(Data$Ansatte)

Data$Hektar <- revalue(Data_spørgeskema_eff$Hektar, c("Færre end 100"=1,"101-200"=2,"201-300"=3,"301-400"=4,"401-
500"=5,"501-600"=6,"601-700"=7, "701-800"=8,"801-900"=9,"901-1.000"=10,"Flere end 1.000"=11))
Data$Hektar <- as.numeric(Data$Hektar)

Data$Køn <- Data_spørgeskema_eff$Køn

Data$Alder <- revalue(Data_spørgeskema_eff$Alder, c("Under 30"=1,"30-40"=2,"41-55"=3,"56-70"=4,"Over 70"=5))
Data$Alder <- as.numeric(Data$Alder)

Data$Uddannelsesniveau <- Data_spørgeskema_eff$Uddannelsesniveau

Data$Ledelseserfaring_landbrug <- revalue(Data_spørgeskema_eff$Ledelseserfaring_landbrug, c("Op til 2 år"=1,"3-4 år"=2,"5-7
år"=3,"8-9 år"=4, "10-13 år"=5,"14-20 år"=6,"Mere end 20 år"=7))
Data$Ledelseserfaring_landbrug <- as.numeric(Data$Ledelseserfaring_landbrug)

Data$Erfaring_landbrug <- revalue(Data_spørgeskema_eff$Erfaring_landbrug, c("Op til 2 år"=1,"3-4 år"=2,"5-7 år"=3,"8-9 år"=4,"10-
13 år"=5, "14-20 år"=6,"21-30 år"=7,"31-40 år"=8,"Mere end 40 år"=9))
Data$Erfaring_landbrug <- as.numeric(Data$Erfaring_landbrug)

Data$Ledelseserfaring_ikkelandbrug <- revalue(Data_spørgeskema_eff$Ledelseserfaring_ikkelandbrug, c("Ingen"=0,"Op til 2
år"=1,"3-4 år"=2,"5-7 år"=3, "8-9 år"=4,"10-13 år"=5,"14-20 år"=6, "Mere end 20 år"=7))
Data$Ledelseserfaring_ikkelandbrug <- as.numeric(Data$Ledelseserfaring_ikkelandbrug)

Data$Erfaring_ikkelandbrug <- revalue(Data_spørgeskema_eff$Erfaring_ikkelandbrug, c("Ingen"=0,"Op til 2 år"=1,"3-4 år"=2,"5-7
år"=3,"8-9 år"=4, "10-13 år"=5,"14-20 år"=6,"21-30 år"=7,"31-40 år"=8, "Mere end 40 år"=9))
Data$Erfaring_ikkelandbrug <- as.numeric(Data$Erfaring_ikkelandbrug)

Data$Efteruddannelse <- revalue(Data_spørgeskema_eff$Efteruddannelse, c("Indenfor den seneste måned"=1,"Indenfor det seneste
halve år"=2, "Indenfor det seneste år"=3,"Indenfor de seneste 2 år"=4, "Indenfor de seneste 3 år"=5,"Indenfor de seneste 5 år"=6, "Mere
end 5 år siden"=7))
Data$Efteruddannelse <- as.numeric(Data$Efteruddannelse)

Data$Mængde_efteruddannelse <- revalue(Data_spørgeskema_eff$Mængde_efteruddannelse, c("Op til 2 dage"=1,"3-5 dage"=2,"6-10
dage"=3,"11-15 dage"=4,"16-20 dage"=5, "Flere end 20 dage"=6))
Data$Mængde_efteruddannelse <- as.numeric(Data$Mængde_efteruddannelse)
```

```
Data$Erfaring_op_til_15_år <- revalue(Data_spørgeskema_eff$Erfaring_op_til_15_år, c("I meget lav grad"=1,"I lav grad"=2,"I nogen
grad"=3, "I høj grad"=4,"I meget høj grad"=5))
Data$Erfaring_op_til_15_år <- as.numeric(Data$Erfaring_op_til_15_år)

