Exploring the Decision Making of Dutch Dairy Farmers Under Policy Uncertainty

Lotte Yanore

Propositions

1. Policy uncertainty can delay and expedite investment timing. (this thesis)

2. Earning capacity is less important than policy uncertainty for Dutch dairy farmers' decision-making. (this thesis)

3. Development aid contributes to the continuation of bad governance.

4. Financial incentives are ineffective for changing behaviour.

5. Requirements of publishing in Q1 journals hinder the development of science in the global south.

6. Equal opportunities cause inequality.

Propositions belonging to the thesis, entitled

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Chapter 1

General introduction

1.1 Policy changes in the Dutch dairy sector

In recent years, Dutch dairy farmers were confronted with several policy changes (Klootwijk et al., 2016, Schulte et al., 2018). Since 1984, the milk quota system has been in place (Figure 1.1). In 2003, the decision was made to abolish the milk quota system by 2015. Before and after the quota abolishment in 2015, farmers invested in farm assets for expansion and milk production increased by 26.6% between 2008 and 2017 (CBS, 2018, Jongeneel et al., 2017). Consequently, several critical deposition values set by the EU were surpassed and the Dutch government had to implement new policies for reducing emissions. To reduce nitrogen emissions, the Integrated approach to nitrogen (PAS) was implemented in 2015. In 2019, a judge ruled that farmers who previously legalised their business through a PAS-notification, needed a permit. To date, there is no solution for these farmers and new nitrogen policies are expected in 2023. The situation surrounding nitrogen emission in the Netherlands has also been referred to as the 'nitrogen crisis' (Erisman, 2021, Stokstad, 2019).

Besides the 'nitrogen crises', new policies to reduce phosphate emissions were announced in 2015. Phosphate rights were implemented in 2018 and these were allocated using a system of 'grandfathering'. This means past production levels were used to determine how many phosphate rights a farmer would get. For farmers who had increased their herd size after 2 July 2015, which was the reference date, this meant they received fewer phosphate rights than required for maintaining their production level. Thus, some farmers had to cull part of their herd or buy additional rights. As such, farmers experienced a lot of policy changes in recent years possibly affecting their decisions.

1.2 Policy uncertainty

Dutch dairy farmers face a myriad of decisions on different time horizons. Decisions range from operational decisions made on a more daily basis to long-term strategic investment decisions into new capital assets. These decisions are subject to risk and uncertainty. In a common distinction between risk and uncertainty, risk is defined as imperfect knowledge where the probabilities of outcomes are known. Whereas with uncertainty there also is imperfect knowledge, but the probabilities of outcomes are not known (Hardaker et al., 2015). However, because objective probabilities of outcomes are rarely known, this distinction is not a useful one. Another common distinction is to say that uncertainty concerns imperfect knowledge, and risk concerns unknown consequences. Several sources of risk can be distinguished, namely: 1) production risk, 2) price and market risk, 3) institutional

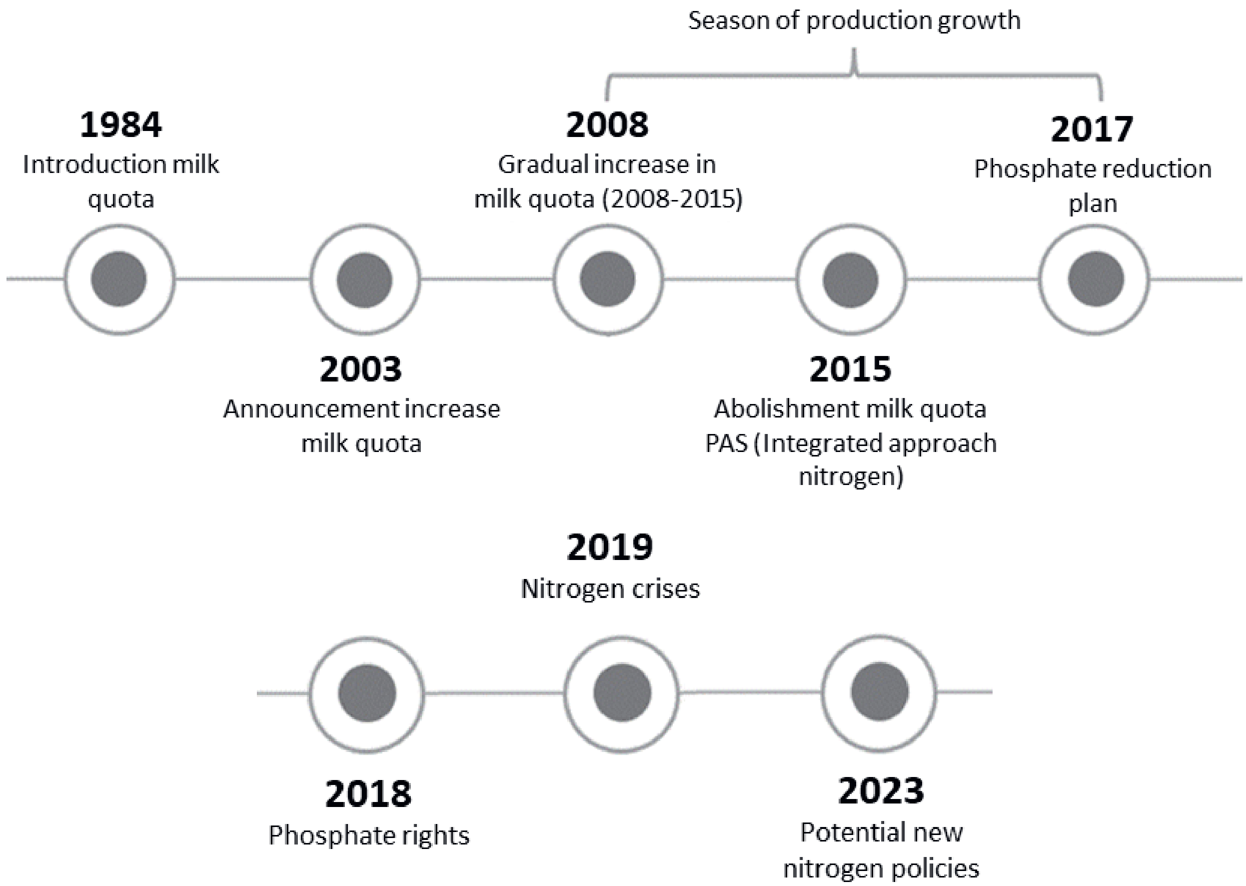

Figure 1.1: Timeline of policy developments relevant to the Dutch dairy sector

risk, 4) personal risk, and 5) financial risk (Hardaker et al., 2015). Production risk relates to the unpredictability of the weather and the performance of crops and livestock. Price and market risk refers to the instability of prices of inputs and outputs. Institutional risk consists of risks related to policies, the actions of other governments and contractual risks when dealing with business partners. Personal risk concerns risks related to major life crises, such as health or family problems. Lastly, financial risk results from the financing method used. In this thesis, we generally assume that probabilities of outcomes are not known objectively. Moreover, it is likely farmers have imperfect knowledge concerning policy developments. As such, we will continue to use the term policy uncertainty.

Previous research shows that policy uncertainty is a primary source of uncertainty for farmers (Flaten et al., 2005, Mittenzwei et al., 2017). Policy uncertainty is particularly important in the agricultural sector, as the sector is characterised by extensive policy interventions (Moschini and Hennessy, 2001). When the milk quota was abolished in 2015, new policies to reduce emissions were expected, but there was no clarity about these policies (Samson et al., 2016). Moreover, the current nitrogen crises cause further policy uncertainty for farmers (Sok and Hoestra, 2023, Stokstad, 2019). The policy changes and their related uncertainty had far-reaching effects on farm financial performance and business development. For example, according to Alfa accountants and the Wageningen University liquidity monitor, the liquidity position of Dutch dairy farmers worsened just after the implementation of the phosphate rights system (Agrimatie, 2021, Alfa Accountants en Adviseurs, 2019).

1.3 Problem statement and objectives

Policy uncertainty is the least studied source of uncertainty (Komarek et al., 2020) and including it in empirical models is complicated (Rodrik, 1991). According to Flaten et al. (2005), research should focus more on policy uncertainty as it is an understudied source of risk in agriculture. Moreover, Niles et al. (2013) argue for the need to include policy uncertainty as an independent variable in models of decision making. However, there are several reasons why incorporating policy uncertainty in empirical models is complicated. First, measurement of policy uncertainty is a problem as it is not always clear what indicators should be used to measure policy uncertainty and because objective historical data is usually not available (Komarek et al., 2020). Second, how policy uncertainty is perceived by the farmers and how farmers react to policy uncertainty is subject to individual beliefs and preferences (Hardaker et al., 2015, Rasmussen et al., 2013). Consequently, there is a lack of understanding about how farmers cope with policy uncertainty.

Existing models based on neo-classical theory, such as those predicting milk supply in the Netherlands, usually do not account for farmers' responses to policy uncertainty. Models based on neo-classical theory often assume, amongst others, risk-neutrality, profit-maximization, and perfect information. Based on such models, milk supply in the Netherlands was predicted to increase after the abolishment of the quota in 2015 (Groeneveld et al., 2016, Jongeneel and van Berkum, 2015, Kempen et al., 2011). These predictions were accurate, as farmers indeed expanded their farms (CBS, 2018, Jongeneel et al., 2017). However, these models do not provide the full picture of the farmers' responses to policy uncertainty. For example, they do not give insight into the different investment strategies of farmers who experience policy uncertainty, what variables influence decisions under policy uncertainty, and how they interrelate. A better understanding of farmers' decision making under policy uncertainty can help policy makers anticipate their responses to policy changes.

The overall objective of this thesis is (an overview of the ROs is given in Figure 1.2):

RO To explore the decision making of Dutch dairy farmers under policy uncertainty.

When studying decisions under (policy) uncertainty, many investment strategies may be relevant. However, commonly used approaches do not consider multiples investment strategies (Smit and Trigeorgis, 2017). For example, a limitation of using the net present value (NPV) criterion is that it only considers two investment strategies: invest now or don't invest. As such, a more comprehensive approach is needed to study farmers' decisions under policy uncertainty. Besides investing now or never, farmers also have the option to postpone an investment and wait for more certainty. The real options approach is often used to compare the option to invest now with the option to invest later (Pindyck, 1990). However, besides investing now and postponing the investment, other strategies may also be relevant (Smit and Trigeorgis, 2017) For example, if future policies would limit business development, anticipating new policies by expanding the farm early may be a strategic way to reduce the effect of these policies on the farms profitability. Currently, there are no theoretical frameworks that can reflect the three investment strategies: anticipating, waiting, and investing, while also considering policy uncertainty. As such, our first objective is:

RO1 To develop a theoretical framework to study farmers' investment behaviour in the presence of policy uncertainty. The theoretical framework can reflect three investment strategies – anticipating, waiting, or not investing as special cases. (Chapter 2)

There are many variables that may explain farmers decision making in general (Edwards-Jones, 2006) and specifically their investment decisions (Aramyan et al., 2007). Samson et al. (2016) studied the expansion decisions of Dutch dairy farmers after quota abolition. They argue that policy changes may influence farmers' expectations about future benefits and costs related to the expansion and thus also influence farmers investments decisions. Thus, farmers would have different expectations about how policy changes may affect them and their farms. Oude Lansink et al. (2001) found that firm-operator, firm family, and variables indicating the firm's ability to attract debt capital are variables influencing farmers decision making. Others have also found that behavioural characteristics such as trust, personality, risk and time preferences and cognitive ability can influence farmers decision making (Austin et al., 2001, Fischer and Wollni, 2018, Willock et al., 1999). However, investment appraisal methods have not been updated to include policy uncertainty and other variables that simultaneously influence investment strategies. As such, our second research objective is:

RO2 To identify and assess the farm -, farmer -, and environmental characteristics that explain and predict investment strategies: anticipate and invest early, wait with investing, or not investing at all. (Chapter 3)

Besides decisions to invest in expansion, farmers also make decisions related to the reduction of nitrogen emission on their farms. The Netherlands has committed itself to reducing nitrogen emission by 50% in 2030, which requires far reaching measures (Erisman, 2021, Stokstad, 2019). As such, for the Netherlands to achieve the objectives to reduce nitrogen emissions, a better understanding of farmers' preferences for the adoption of nitrogen abatement options is important. Farmers can choose from a wide variety of measures to reduce nitrogen emissions on dairy farms (Børsting et al., 2003). These can be categorised as either investment options or management practices. The voluntary uptake of these measures influences how much nitrogen emission is reduced, which makes it important to understand farmers' preferences for nitrogen abatement options.

