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Success with AMS

A quantitative study of what determines success of farmers using Automatic Milking Systems (AMS) in Norway

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NORWEGIAN SCHOOL OF ECONOMICS

Summary

The aim of this thesis is to explain what determines success of Norwegian dairy farmers who use automatic milking systems (AMS). Since the beginning of the 21st century, AMS have accounted for an increasing share of milk production in Norway, where it is estimated that farms using AMS produced 50 % of Norwegian milk in 2017. Earlier literature indicates that AMS can be beneficial compared to conventional milking systems in terms of financial performance, cow health and working conditions, but few studies have considered variation among farmers using AMS.

To understand the variation in success among farmers using AMS, success is measured using both economic and social aspects, including income, job satisfaction, mental wellbeing and family-work balance. It is considered whether farm and farmer characteristics and exploitation of the milking system significantly affect these measurements of financial performance and welfare of dairy farmers. This thesis uses a cross-sectional dataset, including answers from a questionnaire for the year 2017, answered by 739 Norwegian dairy farmers who use AMS. In order to study the economic and social aspects of success, regression and factor analyses are conducted.

The results indicate that farm and farmer characteristics and exploitation of AMS have implications for the economic and social aspects of success. Farm and farmer characteristics as gender, herd size, education, lack of successor, having colleagues and years with AMS are relatively static determinants of success or changeable in the long run. More dynamic variables with impact on success are training in AMS, counselling in AMS and usage of information from the milking system in long term planning, which are changeable in the shorter run. The findings highlight a potential for improvements in the milking system, the positive effects of available training and counselling in AMS and the importance of farmers becoming conversant with the new technology, in order to improve income, job satisfaction, mental wellbeing and family-work balance.

Preface

This thesis has studied whether farm and farmer characteristics and exploitation of the milking system affect the success of dairy farmers who use automatic milking systems. Success has been measured in terms of financial performance and welfare of farmers, considering income, job satisfaction, mental wellbeing and family-work balance. The problem formulation was developed in collaboration with TINE SA.

It has been interesting and educational to gain insight in the automatization of the Norwegian dairy sector. Comparisons of farmers using automatic milking systems have to small extent been covered by previous literature, and we believe this thesis has the potential to contribute to the research field of automatic milking.

We would like to thank our supervisor, Øivind Anti Nilsen. He got us in touch with TINE SA and triggered our interest in the Norwegian dairy sector. The door to his office has always been open, with valuable feedback and advise inside.

A special thanks to Bjørn Gunnar Hansen and Britt Liv Ryland in TINE SA. Hansen has provided priceless insight in the dairy sector and the dataset, and has always been available in case of questions. Ryland has helped us get the data needed in order to answer the problem formulation.

We would also like to thank everyone who during the writing process has provided us with advice or information. We are truly grateful for all help and support.

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1. Introduction

1.1 Background and motivation

Milk production is an essential mainstay of Norwegian agriculture as it accounts for the highest turnover in the sector (Fjellhammer, 2013). Production of milk is a time-consuming process and to improve labour efficiency, automatic milking systems (AMS) were developed (de Koning, 2010). In 2017, more than 20 % of Norwegian dairy farms used AMS and it is estimated that 50 % of the Norwegian milk was produced at farms using AMS (Sigurdsson et al., 2019).

AMS refer to a new milking system technology, where a milking robot is used to milk the herd (de Koning, 2010). The cows enter the robot voluntarily and are milked without the presence of a farmer, which implies changes in the work routines at the farm. Less time is spent in the cowshed, while more time is required monitoring the robot, looking after the herd and analysing data from the milking system.

Compared to conventional milking systems, AMS can be beneficial in terms of financial performance, cow health (Herje & Høva, 2017) and working conditions (de Koning, 2010). Earlier studies of AMS have to a large extent focused on the health and welfare of dairy cows, milk quality and quantity, barn design and the economic impact of AMS (Karttunen, Rautiainen & Lunner-Kolstrup, 2016). This implies that the focus of earlier literature of AMS primarily has been on financial performance and health of dairy cows, and less on the welfare of farmers.

This thesis uses a dataset provided by Ruralis Institute for Rural and Regional Research (Ruralis) and TINE SA which contains information of about 40 % of all Norwegian dairy farms with AMS in 2017. Contrary to earlier studies, this thesis focuses on variation among farmers using AMS, and not variation between those utilizing AMS and conventional milking systems. This thesis also puts the spotlight on dairy farmers using AMS, who have not received much attention in earlier literature. The focus is on the success of farmers in terms of income, job satisfaction, mental wellbeing and family-work balance, which are aspects of importance to farmers but also show potential for improvements. Thus, it is interesting to explore what can affect these measurements in order to potentially improve the financial performance and welfare of dairy farmers using AMS.

1.2 Problem formulation

Based on the background provided in 1.1, this thesis seeks to answer the following question:

What can explain variation in success among dairy farmers who use automatic milking systems?

Success is measured in level of income, degree of job satisfaction, mental wellbeing of farmers and family-work balance. Why these economic and social aspects are relevant in farming when measuring success, is described in section 3.1. This thesis considers whether these measurements are affected by farm and farmer characteristics and exploitation of the milking system.

1.3 Outline

Chapter 1 has provided a brief introduction to this thesis and presented the problem formulation. The following Chapter 2 provides a description of the development of the dairy sector, political regulations and the history of mechanical milking and AMS in Norway. Chapter 3 reviews relevant literature, before Chapter 4 presents the data preparation and statistical methods used to detect why some farmers are more successful than others. Chapter 5 presents empirical findings, including results, discussion, strengths and caveats of the thesis. Lastly, Chapter 6 provides the conclusion to the problem formulation, summarizes the thesis and provides suggestions for future research.

2. Milk production and AMS in Norway

2.1 The development of the Norwegian dairy sector

Norwegian agriculture is in constant development (Zahl-Thanem, Fuglestad & Vik, 2018). Since World War II, the sector has evolved towards bigger, fewer and more specialized farms (Zahl-Thanem et al., 2018), and according to the Norwegian Agrarian Association, dairy farms are among the types of farms experiencing the most drastic decrease in the number of operating farms (Sæther, 2018).

Statistics from Statistics Norway (2019a), show that there has been a steady decrease in the number of dairy farms in Norway since 2002. The decrease is illustrated in Figure 1 below, with a total reduction of 14 573 dairy farms over the last 16 years. This corresponds to at total reduction of 62 % and an annual reduction of 6 % since 2002.

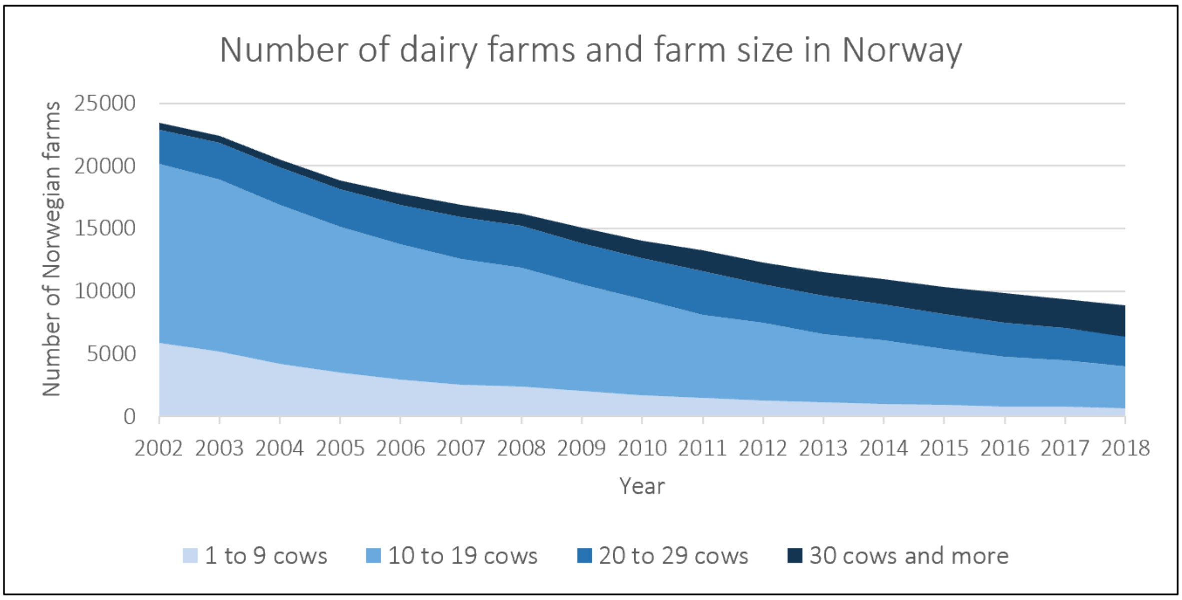

Figure 1 - Development in the number of dairy farms and farm size in Norway from 2002 to 2018
Created based on information retrieved from Statistics Norway (2019a)

Figure 1 also illustrates an increase in the average herd size of farms the past years (Statistics Norway, 2019a). The pie charts in Figure 2 clearly illustrate that the Norwegian dairy sector was dominated by small farms of less than 20 cows in 2002 but became dominated by larger farms of 20 or more cows by 2018. In 2002, the average number of dairy cows per farm was 12, while it increased to nearly 25 cows per farm by 2018.

Figure 2 – Herd size of Norwegian dairy farms in 2002 and 2018
Created based on information retrieved from Statistics Norway (2019a)

Parallel to the decrease in the number of farms and the increase in average herd size, there has been a decrease in the total number of dairy cows in Norway (Statistics Norway, 2019b). Figure 3 illustrates a total reduction of 24 % since 2002, which corresponds to a 2 % annual decrease. This reduction indicates that the increase in average herd size has not compensated for the reduction in the number of dairy farms, resulting in less cows.

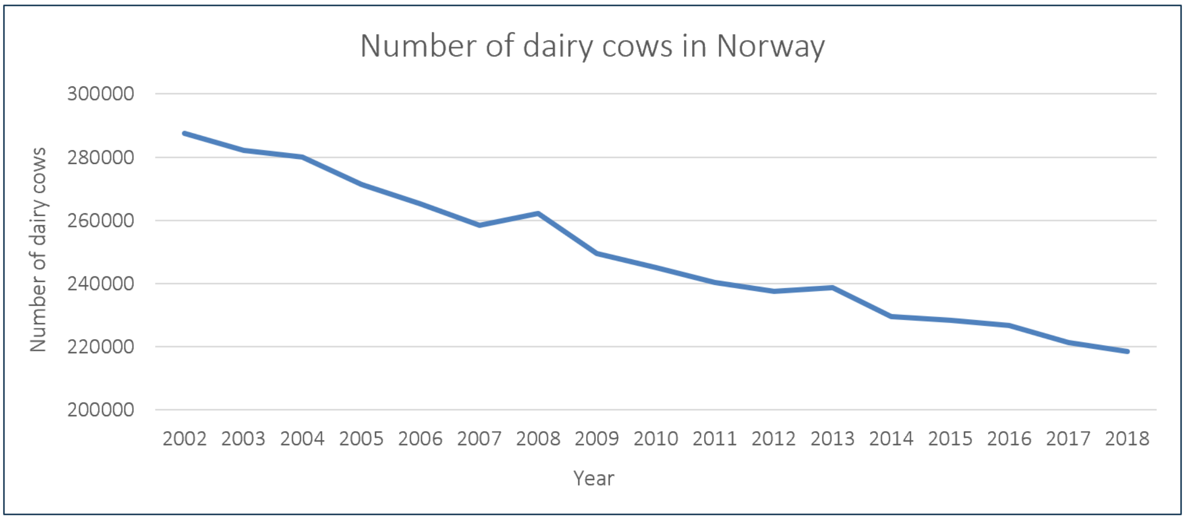

Figure 3 - Development in the number of cows in Norway from 2002 to 2018
Created based on information retrieved from Statistics Norway (2019b)

In 2010, the Central Research Office for Agricultural Associations argued that a continued decrease in the number of dairy cows would result in shortage of delivered milk to the Norwegian market (Fjellhammer, 2013). Statistics Norway (2019b) confirms the predicted decrease in the number of cows. However, the milk yield per cow also increased, which have resulted in a fairly constant production during the last 16 years (NIBIO, 2019). In other words, the productivity, measured in milk yield, has increased in the dairy sector. The improvement in Norwegian milk yield is illustrated in Figure 4, and can be related to technological changes in the dairy sector. The figure illustrates a total increase of 33 %, which corresponds to a 2 % annual increase since 2002.