Data$Opfattelse_erhvervet_rammevilkår <- Data_spørgeskema_eff$Opfattelse_erhvervet_rammevilkår
Data$Attitude_fremtiden <- Data_spørgeskema_eff$Attitude_fremtiden
Data$Indstilling_arbejdet <- Data_spørgeskema_eff$Indstilling_arbejdet

Data$Intelligens <- revalue(Data_spørgeskema_eff$Intelligens, c("Intelligens under gennemsnittet"=1,"Gennemsnitlig intelligent"=2,
"Rimelig intelligent"=3,"Høj intelligens"=4))
Data$Intelligens <- as.numeric(Data$Intelligens)

Data$Ledelsesegenskaber <- Data_spørgeskema_eff$Ledelsesegenskaber
Data$Ledelsesegenskaber <- revalue(Data$Ledelsesegenskaber, c("10 (Højest)"=10))
Data$Ledelsesegenskaber <- revalue(Data$Ledelsesegenskaber, c("-"=NULL))
Data$Ledelsesegenskaber <- as.numeric(Data$Ledelsesegenskaber)

which(colnames(Data_spørgeskema_eff)=="Erfagrupper_sparringspartnere") # 19
which(colnames(Data_spørgeskema_eff)=="Venner_sparringspartnere") # 22

høj_lav_grad <- subset(Data_spørgeskema_eff[19:22])
høj_lav_grad_colnames <- colnames(høj_lav_grad)

Data[,høj_lav_grad_colnames] <- Data_spørgeskema_eff[,høj_lav_grad_colnames]
i <- 1
y <- høj_lav_grad_colnames
for (i in 1:length(høj_lav_grad_colnames))
{
 z <- y[i]
 Data[z] <- revalue(Data[[z]],c("I meget lav grad"=1,"I lav grad"=2,"I nogen grad"=3,"I høj grad"=4,"I meget høj grad"=5))
}

i <- 1
for (i in 1:length(høj_lav_grad_colnames))
{
 z <- y[i]
 Data[z] <- as.numeric(Data[[z]])
}

Data$Sparringspartnere_summeret <-Data$Erfagrupper_sparringspartnere+Data$Familie_sparringspartnere+
Data$Rådgivere_sparringspartnere+Data$Venner_sparringspartnere

Data$Ledelsesegenskaber_forbedret_5_år <- revalue(Data_spørgeskema_eff$Ledelsesegenskaber_forbedret_5_år,
                                   c("Meget forværret"=1, "Forværret"=2, "Ingen ændring"=3, "En vis grad"=4, "I høj grad"=5))
Data$Ledelsesegenskaber_forbedret_5_år <- as.numeric(Data$Ledelsesegenskaber_forbedret_5_år)
Data$Økonomistyring_data <- Data_spørgeskema_eff$Økonomistyring_data
Data$Langsigtet_planlægning <- Data_spørgeskema_eff$Langsigtet_planlægning
Data$Vækst_orientering <- Data_spørgeskema_eff$Vækst_orientering
Data$Samfund_forbruger <- Data_spørgeskema_eff$Samfund_forbruger
Data$Finansiel_tilbageholdenhed <- Data_spørgeskema_eff$Finansiel_tilbageholdenhed
Data$Resten <- Data_spørgeskema_eff$Resten

which(colnames(Data_spørgeskema_eff)=="Værktøjer")
which(colnames(Data_spørgeskema_eff)=="Papir_kuglepen_lommeregner")

Værktøjer <- subset(Data_spørgeskema_eff[24:28])
Værktøjer_colnames <- colnames(Værktøjer)

Data[,Værktøjer_colnames] <- Data_spørgeskema_eff[,Værktøjer_colnames]
i <- 1
y <- Værktøjer_colnames
for (i in 1:length(Værktøjer_colnames))
{
 z <- y[i]
 Data[z] <- revalue(Data[[z]],c("Slet ikke"=0,"I begrænset omfang"=1,"I nogen grad"=2,"I høj grad"=3,"I meget høj grad"=4))
}

i <- 1
for (i in 1:length(Værktøjer_colnames))
{
 z <- y[i]
 Data[z] <- as.numeric(Data[[z]])
```