A large body of literature studied preferences but focussed either on management practices or investment options. The range of topics that were studied includes greenhouse gas mitigation (Glenk et al., 2014, Jones et al., 2013), biodiversity conservation (Greiner, 2016), precision agriculture technology (Thompson et al., 2019), grazing best practices (Greiner et al., 2009), carbon farming (Dumbrell et al., 2016), low emission agricultural practices (Morgan et al., 2015), particular matter abatement (Vissers et al., 2022), and soil conservation (Wossen et al., 2015). Moreover, within investment options or management practices, or between both categories, there are differences in economic consequences in terms of risk and over time. Amongst others, because farmers may perceive adopting farming investments and practices as a way to mitigate policy uncertainty. For example, risk averse farmers may be more willing to adopt nitrogen abatement options then risk taking farmers. A review paper by Iyer et al. (2020) concluded that decisions made in a risky context are influenced by farmers' economic preferences such as risk attitude and time discounting. Moreover, several studies have found an effect of risk attitude and time discounting on farmers' preferences for sustainable farming practices or investment options (Greiner et al., 2009, Wossen et al., 2015). In addition to risk and time preferences, previous research has found that personality traits affect farmer behaviour (Austin et al., 2001). To the best of our knowledge, no previous research has examined farmers' preferences for both investment options and management practices simultaneously. As such, our third objective is:

RO3 To rank Dutch dairy farmers' preferences for nitrogen abatement investment options and management practices and to study if and how they are linked to personality traits, risk attitude and time discounting. (Chapter 4)

Agricultural policy aims, amongst others, to support a viable farm income, resilience of the farming sector, increased farm competitiveness and foster farm knowledge and innovation (European Commission, 2023). However, when policy uncertainty is high and policies are changing, farmers may also experience several obstacles that hamper the development of their business. Business development is a broad construct, that goes beyond more traditional constructs such as profit maximisation and growth (Hansson and Sok, 2021). Farmers experience obstacles to achieving their desired business development. Policy makers can help mitigate the obstacles to business development. However, a clear understanding of these obstacles would be necessary. Obstacles to business development can be quantified using the method proposed by Hansson and Sok (2021). Hansson and Sok (2021) found the following categories of perceived obstacles to business development: access to financial resources, farm characteristics in terms of layout and geographical location, consumer demand, available resources, and options for farm succession. These perceived obstacles give insight into the areas in which farmers experience barriers to the development of their farm. Vissers et al. (2022) found that broiler farmers perceive rules and regulations as the most constraining factor. Using a discrete choice experiment, they also found that farmers attached most weight to the attribute 'exemption from future legislation' in choosing between particular matter abatement technologies alternatives. Previous research has not assessed the perceived obstacles to business development of Dutch dairy farmers nor compared them with others. As such, our fourth research objective is:

RO4 To assess the importance of perceived obstacles to business development of Dutch dairy farmers and compare them to Dutch broiler farmers and a general sample of Swedish farmers. (Chapter 5)

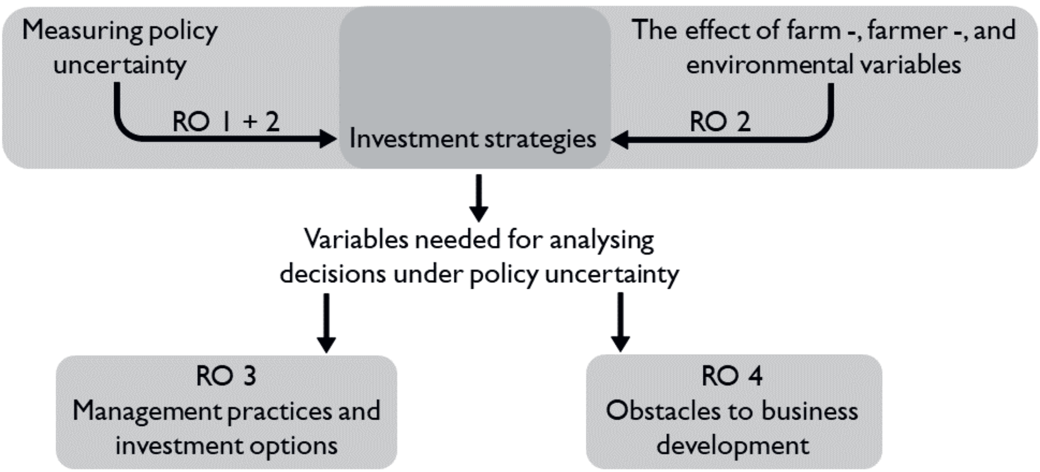

Figure 1.2: Overview of chapters and content

1.5 Thesis outline

Chapter 2 develops a theoretical framework to study three investment strategies: anticipating, waiting, and not investing in an uncertain policy context. The theoretical framework includes several variables to measure policy uncertainty. The framework is applied to a typical Dutch dairy farm, considering to expand production when there is uncertainty about future policies regarding the impact and timing of the phosphate right system. A numerical illustration of the framework is provided. We show under which conditions farmers choose which of the three investment strategies and provide an explanation for observed investment behaviour before and after milk quota abolition in 2015.

Chapter 3 identifies and assesses the farm -, farmer -, and environmental characteristics that explain and predict the investment strategies, i.e., anticipating, waiting and not investing. A Bayesian Network is developed based on several rounds of expert elicitation. In the participatory Bayesian Network, policy uncertainty is modelled as a multidimensional concept that is determined by both objective and behavioural variables.

Chapter 4 analyses the preferences of Dutch dairy farmers for nitrogen abatement investment options and management practices. A best-worst scaling survey experiment is used to rank Dutch dairy farmers' preferences for nitrogen abatement options, which includes investment options and management practices. Based on RO1 and 2, relevant variables to include under policy uncertainty were identified. Moreover, we studied the influence of personality traits, risk attitude and time discounting on the preferences.

Chapter 5 examines perceived obstacles to business development of Dutch dairy farmers and comparing them to those from Dutch broiler and Swedish farmers. We also explored the relationships between perceived obstacles to business development and farm -, farmer -, and environmental characteristics. Likert-scale survey questions were used to measure the importance of perceived obstacles to business development. Factor analysis and Seemingly Unrelated Regression are used to analyse the data.

Chapter 6 provides a general discussion of the result of this thesis. We synthesise the results, discuss policy and business recommendations, discuss limitations and opportunities for future research and present the main conclusions.

Chapter 2

Anticipate, wait, or don't invest? The strategic net present value approach to study expansion decisions under policy uncertainty

This chapter is based on the paper: Yanore, L., Sok, J., Oude Lansink, A.G.J.M., (2022) Anticipate, wait or don't invest? The strategic net present value approach to study expansion decisions under policy uncertainty. Agribusiness: An International Journal. 39 (2). DOI:10/1002/agr.21780

Abstract

Dutch dairy farmers used different investment strategies in their production capacity in the periods around the abolishment of the European Union milk quota. Some farmers anticipated and expanded their production, others waited till expected policies were implemented or did not change their production. We develop a theoretical framework that integrates investment strategies—anticipating, waiting, or not investing—in the presence of policy uncertainty. We provide a numerical illustration of the framework to a typical Dutch dairy farm considering to expand the milk production. Results show that farmers would anticipate when they expect that the right system will be implemented with delay and will have low financial consequences. A low risk aversion reinforces the adoption of the anticipation strategy. The implications for policy and practice are discussed.

Keywords

Dairy farming, investment decisions, policy uncertainty, real options theory, risk attitude, strategic net present value

2.1 Introduction

In the years before and after the abolition of the milk quota in April 2015, the uncertainty about future government policy has been a key factor in investment decision making for Dutch dairy farmers. In 2003, the European Commission announced a gradual increase of milk quota per 2008, and the abolishment of the milk quota system per 2015 (European Commission, 2015). This gradual increase and eventual abolition of the milk quota gave dairy farmers new opportunities to expand their milk production by investing in additional production capacity. However, dairy farmers also operate in an environment that is characterised by uncertainty about future policies and their expectations may also be determined by their past experiences. For example, in the period following the abolition of the dairy quota, farmers may have expected the government to choose for emission grandfathering in the future. Emission grandfathering is the distribution of emission entitlements or production rights based on historical production levels and is used in a large part of actual emission control frameworks (Knight, 2013). Grandfathering was also used to distribute milk quota in the 1980s. If farmers expect the government to use emission grandfathering, then they will have an incentive to expand their production earlier, at least before a date used to determine historical production levels. As such, it is reasonable to assume farmers may consider an anticipation strategy, where they invest early with the expectation of getting more production rights or emission entitlements in case the government introduces new restrictive policies.

As a result of the investments in the expansion of production, the total milk production increased by 26.6% between 2008 and 2017 (CBS, 2018). Worse, this increase in milk production caused an exceedance of the enforced agricultural phosphate production ceiling (Jongeneel et al., 2017). By mid-2015, in response to the observed increase in phosphate emissions, the Dutch government announced the intention to introduce a phosphate right system, without further specification of how this system would be implemented (European Commission, 2017). As of January 2018, farmers were allocated tradable phosphate emission rights. The government used emission grandfathering and distributed production rights based on the farms herd size on July 2, 2015. Farmers who invested in the expansion of production after this reference date were forced to acquire additional phosphate rights or reduce their herd size. The initial uncertainty about the introduction of the phosphate right system, may have influenced farmers investment decisions.

How do farmers cope with uncertainty about future government actions according to investment theory? The net present value (NPV) rule only considers the option to invest now, or not at all. The real options approach (ROA), as opposed to the NPV rule, considers the option strategically postpone the investment until more information is available (Trigeorgis, 1993). The strategic net present value (SNPV) rule allows both the option to strategically postpone and an option to strategically anticipate the behaviour of others by investing early (Smit and Trigeorgis, 2017). Most applications of ROA in the context of dairy farming have focused on production (technical) and market (price) uncertainty (Engel and Hyde, 2003, Odening et al., 2005, Rutten et al., 2018). As shown in the review of Komarek et al. (2020), policy uncertainty is less commonly studied, possibly because probability distributions of policy uncertainty are not easily established in empirical studies, which usually take the frequentist view on probabilities.

A few studies in an agricultural context used the ROA to study the impact of policy uncertainty on farmers' investments (Floridi et al., 2013, Linnerud et al., 2014, Purvis et al., 1995). For example, Floridi et al. (2013) studied investment decisions under policy and technological uncertainty using a two-period model. In the first period, the farmer chooses whether to invest now or postpone the decision. In the second period, the farmer who chose to invest is "locked in" whereas the farmer who postponed can still decide to invest and has more information about some uncertain variables. They modelled policy uncertainty with a stochastic variable, which influences the cashflow, and found that farmers are likely to postpone their investments when faced with uncertainty.

Hence, previous studies have investigated the effect of policy uncertainty on investment decisions by including the option to postpone the investment decision. However, the observation of Dutch dairy farmers anticipating the instalment of new restrictive policies suggests the relevance of anticipation next to postponing an investment decision as a response to policy uncertainty. To our knowledge, no study has investigated the possibility of anticipation in the context of policy uncertainty. In the context of the dairy quota abolition, farmers may have expected that, considering the full lifetime of an investment, they are financially better off when anticipating.

The SNPV approach, developed by Smit and Trigeorgis (2017), includes both the anticipating and waiting strategy in investment decision making and compares these with not investing. In the context of corporate firms, the benefit from the anticipation strategy may materialize, for example, through a larger market share, when one firm invests before other firms enter the market (Smit and Trigeorgis, 2017). If neither waiting nor anticipating are considered profitable, the investors can choose not to invest. The authors developed a tool, called "option games" to quantify the value of anticipation and waiting based on ROA and game theory. Option games are suited mostly for analysing investment decision making in capital-intensive, oligopolistic markets facing demand volatility. The Dutch dairy sector exhibits an atomistic market structure characterized by a large number of producers (mostly family farms) on the supply side. Nevertheless, the value of the investment can still be affected by others, as investing before the implementation of future policies can be beneficial. The idea that investing early can be valuable, as described in the SNPV may thus apply here, as dairy farmers may also have strategic considerations to anticipate an investment in relation to what they expect the government to do. For example, the experience that manure and dairy market regulations that were implemented in the past in the Netherlands were usually based on grandfathering (using historical production levels) implies that investors would be better off investing early.