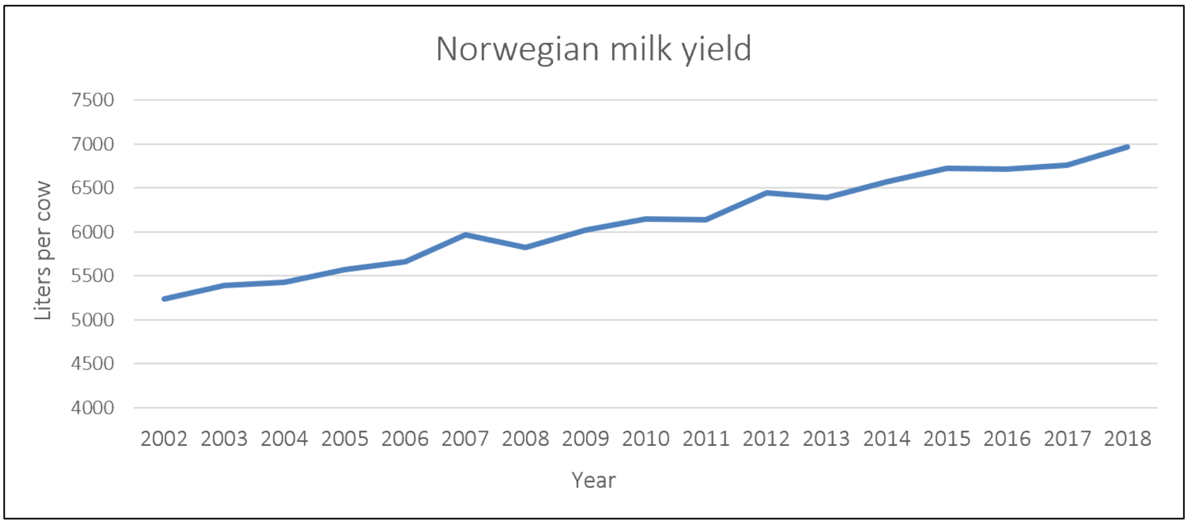

Figure 4 - Development of the Norwegian milk yield from 2002 to 2018
Created based on information retrieved from Statistics Norway (2019b) and NIBIO (2019)

Today, the volume of milk produced in Norway is at a level corresponding to the milk production in the 1950s (Fjellhammer, 2013). Since 1950, the population of Norway has grown by approximately 2 million people (Mellemstrand, 2019; Statistics Norway, 2019c), which implies that the volume of milk produced per capita has been drastically reduced. The reduction of milk per capita is primarily driven by lower demand of milk (Fjellhammer, 2013) and it can consequently have implications for the future of dairy farming. With a situation of stagnating demand, increasing import and more cross-border shopping, the influence on the dairy sector may be serious as it is impossible to maintain an increase in productivity without a continued decrease in the number of farms (The Norwegian Agrarian Association, 2019a).

2.2 Political regulations in Norwegian dairy farming

Norwegian agriculture is heavily regulated by the Government (Zahl-Thanem et al., 2018). The sector is often referred to as a political sector, because it is exposed to more political regulations than other industries. In the dairy sector, quotas and subsidies may be considered the two most important instruments of regulation.

2.2.1 Quotas

A milk quota provides a farmer with the right to produce a given volume of milk within a specific period of time (Norwegian Agriculture Agency, 2019a). Quotas were established in order to adjust the milk production to the marked demand, with the aim of ensuring a predictable milk price for farmers and a stable supply to customers (Bergerud, 2019). The quotas should also ensure a geographically disperse production, and the country is for this reason divided into several production regions serving as geographical borders of quota transfers (Norwegian Agriculture Agency, 2019a). The Norwegian quotas are distributed to the agricultural land of the farms but are tradable within the same production region. In 2019, one agricultural enterprise can gain a total annual quota of up to 900 000 liters of milk, which includes the original quota provided by the Government and additional purchased quotas.

TINE SA[1] provides annual prognoses where the supply and demand of milk for the upcoming year are calculated (The Norwegian Agrarian Association, 2019b). These prognoses serve as basis for discussions between the Government and the dairy industry, to decide whether the milk production should be adjusted. An adjustment of the milk production is done proportionally by deciding the percentage of the total quota each farm can produce. To be more specific, it is decided that each farm can produce 98 % of its quota in 2019 (Ministry of Agriculture and Food, 2018), which implies that the maximal volume of milk produced by one agricultural enterprise is 882 000 liters this year (900 000 * 0.98).

When selling a quota, or part of a quota, the farmer is obligated to sell at least 50 % to the Government (Bergerud, 2019), which allows the Government to regulate the supply of milk to the market. In case of overproduction, the farms producing more than their total quotas

[1] TINE SA is the market regulator of Norwegian milk production (TINE SA, 2019a) and Norway's main producer, distributor and exporter of dairy products (TINE SA, 2019b).

receive economic penalties. At the same time, the Government can choose not to sell the quotas they have obtained through purchase. In case of underproduction, the Government can increase the supply by adjusting all quotas proportionally, as described in the paragraph above. To take an example, it was decided to increase the percentage of the total quota each farm can produce to 104 % in August 2018 (Ministry of Agriculture and Food, 2018). In the opposite case, decreasing this percentage can help the Government overcome overproduction. The quotas can in this way ensure a geographically disperse milk production corresponding to the market demand.

2.2.2 Subsidies

Annually, the Norwegian agricultural sector is supported with an amount of approximately 14 billion NOK (Zahl-Thanem et al., 2018). The amount is negotiated every spring, by the Norwegian Farmers Union, the Norwegian Farmers and Smallholders Union and the Government (Knutsen, 2017). The negotiation starts with the agricultural organizations proposing their claims, before the Government follows with an offer.

Dairy farmers receive support and transfers from the Government through direct and indirect subsidies (Knutsen, 2017). Subsidies determined by production and by district are considered the most relevant types of direct subsidies to Norwegian dairy farmers. Subsidies determined by production are given with the aim of enhancing active and sustainable farming and include a payment per animal or area of land (Norwegian Agriculture Agency, 2019b). The subsidies determined by district are paid per liter of milk produced at the farm, within a given quota (Norwegian Agriculture Agency, 2019c). The size of this payment differs based on the geographic location of the farm, with the aim of compensating for differences in geographic production conditions. In addition to these direct subsidies, Norwegian farmers receive support through indirect subsidies to research, teaching and counselling (Knutsen, 2017). The subsidies are important to recognize as they partially determine the supply of milk to the Norwegian market.

2.2.3 The Agreement on Agriculture

Norway has been a member of the World Trade Organization (WTO) since 1995 (World Trade Organization, 2019), which implies that Norway has to comply with the Agreement on Agriculture. The Agreement on Agriculture was established in 1995 and include commitments related to market access, export subsidies and aggregated support to farmers (Knutsen, 2017).

In addition, it harmonizes regulations for animal health, quality labelling and origin marking, to prevent barriers to trade. In 2015, the members of WTO agreed to remove remaining export subsidies. Most developed countries had to eliminate the export subsidies with immediate effect, while Norway, Canada and Switzerland were given the opportunity to remove the subsidies within 2020.

In 2016, the agreement was approved by the Norwegian Parliament, meaning that by the end of 2020 all export subsidies to dairy products, pork and processed agricultural products are to be removed in Norway (Knutsen, 2017). Consequently, the Norwegian milk production has to be reduced by 100 million liters, corresponding to a 7 % decrease (Olsson, Befring, Ellingsen, Kalstad & Øwre, 2019). It is estimated that this equals a revenue loss of 1 billion NOK and in 2020, TINE SA forecast a reduction of 400 man-years as a consequence of the termination of export subsidies. The reduction in milk production is expected to be large the upcoming year of 2020, and farmers anticipate the agreement to have a considerable impact on the dairy sector and their farm business. In order to reduce the milk production, while maintaining a geographically disperse production, the Government and the Norwegian Agrarian Association are collaborating on a contingency plan.

2.3 The history of mechanical milking and AMS in Norway

The idea of mechanical milking was introduced more than 100 years ago (Ordolff, 2001). However, it took more than 50 years for the idea to get a breakthrough and milking machines to become common installations at dairy farms. Already with the first milking machine, the work routines at the farm started to change towards more focus on foremilking, udder preparation and attachment and detachment of milking clusters. Today, all commercial Norwegian dairy farms utilize a form of mechanical milking, where bucket milking machines, pipeline milking machines and milking parlours are common. These are denoted as conventional milking systems.

The concept of AMS, which has its origin from mechanical milking, has increased rapidly in popularity the recent years (de Koning, 2010). Compared to traditional mechanical milking, AMS completely automize the milking process. The system was developed in order to cope with an increasing cost of labour in dairy farming and to improve the labour efficiency in the time-consuming milking process.

With AMS, the milking process can be conducted without the presence of a farmer, as the cows voluntarily enter a robot for milking (The Open University, 2008). When a cow enters the milking robot, the robot determines whether the cow is fit for milking based on the liters of milk in its udder and time since last milking. After this evaluation, the cow is either milked or leaves the milking robot and comes back later. Once it is decided that the cow is fit for milking, the robot feeds the cow with high quality food which serves as an encouragement for entering the milking robot.

The robot uses lasers and ultrasound sensors to locate and attach the cow’s teats to the machine (The Open University, 2008). Before and after milking, the cow’s teats are disinfected to prevent bacteria from getting into the udder. The milk from each teat goes through a pipe and into a quality sensor, where the milk is checked for pus, blood, water or other abnormalities, with the aim of checking whether the milk is fit for human consumption. When the sensor detects abnormalities, the milk is automatically diverted into a bucket and never gets into the system together with the high-quality milk.

The installation of AMS influences the work routines at the farm (de Koning, 2010). The farmer no longer needs to be present in the cowshed during milking but has to dedicate more time to monitor the herd. The milking robot notifies the farmer when too long time has passed since last milking of a cow, and it is then the responsibility of the farmer to guide this cow to the robot for milking. When milking a cow, the robot automatically generates information concerning cow health and milk quality. This information is stored in a herd management program, which can be useful for farmers when taking farm management decisions (Dairy Australia Limited, 2014). Due to the changes in the work routines, farmers and their herd often experience an adaptation period when installing AMS.

In year 2000, the first farms in Norway installed AMS (Stræte, Vik & Hansen, 2017), and since then the milking system has become a common installation at Norwegian dairy farms. In 2017, the number of milking robots in Norway was 1 957 and approximately 23 % of all dairy farms used AMS in milk production (Sigurdsson et al., 2019). There is a tendency that farms with larger herds invest in AMS or increase the herd size after the investment, as 42.4 % of the Norwegian cows in 2017 lived at farms using AMS. It is estimated that approximately 50 % of the Norwegian milk in 2017 was produced at farms using AMS.

A comparison of the usage of AMS within the Nordic countries in 2017 is presented in Table 1. It can be noted that Norway had the highest number of farms using AMS in 2017, and that only Denmark had a higher number of milking robots than Norway. However, Norway has a higher number of dairy farms than the other countries, and consequently only Finland had a lower percentage of farms using AMS than Norway.

Table 1 - AMS in the Nordic countries in 2017
Created based on information retrieved from Sigurdsson et al. (2019)

	Denmark	Finland	Iceland	Norway	Sweden
Number of dairy farms	3 106	6 806	573	8 154	3 614
Number of farms using AMS	702	1 075	181	1 841	1 012
Percentage of farms using AMS	23 %	16 %	32 %	23 %	28 %
Number of milking robots	2 055	1 593	222	1 957	1 926

3. Relevant literature

3.1 Success in dairy farming

The view on success is individual and studies suggest that there are clear gender differences when men and women are asked to define success in personal and professional life (Dyke & Murphy, 2006). In farming, there is no consensus among experts with regards to what farmers consider most important within their occupation (Fairweather & Keating, 1994).