```
}

Data$Værktøjer_summeret <-
Data$Værktøjer+Data$Bogføringsprogrammer+Data$Drift_benchmarking+Data$Computere_maskiner+
Data$Papir_kuglepen_lommeregner

Data$Analyse_regnskabstal <- Data_spørgeskema_eff$Analyse_regnskabstal

Data$Overskud_ændring <- Data_spørgeskema_eff$Overskud_ændring

Data$Ansatte_efteruddannelse <- revalue(Data_spørgeskema_eff$Ansatte_efteruddannelse, c("0 dage"=0, "1-2 dage"=1, "3-4 dage"=2,
"5-7 dage"=3, "8-10 dage"=4, "Flere end 10 dage"=5))
Data$Ansatte_efteruddannelse <- as.numeric(Data$Ansatte_efteruddannelse)

#======================#
#### Correlations with WR ####
#======================#
cor.test(Data$Efficiensscorer_vægte,Data$Ansatte,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Hektar,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Alder,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Ledelseserfaring_landbrug,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Erfaring_landbrug,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Efteruddannelse,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Mængde_efteruddannelse,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Erfaring_op_til_15_år,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Opfattelse_erhvervet_rammevilkår,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Attitude_fremtiden,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Indstilling_arbejdet,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Intelligens,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Ledelsesegenskaber,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Erfagrupper_sparringspartnere,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Familie_sparringspartnere,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Rådgivere_sparringspartnere,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Venner_sparringspartnere,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Sparringspartnere_summeret,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Ledelsesegenskaber_forbedret_5_år,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Langsigtet_planlægning,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Vækst_orientering,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Samfund_forbruger,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Finansiel_tilbageholdenhed,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Resten,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Værktøjer,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Bogføringsprogrammer,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Drift_benchmarking,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Computere_maskiner,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Papir_kuglepen_lommeregner,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Værktøjer_summeret,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Ansatte_efteruddannelse,method="spearman")
cor.test(Data$Efficiensscorer_vægte,Data$Økonomistyring_data,method="spearman")
wilcox.test(Data$Efficiensscorer_vægte[Data$Køn=="Kvinde"],Data$Efficiensscorer_vægte[Data$Køn=="Mand"])
wilcox.test(Data$Efficiensscorer_vægte[Data$Analyse_regnskabstal=="Ja"],Data$Efficiensscorer_vægte[Data$Analyse_regnskabstal=
="Nej"])
wilcox.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Efficiensscorer_vægte[Data$Bedriftstype=="Konventi
onel planteavl"|Data$Bedriftstype=="Økologisk planteavl"])

cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Ansatte[Data$Bedriftstype=="Svinebrug"],method="spea
rman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Hektar[Data$Bedriftstype=="Svinebrug"],method="spea
rman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Alder[Data$Bedriftstype=="Svinebrug"],method="spear
man")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Ledelseserfaring_landbrug[Data$Bedriftstype=="Svinebr
ug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Erfaring_landbrug[Data$Bedriftstype=="Svinebrug"],me
thod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Efteruddannelse[Data$Bedriftstype=="Svinebrug"],meth
od="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Mængde_efteruddannelse[Data$Bedriftstype=="Svinebr
ug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Erfaring_op_til_15_år[Data$Bedriftstype=="Svinebrug"]
,method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Opfattelse_erhvervet_rammevilkår[Data$Bedriftstype==
"Svinebrug"],method="spearman")
```