In this article, we develop a theoretical framework to study farmers investment behaviour in the presence of policy uncertainty. The theoretical framework can reflect three investment strategies – anticipating, waiting, or not investing as special cases. We apply this framework to a typical Dutch farm considering an investment in production expansion in the presence of policy uncertainty about the timing of a phosphate right system. The outcomes of the numerical illustration show under which conditions the farmer chooses which strategy, and as such, they also provide an explanation of the observed investment behaviour of farmers before and after the abolition of the milk quota in 2015.

Apart from developing a theoretical framework for modelling farmers investment decisions under policy uncertainty, our paper also contributes to the literature by providing valuable insights into the role of policy uncertainty and economic conditions in farmer investment decisions These insights are relevant for policy and practice to help farmers avoiding situations of financial distress as a result of an improper risk assessment.

2.2 Theoretical framework

In this section, we describe the theoretical framework that was developed to study the effect of policy uncertainty on investment strategies. The model is inspired by the SNPV as it was developed by Smit and Trigeorgis (2017). The advantage of the SNPV over the ROA is that it considers the strategic anticipation option, whereas the ROA only considers the strategic option to postpone the investment. However, the SNPV is in principle an expansion of the ROA that provides more flexibility and therefore can be applied to markets with specific dynamics. In our paper, these dynamics are the anticipation of farmers that new policies will be implemented and the potential benefit of investing early. In the ROA, these potential benefits are not taken into consideration. As such, the SNPV has the same merits as the ROA, only it adds in additional flexibility. A disadvantage of the SNPV in comparison to the ROA may be the increased modelling complexity.

Let us consider a decision maker, considering to invest in an expansion which requires an initial investment *I* and which generates a yearly future cash flow CF_h. The NPV of the investment is given by:

$$\mathrm{NPV} = \max\left(0, -I + \sum_{t=1}^{T} \frac{\mathrm{CF}_h}{(1+r)^t}\right) \quad (1)$$

where t is the period, T is the useful life of the investment and r is the risk-adjusted discount rate. The risk-adjusted discount rate is given by $r = i + k$, where i is the risk-free discount rate and k is the risk premium. The risk premium represents the riskiness of the project and the risk attitude of the decision maker(Finger, 2016, Hillier et al., 2016). A higher risk premium reflects a riskier project and/or a more risk-averse decision maker. The maximization operand in (*1*) reflects that the decision maker only invests if the project is 'in the money', i.e. in case $-I + \sum_{t=1}^{T} \frac{CF_h}{(1+r)^t} > 0$.

The NPV in Equation (1) assumes a constant cash flow over the entire project period. We now extend this NPV by introducing a negative shock (*S*) that arrives at time $t = S$, and which results in a yearly cash flow CF_l, where $\mathrm{CF}_l < \mathrm{CF}_h$,:

$$\mathrm{NPV}_l = \max\left(0, -I + \sum_{t=1}^{S} \frac{\mathrm{CF}_h}{(1+r)^t} + \sum_{t=S+1}^{T} \frac{\mathrm{CF}_l}{(1+r)^t}\right) \quad (2)$$

Next, we introduce uncertainty about *whether* the shock will occur through a probability *p*, reflecting the decision makers perception of the probability that the shock occurs at time $t = S$. Hence, equation (2) is rewritten to reflect the NPV of our base situation (NPV_b):

$$\mathrm{NPV}_b = \max\left(0, -I + \sum_{t=1}^{S} \frac{\mathrm{CF}_h}{(1+r)^t} + (1-p) \sum_{t=S+1}^{T} \frac{\mathrm{CF}_h}{(1+r)^t} + p \sum_{t=S+1}^{T} \frac{\mathrm{CF}_l}{(1+r)^t}\right) \quad (3)$$

We next present two potential strategies for the decision maker and show how the NPV can be calculated in each situation. In the first strategy, the decision maker may choose to wait till period $t = S$ to invest. The waiting strategy results in new information to arrive at $t = S$, i.e. *whether* the negative shock occurs. In case a negative shock does occur, then the decision maker adjusts the investment downward to I_l in line with the lower yearly cash flow (CF_l) after $t = S$; if the negative shock does not occur, the higher investment level I_h associated with the high cash flow CF_h is chosen. The NPV in case of waiting (NPV_w) is calculated as:

$$\mathrm{NPV_w} = p \max\left(0, \frac{-I_l}{(1+r)^S} + \sum_{t=S+1}^{T+S} \frac{\mathrm{CF}_l}{(1+r)^t}\right) + (1-p) \max\left(0, \frac{-I_h}{(1+r)^S} + \sum_{t=S+1}^{T+S} \frac{\mathrm{CF}_h}{(1+r)^t}\right) \tag{4}$$

Note that the investment costs I_l and I_h are discounted because the decision maker invests in period $t = S$. Since the total investment life differs across the different strategies We now use the equivalent annualized annuity[1] of the NPV_w to determine the optimal investment decision(Hillier et al., 2016). The value of the option to wait with the investment (WV) until new information has arrived is calculated as:

$$WV = \max\left(0, NPV_w - NPV_b\right) \tag{5}$$

The second potential strategy for the decision maker is the option to anticipate the shock and invest early. A decision maker who anticipates the shock and invests early believes there is a specific advantage of investing before the potential arrival of the shock. The advantage of anticipating materializes through a cash flow CF_a after the shock has occurred. Hence, the investor expects that anticipation generates an advantage that comes through a cash flow that is higher after the shock has occurred than the cash flow would have been if the investor had not invested early.

Using (3), the NPV of anticipation (NPV_a) is calculated as:

$$\mathrm{NPV}_a = \max\left(0, -I + \sum_{t=1}^{S} \frac{\mathrm{CF}_h}{(1+r)^t} + (1-p) \sum_{t=S+1}^{T} \frac{\mathrm{CF}_h}{(1+r)^t} + p \sum_{t=S+1}^{T} \frac{\mathrm{CF}_a}{(1+r)^t}\right) \tag{6}$$

The value of the option to anticipate (AV) is given by:

$$AV = \max\left(0, NPV_a - NPV_b\right). \tag{7}$$

[1] The equivalent annualised annuity (EAA) cashflow is calculated as:

$$EAA_j = \frac{r \times NPV_j}{1 - (1+r)^{-(T+\alpha S)}}$$

Here r is risk free discount rate, k is the risk loading and T is the total number of periods. In the anticipation strategy, the investment life is T years, and in the waiting strategy, it is T+S years. Remember α is 1 in the case of waiting, and 0 in the base case and anticipation strategy.

The different investment strategies, i.e. no investment, anticipating, and waiting can be combined into a theoretical framework, which computes the Strategic Net Present Value (*SNPV*):

$$\begin{aligned} \mathrm{SNP}V = \max_{\alpha,\beta}\Bigg[& \alpha \max\left(0, -I + \sum_{t=1}^{S} \frac{\mathrm{CF}_h}{(1+r)^t} + (1-p) \sum_{t=S+1}^{T} \frac{\mathrm{CF}_h}{(1+r)^t} + \right. \\ & \left. p(1-\beta) \sum_{t=S+1}^{T} \frac{\mathrm{CF}_l}{(1+r)^t} + p\beta \sum_{t=S+1}^{T} \frac{\mathrm{CF}_a}{(1+r)^t} \right) + \\ & (1-\alpha)p \max\left(0, \frac{-I_l}{(1+r)^S} + \sum_{t=S+1}^{T+S} \frac{\mathrm{CF}_l}{(1+r)^t}\right) + \\ & (1-\alpha)(1-p) \max\left(0, \frac{-I_h}{(1+r)^S} + \sum_{t=S+1}^{T+S} \frac{\mathrm{CF}_h}{(1+r)^t}\right)\Bigg] \end{aligned} \quad (8)$$

The maximization problem in equation (8) solves for the values of α and β that maximize the SNPV. α and β are dummy variables that take the value of either 0 or 1. It can be easily verified that the NPV_b from equation (3) results if α and β are 0. If both α and β are 1, then the anticipation strategy, with the net present value given by NPV_a in equation (6), is optimal. Finally, if α is 0 and β takes the value of either 0 or 1, then the waiting strategy, with the NPV given by NPV_w in (4), is optimal.

The optimal investment decision – anticipating, waiting, or not investing at all – as the outcome of equation (8) can be further simplified as:

$$\mathrm{SNPV} = \mathrm{NPV}_b + \max(\mathrm{AV}, \mathrm{WV}) \quad (9)$$

Note that both AV and WV are non-negative. Hence, the decision maker should anticipate, i.e. invest early, if the $SNPV > 0$ and $AV > WV$. The investment should be postponed if the $SNPV > 0$ and $WV > AV$. The decision maker should not invest if the $SNPV = 0$. In that case, there is no value in anticipating nor postponing the investment.

The SNPV as we have developed it here based on the idea that investors have strategic considerations when deciding the timing of their investment in production capacity. This is in line with the ideas based on which Smit and Trigeorgis (2017) developed their SNPV framework. However, since the market conditions and the Dutch dairy sector are different from the intended application of Smit and Trigeorgis (2017), our model is quite different. Besides that, we look at an interaction between the investor and the government whereas Smit and Trigeorgis (2017) study the interaction between investors.

2.3 Numerical Illustration

The SNPV framework is applied to an investment in the expansion of the barn capacity and herd size of a typical Dutch dairy farm. To do so we use a numerical example. The farmer makes the investment decision in the presence of uncertainty about a future policy. This policy, the "shock" in the theoretical framework, may reduce the number of cows the farmer is allowed to keep on the farm. The total reduction depends on the number of cows the farmer owns on a specific date. Thus, there may be a value of anticipating as the farmer can keep more cows at the future reference date. However, postponing the investment may also be beneficial as this will give the farmer full knowledge of whether the investment will be profitable.

We assume the farmer currently operates a farm with 100 cows. The investment in production expansion will let the farm size increase to 180 cows. The initial farm size is close to the average number of cows held on Dutch dairy farms in 2017. The farm size after the expansion is large but realistic; about 13% of the dairy farms had more than 150 cows in 2017 (BINternet, 2020). It is further assumed that the farmer faces no other capacity restrictions.

The investment is an initial cash outflow (I), which is expected to generate a cash inflow (IF) and cash outflow (OF) stream. The cash outflows are split up into a variable cash outflow OF_{var} and a fixed cash outflow OF_{fix}. The cash flows *I* and OF_{fix} correspond with the concept of sunk or committed cost[2] and do not change with the farm size.

In the NPV calculations without the strategy considerations, two cash flow streams apply:

$$\mathrm{CF}_h = IF - OF_{var} - OF_{fix} \tag{10}$$

$$\mathrm{CF}_l = (1-f)(IF - OF_{var}) - OF_{fix} \tag{11}$$

where CF_h correspond with the (high) cash flow before the shock, CF_l is the (low) cash flow received after the shock, and f is the expected consequence of the shock in terms of a reduction in the number of cows the farmer is allowed to keep on the farm.

To include the strategic considerations in the NPV calculations, two additional cash flow streams are received after the shock apply. The cash flow corresponding with the waiting strategy is:

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[2] 'A committed cost is an investment that a business entity has already made and cannot recover by any means, as well as obligations already made that the business cannot get out of' (accountingtools.com).

$$\mathrm{CF}_w = (1-f)\big(IF - OF_{var} - OF_{fix}\big) \quad (12)$$

The farmer now has full knowledge of the cash flow outlay and will avoid the burden of committed costs. This also means that the initial cash outflow (i.e. the investment) will be adjusted to the allowable number of cows (referred to as I_l) in equations (4) and (8).

The cash flow corresponding with the anticipation strategy is:

$$\mathrm{CF}_a = (1-g)(IF - OF_{var}) - OF_{fix} \quad (13)$$

Compared to the cash flow in (11), the change is g instead of f. So g as before represents the expected consequence of the shock in terms of a reduction in the number of cows the farmer is allowed to keep on the farm, but $\mathrm{f} > \mathrm{g}$.