Traditionally, most empirical research focuses on economic aspects of success, as for instance annual income or return on assets (ROA). In farming, it is traditionally argued that farmers are motivated by maximized profits, as good farmers choose courses of action that yield improved economic returns (Fairweather & Keating, 1994). Improved economic performance is also known to be one of the main reasons for investing in new technology at dairy farms (Dijkhuizen, Huirne, Harsh & Gardner, 1997). According to Herje and Høva (2017) [2], AMS in milk production increase the income and general profitability of farms after a transition period of four years, compared to conventional milking systems. Then, it is interesting to explore if a better implementation and exploitation of the milking system result in improved financial performance.

Scholars argue that farmers' goals are broader than purely economic (Fairweather & Keating, 1994). Today, there is a growing recognition for social aspects of success, as for instance job satisfaction. Job satisfaction, or wellbeing at work as referred to by Baptiste (2008), relates to among others job security, working conditions and the nature of the work undertaken. There is a potential for improvements in terms of job security within agriculture as it is considered a challenging profession with high numbers of occupational accidents, injuries and disabling health conditions (Karttunen et al., 2016). Studies suggest that AMS may create healthier working places (Karttunen et al., 2016) and improved working conditions in terms of flexibility and a more modern lifestyle are shown to be of motivation and importance when deciding to invest in AMS (Hansen, 2015). The nature of the work at the farm also changes when using AMS, as farmers no longer have to be present in the cowshed during milking but

[2] The master thesis of Herje and Høva serves as basis for an article published in the International Food and Agribusiness Management Review in 2018. As this article only partially includes the themes of the master thesis, it is decided to refer to the master thesis.

have to be on duty 24 hours a day in case of technological errors (Ordolff, 2001). With a potential for improvements in job security, healthier working conditions and changes in work routines at the farm, it is interesting to investigate what explains variation in job satisfaction among farmers using AMS.

Mental wellbeing is considered another important social aspect in dairy farming. The rural areas, where farms are located, contribute to geographical isolation and inaccessibility to services, and studies report high risk of psychological distress among farmers (Hounsome, Edwards, Hounsome & Edwards-Jones, 2012). Farmers report that they are stressed due to a heavy workload, health problems, challenging economic situations and loneliness (Kallioniemi, Simola, Kaseva & Kymäläinen, 2016). These stressors indicate that farming as an occupation can be mentally challenging, which is reflected in the high rates of suicide among farmers, reported in several countries (Hounsome et al., 2012). Improvements of physical and mental health are common motivations for investing in AMS (Mathijs, 2004), which indicate that maintaining a good mental health is important to dairy farmers, but it is not agreed if AMS actually increase or decrease farmers' occupational stress (Mathijs 2004; Kartunen et al., 2016). Since the risk of psychological distress among farmers is high and mental wellbeing is of importance, it is interesting to study what affects the mental wellbeing of farmers using AMS.

Scholars highlight the enhancement of family life as important to farmers when making decisions (Fairweather & Keating, 1994), and whether farmers experience farming as compatible with a good family life is therefore an important social aspect. In Norway, the main recruitment to the farming sector is through family, which implies that farmers combine business and family life in a complex and personal way compared to other occupations (Melberg, 2009). Traditionally, gender roles have been clearly defined in Norwegian dairy farming, where men were the main farmers and the main responsibility of women was family caretaking (Hårstad, 2019). Generally, equal division of family related responsibilities has been less of a focus in rural than in urban areas in Norway, and even when a woman is the main farmer, research indicate that she uses more time than her husband on family related activities. Studies show that AMS may allow farmers to spend more time with their family, by releasing time that can be used to take care of children and participate in social activities (Stræte et al., 2017; Mathijs, 2004), which could potentially enable a more equal division of family related responsibilities at the farm. Knowing that there is an unequal division and that family life is important to famers, it is believed that a family related measurement can capture an essential social aspect of farmers' success when using AMS.

Success is defined individually, and there is no consensus among experts with regards to what is the optimal set of farmers' goals (Fairweather & Keating, 1994). In this thesis, both economic and social aspects are taken into consideration by including success in terms of income, job satisfaction, mental wellbeing and family-work balance. It is clear that these aspects are important to farmers but also show potential for improvements. Thus, it is interesting to explore what can affect these measurements in order to potentially improve the financial performance and welfare of dairy farmers using AMS. It may be argued that by including both economic and social aspects of success, this thesis has a broader and perhaps a more realistic view on success in automated dairy farming, compared to what has been the focus of earlier studies.

3.2 Dairy farmers' experiences with advanced farming technology

Earlier studies consider differences between AMS and conventional milking systems and find that AMS can be beneficial both for the herd and the farmer. Considering the situation of the cows, it is shown that AMS improve milk yields (de Koning, 2010), facilitate easier detection of diseases, improve cow health and enhance fertility (Tse, Barkema, DeVries, Rushen & Pajor, 2017). AMS can also reduce labour demand, increase flexibility at work, improve the social life of farmers (de Koning, 2010) and result in less routine activities (Woodford, Brajenrig & Pangborn, 2015). Contrary, AMS require farmers to be on duty 24 hours a day (de Koning, 2010), increase the capital costs (Steenveld, Tauer, Hogeveen & Lansink, 2012) and can potentially result in lower milk quality (Klungel, Slaghuis & Hogeveen, 2000).

Hansen (2015) explores why Jæren has a high rate of adoption of AMS compared to other Norwegian regions. 19 dairy farms in Southern Norway are visited and interviewed by the researcher, where 14 of the farms are located in Jæren. The high rate of adoption in Jæren is explained as a combination of agricultural technological knowledge and dense networks. Interviews with farmers suggest that the presence of a dense network contributes to knowledge sharing, inspiration and motivation. Hansen (2015) also finds that the main motivations for investing in AMS are increased flexibility, reduced workload and more interesting farming.

Lunner-Kolsrup, Horndahl and Karttunen (2018) conduct a pilot study which considers how farmers use and experience working with advanced farming technology and automated systems. The study considers ten farmers from four modern technological Swedish farms, using semi-structured interviews and transect walks. The findings indicate that there are several potential challenges related to AMS. According to the study, learning of new technology, reliability and non-compatibility of the automated systems, training and support during instalment and start-up, large amount of generated data, frequent alarms and changed work routines are the main challenges related to new technology and automated systems in farming.

Hansen and Jervell (2014) explore how four farms using AMS, located in South-Eastern Norway, manage the implementation of AMS differently. Interviews are used to evaluate how successful the investments in AMS are, using milk yield as the measurement of performance. Findings show that new technology can be implemented with different results. Continuous gradual change, former change experience, inner motivation, deliberate use of consultants and careful planning in case of joint farming have positive impacts on the performance both during and after the implementation.

Karttunen et al. (2016) explore occupational health and safety risks at farms using AMS. The study is based on a survey of 228 Finnish dairy farmers, including 131 men and 97 women. In total, 98.2 % of the participants state that AMS reduce the general physical strain at work. Contrary, 42.5 % state that cleaning of the milking robot results in psychical strain. A great majority has the impression that AMS reduce occupational injuries. In total, 47.8 % of the participants state that their general mental health improves when using AMS. Nightly alarms cause stress for 71.5 % of the participants and only 17.5 % feel confident in their own skills when managing the AMS. Lastly, 74.1 % state that AMS provide greater flexibility at work, increased leisure time, improved quality of life and higher productivity of farm work.

Alpass et al. (2004) study stress in relation to adoption of new technology in dairy farming and its relationship to age and gender. Their study is based on a survey of 985 farmers in New Zealand, including 869 men and 125 women. According to the study, frequent sources of stress among dairy farmers are time pressure, machinery breakdowns, weather and government policies. Less frequent sources of stress are understanding new technologies, obtaining information about it and deciding whether to adapt it. The study finds that old farmers experience higher levels of stress than young farmers when understanding new technologies, obtaining information about it and making decisions about whether to adopt it. Female farmers experience higher levels of stress than men when understanding new technologies and when balancing work and family responsibilities.

Earlier studies on AMS have mainly considered differences between AMS and conventional milking systems. These studies indicate that AMS can be beneficial in terms of financial performance, cow health and working conditions, but might also lead to disadvantages. Earlier literature also focuses on farmers' experiences with advanced milking technology by considering the impact of AMS on health, safety and stress of dairy farmers. However, few studies have covered variation in success among farmers using AMS in terms of income, job satisfaction, mental wellbeing or family-work balance, or considered how these are affected by farm and farmer characteristics and exploitation of the milking system. The few studies that have are mainly qualitative and consider only some of the variables available for this thesis. Due to this scarcity in the literature, this thesis, which quantitatively explains variation in success when using AMS, has the potential to contribute to the research field of dairy farming.

4. Data and method

4.1 The dataset

This thesis uses cross-sectional datasets provided by Ruralis and TINE SA, which include responses from a questionnaire answered by Norwegian dairy farmers and descriptive information of the farms, as for instance herd size. The questionnaire was answered by farmers late 2017 or early 2018, which implies that the data provides a good picture of the situation on dairy farms delivering milk to TINE SA in 2017. In total, the dataset contains observations of 739 farms using AMS. In comparison, the number of Norwegian dairy farms using AMS in 2017 was 1 841, which means that this thesis has data of about 40 % of the total number of dairy farms in Norway with AMS in 2017.

When conducting statistical analyses, it is important that the dataset is representative of the true population of interest (Wooldridge, 2016). The dataset used in this thesis provides information concerning farms delivering milk to TINE SA and where farmers have chosen to answer a questionnaire. It is therefore a possibility that these farmers have other characteristics and prerequisites than the rest of the population. To investigate the representativeness of the dataset, it would be interesting to compare essential variables across the dataset and the population. However, the prepared dataset used in this thesis only contains information concerning farms using AMS, which may have different characteristics than farms using conventional milking systems. For instance, it is common to increase the herd size when changing from conventional milking systems to AMS (Stræte, 2019). Therefore, it is not considered correct to compare the dataset to all Norwegian dairy farms, because the true population only includes dairy farms with AMS. Gaining information of the true population is challenging, as only characteristics of all dairy farms are publicly available. According to internal sources in TINE SA (B. G. Hansen, personal communication, October 25th, 2019), the average number of cows in the true population is 48 in 2018. In the dataset available for this thesis, the average number of dairy cows is 47 in 2017, implying small differences between the dataset and the true population in herd size. However, with other potential differences between the observed data and the true population, one should be more careful with direct interpretations from the analyses than in case of random sampling.

4.1.1 Preparing the data

This thesis uses three datasets, which are combined through merging. Some Norwegian farms received new production identities (ID's) in an earlier merger of two counties and the dataset with the answers from the questionnaire is first updated to include the correct producer identity for every farm. Then, herd sizes of Norwegian dairy farms in 2017 are merged into the dataset. The datasets available for this thesis include observations of dairy farms using AMS and conventional milking systems. As this thesis only focuses on farms using AMS, all observations of farms using conventional milking systems are deleted from the datasets. Consequently, all future references to "farmers" in this thesis refer to farmers using AMS, unless otherwise specified. Variables that are not considered of interest, especially those containing many missing values, are deleted.

Most answers from the questionnaire are registered as a number indicating an alternative answer chosen. For most of the variables, the numbers indicate farmers' positions on a scale, going from "never" to "very often" or "I strongly disagree" to "I strongly agree". These are ordinal variables and when working with ordinal data it may be necessary to reverse the coding of variables in order for high scores to reflect either positive or negative effects (Pett, Lackey & Sullivan, 2003). It is decided to rotate some variables in order for a higher value to indicate a better scenario. To illustrate what is done, an example can be taken into consideration. One question asked farmers if they have been stressed because of work during the last six months. They were asked to answer on a scale from 1 to 11, where 1 indicates that they have not been stressed at all and 11 indicates that they feel stressed quite often. This variable is rotated, in order for the value 11 to indicate the positive scenario, namely that farmers have not been stressed at all. The higher the values for the rotated variable, the less stressed farmers have been during the last six months. Ordinal variables are coded as integers from 1 to the number of alternative answers for each question, where 1 is least preferable.