```
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Attitude_fremtiden[Data$Bedriftstype=="Svinebrug"],m
ethod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Indstilling_arbejdet[Data$Bedriftstype=="Svinebrug"],m
ethod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Intelligens[Data$Bedriftstype=="Svinebrug"],method="s
pearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Ledelsesegenskaber[Data$Bedriftstype=="Svinebrug"],m
ethod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Erfagrupper_sparringspartnere[Data$Bedriftstype=="Svi
nebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Familie_sparringspartnere[Data$Bedriftstype=="Svinebr
ug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Rådgivere_sparringspartnere[Data$Bedriftstype=="Svin
ebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Venner_sparringspartnere[Data$Bedriftstype=="Svinebr
ug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Sparringspartnere_summeret[Data$Bedriftstype=="Svin
ebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Ledelsesegenskaber_forbedret_5_år[Data$Bedriftstype=
="Svinebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Langsigtet_planlægning[Data$Bedriftstype=="Svinebrug
"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Vækst_orientering[Data$Bedriftstype=="Svinebrug"],me
thod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Samfund_forbruger[Data$Bedriftstype=="Svinebrug"],m
ethod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Finansiel_tilbageholdenhed[Data$Bedriftstype=="Svineb
rug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Resten[Data$Bedriftstype=="Svinebrug"],method="spear
man")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Værktøjer[Data$Bedriftstype=="Svinebrug"],method="sp
earman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Bogføringsprogrammer[Data$Bedriftstype=="Svinebrug"
],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Drift_benchmarking[Data$Bedriftstype=="Svinebrug"],
method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Computere_maskiner[Data$Bedriftstype=="Svinebrug"],
method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Papir_kuglepen_lommeregner[Data$Bedriftstype=="Svi
nebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Værktøjer_summeret[Data$Bedriftstype=="Svinebrug"],
method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Ansatte_efteruddannelse[Data$Bedriftstype=="Svinebru
g"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"],Data$Økonomistyring_data[Data$Bedriftstype=="Svinebrug"],
method="spearman")
wilcox.test(Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"][Data$Analyse_regnskabstal=="Ja"],
        Data$Efficiensscorer_vægte[Data$Bedriftstype=="Svinebrug"][Data$Analyse_regnskabstal=="Nej"])

cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Ansatte[Data$Bedriftstype!="Svinebrug"],method="spear
man")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Hektar[Data$Bedriftstype!="Svinebrug"],method="spear
man")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Alder[Data$Bedriftstype!="Svinebrug"],method="spearm
an")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Ledelseserfaring_landbrug[Data$Bedriftstype!="Svinebru
g"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Erfaring_landbrug[Data$Bedriftstype!="Svinebrug"],met
hod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Efteruddannelse[Data$Bedriftstype!="Svinebrug"],metho
d="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Mængde_efteruddannelse[Data$Bedriftstype!="Svinebru
g"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Erfaring_op_til_15_år[Data$Bedriftstype!="Svinebrug"],
method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Opfattelse_erhvervet_rammevilkår[Data$Bedriftstype!="
Svinebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Attitude_fremtiden[Data$Bedriftstype!="Svinebrug"],met
hod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Indstilling_arbejdet[Data$Bedriftstype!="Svinebrug"],me
thod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Intelligens[Data$Bedriftstype!="Svinebrug"],method="sp
earman")
```