Table 2.1 summarises the default parameter values used in the numerical illustration to show under which conditions the farmer should anticipate, wait or not invest. The investment and cash flow parameters used in this numerical illustration are taken from a commonly used reference guide (known as KWIN) for the Dutch dairy sector that contains all sorts of quantitative base values that advisors, farmers, students, or researchers use to perform financial analyses(Blanken et al., 2018). As such, our numerical illustration is based on the indicators from this reference guide and not on real data from dairy farms. The cash inflow IF is based on a constant milk price of €35.5 per 100 kg milk and an average milk production of 8500 kg per cow (Blanken et al., 2018). The variable cash outflow OF_{var} includes expenditures for feeding, animal health and reproduction, cow replacement, soil fertilization, etc. It also included expenditure for cow replacement, assuming the farmer replaces 20% of the herd per year. The fixed cash outflow OF_{fix} includes interest and maintenance expenditures. For a more detailed description of all inflow and outflow items for a typical Dutch dairy farm, we refer to the KWIN reference guide.

In the analyses that will follow, we vary the policy uncertainty and risk attitude parameters in different configurations. These parameters are subjective in nature (Hardaker and Lien, 2010) and reflect a range of beliefs of the farmers concerning the uncertainty they experience. To explore the robustness of our results to price changes, the optimal investment decision will also be analysed for a range of possible milk prices.

Table 2.1: Parameter values or ranges.

Category	Symbol	Description	Unit	Value or range	Based on
Cash flow	I	Initial investment outlay	€	394,240	Blanken et al. (2018)
	IF	Yearly cash inflow[1]	€	241,440	
	OF_{var}	Yearly variable cash outflow	€	158,960	
	OF_{fix}	Yearly fixed cash outflow	€	17,742	
Policy uncertainty	S	Perceived timing when the phosphate right system is introduced	year	1–10	-
	p	Perceived probability that the phosphate right system is introduced	%	0–100	-
	f	Expected consequence in terms of a reduction in the number of cows (for NPV_b and NPV_w)	%	30	-
	g	Expected consequence in terms of a reduction in the number of cows (for NPV_a)	%	20	-
Risk attitude	i	Risk-free discount rate	%	5	Schulte et al. (2018)
	k	Risk premium	%	0–12	

[1] Based on a milk price of € 35.5 per 100 kg of milk and an average milk production of 8,500 kg per cow.

2.4 Results

We begin by showing in Figures 2.1 and 2.2 the results of the joint impact of risk attitude and perceived probability of the introduction of the phosphate right system on the optimal investment decision. We vary k and p while keeping s constant, the perceived timing when the policy is introduced, at 3 years, and all other parameters at their default value (Table 2.1). In Figure 2.1, we report the absolute values of the NPV of the two strategies, waiting ($\mathrm{NPV_w}$) and anticipation ($\mathrm{NPV_a}$) for a range of values of p and k. Figure 2.2 presents the results in a complementary way by showing the optimal investment strategy for each combination of p and k.

The value of both investment strategies in Figure 2.1 decreases when p increases. The NPV of the anticipation strategy reduces more quickly and has a steeper slope than the NPV of the waiting strategy. The intersections in Figure 2.1 indicate when the waiting and anticipation strategies are equally attractive. When the risk premium increases, the $NPV_w = NPV_a$ intersect is at a lower value of p, meaning that risk-averse farmers are more likely to postpone the investment.

The three investment strategies – anticipating, waiting, or not investing, are represented in Figure 2.2 by the white, dotted, striped, and black areas. For highly risk-averse farmers ($k \geq 10.5\%$) it is optimal not to invest, even when they do not expect the introduction of the phosphate right system (black area). The remaining three areas show when the two other investment strategies are optimal for different combinations of k and p. In the dotted area, the value of waiting is positive, but the value of anticipation exceeds this value. At very low levels of risk aversion ($k < 3\%$), the anticipation strategy is always optimal to take. Presumably, k and p go hand in hand as more risk-averse farmers more strongly expect a restrictive policy. Farmers who can be characterized by high risk aversion likely adopt the waiting strategy to cope with policy uncertainty.

Next, we vary k and s in discrete steps while keeping p, the perceived probability that the policy is introduced, at 50 percent, and all other parameters at their default value (Table 2.1). Thus, we now look into the joint influence of risk attitude and the perceived timing of the introduction of the phosphate right system on the optimal investment decision. The results of this step are presented in Figures 2.3 and 2.4, in a comparable manner as in Figures 2.1 and 2.2 but in bar graphs given the discrete nature of the time unit used. The legend in Figure 2.4 is the same as in Figure 2.2.

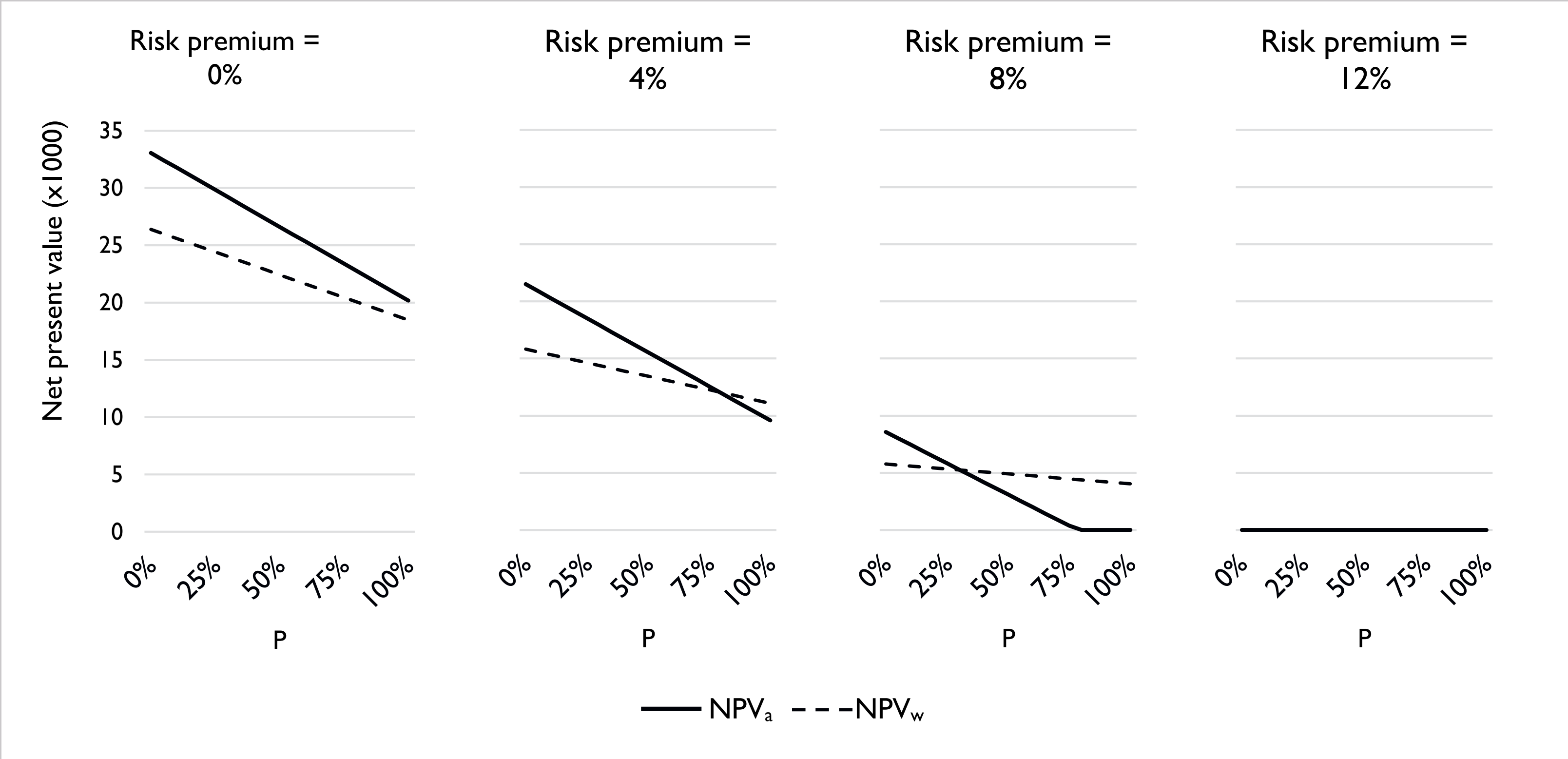

Figure 2.1: The NPV for different risk premia, k, for varying perceived probabilities, p. The timing of the shock is $S = 3$ and all other parameters are kept constant at the value reported in Table 2.1.

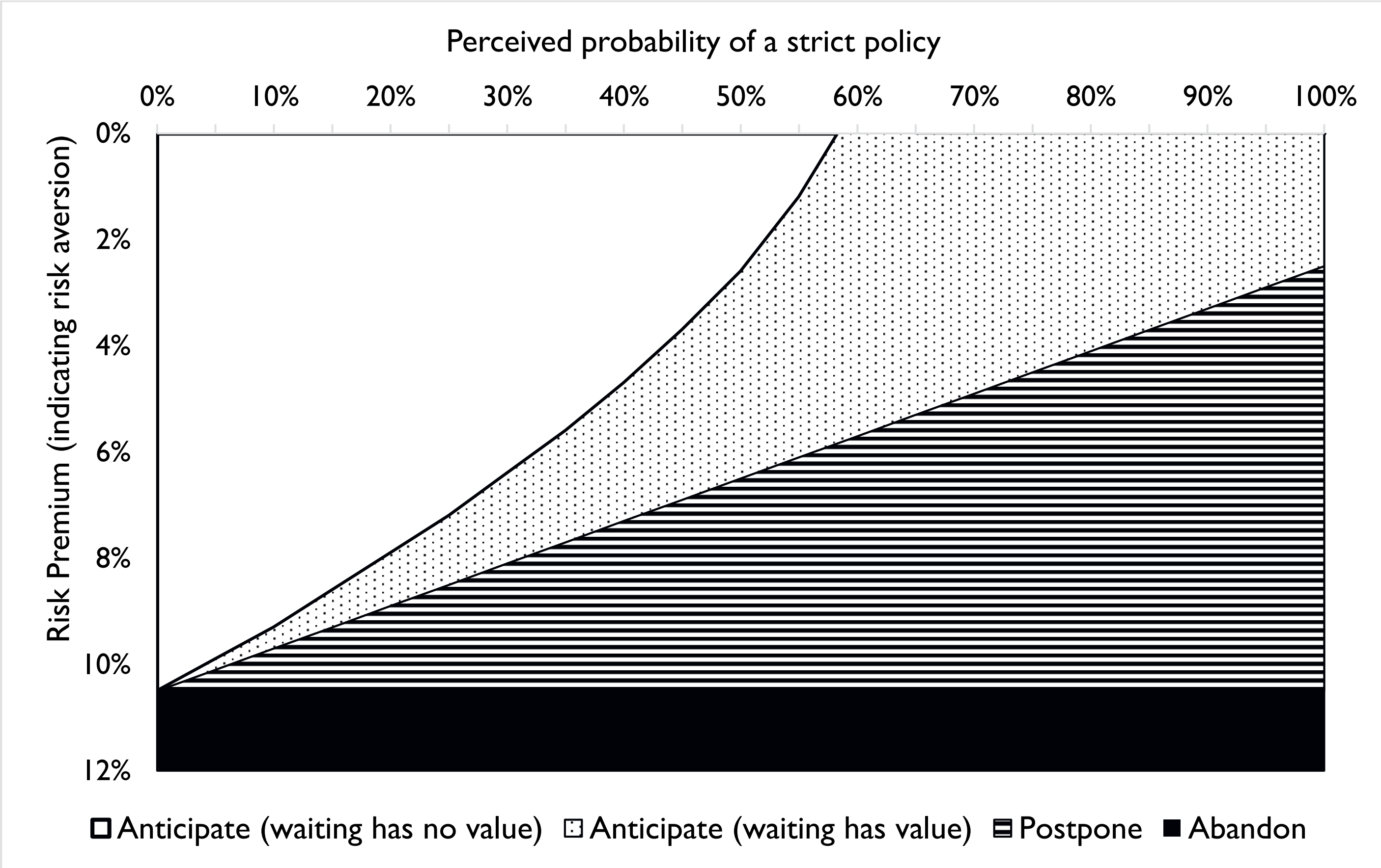

Figure 2.2: Optimal investment strategy while varying risk premium and probability on strict policy, $S = 3$ and all other parameters are kept constant.