It is decided to make some of the ordinal variables into binary variables. This is applied for variables that are included as independent variables in the analysis and is done because it is recommended that categorical variables are binary indicators when entered into a model as independent variables (Long & Freese, 2003). The variables are recoded from ordinal variables taking values on a scale, to dummies taking the value 1 or 0. For instance, the variable originally indicating to which degree farmers feel they have received sufficient training in

AMS, on a scale from strongly disagree to strongly agree, becomes a dummy taking the value 1 when the farmer agrees and the value 0 when the farmer does not agree.

In addition to using the variables directly, rotated or as dummies, an additional variable is created. An interesting aspect to investigate in this thesis is whether the time since investments in AMS impacts the success. A variable containing years since investments in AMS is therefore created based on the date of investment in AMS, measured in years since January 1st, 2018.

4.1.2 Descriptive statistics

Descriptive statistics of the most essential variables in the prepared dataset is found in Table 2 on page 25. It can be noted that the number of observations varies for the different variables because farmers have not necessarily answered all questions in the questionnaire, resulting in missing values.

Herd size and years with AMS are continuous variables, measuring the number of cows at the farm and years since the farm invested in AMS. Income is an ordinal variable measured in intervals of 100 000 NOK. The variables satisfaction with workday, satisfaction with work security, satisfaction with work environment, flexible workday and optimistic view on the future take values from 1 to 11, where a higher value indicates that farmers are more satisfied, have a more flexible workday and have a more optimistic view on the future. The variables showing absence of stress, loneliness, financial concerns, worries related to health and tiredness indicate to which degree farmers recognize these feelings, where a higher value indicates less stress, loneliness, concerns, worries or tiredness. Time spent on cooking, time spent on housework and time with family and children take values from 1 to 5, where a higher value indicates that farmers spend more time than their partner on family related activities. Sufficient time with family, sufficient time for friends and activities, suitable workload during weekends, feeling valued as a farmer and low degree of physical work take values from 1 to 11, where a higher value indicates more time for family, friends and activities, a more suitable workload, farmers feeling more valued and farmers having less physical work.

The variable female contains information about the gender of the farmers and takes the value 1 if the farmer is female and 0 if the farmer is male. Education is 1 if the farmer has education in agriculture at university level, and 0 if not. Lack of successor takes the value 1 if the farmer does not have a successor, and 0 if there is a successor. Colleagues is 1 if the farmer works with others at the farm, and 0 if not. This variable includes both joint farming and collaboration with assistants or family members at the farm. The variable training in AMS takes the value 1 if the farmer has received sufficient training in AMS, and 0 if not. Counselling in AMS takes the value 1 if the farmer has adequate counselling available, and 0 if not. Long term planning using AMS is also a dummy, taking the value 1 if the farmer uses information from the milking system in long term planning of the farm business, and 0 if not.

The descriptive statistics in Table 2, illustrate that the dataset contains information of farms that have recently invested in AMS and farms that invested in AMS when the technology was first introduced in Norway at the beginning of the 21st century. The descriptive statistics show that the majority of farmers using AMS are satisfied with their work, in terms of workday, security, environment and flexibility. In terms of stress, loneliness, financial concerns, worries related to health and tiredness there is a disperse variation among farmers. It is also interesting to notice that the majority of farmers using AMS dedicates less time to family related activities than their partner, especially on cooking and housework. Table 2 also show that few farmers have agricultural education or lack a successor, and less female than male farmers are included in the dataset. A considerable share of the dairy farmers lacks sufficient training and counselling in AMS, or do not utilize information from the milking robot in long term planning of the farm business.

Table 2 - Descriptive statistics

Continuous variables	N	Mean	Median	Std.dev.	Min.	Max.
Herd size	718	47.2	44.9	16.8	11.5	125.9
Years with AMS	723	5.6	5.0	3.4	0.2	17.4

Ordinal variables	N	Mean	Median	Std.dev.	Min.	Max.
Income	739	5.7	6	2.1	1	9
Satisfaction with workday	739	8.7	9	1.9	1	11
Satisfaction with work security	739	8.9	9	1.7	1	11
Satisfaction with work environment	739	9.0	9	1.7	1	11
Flexible workday	739	8.3	9	2.0	1	11
Optimistic view on the future	739	8.3	9	2.0	1	11
Absence of stress	739	4.7	4	2.5	1	11
Absence of loneliness	739	6.8	7	2.8	1	11
Absence of financial concerns	739	6.5	6	3.0	1	11
Absence of worries related to health	739	7.4	8	3.0	1	11
Absence of tiredness	739	4.6	4	2.4	1	11
Time spent on cooking	655	2.1	1	1.4	1	5
Time spent on housework	657	2.0	1	1.3	1	5
Time with family/children, afternoons and evenings	593	2.5	2	0.9	1	5
Time with family/children, weekends	611	2.6	3	0.7	1	5
Sufficient time with family	739	6.2	6	2.4	1	11
Sufficient time for friends and activities	739	5.6	6	2.5	1	11
Suitable workload during weekends	739	3.6	3	2.5	1	11
Feeling valued as a farmer	739	6.0	6	2.9	1	11
Low degree of physical work	739	7.5	8	1.9	1	11

Binary variables	N	0	1
Female	739	85.8 %	14.2 %
Education	739	86.7 %	13.3 %
Lack of successor	739	93.0 %	7.0 %
Colleagues	739	69.6 %	30.4 %
Training in AMS	739	40.2 %	59.8 %
Counselling in AMS	739	23.8 %	76.2 %
Long term planning using AMS	739	39.5 %	60.5 %

4.2 Statistical methods

In this thesis, both regression and factor analysis are used in order to analyse the dataset. Regression analysis is used to study the relationship between observed variables, while factor analysis allows for studying relationships between observed and unobserved variables.

4.2.1 Regression analysis

Regression analyses are conducted, using income as the dependent variable. In the dataset available, income is an ordinal variable measured in intervals of 100 000 NOK, meaning that for instance all farmers earning from 200 000 NOK to 299 999 NOK are considered the same. Ideally, it would have been desirable with continuous financial data of income, but the intervals can be used in order to detect why some farmers have a higher level of income, and thereby are more successful.

This thesis utilizes ordinary least squares (OLS) regression. OLS regression is used to study the relationship between an observed dependent variable and several observed independent variables, by minimizing the sum of the squared residuals (Wooldridge, 2016). The general formula of OLS regression (level-level model) is presented below, where a one-unit change in the independent variable (x) is associated with a β change in the dependent variable (y), keeping all other variables constant.

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_k x_{ik} + \varepsilon_i$$

Income is an ordinal variable coded as consecutive integers from 1 to 9, which have implications for which regression method to use. Using a linear regression model for ordinal data has been proven to lead to incorrect conclusions because an ordinal dependent variable violates the assumptions of a linear regression model (Long & Freese, 2003). The assumptions are violated because categories of ordinal data can be ranked, but the distance between the categories are commonly unknown. In many cases, it cannot be argued that the distance between alternative 1 and 2, is the same as the distance between 2 and 3, and thereby the linear regression model is not the best choice. In this thesis, the distance between the alternatives is known. Each alternative contains intervals of 100 000 NOK, which means that the distance between alternative 1 and 2 is the same as the distance between 2 and 3. Thus, the data can be treated as continuous and a linear regression model can be used even though the data of the dependent variable is ordinal.

It can be noted that regression models for ordinal outcomes have been conducted with income as the dependent variable. These show similar results compared to the OLS regression. Due to the concurrent results and the arguments presented in the paragraph above, it is decided to conduct OLS regression for the aim of this thesis.

In addition to the OLS regression, it is decided to report the results of an interval regression (intreg). This is a model designed for interval data, left-censored data, right-censored data and point data (Stata, 2019). The data should be stored with an upper and lower limit for each observation. This means that for instance all farmers earning from 200 000 NOK to 299 999 NOK, will be registered with a lower limit of 200 000 NOK and an upper limit of 299 999 NOK. This requires a re-coding of income, from one ordinal variable representing an interval in form of an integer, to two variables representing the lower and upper limit.

4.2.2 Factor Analysis

Factor analysis is a commonly used statistical method, which originates from the field of psychology where subjective opinions are taken into consideration (Pett et al., 2003). Factor analysis is the creation of a statistical model that relates a set of manifest variables to one or more factors (Beaujean, 2014). The manifest variables are directly observed and registered in a dataset, while a factor is a latent variable, which value cannot be directly observed. Each factor contains several items, which are manifest variables from the dataset. It is important to comment that factor analysis is not a single statistical method, but rather a term covering different methods grouping a smaller set of manifest variables into factors, based on identified interrelationships (Pett et al., 2003). This thesis, focus on the methods of exploratory factor analysis and structural equation modelling.

The basic idea of factor analysis is to find a set of unobserved latent factors (F) fewer than the observed manifest variables (x) (Jöreskog, Olsson & Wallentin, 2016). Items are given factor loadings (λ) for the identified factors, which indicates the relevance of the manifest variable in defining the factor (Beaujean, 2014).

The linear factor analysis model is the following (Jöreskog et al., 2016):

$$x_i = \lambda_{i1} F_1 + \lambda_{i2} F_2 + \ldots + \lambda_{ik} F_k + \delta_i, \qquad \text{where } i = 1, 2, \ldots, p$$

x_i	Item i
$F_{1, 2, \ldots, k}$	Underlying latent factor 1, 2, …, k
$\lambda_{i\,1, 2, \ldots, k}$	Factor loading of item i on factor 1, 2, …, k
δ_i	Unique part of x_i, uncorrelated with $F_1, F_{2, \ldots,} F_k$

Exploratory factor analysis

Exploratory factor analysis (EFA) is a statistical method used to reduce data by extracting factors from a dataset without specifying the number and pattern of factor loadings between manifest variables and factors (Beaujean, 2014). EFA can be used by researchers to explore the underlying dimensions of the construct of interest (Pett et al., 2003), and the method can be useful when there is no hypothesized structure for the latent variable model (Beaujean, 2014). The basic assumption of EFA is that within a dataset of manifest variables, a set of underlying factors exists that can explain interrelationships among manifest variables (Pett et al., 2003).

After designing and collecting data in the form of a questionnaire, the first step of an EFA is to develop a correlation matrix of the potential items (Pett et al., 2003). The correlation matrix provides the researcher with an understanding of which manifest variables might cluster. Generally, correlations above 0.4 are considered to represent strong relationships, while correlations between 0.2 and 0.4 represent moderate relationships (Shortell, 2001).

Thereafter, the initial factors can be extracted (Pett et al., 2003). Several extraction approaches can be applied, where all have their own proponents and critics. This thesis utilizes principal component analysis, which creates factors existing of observed variables from the dataset such that all the variance of the observed variables can be explained by the factor where they are included.

After extracting the factors, this thesis uses the Kaiser-Guttman rule of eigenvalues and a scree plot with the Cattell criteria to determine how many factors to retain. The Kaiser-Guttman rule states that only factors with an eigenvalue larger than 1.00 should be retained, which are factors accounting for more than their share of the total variance in the items (Pett et al., 2003). A scree plot is a visualization of the factors and the eigenvalues, where a ruler is laid across the lower eigenvalues to detect where they form a straight line. According to the Cattell criteria all factors above the straight line in the scree plot should be retained, as these factors account for a considerable amount of the total variance in the items.