```
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Ledelsesegenskaber[Data$Bedriftstype!="Svinebrug"],met
hod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Erfagrupper_sparringspartnere[Data$Bedriftstype!="Svin
ebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Familie_sparringspartnere[Data$Bedriftstype!="Svinebru
g"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Rådgivere_sparringspartnere[Data$Bedriftstype!="Svineb
rug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Venner_sparringspartnere[Data$Bedriftstype!="Svinebru
g"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Sparringspartnere_summeret[Data$Bedriftstype!="Svine
brug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Ledelsesegenskaber_forbedret_5_år[Data$Bedriftstype!=
"Svinebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Langsigtet_planlægning[Data$Bedriftstype!="Svinebrug"]
,method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Vækst_orientering[Data$Bedriftstype!="Svinebrug"],met
hod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Samfund_forbruger[Data$Bedriftstype!="Svinebrug"],me
thod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Finansiel_tilbageholdenhed[Data$Bedriftstype!="Svinebr
ug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Resten[Data$Bedriftstype!="Svinebrug"],method="spear
man")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Værktøjer[Data$Bedriftstype!="Svinebrug"],method="spe
arman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Bogføringsprogrammer[Data$Bedriftstype!="Svinebrug"],
method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Drift_benchmarking[Data$Bedriftstype!="Svinebrug"],me
thod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Computere_maskiner[Data$Bedriftstype!="Svinebrug"],
method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Papir_kuglepen_lommeregner[Data$Bedriftstype!="Svin
ebrug"],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Værktøjer_summeret[Data$Bedriftstype!="Svinebrug"],m
ethod="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Ansatte_efteruddannelse[Data$Bedriftstype!="Svinebrug"
],method="spearman")
cor.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"],Data$Økonomistyring_data[Data$Bedriftstype!="Svinebrug"],
method="spearman")
wilcox.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"][Data$Køn=="Kvinde"],Data$Efficiensscorer_vægte[Data$B
edriftstype!="Svinebrug"][Data$Køn=="Mand"])
wilcox.test(Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"][Data$Analyse_regnskabstal=="Ja"],
        Data$Efficiensscorer_vægte[Data$Bedriftstype!="Svinebrug"][Data$Analyse_regnskabstal=="Nej"])

#============================================================#
#### Correlations personal aspects and traits and leadership and management ####
#============================================================#
Personal <- cbind("Kundenummer"=Data$Kundenummer, "Bedriftstype"=Data$Bedriftstype,
"Efficiensscorer"=Data$Efficiensscorer_vægte, "Ansatte"=Data$Ansatte,"Hektar"=Data$Hektar,
            "Alder"=Data$Alder, "Ledelseserfaring"=Data$Ledelseserfaring_landbrug, "Erfaring_landbrug"=Data$Erfaring_landbrug,
"Efteruddannelse"=Data$Efteruddannelse, "Mængde_efteruddannelse"=Data$Mængde_efteruddannelse,
"Erfaring_op_til_15_år"=Data$Erfaring_op_til_15_år,
"Opfattelse_erhvervet_rammevilkår"=Data$Opfattelse_erhvervet_rammevilkår, "Attitude_fremtiden"=Data$Attitude_fremtiden,
"Indstilling_arbejdet"=Data$Indstilling_arbejdet, "Intelligens"=Data$Intelligens, "Ledelsesegenskaber"=Data$Ledelsesegenskaber,
"Resten"=Data$Resten, "Køn"=Data$Køn)

Personal <- data.frame(cbind("Ansatte"=Data$Ansatte,"Hektar"=Data$Hektar, "Alder"=Data$Alder,
"Ledelseserfaring"=Data$Ledelseserfaring_landbrug, "Erfaring_landbrug"=Data$Erfaring_landbrug,
"Efteruddannelse"=Data$Efteruddannelse, "Mængde_efteruddannelse"=Data$Mængde_efteruddannelse,
"Erfaring_op_til_15_år"=Data$Erfaring_op_til_15_år
"Opfattelse_erhvervet_rammevilkår"=Data$Opfattelse_erhvervet_rammevilkår, ”Attitude_fremtiden"=Data$Attitude_fremtiden,
"Indstilling_arbejdet"=Data$Indstilling_arbejdet, "Intelligens"=Data$Intelligens, "Ledelsesegenskaber"=Data$Ledelsesegenskaber,
"Resten"=Data$Resten))