While both investment strategies decrease in p (Figure 2.1), they have opposite effects in s. The value of anticipation increases with a delayed or late policy implementation because the farmer expects to receive the high cash flow CF_h for a longer time (Figure 2.3). The value of waiting decreases because the farmer will receive the cash flow later in time, resulting in a lower present value. Figure 2.3 further shows that for higher levels of risk aversion the economic values of both strategies become more comparable. At $k = 8\%$, switching strategies – from waiting to anticipation – occurs at $s = 5$ but the difference in net present value is limited.

For highly risk-averse farmers (k ≥ 10.5%) it is optimal not to invest for the full range of S (black bars in Figure 2.4). At very low levels of risk aversion (k < 3%), the anticipation strategy is only disregarded when the farmer expects the introduction of the phosphate right system the year after the investment.

In the results presented so far, a milk price of € 35.5 per 100 kg of milk was assumed (Table 2.1). To study the robustness of our results, we vary the milk price while s is at 3 years, p is at 50%, k is at 6% and all other parameters are at their default value (Table 2.1). The optimal investment strategy is sensitive to milk price changes (Table 2.2). The strategic NPV (SNPV) is € 9,474 with an unchanged milk price. The anticipation value is positive (€ 2,857), the waiting value is 0, implying the farmer should anticipate. Milk price increases of 5% and 10% do not change the strategy; the anticipation value increases, and the waiting value decreases.

We varied the milk price to study the robustness of our results to changes in the milk price. When the milk price decreases by 5%, the anticipation value is 0, and the waiting value exceeds the anticipation value. If the farmer postpones the investment, a negative effect of a strict policy is avoided. However, if the farmer anticipates and the strict policy is implemented this would lead to a financial loss. The strategy of waiting has now become optimal. A further decrease in the milk price (-10%) causes the optimal investment decision to switch from postponing to not investing. The investment is no longer profitable, and the farmer should choose not to invest. The SNPV cannot be less than 0 because both the $\mathrm{NPV_b}$, the waiting value and the AV cannot be less than 0. Though the optimal investment strategies are affected by the milk price, the direction of the effect of policy uncertainty and risk attitude on the optimal investment strategy will not be affected by changes in the milk price.

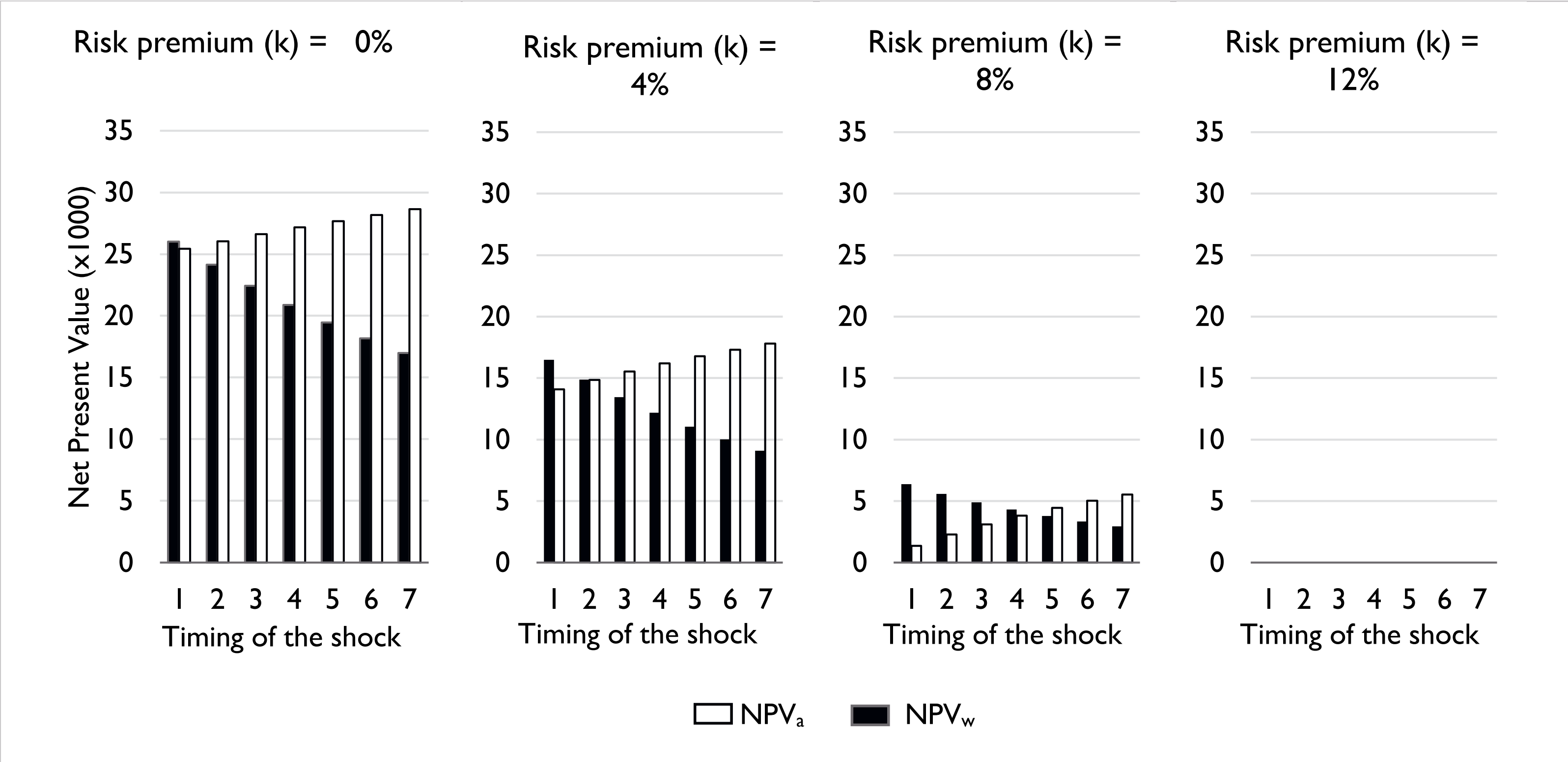

Figure 2.3: The NPV for different risk premia and different perceived timings of the shock, with p = 50% and all other parameters kept constant

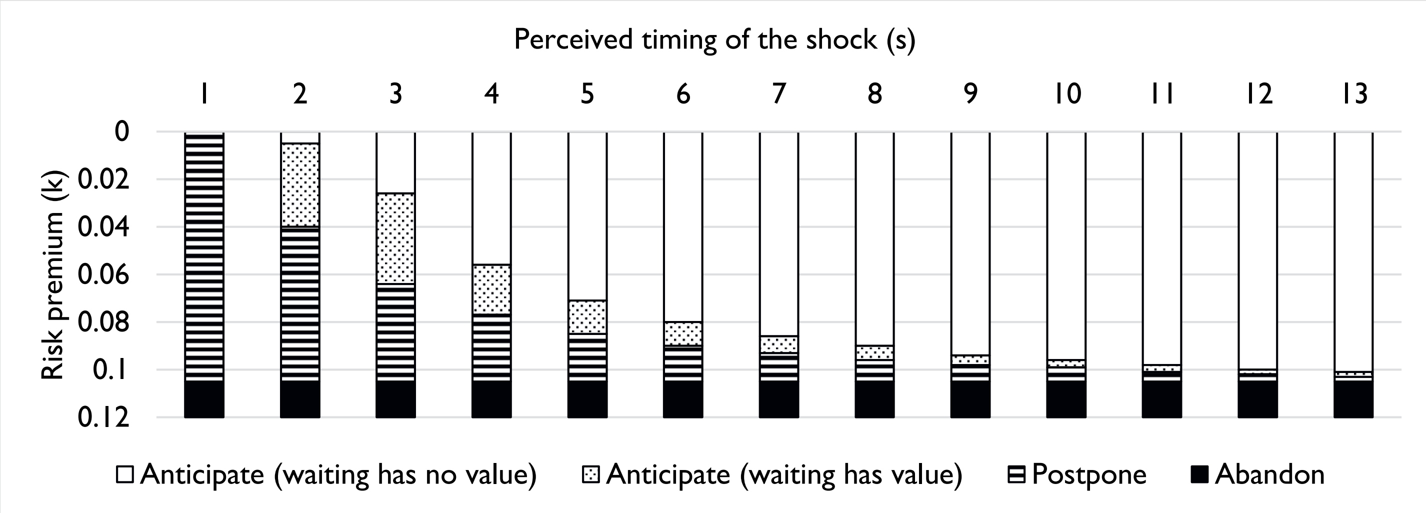

Figure 2.4: Optimal investment strategy while varying *k* and *s*, p = 50% and all other parameters are kept constant.

Table 2.2: The optimal investment decision at different values of the milk price.

Milk price change **Milk price per 100 kg**	**-10%** **€32.0**	**-5%** **€33.7**	 **€35.5**	**+5%** **€37.3**	**+10%** **€39.1**
NPV_b	0	0	6616	17432	28247
WV	0	1867	2477	0	0
AV	0	0	2857	3275	3694
SNPV	0	1867	9474	20707	31940
Optimal strategy:	No investment	Postpone	Anticipate →		

Note: All parameters, except milk price, are kept constant, S = 3, p = 50% and k = 6%

2.5 Discussion

This section first discusses the main findings and this is followed by the policy implications.

2.5.1 Discussion of the main findings

Our study was dedicated to the question of how farmers make investment decisions in the presence of policy uncertainty. This was stirred by the observation of many Dutch dairy farmers investing in the expansion before and after the abolition of the dairy quota system, while new restrictive policies to limit emissions could reasonably be expected. We developed a general framework that is capable of calculating the NPV of three investment strategies for production expansion in the presence of policy uncertainty: anticipate, wait and not invest. The anticipation strategy provides an explanation for the observed investment behaviour of dairy farmers. The outcomes of the numerical illustration showed under which conditions the farmer anticipates, waits, or chooses not to invest.

Apart from the main analysis on policy uncertainty, we analysed the robustness of our results to changes in the milk price (while keeping policy uncertainty constant). However, in future analysis interested in studying price uncertainty, data could be used to study the effect of a dynamic milk price. In this paper we did not include dynamic milk price as we were not interested in studying price uncertainty. We assumed the farmer only had to deal with one source of uncertainty at a time, that is easily defined and quantifiable using a single probability value. In practice, policy and price uncertainty can be interrelated, as the period before and after the abolishment of the milk quota has shown. A restrictive policy (a quota) affects the milk price (volatility) while increasing milk prices may trigger investments, which in turn will increase the production and simultaneously the level of emissions. To empirically quantify the effect of both uncertainties on investments, likely a combination of the frequentist and subjectivist views on probabilities has to be taken (Hardaker and Lien, 2010, Komarek et al., 2020). Due to the unavailability of data about policy uncertainty, a suitable approach may be to combine historical data about prices with expert judgments in a Bayesian network approach (Werner et al., 2017).

We highlighted the subjective nature of the parameters used in this study describing policy uncertainty and risk attitude in the framework. In the numerical illustration, these parameters were varied in a range of possible values to show which investment strategy is selected under which parameter settings. Constant risk and exponential time preferences were hereby assumed. The elicitation of risk and time preferences in a survey and experimental farmer behaviour research is a current theme in the agricultural economics literature (e.g. Bocquého et al., 2013, Hermann and Musshoff, 2016). If farmers time preferences are indeed (quasi-)hyperbolic instead of exponential, farmers would be present biased. This means that they perceive more utility from cash flows received in the present compared to cash flows received in the future. For present-biased farmers, the anticipating strategy is more attractive. Besides time preferences, farmers' risk preferences may be a time-variant personality trait (Guiso et al., 2018, Schulte et al., 2018). As such, the SNPV of a farmer today may need to be calculated with a different risk premium as the SNPV calculated 10 years from now. However, within one SNPV calculation, the same risk premium should be used as it should include the risk attitude of today to determine the SNPV of today. Moreover, the s-shaped utility function from cumulative prospect theory (Bocquého et al., 2013) indicates that different risk premia should be used depending on the current endowment of the farmer. More prosperous farmers may thus be willing to take more risks than less prosperous farmers.