After the initial factors are extracted and retained, it is common to rotate the factors (Pett et al., 2003). Factor rotation is the process of turning the reference axis of the factors about their origin and is done in order to improve the meaningfulness and interpretation of the retained factors. There are two main methods of rotation, orthogonal and oblique rotation methods, where there are no strong arguments favouring one method (Hair, Black, Barbin & Anderson, 2014). This thesis utilizes promax rotation, which is a commonly used oblique rotation technique. An oblique rotation method is chosen because it has less strict assumptions, as it does not rule out correlation between the factors. The rotated factors are presented in a matrix, including factor loadings for each item (Pett et al., 2003). A factor loading indicates how relevant an item is in defining a factor, and a higher value indicates higher relevance (Beaujean, 2014). In general, a factor is considered weak or unstable if it has less than three items, and in a solid factor all items have a factor loading of 0.5 or higher (Osborne, Costello & Kellow, 2008).

A number of factors are extracted and retained through an EFA. However, researchers are sceptical towards using rigid guidelines when retaining the factors, and the ultimate criteria for determining the final number of factors are interpretability and usefulness of the factors (Pett et al., 2003). This means that one should evaluate and potentially modify the number of factors after conducting an EFA.

Structural equation modelling

When the factors have been identified, the next step is to use the factors as predictors or outcome variables in further analysis (Jöreskog et al., 2016). This is the goal of structural equation modelling, which considers manifest variables and latent variables and the relationship between them (Beujean, 2014).

A structural equation model (SEM) consists of two parts (Beaujean, 2014). The first is a latent variable model, which defines factors. This model can be referred to as a confirmatory factor analysis (CFA) which assesses to which extent a hypothesis, defining a set of factors, fits the data (Pett et al., 2003). It is used when researchers have previous knowledge about the data or to test factors identified through an EFA. The second part of the SEM is a structural model, which identifies a regression-like relationship between potential latent and manifest variables (Beaujean, 2014).

There are several estimation methods, or estimators, to choose from when conducting structural equation modelling. In this thesis, the dataset contains farmers' answers from a questionnaire, where most answers are given on a scale. Most answers are coded as consecutive integers from 1 to the number of alternative answers for each question. This type of ranking in form of integer values is classified as ordinal data. Estimators, like maximum likelihood, that assume continuous data are not appropriate to use when the items are ordinal. Ordinal data should be treated differently because the values of ordinal data only indicate a ranking and not a distance between alternatives. Diagonally weighted least squares (DWLS) is an estimator specially designed for ordinal data (Li, 2016). According to Li (2016), using DWLS results in less biased factor loadings compared to other estimators when the data is ordinal. In this thesis, all items are coded as ordinal and DWLS is chosen as the preferred estimator, due to the ordinal dimension of the data.

It may be argued convenient to present the findings of a SEM using a path diagram (Beaujean, 2014). A path diagram shows the relationship between the latent and manifest variables, with geometric figures representing the variable types and arrows representing the relationships. Figure 5 illustrates a path diagram as presented in the findings of this thesis. Items and independent variables, which are manifest variables from the dataset, are illustrated as square boxes. The factor, which in the SEMs of this thesis is the dependent variable, is presented as a big circle. The error terms, which are the variation of the items left unaccounted for by the factor (Jöreskog et al., 2016) are illustrated as smaller circles. Each single-headed arrow implies a direct relationship. The items have arrows pointing towards them, indicating that the factor is the underlying construct of the items. The independent variables have arrows pointing from them to the factor, illustrating that they explain variation in the factor.

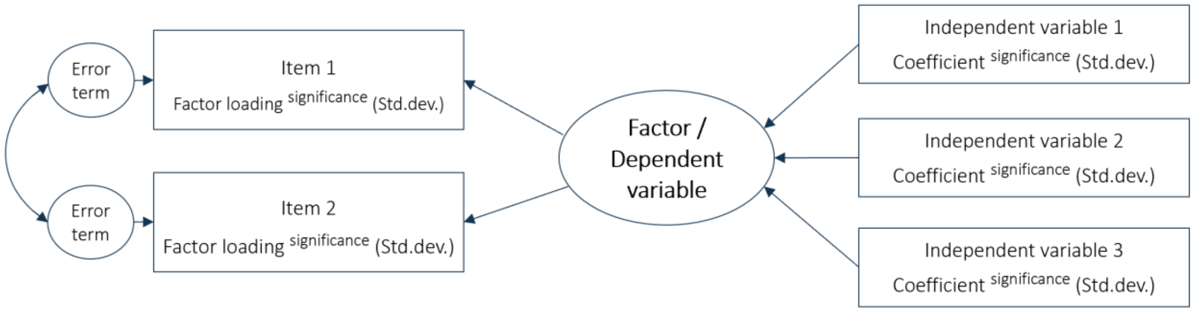

Figure 5 - Illustration of a path diagram of a SEM

Once a SEM has been conducted, one need to study the model fit. Fit measures are used to evaluate how well the model fits the underlying data (Hooper, Coughlan & Mullen, 2008). A variety of fit indices can be used to evaluate a SEM, including chi-square, root mean square error of approximation (RMSEA), comparative fit index (CFI) and Tucker Lewis Index (TLI). There are both advantages and disadvantages with all these measures, and it is recommended to report several fit measures in order to reflect the different aspects of model fit.

The *chi-square* (χ^2) considers the size of the deviation between the sample and fitted covariance matrices and is one of the traditional and popular measurements for model fit (Hooper et al., 2008). It is chosen to interpret this measure carefully due to its sensitivity to large sample sizes. Using the relative chi-square (χ^2/df), where a value below 2 indicates a good fit, can decrease the problem of over-rejection. *RMSEA* measures how well the model would fit the populations covariance matrix and has in the later years been considered one of the most informative fit indices. Generally, a value below 0.08 indicates a good fit and everything above is a poor fit. *CFI* compares the sample covariance matrix of the proposed model with a null model, where none of the measured variables are correlated. It has grown in popularity because it is one of the fit measures least affected by the sample size. A value above 0.90 is needed to ensure that there are no misspecifications, and a value above 0.95 indicates a good fit. The *TLI* compares the chi-square of the proposed model with the null model. Like the CFI, it is recommended because it is resilient against variations in sample size. For the TLI, a value above somewhere between 0.90 and 0.95, indicates a good model fit.

In case of a poor model fit, the model may be incorrectly specified (Hooper et al., 2008). The poor fit may be caused by inclusion of items that should not have been included or lack of correlation between error terms of the items. Removing weak items can be justified as these are less relevant in explaining the underlying factor. Correlation should only be included when having a solid justification because it implies that issues not specified in the model cause correlation between the items. When correlation between error terms of items is included, it is illustrated as a double-headed arrow between the error terms of the items.

Why use factor analysis?

The dataset of this thesis includes dairy farmers' responses to a variety of questions, where some of the questions cover the same topic. In addition to regression analysis, it is therefore considered useful to utilize a method where each question not necessarily has to be assessed individually. The alternative to a factor analysis is to run separate regressions with each item as dependent variables, which is inexpedient as the items are narrow measurements of success. A factor analysis allows for consideration of multiple subjective questions, covering the same topic, as one unobserved variable. Using factor analysis is expedient when the aim is to measure social aspects using broader measurements of success. Even though factor analysis is not yet a commonly used method among economists, it should be noted that it has increased in popularity, especially during the last 30 years (Beaujean, 2014). Today, factor analysis is used in a variety of academic disciplines as science, clinical professions, business and humanities.

5. Empirical findings

5.1 Results

5.1.1 Regression analysis

Income is a commonly used economic aspect of success and is analysed using OLS regression and interval regression. Income is not included as a part of a factor because it may be considered a strong measurement of success standing alone. The regression models are the following:

$$\begin{aligned}\text{Income}_i \quad = \quad & \beta_0 + \beta_1 \text{ Female}_i + \beta_2 \text{ Education}_i + \beta_3 \text{ (Lack of successor)}_i \\ & + \beta_4 \text{ Colleagues}_i + \beta_5 \text{ (Long term planning using AMS)}_i \\ & + \beta_6 \text{ (Training in AMS)}_i + \beta_7 \text{ (Years with AMS)}_i + \varepsilon_i\end{aligned}$$

$i = 1, 2, \ldots, 723$

The results of these regressions are presented in Table 3, where income is an ordinal variable measured in intervals of 100 000 NOK. Regression 1 is an OLS regression, where the coefficients are measured in 1/100 000 NOK. β * 100 000 NOK represents the absolute change in income, in regression 1, as a result of a one-unit change in an independent variable, keeping all other independent variables constant. Regression 2 is an interval regression, where the coefficients are measured in absolute values of NOK.

The regression models show that female farmers have lower success than male farmers measured in income, at a 1 % significance level. At the same level of significance, the models indicate that colleagues and years with AMS are positively correlated with income. Income increases when farmers have education in agriculture from university or received training in AMS, at a 5 % significance level. Usage of information from the milking system in long term planning negatively affect income at a 5 % significance level. Lack of successor negatively affects income at 5 % significance level in regression 1 and at a 1 % significance level in regression 2. The regressions indicate that successor and gender have the largest impact on income. On average, female farmers earn 71 000 NOK less than male farmers and not having a successor negatively impacts income by 75 000 NOK, according to the OLS regression.

According to the interval regression, female farmers earn on average 91 000 NOK less than male farmers and not having a successor on average reduce the income by 98 000 NOK.

Table 3 - Regression models of income[3] (N = 723)
*Standard error in parenthesis. Significance level: * = 10 % ** = 5 % *** = 1 %*

VARIABLES	(1) OLS Income	(2) Intreg Income
Female	-0.709*** (0.222)	-91 218*** (26 489)
Education	0.567** (0.222)	66 006** (26 555)
Lack of successor	-0.749** (0.301)	-97 840*** (34 135)
Colleagues	0.458*** (0.169)	57 025*** (20 908)
Long term planning using AMS	-0.384** (0.157)	-47 559** (19 236)
Training in AMS	0.375** (0.156)	47 300** (19 222)
Years with AMS	0.123*** (0.023)	14 901*** (2 994)
Intercept	4.930*** (0.199)	350 389*** (24 896)
Number of observations	723	723
R^2	0.092	-

[3] Income is often included as the dependent variable in log-level regression models, which allows for interpretation of the regression coefficients in percentage. In this thesis this is not expedient, as income is an ordinal variable.

5.1.2 Exploratory factor analysis

The aim of the EFA is to explore the underlying dimensions of the dataset and to detect factors measuring multivariate social aspects of success. Factors can capture multivariate social aspects of success because it reflects the subjective opinion of dairy farmers by considering their answers to several questions in the questionnaire, simultaneously. An EFA is conducted using a pre-specified selection of the dataset, including 19 manifest variables which relate to work situation, work-related concerns, participation in family life and quality of life. The 19 variables included in the EFA are potential items of factors measuring social aspects of success, and variables that are believed to explain variation in success, as for instance gender, education and age, are therefore not included in the EFA.

In Table 4, a correlation matrix including these 19 variables is presented. The matrix shows several moderate and strong correlations, which indicate that interrelationships exist among the manifest variables and that underlying factors can be found. For instance, the correlations are high between the variables measuring time spent on cooking, on housework and with family and children, implying that these manifest variables might serve as items in the same latent factor.