Ledelse <- data.frame(cbind("Erfagrupper_sparringspartnere"=Data$Erfagrupper_sparringspartnere,
"Familie_sparringspartnere"=Data$Familie_sparringspartnere, "Rådgivere_sparringspartnere"=Data$Rådgivere_sparringspartnere,
"Venner_sparringspartnere"=Data$Venner_sparringspartnere, "Sparringspartnere_summeret"=Data$Sparringspartnere_summeret,
"Ledelsesegenskaber_forbedret_5_år"=Data$Ledelsesegenskaber_forbedret_5_år,
 "Langsigtet_planlægning"=Data$Langsigtet_planlægning, "Vækst_orientering"=Data$Vækst_orientering,
"Samfund_forbruger"=Data$Samfund_forbruger, "Finansiel_tilbageholdenhed"=Data$Finansiel_tilbageholdenhed,
"Værktøjer"=Data$Værktøjer, "Bogføringsprogrammer"=Data$Bogføringsprogrammer,
```

```
"Drift_benchmarking"=Data$Drift_benchmarking, "Computere_maskiner"=Data$Computere_maskiner,
"Papir_kuglepen_lommeregner"=Data$Papir_kuglepen_lommeregner, "Værktøjer_summeret"=Data$Værktøjer_summeret,
"Ansatte_efteruddannelse"=Data$Ansatte_efteruddannelse, "Økonomistyring_data"=Data$Økonomistyring_data))

Col_Personal <- colnames(Personal)
Col_Ledelse <- colnames(Ledelse)
Korrelationer <- cbind(Col_Personal)
Korrelationer <- Korrelationer[-1,]
str(Data)
str(Personal)
str(Ledelse)

pv <- data.frame("Erfagrupper_sparringspartnere"=rep(0,14), "Familie_sparringspartnere"=0,
            "Rådgivere_sparringspartnere"=0, "Venner_sparringspartnere"=0,
            "Sparringspartnere_summeret"=0, "Ledelsesegenskaber_forbedret_5_år"=0,
            "Langsigtet_planlægning"=0, "Vækst_orientering"=0, "Samfund_forbruger"=0,
            "Finansiel_tilbageholdenhed"=0, "Værktøjer"=0, "Bogføringsprogrammer"=0,
            "Drift_benchmarking"=0, "Computere_maskiner"=0, "Papir_kuglepen_lommeregner"=0,
            "Værktøjer_summeret"=0, "Ansatte_efteruddannelse"=0, "Økonomistyring_data"=0)
rownames(pv) <- Col_Personal

i <- 1
p <- 1
a <- 1
b <- 1

for (i in 1:length(Personal))
{
  a <- as.numeric(unlist(Personal[i]))

  for (p in 1:length(Ledelse))
  {
    b <- as.numeric(unlist(Ledelse[p]))
    pvs <- cor.test(a,b)
    pv[i,p] <- pvs$p.value
  }
}

Korrelationer <- data.frame(cor(Personal,Ledelse, method="pearson"))

write_xlsx(Korrelationer,
        "/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Korrelationer_personlighed_ledelse.xlsx")
write_xlsx(pv,
        "/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Pv_personlighed_ledelse.xlsx")

#==============================================#
#### Correlations decision-making process and leadership style ####
#==============================================#
Decision <- data.frame(cbind("Erfagrupper_sparringspartnere"=Data$Erfagrupper_sparringspartnere,
"Familie_sparringspartnere"=Data$Familie_sparringspartnere,"Rådgivere_sparringspartnere"=Data$Rådgivere_sparringspartnere,
"Venner_sparringspartnere"=Data$Venner_sparringspartnere,
"Sparringspartnere_summeret"=Data$Sparringspartnere_summeret,"Værktøjer"=Data$Værktøjer,
"Bogføringsprogrammer"=Data$Bogføringsprogrammer, "Drift_benchmarking"=Data$Drift_benchmarking,
"Computere_maskiner"=Data$Computere_maskiner, "Papir_kuglepen_lommeregner"=Data$Papir_kuglepen_lommeregner,
"Værktøjer_summeret"=Data$Værktøjer_summeret, "Økonomistyring_data"=Data$Økonomistyring_data))