Future research could extend our framework by allowing for flexibility in the risk and time preferences, possibly based on an empirical data collection of these preferences. The basic or extended SNPV could be taken as the presented maximization problem (see Section 2) to simulate decision problems under policy uncertainty, e.g. the farmers' willingness to invest in farm technologies that are currently being proposed to reduce emissions and environmental harm. There will be a value of anticipation when an investment before new policies, could lead to a benefit after policy implementation.

Furthermore, risk and time preferences have also been linked to personality psychology and entrepreneurial behaviour (e.g. Borghans et al., 2008). It may well be that the entrepreneurial-oriented farmers more quickly adopt an anticipation strategy when considering to invest despite being surrounded by high policy uncertainty. In survey research on farmers' perceived obstacles for business development, it was found that extraversion and openness explain these perceptions (Hansson and Sok, 2021). Farmers who scored higher on these personality traits experienced fewer obstacles in developing their businesses. Both personality traits are associated with entrepreneurial behaviour (Zhao et al., 2010). Future research could be dedicated to finding explanations from entrepreneurial and personality psychology to understand investment decision making in the presence of policy uncertainty.

2.5.2 Policy implications

In our analyses, we studied a situation in which a dairy farmer wished to expand the farm but didn't have full information about the introduction of the phosphate right system. The policy uncertainty was represented by a combination of parameters in the framework. These parameters captured expectations of the farmer about the likelihood (probability), timing, and expected financial consequences of the introduction of the phosphate right system. We showed for this particular case that an anticipation strategy is optimal when the farmer expects that the phosphate right system will be implemented with delay and will have low financial consequences. Thus, if policymakers communicate 'uncertainty' about the timing of the implementation of restrictive policies and remain unclear about the financial implications, farmers may be more prompted to invest early. A low risk aversion reinforces the adoption of this strategy under these circumstances.

The insights generated in this study emphasize the importance of understanding farmers' responses to government interventions. First of all, policymakers need to carefully estimate how farmers respond to either revealing or not revealing information about an intended action. While not formally taken into account in our framework and analyses, we recommend policymakers also take into consideration how the experiences of farmers with restrictive policies and regulations in the past affect expectations. Previous research has shown that past behaviour can influence farmers' behaviour (Cohen et al., 2008). Former manure and dairy market regulations were based on historical production levels (grandfathering). Farmers likely take these experiences into account in their investment decisions following a quota abolishment.

Also, farm advisors can play an important mediating role between policy makers and farmers in assuring proper communication of the risks and uncertainties and avoiding situations of financial distress. Farmers often act simultaneously as owners and as the main labour providers in (family) farm businesses. The operator or entrepreneur defines the goals at the strategic and tactical levels. Support from several 'gatekeepers' for the provision of strategic information regarding for example policy developments is hereby indispensable. This information is often provided by advisors affiliated with bank and accountancy firms active in the agricultural sector(e.g Hilkens et al., 2018). These advisors are key referents in the investment decision making process. Moreover, previous research has shown that extension services can influence investment decisions (Nobre and Grable, 2015).

2.6 Conclusion

In conclusion, we found that the anticipation strategy is optimal when the farmer expects that the policy will be implemented with delay and will have low financial consequences. A low risk aversion reinforces the adoption of this strategy. As such, when the government communicates uncertainty about the timing of policy implementation, farmers may choose to invest early. We also saw that a higher milk price makes anticipation more valuable. These results imply the importance of understanding farmers' decision timing and investment strategies for policymakers.

Chapter 3

Do Dutch farmers invest in expansion despite increased policy uncertainty? A participatory Bayesian network approach

This chapter is based on the paper: Yanore, L., Sok, J., & Oude Lansink, A. (2023). Do Dutch farmers invest in expansion despite increased policy uncertainty? A participatory Bayesian network approach. *Agribusiness*, 1–23. https://doi.org/10.1002/agr.21834

Abstract
An important but understudied factor influencing strategic decisions of farmers is policy uncertainty. Increased policy uncertainty may expedite the timing of investments in expansion, a phenomenon that has been observed in the Dutch dairy sector in recent years. Using a participatory Bayesian network, we aimed to identify and assess the farm, farmer, and environmental characteristics that explain and predict investment strategies. The variable policy uncertainty is modelled as a multidimensional concept that is a function of objective and subjective variables. We found that the most important variables influencing investment timing are succession, risk attitude, perceived policy uncertainty, and earning capacity. The insights derived from this study are useful for policy advisors, finance providers, farm advisors, and also farmers themselves to enhance their understanding of why and when farm investments are likely to occur despite the high level of policy uncertainty.

Keywords
Policy uncertainty, farmer behaviour, investment timing, Bayesian network, risk attitude, succession

3.1 Introduction

Agricultural activities are inherently connected to uncertainty about future income because of dependence on markets and the natural environment. Previous research has shown that policy uncertainty – i.e. the institutional environment - is also a primary source of uncertainty for farmers (Flaten et al., 2005, Mittenzwei et al., 2017, Vissers et al., 2022). According to Moschini and Hennessy (2001) policy uncertainty is especially relevant in agriculture, because many countries have an extensive system of policy interventions focused on agriculture. Despite its relevance, policy uncertainty is the least studied among the different sources of uncertainty in farming and agriculture (Komarek et al., 2020). Policy uncertainty affects primarily the strategic management of farms, and more specifically the investment decisions and their timing. Environmental policy uncertainty among farmers in the Netherlands has further increased due to the potential introduction of more stringent regulations to reduce nitrogen emissions (De Pue and Buysse, 2020, Stokstad, 2019). In 2020, the highest administrative court suspended permits for construction projects, both in the agricultural sector as well as in other sectors. The court ruled that the Nitrogen Action Program could no longer be used as a basis for granting these permits. One of the alternative policies being considered by politicians is a mandatory buyout program for farms located close to protected natural areas.

Increased policy uncertainty may expedite the investment (e.g. Hassett and Metcalf, 1999), a phenomenon that has been observed in the Dutch dairy sector in recent years. There are three investment strategies: anticipate policy uncertainty and invest early, wait with investing, or not investing at all (Yanore et al., 2022). While it was highly uncertain how environmental policies and regulations related to phosphate emissions would evolve, Dutch dairy farmers invested in expanding milk production, resulting in a milk supply increase of 22 % between 2012 and 2017 (CBS, 2018). Farmers anticipating policy changes related to phosphate emission by investing early in production expansion between July 2015 and 2018, were forced *ex-post* to reduce their herd size or buy additional rights to stick to the maximum allowable phosphate emission level.

This study aims to identify and assess the farm -, farmer - and environmental characteristics that explain and predict investment strategies: anticipate and invest early, wait with investing, or not investing at al. This study also explores the role of policy uncertainty in the investment decision. The empirical analysis focuses on the decision of Dutch dairy farmers to invest in the expansion of the barn capacity and herd size.

Most studies that investigate how policy uncertainty affects farm investment behaviour use a net present value or real options approach to conceptually underpin the investment strategies. However, including policy uncertainty as a variable in empirical models for predicting farm investments remains complicated (Rodrik, 1991). First, measurement problems can make it challenging to include policy uncertainty in empirical investment models. While historical data is usually available to quantify e.g. price uncertainty or variation in yield, such objective data are generally lacking for policy uncertainty (Komarek et al., 2020). Linnerud et al. (2014), who used real options theory, addressed the lack of data on policy uncertainty in Norway by using qualitative information on policy statements and decisions. As measuring actual policy uncertainty is indeed challenging, it is possible to simulate policy uncertainty using a geometric Brownian motion or a Poisson jump process. However, Hassett and Metcalf (1999) show that the chosen stochastic process largely determines the effect of uncertainty on investment timing and argue that much of the literature uses inappropriate methods for modelling (tax) policy uncertainty. Thus, simulating policy uncertainty is challenging.

Second, policy uncertainty is not an objectively measurable entity, as it is subject to farmers' beliefs and preferences (Hardaker et al., 2015, Rasmussen et al., 2013). How uncertainty is perceived is related to individual differences, such as risk attitude and personality traits (e.g. van Winsen et al., 2016, Weller and Tikir, 2011). Surveys and experimental approaches are often used to study how policy uncertainty is perceived and how it affects decision making and behaviour. For example, van Winsen et al. (2016) used a survey and structural equation modelling to study the relation between risk attitude, risk perception and risk management strategies. They found that farmers risk attitude is an important factor determining their perception of institutional, production and price risk. Wilson and Sumner (2004) adopted a time-series econometric approach to examine determinants of dairy quota value changes. They interviewed Californian dairy producers to obtain *ex*-post subjective expectations about potential changes in future cash flow return from the quota program. These expectations of policy uncertainty were then added as an explanatory variable in the model together with other objectively measured variables. Samson et al. (2016) studied the expansion decisions of Dutch dairy farmers after quota abolition. They argue that policy changes may influence farmers' expectations about future benefits and costs related to the expansion. Farmers would thus have different expectations about how policy changes may affect them and their farms.

The question then is: How to account for individual differences in studying farmer investment timing in the context of policy uncertainty? Earlier studies have demonstrated that a Bayesian Network (BN) methodology is a promising way forward (Chen and Pollino, 2012, Gambelli and Bruschi, 2010, Yet et al., 2020). A BN is a probabilistic graphical model of a set of random variables and their probabilistic dependencies. They can be constructed in a data-driven or a participatory way using expert knowledge, or a combination of the two (Werner et al., 2017). As such, they can handle a multitude of (stochastic) variables, they can include variables for which objective measures are missing (Chen and Pollino, 2012, Yet et al., 2016), and they can represent links across knowledge domains in an exploratory manner (Poppenborg and Koellner, 2014). Because of the challenges with including policy uncertainty, we make use of the participatory method based on expert knowledge. Moreover, an exploratory BN approach is promising as Assefa et al. (2017) argue that open-ended and exploratory approaches for data collection are useful in a context of risk management as farmers may perceive quantitative approaches as unnatural. Several studies have used participatory BN approaches in agricultural and environmental sciences to analyse farmers decision making in isolation (Gambelli and Bruschi, 2010, Torabi et al., 2016) or in conjunction with the effects on the natural environment (Bonneau de Beaufort et al., 2015, Carmona et al., 2013). The types of decisions that were studied include participation in biodiverse carbon planting (Torabi et al., 2016), farm exit (Gambelli and Bruschi, 2010), practice change (Moglia et al., 2018), and land-use change (Celio and Grêt-Regamey, 2016).

We contribute to the literature as we apply a novel method (a BN) to quantify policy uncertainty in the context of farmers adoption of different investment strategies, that is, anticipating, waiting, and not investing. Moreover, we contribute to the literature by including financial, behavioural, and socio-economic factors in one model to explain investments by dairy farmers. The insights derived from this study are useful for policy advisors, finance providers, farm advisors, and farmers to enhance their understanding of why and when farm investments are likely to occur despite the high level of policy uncertainty. This could improve farmers investment decisions and inform more effective policy.

The next section presents a theoretical framework for studying investment timing under policy uncertainty. In section 3, we describe the procedure for developing the BN, that is, we describe the selection of variables and the development of the network structure. Section 4 presents the results of the BN and section 5 provides a discussion and conclusions.

3.2 Investment timing under policy uncertainty

This section describes the conceptual framework for farmer investment decision making adopted in this paper. The model provides the conceptual basis for the main target variable in the BN, that is, the investment strategy (anticipating, waiting, and not investing). Furthermore, the conceptual framework provides the theoretical underpinning for the variables we expect the experts will mention as important factor influencing the investment strategies.

The classical Net Present Value framework for investment selection suggests that farmers face dichotomous investment decisions, that is, they can only choose between investing now or not at all. More realistically, farmers can choose between investing now, or at several different moments in the future, or not at all. This is the situation that is covered by the Real Options theory, suggesting that farmers have the option to wait for new information to arrive before deciding on an investment (Pindyck, 1990).

Whereas the Real Options approach will be sufficient to deal with a range of uncertainties, several studies have shown that increased uncertainty may lead to the decision to invest early (Hassett and Metcalf, 1999, Smit and Trigeorgis, 2017, Welling, 2016). Based on the work of Smit and Trigeorgis (2017), Yanore et al. (2022) proposed an economic framework to calculate the value of three investment strategies in the presence of policy uncertainty. The optimal investment strategies – anticipating and investing early, waiting, or not investing at all – can be presented in a strategic net present value (SNPV) framework as:

$$SNPV = NPV_b + max(AV, WV)$$

where NPV_b reflects the net present value of a base situation without strategy considerations, AV is the anticipation value, and WV is the waiting value. The decision maker should anticipate, i.e. invest early, if the $SNPV > 0$ and $AV > WV$. The investment should be postponed if the $SNPV > 0$ and $WV > AV$. The decision maker should not invest if the $SNPV = 0$. In that case, there is no value in investing early nor postponing the investment.