Table 4 - Pearson correlation matrix (N = 534)

	Satisfaction with workday	Satisfaction with work security	Satisfaction with work environment	Flexible workday	Optimistic view on the future	Absence of stress	Absence of loneliness	Absence of financial concerns	Absence of worries related to health	Absence of tiredness	Sufficient time with family	Sufficient time for friends and activities	Suitable workload during weekends	Time spent on cooking	Time spent on housework	Time with family/children, afternoons/evenings	Time with family/children, weekends	Feeling valued as a farmer	Low degree of physical work
Satisfaction with workday	1.00																		
Satisfaction with work security	0.45	1.00																	
Satisfaction with work environment	0.63	0.62	1.00																
Flexible workday	0.45	0.24	0.36	1.00															
Optimistic view on the future	0.54	0.34	0.50	0.37	1.00														
Absence of stress	0.29	0.16	0.19	0.22	0.25	1.00													
Absence of loneliness	0.31	0.16	0.27	0.17	0.27	0.40	1.00												
Absence of financial concerns	0.25	0.13	0.18	0.12	0.23	0.41	0.41	1.00											
Absence of worries related to health	0.31	0.18	0.21	0.17	0.21	0.27	0.32	0.38	1.00										
Absence of tiredness	0.31	0.16	0.20	0.19	0.25	0.55	0.36	0.41	0.48	1.00									
Sufficient time with family	0.42	0.22	0.33	0.36	0.41	0.35	0.23	0.28	0.15	0.36	1.00								
Sufficient time for friends and activities	0.40	0.22	0.32	0.35	0.41	0.37	0.19	0.25	0.22	0.42	0.75	1.00							
Suitable workload during weekends	0.21	0.01	0.10	0.15	0.17	0.21	0.24	0.15	0.17	0.25	0.36	0.34	1.00						
Time spent on cooking	-0.02	0.06	0.02	0.05	-0.02	-0.06	0.09	-0.03	-0.05	-0.07	0.00	-0.06	-0.05	1.00					
Time spent on housework	0.04	0.08	0.05	0.04	0.00	-0.03	0.07	0.04	0.00	-0.04	0.02	-0.04	0.02	0.74	1.00				
Time with family/children, afternoons/evenings	0.09	0.13	0.09	0.14	0.05	0.07	0.08	0.09	-0.04	0.01	0.19	0.12	0.04	0.50	0.58	1.00			
Time with family/children, weekends	0.14	0.16	0.15	0.13	0.09	0.12	0.12	0.11	0.00	0.07	0.20	0.14	0.10	0.40	0.46	0.73	1.00		
Feeling valued as a farmer	0.17	0.12	0.21	0.13	0.30	0.13	0.27	0.19	0.11	0.16	0.17	0.15	0.22	0.03	0.01	0.03	0.06	1.00	
Low degree of physical work	-0.10	-0.06	-0.06	-0.08	-0.09	0.02	0.12	-0.03	-0.12	0.02	-0.10	-0.13	0.15	-0.09	-0.13	-0.03	-0.02	0.13	1.00

Correlation above 0.4

Correlation from 0.2 to 0.4

The next steps of the EFA are to extract factors and determine how many factors to retain. In total, 19 factors are extracted using principal component analysis. In Table 5, the ten factors with the highest eigenvalues are presented. According to the Kaiser-Guttman rule, factor 1, 2, 3, 4 and 5 should be retained for further analysis, as they have eigenvalues larger than 1.00.

Table 5 – The ten factors with the highest eigenvalues extracted through EFA (N = 534)

Factor	Eigenvalue
Factor 1	4.887
Factor 2	2.702
Factor 3	1.690
Factor 4	1.312
Factor 5	1.258
Factor 6	0.974
Factor 7	0.788
Factor 8	0.748
Factor 9	0.684
Factor 10	0.640

The scree plot of the 19 extracted factors is presented in Figure 6. According to the Cattell criteria factor 1, 2, 3, 4 and 5 should be retained, as they are located above the straight line drawn through the smaller eigenvalues. This is coherent with the Kaiser-Guttman rule, and it is decided to retain these five factors for further analysis.

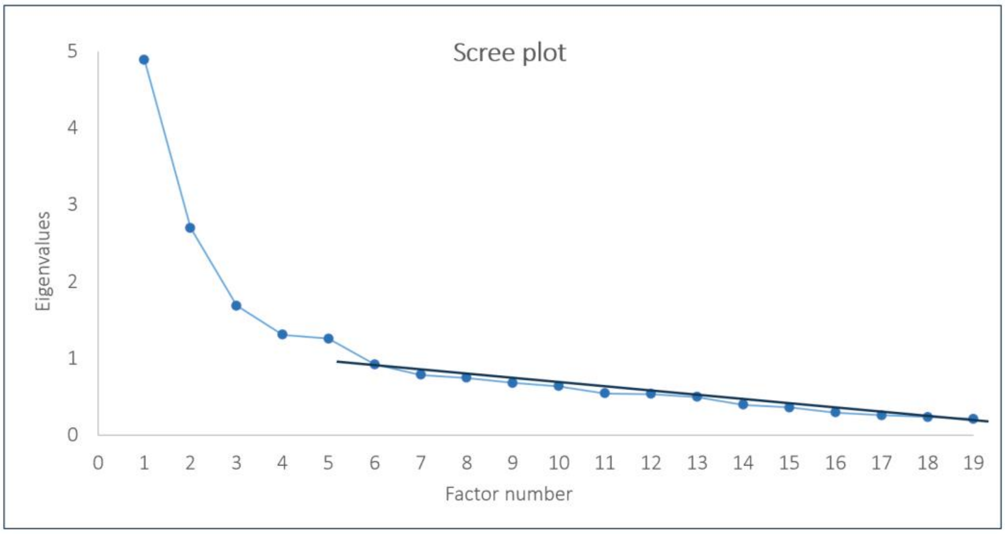

Figure 6 - Scree plot of factors extracted through EFA (N = 534)

The five retained factors are rotated and factor loadings are calculated. Each manifest variable is included in one or more factor as an item. In Table 6, the factors with their corresponding items and factor loadings are presented. Only factor loadings above 0.3 are shown, as this is considered the minimum loading of an item (Osborne et al., 2008; Pett et al., 2003).

The names of the factors are defined by the researcher and should be descriptive and representative of all items included in each factor, as it is the names of the factors that are communicated to the reader in the results of a study (Pett et al., 2003). In this thesis, it is chosen to label Factor 1 job satisfaction, as it includes satisfaction with workday, satisfaction with work security, satisfaction with work environment, degree of flexibility at work and level of optimistic view on the future as items. Factor 2 is labelled mental wellbeing as it includes absence of stress, loneliness, financial concerns, worries related to health and tiredness, which are aspects of mental health. Factor 4 is labelled family-work balance, as it includes family-related activities as cooking, housework and time with family and children during afternoons, evenings and weekends. It is believed that these names are descriptive and representative of all items included in each factor.

Knowing that the ultimate criteria for determining the number of factors are interpretability and usefulness (Pett et al., 2003), it is decided not to use all five factors in structural equation modelling. As this thesis aims to use factors to describe social aspects of success, only factors measuring farmers' success are considered useful. Factor 1, 2, and 4 are included in further analysis and it is described in section 3.1 how relevant literature accentuates the importance of job satisfaction, mental wellbeing and family-work balance in farming. Factor 3 and 5 are considered challenging to use, keeping the aim of this thesis and findings from relevant literature in mind. Therefore, only factor 1, 2 and 4 are considered in further analysis as social aspects of success. Most items in these three factors have factor loadings above 0.5, which indicate solid factors.

Table 6 - Retained factors, presented with factor loadings of items (N = 534)

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Satisfaction with workday	0.710				
Satisfaction with work security	0.806				
Satisfaction with work environment	0.889				
Flexible workday	0.453		0.359		
Optimistic view on the future	0.624				
Absence of stress		0.627			
Absence of loneliness		0.600			0.352
Absence of financial concerns		0.760			
Absence of worries related to health		0.763			
Absence of tiredness		0.723			
Sufficient time with family			0.830		
Sufficient time for friends and activities			0.822		
Suitable workload during weekends			0.585		0.404
Time spent on cooking				0.816	
Time spent on housework				0.859	
Time with family/children, afternoons and evenings				0.845	
Time with family/children, weekends				0.761	
Feeling valued as a farmer					0.596
Low degree of physical work					0.789

5.1.3 Structural equation modelling

Three factors identified through the EFA, presented in Table 6, are to be used in separate SEMs. This thesis includes job satisfaction (Factor 1), mental wellbeing (Factor 2) and family-work balance (Factor 4) as measurements of social aspects of success. Each SEM consists of a latent variable model and a structural model, where the latent variable models, or CFAs, assess the strengths of the three factors identified through the EFA. The structural models identify the regression-like relationship between manifest variables and the three standardized factors. In this way, each SEM aims at detecting whether farm and farmer characteristics and exploitation of the milking system can explain variations in the measurements of success.

The results from each SEM are presented as path diagrams. The explanation of how to read this diagram is provided on page 30 and illustrated in Figure 5 on page 31. When conducting the SEMs, it is decided to disregard all variables from the dataset which are not utilized in the models. Due to missing observations and different manifest variables in each model, the number of observations varies across the SEMs and compared to the EFA. When the number of observations is different in the EFA and the SEMs, the factor loadings change and the latent variable model in the SEMs re-evaluate the strengths of the factors.

Job satisfaction

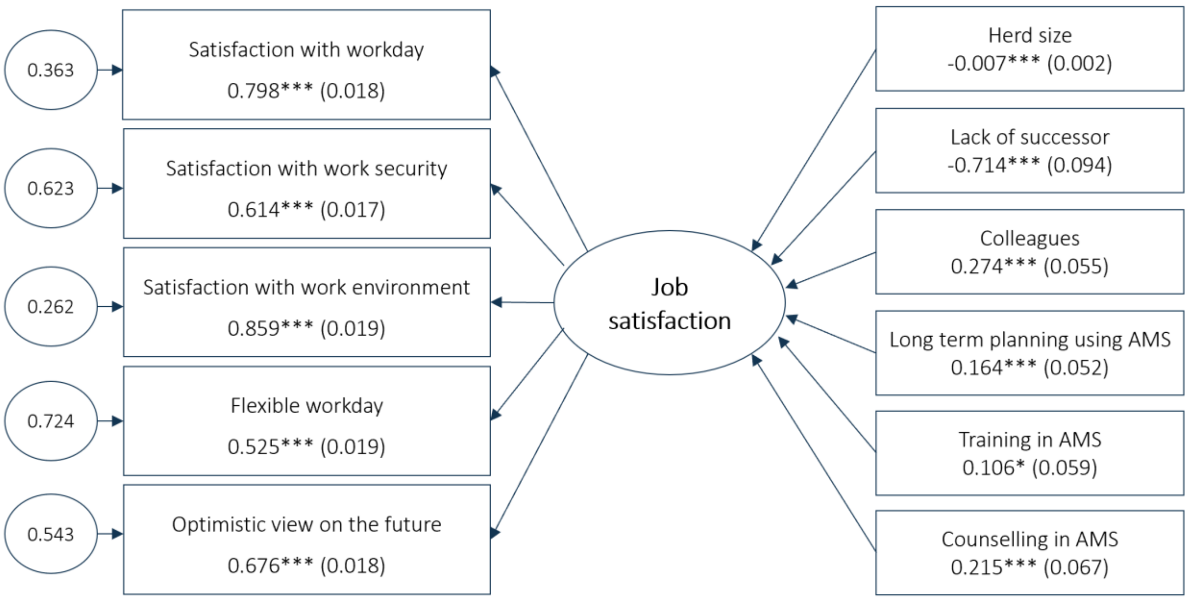

Figure 7 - SEM of the standardized factor of job satisfaction (N = 718)
*Significance level: * = 10 % ** = 5 % *** = 1 %*

Figure 7 presents the factor of job satisfaction as the dependent latent variable. It illustrates that job satisfaction is a factor existing of five items. These items are satisfaction with workday, satisfaction with work security, satisfaction with work environment, degree of a flexible workday and level of optimistic view on the future. This is factor 1 identified through the EFA. The latent variable model confirms that all items have a significant factor loading above 0.5, indicating that job satisfaction is still a strong factor.

The manifest variables with significant impact on job satisfaction, serving as independent variables, are herd size, lack of successor, having colleagues, usage of information from the AMS in long term planning, training in AMS and counselling in AMS. Herd size and lack of successor impact job satisfaction negatively at a 1 % significance level. Having colleagues, using information from the AMS in long term planning and counselling in AMS have positive impacts on job satisfaction at a 1 % significance level. At a 10 % significance level, it has a positive impact that farmers have received sufficient training in AMS. The results indicate that lack of successor has the greatest impact on job satisfaction, while having colleagues and availability of counselling have a greater impact than training in AMS and usage of information from the milking system. This structural model provides a good fit with relative chi-square (81/29), CFI (0.989), TLI (0.996) and RMSEA (0.050).