Leadership <- data.frame(cbind( "Ledelsesegenskaber_forbedret_5_år"=Data$Ledelsesegenskaber_forbedret_5_år,
 "Langsigtet_planlægning"=Data$Langsigtet_planlægning, "Vækst_orientering"=Data$Vækst_orientering,
"Samfund_forbruger"=Data$Samfund_forbruger,"Finansiel_tilbageholdenhed"=Data$Finansiel_tilbageholdenhed,
"Ansatte_efteruddannelse"=Data$Ansatte_efteruddannelse))

Col_Decision <- colnames(Decision)
Col_Leadership <- colnames(Leadership)
Korrelationer <- cbind(Col_Decision)
Korrelationer <- Korrelationer[-1,]
str(Data)
str(Decision)
str(Leadership)

pv <- data.frame("Ledelsesegenskaber_forbedret_5_år"=rep(0,12),
            "Langsigtet_planlægning"=0, "Vækst_orientering"=0, "Samfund_forbruger"=0,
            "Finansiel_tilbageholdenhed"=0, "Ansatte_efteruddannelse"=0)
rownames(pv) <- Col_Decision
```

```
i <- 1
p <- 1
a <- 1
b <- 1

for (i in 1:length(Decision))
{
 a <- as.numeric(unlist(Decision[i]))

 for (p in 1:length(Leadership))
 {
  b <- as.numeric(unlist(Leadership[p]))
  pvs <- cor.test(a,b)
  pv[i,p] <- pvs$p.value
 }
}

Korrelationer <- data.frame(cor(Decision,Leadership, method="pearson"))

write_xlsx(Korrelationer,
       "/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Korrelationer_decision_leadership.xlsx")
write_xlsx(pv,
       "/Users/kirstinemoseschade/Dropbox/Universitet/Speciale/Pv_decision_leadership.xlsx")

#====================#
#### Other correlations ####
#===================#
cor.test(Data$Alder,Data$Erfaring_landbrug) # 0.77 0.00
cor.test(Data$Alder,Data$Mængde_efteruddannelse) # -0.22 0.18
cor.test(Data$Erfaring_landbrug, Data$Mængde_efteruddannelse) # -0.23 0.15
cor.test(Data$Vækst_orientering, Data$Værktøjer_summeret) # 0.34 0.03
cor.test(Data$Ansatte, Data$Alder)
cor.test(Data$Ansatte, Data$Ledelseserfaring_landbrug)
cor.test(Data$Ansatte, Data$Erfaring_landbrug)
cor.test(Data$Ansatte, Data$Efteruddannelse)
cor.test(Data$Ansatte, Data$Mængde_efteruddannelse) # 0.32 0.04
cor.test(Data$Ansatte, Data$Erfaring_op_til_15_år)
cor.test(Data$Ansatte, Data$Opfattelse_erhvervet_rammevilkår)
cor.test(Data$Ansatte, Data$Attitude_fremtiden)
cor.test(Data$Ansatte, Data$Indstilling_arbejdet) # 0.30 0.06
cor.test(Data$Ansatte, Data$Intelligens)
cor.test(Data$Ansatte, Data$Ledelsesegenskaber)
cor.test(Data$Ansatte, Data$Resten)

cor.test(Data$Hektar, Data$Alder)
cor.test(Data$Hektar, Data$Ledelseserfaring_landbrug)
cor.test(Data$Hektar, Data$Erfaring_landbrug)
cor.test(Data$Hektar, Data$Efteruddannelse) # -0.27 0.10
cor.test(Data$Hektar, Data$Mængde_efteruddannelse) # 0.31 0.05
cor.test(Data$Hektar, Data$Erfaring_op_til_15_år)
cor.test(Data$Hektar, Data$Opfattelse_erhvervet_rammevilkår)
cor.test(Data$Hektar, Data$Attitude_fremtiden)
cor.test(Data$Hektar, Data$Indstilling_arbejdet) # 0.43 0.006
cor.test(Data$Hektar, Data$Intelligens)
cor.test(Data$Hektar, Data$Ledelsesegenskaber)
cor.test(Data$Hektar, Data$Resten)
```