In the base situation, the entire cash flow over period T is separated into two parts by a negative shock S that will occur with probability p and reflects the moment a policy change takes place that lowers the cashflow from CF_h to CF_l. The cashflows are discounted with discount rate r at time period t. This situation can be written as:

$$NPV_b = max\left(0, -I + \sum_{t=1}^{S} \frac{CF_h}{(1+r)^t} + (1-p) \sum_{t=S+1}^{T} \frac{CF_h}{(1+r)^t} + p \sum_{t=S+1}^{T} \frac{CF_l}{(1+r)^t}\right)$$

In the NPV calculation for the waiting strategy (NPV_w), the investment I does not take place at $t = 0$, as in NPV_b, but at $t = S$. Thus, I is replaced by $\frac{I_S}{(1+r)^S}$ and the period is extended with $T + S$. The value of waiting for WV is calculated as $max\ (0, NPV_w - NPV_b)$.

In the NPV calculation for the anticipation strategy (NPV_a), the investment I takes place at $t = 0$, as in NPV_b. Here the difference is in the expectation of the value of the cashflow, CF_a, being received after S. The advantage of investing early materializes through a higher cash flow, $CF_a > CF_l$. The value of anticipation AV is calculated as $max\ (0, NPV_a - NPV_b)$.

The SNPV framework thus suggests three potential investment strategies: anticipate, wait, or do not invest. Please note that in what follows, our study did not empirically estimate the parameters of this model based on the presented equations, but considered these three strategies as the target variable to be explained in the BN. These strategies are, in this framework, a function of the earning capacity of the farm, the subjective expectations about if, when, and how new policy affects cash flow (uncertainty), and risk and time preferences. The earning capacity is the farm's capacity or ability to earn cash in the future, which is affected by a range of financial, technical, and managerial variables. Examples of technical and financial variables that determine earning capacity include the capital structure and the size and intensity of the farm (e.g. Aderajew et al., 2019). The earning capacity can be sufficient to invest in expansion, but there can be no opportunities to grow because of, either or both, internal and external circumstances. It matters e.g. where the farm is on the life cycle (from entry to exit) and what the probability of succession is (e.g. Calus et al., 2008). But even when succession is assured, it may be that investing in expansion is uncertain due to external, neighbouring, and environmental variables (Samson et al., 2016). The reader should note that besides the NPV, investors are likely to consider other methods for investment appraisal such as the internal rate of return and the payback period (Atrill and McLaney, 2006).

The formation of expectations and preferences differ by individual. Differences in long-term investment decision making and behaviour can be partially captured in economic models by parameters representing risk and time preferences. How these risk and time preferences affect investment decisions in response to policy uncertainty in a farming context is not studied extensively. Previous work using the SNPV framework suggests that risk-averse farmers are more (less) likely to adopt the waiting (anticipation) strategy in response to policy uncertainty(Yanore et al., 2022). Regarding time preferences, in a more general uncertain environment, it has been suggested that investment behaviour is better described by hyperbolic preferences (Grenadier and Wang, 2007). Next to risk and time preferences, concepts from the social sciences are increasingly used to understand entrepreneurial and strategic behaviour, in particular, the concepts of goals, personality traits, and values (Hansson and Sok, 2021).

3.3 Methods

This section describes the method for developing a participatory BN based on expert elicitations. When we asked experts to provide their input, we presented them with the context of an expansion of a typical Dutch dairy farm involving an investment in barn capacity and herd size. The dairy farmer takes the investment decision in the presence of uncertainty about the direction of future environmental policies that potentially pose more restrictions on production. The experts were to consider a farmer who chooses one of three investment strategies, anticipating, waiting and not investing as described in the conceptual framework.

3.3.1 Bayesian Network

A Bayesian network (BN) is a directed acyclic graph consisting of three elements: nodes, arcs, and conditional probability tables (Charniak, 1991, Zhang and Poole, 1996). The nodes are the networks' variables, which can take different states (Cain, 2001, Cain et al., 1999). In what follows, we will use the term “node” and “variable” interchangeably. The arcs in a BN are the links between nodes. The causal relationship between nodes determines whether they are called parent nodes or child nodes. For example, if A influences B, then A and B are parent and child, respectively. The arcs indicate the (in)dependence between the nodes and determine the required probability distributions (Charniak, 1991, Zhang and Poole, 1996). These probability distributions are called conditional probability tables (CPTs) and form the third element of a BN. Every child node in a BN has a CPT, which determines the strength of the causal relationship. CPTs are indexed by all combinations of states of the parent and child nodes. A BN can be constructed in a data-driven way, a participatory way using expert knowledge, or a combination of the two. In this study we used the participatory way as data about policy uncertainty is not available.

3.3.2 Expert selection

The selection of experts was based on expert profiles specifying the essential and desired expertise of the participants. Essential expertise included knowledge about farm investments, decision making, behaviour, and the agricultural sector in North-western Europe. Desired expertise included knowledge of recent policy changes in the Netherlands, the dairy sector, and professional experience with farmers. Based on this expert profile, the following roles were identified: (i) employees of companies providing farm extension and advisory services, such as banks or accountants, and (ii) researchers studying farm investment decisions in the agricultural sector. Two employees of Alfa Accountants and Advisors reached out to their network, thus giving us access to a number of farm advisors from Alfa accountants and financial advisors from banks. Moreover, we approached a number of researchers who matched the expert profile. In the appendix we describe how many experts were contacted, participated and their areas of expertise (Appendix 3.A, Table 3.A1).We followed published guidelines to develop a BN with expert elicitation (Cain, 2001, Chen and Pollino, 2012, Marcot et al., 2006) and distinguished five steps (Figure 2.1): (1) select variables, (2) determine the preliminary network structure, (3) evaluate and further develop the network structure, (4) elicit the CPTs, and (5) analyse. In the next section, we describe each step in more detail.

3.3.3 Steps

3.3.3.1 Select variables (step 1)

Based on a workshop with experts, we determined the list of variables for inclusion in the BN model. Before the actual workshop, we hosted two test sessions with both scientists and a farmer to fine-tune the workshop design. Six experts confirmed their participation in the workshop, however, two of the experts were unable to participate due to restrictions related to Covid-19. The remaining four participants included two farmers, an accountant from a Dutch agricultural accountancy firm (Alfa), and a relationship manager from a Dutch bank that is active in the agricultural sector (Rabobank).

We selected the variables that workshop participants mentioned most frequently. One often mentioned variable was "farmer personality". Unlike the other variables, "farmer personality" needed to be operationalized. To do so, we

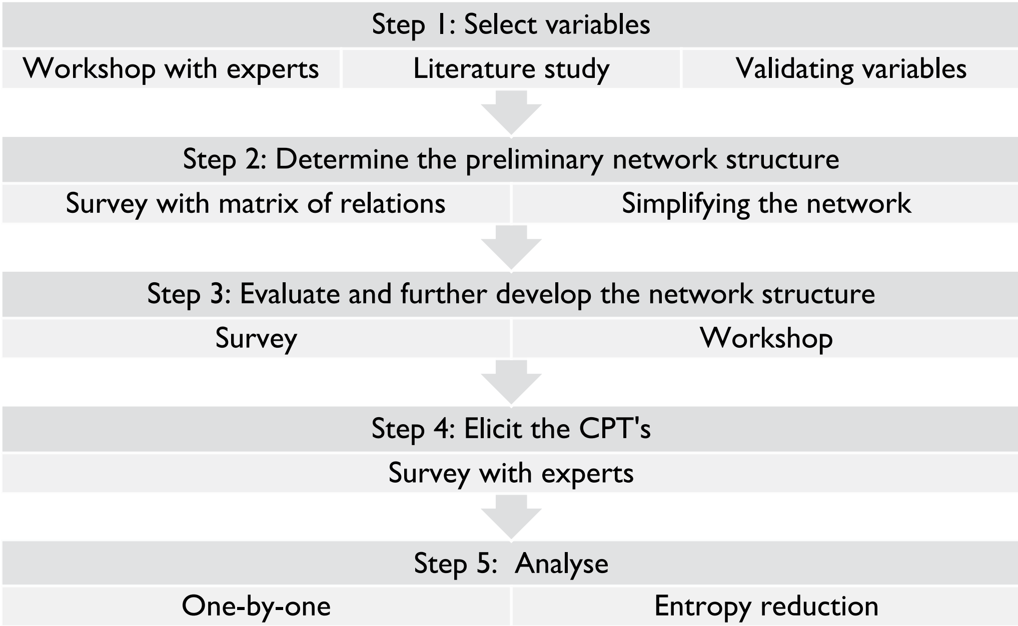

Figure 3.1: Overview of the steps

conducted a short literature review with combinations of the following search terms: agricultur*, farm*, investment decisions, and personality. Based on this we selected the Big five personality traits and risk preferences. We then organized a meeting with a new group of experts to verify the selection of the variables from the workshop's results and the literature study. This was done in an open discussion format. Based on feedback from this group, we determined the final list of variables for inclusion in the network.

3.3.3.2 Determine the preliminary network structure (step 2)

In step 2, we selected 12 experts using the previously described expert profile and asked them to fill out a symmetric contingency table. Four of these experts also participated in step 1. For each pair of variables, experts rated the strength of the relation on a scale from 1 to 4. The four options they could choose from were: 1) there is no link, 2) there is a link, 3) there is a strong link, and 4) there is a very strong link. We established a first BN structure by including all links with a score (*s*) of 2 or higher. The score was calculated as

$$s = m - 0.253 * \sigma$$

where m is the mean value of all individual participants, -0.253 is the z-score, and σ is the standard deviation. We used the z-score (-0.253) to indicate the top 60%

of the distribution. We used the standard deviation and z-score because it reduces the effect of the outliers on the strength's score.

The next step was to determine the most logical direction of the links and the states of each variable (e.g., risk attitude had three states: risk-taking, risk-neutral, and risk-averse). For the variables we had data for, we determined the states using the distribution as found in the data. For the other variables we used common sense and literature to determine the states. In step 3, we proposed the direction of the links and states of the variables to the experts and discussed the need make any required improvements. Before this, we had to reduce the complexity of the network. The network was too complex, because determining all resulting CPTs with experts would not be feasible (van der Gaag et al., 1999). To reduce the complexity, we first removed links with the lowest score for nodes with more than three links. Second, we removed nodes that did not have direct or indirect links with the main variable of interest, the investment timing node. Thirdly, we adjusted two links with CPTs which could otherwise not be elicited using the Noisy-MAX approach. For CPTs to be elicited with the Noisy-MAX approach, you determine the parent states "order of strength". The parent node with the strongest influence on the child node has the highest "order of strength". For two of the links, determining this "order of strength" was not considered logical by the research team and thus needed adjustment to enable the experts to make the required estimates. This adjustment had a minimal impact on the overall network structure.

3.3.3.3 Evaluate and further develop the network structure (step 3)

We evaluated the network using a questionnaire that was sent to six experts, who were selected using the same expert profile that was previously described. Two of these experts also participated in the workshop organized in step 1 and four experts joined for the first time. We asked them to evaluate the selection of variables and indicate if important variables were missing. We also asked them to evaluate the network structure, that is, the links and their directions. Finally, we asked them to evaluate the proposed states of the variables. Subsequently, a second workshop was organized with the same six experts to jointly discuss the questionnaire results and any significant disagreement. The network structure was further developed based on the outcomes of this workshop.

3.3.3.4 Elicit the CPTs (step 4)

We selected five experts, who were all part of the workshop in step 3. This number is within the recommended range for such an exercise (Werner et al., 2017). The

BN literature distinguishes two approaches: the consensus and the individual approach (Renooij, 2001, van der Gaag et al., 1999). We opted for the individual approach because of time constraints and to prevent that certain experts would dominate the elicitation process (Werner et al., 2017).