Mental wellbeing

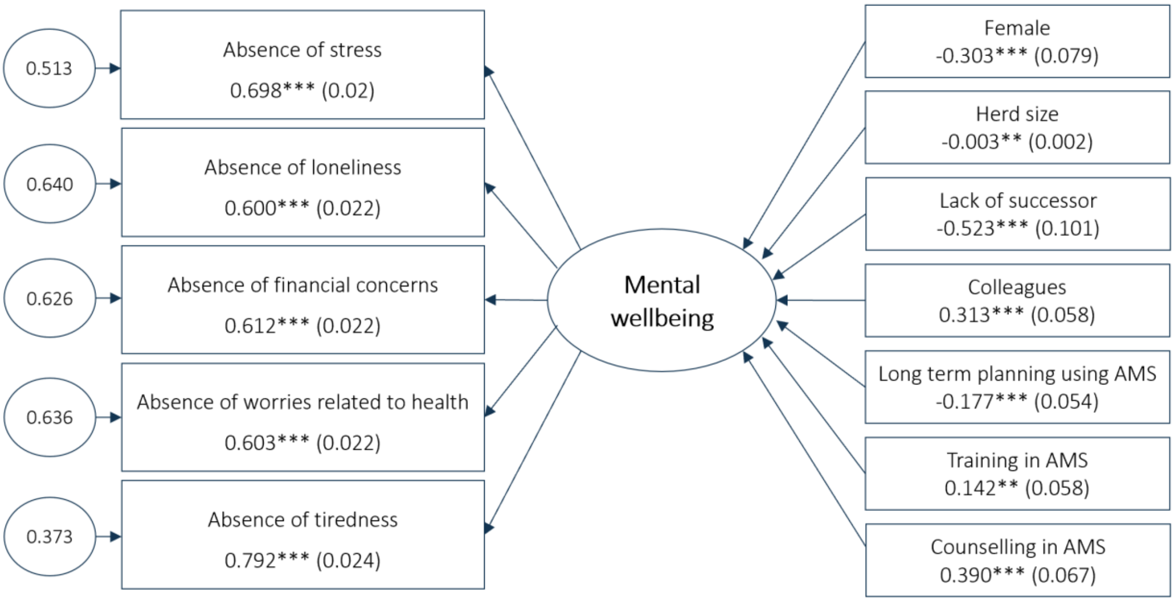

Figure 8 - SEM of the standardized factor of mental wellbeing (N = 718)
*Significance level: * = 10 % ** = 5 % *** = 1 %*

Figure 8 presents mental wellbeing as the dependent latent variable. Mental wellbeing is a factor containing absence of stress, loneliness, financial concerns, worries related to health and tiredness as items. This is factor 2 identified through the EFA. The latent variable model confirms that all items have a significant factor loading above 0.5, indicating that mental wellbeing is still a strong factor.

The SEM explains variation in mental wellbeing by gender, herd size, lack of successor, having colleagues, usage of information from the AMS in long term planning, training in AMS and counselling in AMS. According to the SEM, being a female farmer, not having a successor and usage of information from the AMS in long term planning influences the wellbeing of farmers negatively at a 1 % significance level. Having a larger herd size leads to lower wellbeing at a 5 % significance level. Contrary, having colleagues and available counselling in AMS increase the wellbeing at a 1 % significance level. At a 5 % significance level, having sufficient training in AMS also increases farmers' mental wellbeing. Also in this SEM, lack of successor has the greatest impact on the factor. Gender, having colleagues and counselling have a greater impact than usage of information and having training. The structural model provides a good fit in terms of relative chi-square (52/33), CFI (0.993), TLI (0.998) and RMSEA (0.029).

Family-work balance

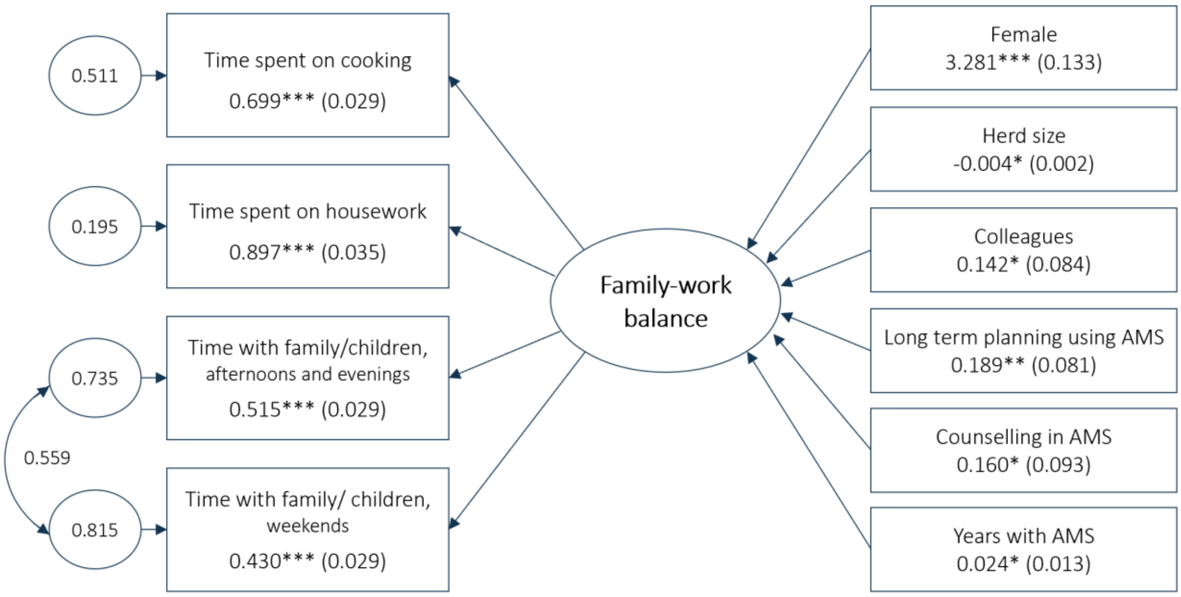

Figure 9 - SEM of the standardized factor of family-work balance (N = 567)
*Significance level: * = 10 % ** = 5 % *** = 1 %*

Figure 9 presents family-work balance as the dependent latent variable. It illustrates family-work balance as a factor existing of time spent on cooking, time spent on housework, time with family and children during afternoons and evenings and time with family and children during weekends as items. This is factor 4 identified through the EFA, with an added covariance (0.559) between the error terms of two items. This covariance may be justified as both items measure time with family and children and when the items are strongly correlated, it is reasonable to believe that the underlying factor is not able to capture all covariance between them. This covariance improves the model fit. The latent variable model confirms that most items have significant factor loadings above 0.5, indicating that family-work balance is still a strong factor.

The independent variables explaining variation in family-work balance are gender, herd size, having colleagues, usage of information from AMS in long term planning, counselling in AMS and years since investment in AMS. Being a female farmer has a positive impact on family-work balance at a 1 % significance level. Less time is spent with the family as the herd size increases, significant at a 10 % level. Having colleagues, having counselling available and years with AMS positively affect family-work balance at a 10 % significance level. Using information from the milking system in long term planning positively affects family-work balance at a 5 % significance level. Gender has by far the greatest impact, while having colleagues, usage of information from the milking robot in long term planning and availability of counselling have a smaller impact. This structural model provides a good fit with relative chi-square (50/19), CFI (0.987), TLI (0.996) and RMSEA (0.054).

5.2 Discussion of results

Farm and farmer characteristics

Traditionally, gender roles have been clearly defined in Norwegian dairy farming (Hårstad, 2019). When dairy farming became more specialized, technological and efficient, farming became more of a one-man occupation, as machines took over several operations at the farm. Operations taken over, as milking, were mainly carried out by women, which implied that the male farmers were now able to run the farm alone. This made farming more of a masculine occupation and contributed to a clear separation between the genders, where men were the main farmers and the main responsibility of women was family caretaking. Studies suggest that parts of this traditional division still are preserved, and it is therefore expected that the findings of this thesis show gender differences among dairy farmers using AMS.

The results indicate that gender impacts the economic and social aspects of success, in terms of mental wellbeing, family-work balance and income. The findings of this thesis show that female farmers have poorer mental wellbeing than men, which is coherent with the study of Alpass et al. (2004). Their study finds that female farmers experience higher levels of stress than men, when understanding new technologies in dairy farming. Another source of stress for female farmers is to find a good balance between work and family responsibilities. Women have traditionally been responsible for care and household tasks at the farm (Brandt, 2003), and it is interesting to observe that the findings of this thesis indicate a traditional division of duties even when women are the main farmers. The positive relationship between female farmers and time spent with family, is coherent with earlier research finding that even when the woman is the main farmer, she dedicates more time to family related activities than her partner (Hårstad, 2019).

A study of success by Dyke and Murphy (2006) conclude that clear gender differences exist when men and women are asked to define success in personal and professional life. Their findings indicate that men are more focused on material success, while women focus more on work-life balance and relationships. This can imply that men spend more time working, while women spend more time on off-farm activities, as a consequence of different priorities. This thesis finds that male farmers generate higher income than female famers, which may reflect that men are more focused on material success and therefore spend more time working at the farm.

Herd size is negatively related to job satisfaction, mental wellbeing and family-work balance of dairy farmers. There may be several reasons for these relationships. First of all, a larger herd implies a heavier workload for farmers, who state they are already overworked (Natvig, 2003). Farmers remark that they spend much time monitoring the herd and analysing data from the milking robot (Stræte et al., 2017), which are tasks increasing in workload when the herd size grow. The increased workload may create lower job satisfaction and mental wellbeing as it implies less flexibility and more mental strain. It also implies less time for other activities, including time spent with family. In addition, a larger herd means that farmers have less time to spend with each cow. Since the cows are the essential input in milk production, it is reasonable to assume that farmers' job satisfaction and mental wellbeing are closely related to the welfare of the animals and that farmers are more satisfied when they have time to make sure every cow is content. Due to the increased workload and less time to spend on each cow, the negative relationships between herd size and job satisfaction, mental wellbeing and family-work balance seem reasonable.

It is noteworthy that herd size has no significant impact on income, neither directly nor in squared form. This is unexpected, as a larger herd size implies higher milk yield and farmers should thereby generate higher income when they have more cows. Herje and Høva (2017) find that herd size is positively related to income, which is coherent with earlier studies. It is believed that the insignificance of herd size in this thesis is a consequence of the ordinal coding of income. Earlier studies, as the thesis of Herje and Høva (2017), analyse continuous financial data of income, which has not been available for this thesis. In the dataset available for this thesis, income is coded as ordinal data and reported in intervals of 100 000 NOK, and each interval can therefore include a variety of herd sizes. Consequently, the regression model is unable to detect a relationship between herd size and income.

The results of the regression analyses indicate that agricultural education at university level has a positive effect on income. Generally, it has been challenging to find a direct impact of education on economic performance in agriculture, because the climate and land surface-area intensity of farming limit the potential for raising labour productivity through improvement of human capital (Huffman, 2001). However, climate and land surface-area intensity are believed to be stronger constraints in crop production than in milk production, and according to Hansen and Greve (2015), education has a clear effect on the economic performance of dairy farmers. They find that farmers with agricultural education have substantially higher income than farmers without relevant education, because education entails better use of resources and improves problem solving processes, which enhance profitability. The positive relationship between agricultural education at university level and income among dairy farmers found in this thesis, is coherent with the findings of Hansen and Greve (2015).

Lacking a successor has negative impact on job satisfaction, mental wellbeing and income of dairy farmers. The concept of intergenerational succession has been important at family farms globally and the fact that succession is still practised today, indicates that the concept is deeply embedded in the values and culture of farmers (Melberg, 2009). Farmers also combine farming business and family in a complex and personal way compared to other occupations (Melberg, 2009), and previous studies recognize the importance of inheritance and succession in decision-making in farming (Potter & Lobley, 1992). Even when the farm business cannot provide a sufficient standard of living financially, farmers are in most cases not willing to sell their farm, implying that farms are of high symbolic value (Mishra, El-Osta & Shaik, 2010). Thus, it seems reasonable that when farmers know the farm will be looked well after when they retire, they are more content with their work situation and have less worries. This supports the negative impact lack of successor has on job satisfaction and mental wellbeing, reported in this thesis. Whether farmers have successors is also recognized to have an impact on capital accumulation and business expansion (Potter & Lobley, 1992), implying that it influences income. According to Potter and Lobley (1992), farmers of all ages that lack successors are likely to simplify the enterprise structure of the farm, compared to those having successors. Thus, the negative relationship between lack of successor and income found in this thesis, can be explained by decreased motivation and willingness to invest in new technology and overall improvements at the farm.

According to the results, success in terms of income, job satisfaction, mental wellbeing and family-work balance, improve when farmers have colleagues. Hansen (2015) shows the importance of social networks in order to explain high adoption rates of AMS, where social networks contribute to expertise, new ideas, inspiration and motivation. Colleagues enhance farmers' social networks and when farmers have discussion partners available at the farm, it can contribute to knowledge sharing, inspiration and motivation as described by Hansen (2015). Knowledge sharing is believed to improve the financial performance in terms of income, while social relations, inspiration and motivation can benefit job satisfaction and mental wellbeing. Working with others also implies a division of labour at the farm, which may be positively correlated with job satisfaction, mental wellbeing and family-work balance because farmers are less likely to be overworked.

The findings of this thesis indicate that family-work balance and income are positively correlated with the number of years AMS have been used at farms. Lunner-Kolsrup et al. (2018) detect that learning new farming technology is time-consuming and farmers spend much time learning how to interact with new technology. Even after attending introductory training courses, farmers spend much time "learning-by-doing" at the farm to get familiar with the milking robot. Thus, implementations of AMS require transition periods, and it is reasonable that time with family is limited the first years after investing in AMS and then gradually increase as the farmers become familiar with the milking system. According to Herje and Høva (2017), the income of farms using AMS exceeds the income at farms using conventional milking systems after a transition period of four years. This implies that income of farmers using AMS is increasing with the years after the installation, which is coherent with the findings of this thesis.

In addition to the farm and farmer characteristics discussed above, it is tested whether age has an impact on success. According to Alpass et al. (2004), older farmers experience new technology to be more challenging than younger farmers, and it is expected that age should impact the economic and social aspects of success at farms using AMS. The results indicate that age has no significant impact on either income, job satisfaction, mental wellbeing or family-work balance. A hypothesis is that even though older farmers may struggle with the technical features of the milking system, they are normally more experienced farmers. Thus, they may have accumulated expertise that younger farmers are lacking, which can improve income, job satisfaction, mental wellbeing and family-work balance. When considering age at farms using AMS, the positive effect of expertise is believed to equalize the negative effect of advanced technology.

Exploitation of the milking system

The results indicate that sufficient training in AMS has positive impact on income, job satisfaction and mental wellbeing of farmers. Implementations of AMS change the work routines of farmers drastically (de Koning, 2010). Farmers spend less time milking and interacting with the cows, and more time monitoring the milking robots, interpreting data from the milking systems and observing the herds. These changes can be challenging. Scholars also find it challenging for farmers to learn new milking technology and understand the technical functions and settings of a new system (Alpass et al., 2004; Lunner-Kolstrup et al., 2018). Training can be important to overcome these challenges and make farmers better equipped to operate the milking system, which can improve their satisfaction, wellbeing and ability to generate income.

This thesis shows that available counselling in AMS has a positive impact on job satisfaction, mental wellbeing and family-work balance. When using advanced technology as AMS, machinery breakdown is always a risk. Complex technological errors may require farmers to seek external assistance and it is recommended that the type of milking robot is chosen based on which brand can provide local service and support (Dairy Australia Limited, 2014). Alpass et al. (2004) find that a frequent source of stress related to new milking technology is machinery breakdowns and according to Karttunen et al. (2016), few farmers feel confident in their own skills when managing technical features of AMS. This implies a need for counselling after the installation of the milking system and introductory training. Having counselling can also be timesaving as technological errors can be solved more efficient, which release time for other activities and family. It seems reasonable that counselling increases the social aspects of success, because it reduces down-time and improves farmers' competence, self-efficacy and ability to operate the milking system.

When comparing four farms using AMS, Hansen and Jervell (2014) find that deliberate use of consultants results in improved milk yield, and one would therefore expect the use of counselling to increase income. The results of this thesis imply that income is not affected by the availability of counselling, which may be because the ordinal coding of income cause limited variation in income when having variation in counselling.

According to the analyses, job satisfaction, mental wellbeing, family-work balance and income are affected when information from AMS is used in long term planning at farms. AMS generate information of milk quality, health and breeding of each cow, and stores this in a herd management program (Dairy Australia Limited, 2014). This information is collected automatically and can be used to make reports and graphs which can be useful for farmers when making farm management decisions. Earlier studies show both positive and negative implications of the data generated from the AMS. According to Dairy Australia (2014), using information from the milking robot allows farmers to detect diseases early and make proactive decisions to increase the whole-farm productivity. The findings of this thesis show that job satisfaction and family-work balance improve when information is used in long term planning, which might be related to the easier detection of diseases and proactive decision making highlighted by Dairy Australia (2014). However, Lunner-Kolsrup et al. (2018) find that farmers have difficulties interpreting the large amount of data generated from AMS. Information overload might be the reason why this thesis finds a negative relationship between usage of information from the milking robot in long term planning and mental wellbeing. This highlights a potential for improvements in the herd management program and the importance of farmers becoming conversant with the new technology to remove the problem of information overload. With contradictory findings in the literature concerning the usage of information from AMS, it is interesting that this thesis finds both positive and negative effects on the social aspects of success, depending on which measurement is considered.

Herje and Høva (2017) find that farms using AMS gain higher income than farms with conventional milking systems, due to higher milk yields and improved milk quality. It is reasonable to assume that when farmers are able to use and interpret the generated information from AMS correctly, it may generate higher income by improving milk quality and quantity. However, in this thesis, using information from the milking robot in long term planning results in lower income. This may be because the positive effects of disease detection and proactive decisions are dominated by the negative effect of information overload.

Implications of the findings

The results indicate that variations in success with AMS, measured in income, job satisfaction, mental wellbeing and family-work balance, can be explained by farm and farmer characteristics and exploitation of the milking system. Farm and farmer characteristics such as gender, herd size, education, lack of successor, having colleagues and years with AMS determine the success of farmers. Gender and years with AMS may be considered static, while the other variables are changeable in the long run. Exploitation of AMS in terms of sufficient training, availability of counselling and usage of information from the milking robot in long term planning also impact the financial performance and welfare of dairy farmers. These variables are more dynamic and changeable in the shorter run, as instantaneous facilitation is possible.

The finding that using information from the milking robot may improve job satisfaction and family-work balance but deteriorate income and mental wellbeing indicates a potential for improvements in the herd management program and farmers' analytic skills, to overcome the problem of information overload. The findings of this thesis also show the importance of training and supporting farmers using AMS, which is believed to be related to enhanced competence, improved ability to operate the milking systems and reduced down-time due to technological errors. The findings of this thesis highlight a potential for improvements in the herd management program, the positive effect of available training and counselling in AMS and the importance of farmers becoming conversant with the new technology in order to improve the financial performance and welfare of farmers.

5.3 Strenghts and caveats of the thesis

Few studies have covered differences among farmers using AMS in terms of income, job satisfaction, mental wellbeing or family-work balance. In contrast to the few earlier studies that have, this thesis takes a quantitative approach and uses data of a considerable share of the Norwegian farms using AMS. Thus, it is believed that this thesis may contribute with valuable insight to the research field of automatic milking.

This thesis uses structural equation modelling to consider job satisfaction, mental wellbeing and family-work balance as measurements of success. An essential caveat of structural equation modelling, that is clear for economists familiar with regression analysis, is that the magnitude of the independent variables' coefficients cannot be directly interpreted. The coefficients from an OLS regression can be interpreted in terms of change in the dependent variable caused by a change in one independent variable, keeping all other variables constant. In structural equation modelling, it is common to comment whether the independent variables have significant positive or negative effect on factors and compare the size of the coefficients with each other when having standardized the model. When writing this thesis, this limitation has been examined and it is clear that the research field has yet left to develop a commonly approved method to interpret the magnitude of the coefficients (N. Q. Le, personal communication, October 31st, 2019).

Even though the magnitude of the independent variables' coefficients cannot be directly interpreted, structural equation modelling is beneficial for this thesis. The dataset includes dairy farmers' responses from a questionnaire, where some questions cover similar topics. Thus, it is useful to utilize factor analysis that allows for consideration of multiple answers as one unobserved variable, instead of considering observed variables individually. With factor analysis it is possible to consider job satisfaction, mental wellbeing and family-work balance as constructs consisting of several items, and explore how farm and farmer characteristics and exploitation of the milking system impact these measurements in terms of a positive or negative relationship.

6. Conclusion

This thesis studies what determines success of Norwegian dairy farmers using AMS. Success is measured using economic and social aspects, including income, job satisfaction, mental wellbeing and family-work balance. Since the first milking robot was installed in Norway in year 2000, the percentage of farms using AMS has increased rapidly and in 2017, 23 % of all Norwegian dairy farms used AMS in milk production. With several new investments in AMS annually, the findings of this thesis may provide valuable insight, relevant for an increasing percentage of dairy farms in Norway. Previous research has to a small extent covered variation among farmers using AMS or focused on farmer's welfare, and the aim of this thesis is to put the spotlight on the farmer, by providing insight in whether farm and farmer characteristics and exploitation of AMS influence the financial performance and welfare of dairy farmers.

This thesis uses a dataset with observations of 739 Norwegian dairy farms using AMS, which accounts for about 40 % of all farms with AMS in Norway in 2017. This dataset includes farmers' responses from a questionnaire, and in order to take full advantage of the data, both regression and factor analyses are conducted. Regressions are conducted in order to explore what determines the income of farmers using AMS. The factor analysis allows for consideration of multiple questions, covering the same topic, as one unobservable variable. Three factors, labelled job satisfaction, mental wellbeing and family-work balance, are identified through an EFA. These are included as dependent variables in separate SEMs, with the aim of exploring what affects the welfare of farmers using AMS.

The results of the regression and factor analyses indicate that farm and farmer characteristics and exploitation of AMS have implications for the economic and social aspects of success. Farm and farmer characteristics such as gender, herd size, education, lack of successor, having colleagues and years with AMS are relatively static determinants of success or changeable in the long run. More dynamic variables as sufficient training, availability of counselling and usage of information from the milking robot in long term planning also impact success, and are changeable in the shorter run. The findings highlight a potential for improvements in the milking system, the positive effect of available training and counselling in AMS and the importance of farmers becoming conversant with the new technology in order to improve income, job satisfaction, mental wellbeing and family-work balance.

Finally, it is interesting to make suggestions for further research. In this thesis, success is measured in level of income, degree of job satisfaction, mental wellbeing of the farmers and family-work balance. It is also rewarding to study other measurements of success, such as milk quality. Milk quality is interesting as it is an indicator of economic efficiency and cow health. However, to consider milk quality of farms using AMS can be challenging because farmers can programme the milking robot to separate milk of poor quality while milking. Norwegian farmers receive an extra payment when delivering milk of high quality and receive economic penalties when the quality is poor. Thus, it is reasonable to assume that farmers programme their milking robots to consider milk quality parameters as levels of free fatty acids, total bacterial plate counts and somatic cell counts when diverting poor-quality milk. Furthermore, milk might be necessary for other purposes at the farm, as to feed calves, and with a milking robot it is possible to use the milk of poorest quality for these purposes. Today, milk delivered to TINE SA from farms with AMS is mainly of high quality, and to consider the true impact of farm and farmer characteristics and exploitation of the milking system on milk quality, information of both high-quality milk and poor-quality milk is required. Only when having information on whether farmers separate milk and of which quality, milk quality can be used as a valid indicator of economic efficiency and cow health. It is encouraged to obtain this information for future research.

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