Eliciting a large number of probabilities is a challenging cognitive task (Werner et al., 2017), so we opted for the Noisy MAX approach to obtain CPTs for the more complex nodes (with more than two parents). The Noisy-MAX approach reduces the number of parameters needed to construct a CPT table (Díez, 1993, Pearl, 1988). It also allows for including a so-called *Leak*, which is an auxiliary cause that allows to include the effect of causes that are not explicitly modelled in the network (Zagorecki and Druzdzel, 2012). Including a leak is common practice when applying the Noisy-MAX (Zagorecki and Druzdzel, 2012).

The individual expert assessments were aggregated using the equal weighing method. Equal weighting increases statistical accuracy as the number of experts providing an estimate increases (Werner et al., 2017). The network probabilities obtained with this method were compared with those obtained via a distance-based weighing method, to check the effect of outliers in the probability estimations.

3.3.3.5 Analyse (Step 5)

With the developed network structure and the construction of the CPT tables, we performed several analyses. The network was built and analysed in *R 4.0.2.* using the *rSMILE* (BayesFusion, 2021). Two methods were used to analyse the network. Firstly, we studied the relative strength of the effect of the variables on the perceived policy uncertainty and investment timing. The relative strength was determined using the entropy reduction method, as described by Marcot (2012). Only the variables that had a direct or indirect causal effect on the outcome variable were included. As a follow-up, we used a so-called one-by-one approach to study the effect of some of the variables on the two nodes of interest (Marcot, 2012). Using this approach, we change the states of the variables that influence these two variables one by one and observe the effect on the fractions of the states. The five variables with the strongest influence, according to the entropy reduction results, were analysed using this one-by-one approach.

3.4 Results

3.4.1 Network structure

The experts thought about variables and links in the BN in the context of an investment in barn capacity and herd size expansion for a typical Dutch dairy farm. The farmer has to consider which investment strategy to choose in the presence of uncertainty due to the potential introduction of more stringent environmental policies: should they anticipate by investing early, invest later, or not invest at all? These investment strategies are derived from the Strategic NPV as described in section 2.

Figure 3.2 and Table 3.1 show the network structure resulting from the five steps, including the selection of variables and the links between these variables. The percentages in this network structure are a result of the CPT elicitation exercise. Table 3.1 provides the definitions of the variables and their states. There are four categories of variables the experts identified, financial variables, policy uncertainty variables, farm variables and farmer characteristics variables.

Experts considered policy uncertainty as a multidimensional concept that is a function of a farm, a farmer, and an environmental variable. The level of (perceived) policy uncertainty increases with a higher intensity (milk per hectare), risk aversion, and closer proximity to natural areas (Natura 2000 areas). The experts proposed to include these variables as they expect farms situated closer to natural areas, and operating with higher intensity, are more vulnerable to policies seeking to lower environmental emissions. How strongly farmers perceive policy uncertainty depends on their personalities, which is why the experts expected that risk attitude is also affecting the policy uncertainty node. Risk-taking farmers perceive a lower uncertainty than risk-averse farmers. In the SNPV framework, a risk-taking farmer would have a negative risk premium. However, such an option was not included in the analysis of the SNPV framework. Thus, when we refer to a risk-taking farmer in this paper, we refer to farmers with a low risk premium in comparison to other farmers.

The earning capacity was finally represented by three financial indicators: 1) the earnings before interest, taxes, depreciation, and amortization (EBITDA), 2) the debt-to-asset ratio (D/A-ratio), and 3) the intensity. All indicators describe different aspects of financial performance (Hillier et al., 2016). It is expected that a higher EBITDA, a lower D/A-ratio, and a higher intensity result in a lower earning capacity.

The characteristics of farmers in the BN were represented by risk attitude, personal values, and four of the "Big Five" personality traits: openness, conscientiousness, extraversion, and agreeableness. In step 1 the first thing the participants mentioned as relevant for the farmers decision was the farmers' personality. To operationalize this variable, we did a literature study and verified this in a second meeting with a smaller group of experts (Appendix 3.A, Table 3.A1, step 1b). Neuroticism was excluded from the network in step 2 as it did not have any direct or indirect links with the investment timing. The personality traits, in particular *openness* and *extraversion*, are associated with entrepreneurial behaviour

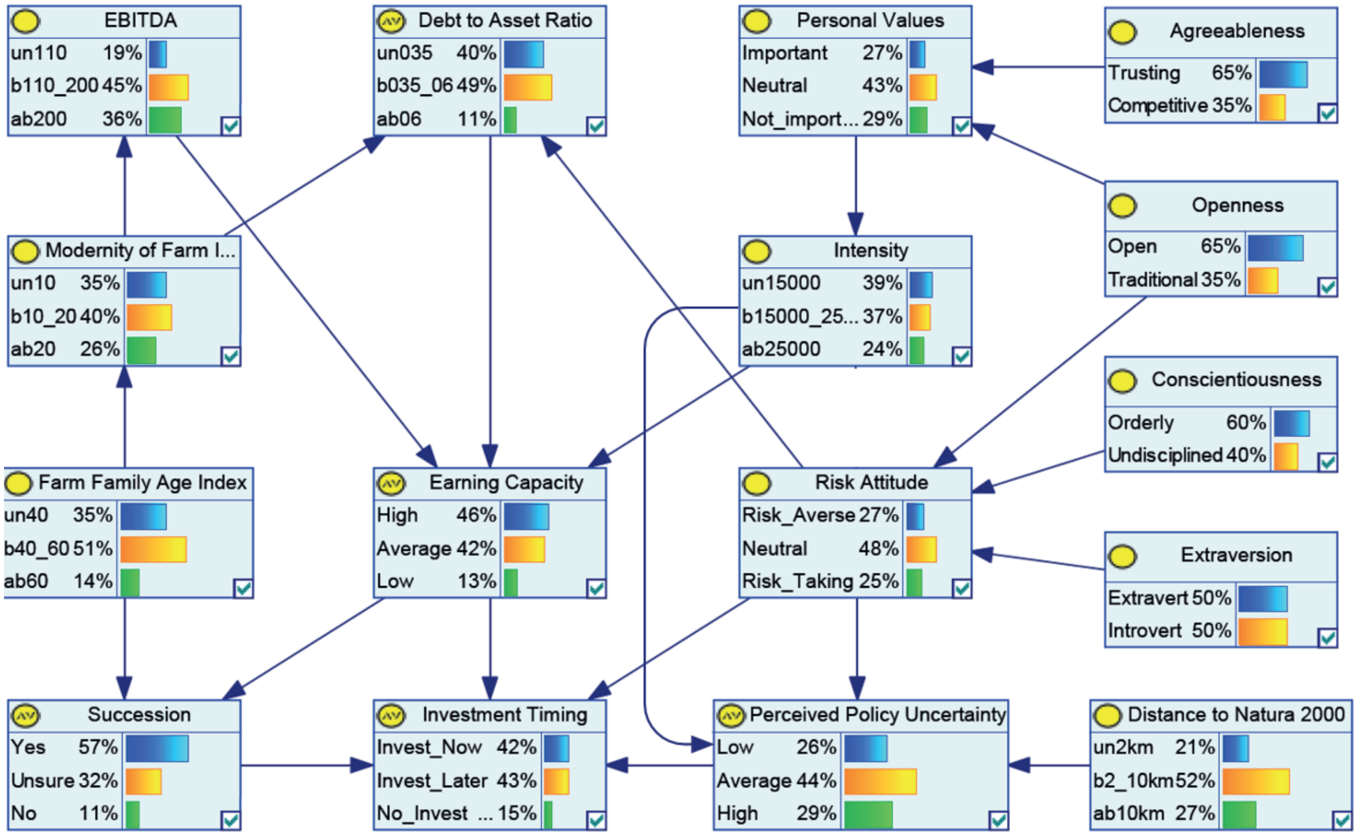

Figure 3.2: Network structure with probability distributions

Note: This figure shows all the factors that were selected by the experts, their links and the probability distributions which were based on the Noisy-MAX estimations of the experts.

Table 3.1: Categories, variables, definitions, states, and child nodes of the Bayesian Network

Category	Variable	Definition	States	Child nodes
N.A.	The investment timing	The moment at which the farmer invests	Invest now Invest later Does not invest	None
Financial variables	Earning capacity	The earning capacity the farm has to invest.	Low Average High	Investment timing Succession
Financial variables	Debt to asset ratio	The height of the debt in comparison to the total value of the company's total assets.	Below 0,35 0,35-0,6 Above 0,6	Earning capacity
Financial variables	EBITDA	The income of the farm before deducting interest, taxes, depreciation, and amortization.	Below €110.000 €110.000-€200.000 Above €200.000	Earning capacity
Financial variables & Policy uncertainty	Intensity (milk/ha)	The farms' milk production per ha land. Farms with higher intensity are exposed to a higher risk of policy interventions.	Below 15.000 kg/ha 15.000-25.000 kg/ha Above 25.000 kg/ha	Earning capacity Perceived policy uncertainty
Farm variables	Farm Family Age Index	The average age of all the people working on the farm.	Below 40 years 40 – 60 years Above 60 years	Succession Modernity
Farm variables	Succession	Whether the principal owner has a successor.	Yes Unsure No	Investment timing
Farm variables	Modernity of farm infrastructure	The modernity (age) of the infrastructure which holds the dairy cows.	Below 10 years 10–20 years 20 years	EBITDA Debt to Asset ratio

Policy uncertainty	Perceived policy uncertainty	The extent to which the principal owner perceives uncertainty related to policies.	Low Average High	Investment timing
Policy uncertainty	Distance to Natura 2000	The distance of the farm to protected natural areas called Natura 2000 areas. Farms close to these areas are exposed to a higher risk of policy interventions.	Below 2 km 2-10 km Above 10 km	Perceived policy uncertainty
Policy uncertainty & Char. of the farmer	Risk attitude	Describes to what extent the principal owner is willing to take a risk.	Risk-averse Risk-neutral Risk-taking	Investment timing Perceived Policy uncertainty
Char. of the farmer	Personal values	How relevant the owner finds biodiversity, outdoor grazing, and sustainability	Not important Neutral Important	Intensity
Char. of the farmer	Openness	The principal owner scores high if he/she is full of ideas and quickly changes his/her opinion and low if he/she is traditional and pragmatic.	Traditional Open	Personal Values Risk Attitude
Char. of the farmer	Conscientious ness	The principal owner scores high when orderly/ambitious/goal-oriented and low when undisciplined/sometimes careless.	Undisciplined Orderly	Risk Attitude
Char. of the farmer	Extraversion	The principal owner scores high when is assertive/likes to challenge himself, and low when reluctant/careful.	Introvert Extravert	Risk attitude
Char. of the farmer	Agreeableness	The principal owner scores high when he/she is modest and trusting, and low when he/she is competitive and sometimes arrogant.	Competitive Trusting	Personal Values

(Hansson and Sok, 2021). The personal values describe how farmers differ in the extent to which they appreciate biodiversity, outdoor grazing, and sustainability. It is expected that these personal values are more important for farmers who score higher on the personality traits of agreeableness and openness.

Other variables that were added to the BN were: the modernity of the farm infrastructure, the farm family age index (Burton, 2006, Zhao and Seibert, 2006), and succession. The modernity of the farm infrastructure affects the size of the depreciation (EBITDA) and the capital structure (D/A-ratio). The experts think that a higher farm family age index likely results in lower modernity of the farm infrastructure and a higher likelihood of having no successor.

Each node in the network structure has a conditional probability table (CPT) that defines the strength and direction of the effect the parent nodes have on a child node. An example of a CPT from our network is given in Table 3.2, which is a result of the step described in section 3.4. The likelihood that a farmer will have a successor in the BN is a function of the farm family age index and the earning capacity. The bold row represents the combination of states where the farm family age index is above 60 and the earning capacity is high. The resulting probability distribution for succession then is: Yes (44%), Unsure (27%), and No (28%). Based on the CPT, the probability distributions shown in Figure 3.1 are calculated. We can now show what happens in the network if a farmer is expected to choose the invest now, later not at all strategy. By feeding this "evidence" into the network, we can calculate updated probability distributions of the other variables' states (Appendix 3.A: Figures 3.1, 3.2 and 3.3). We find that the variables with a direct link to the investment timing have the strongest effect, that is: risk attitude, earning capacity, perceived policy uncertainty and succession.

3.4.2 Sensitivity analysis

Figure 3.3 shows how substantial all variables are for the likelihood farmers adopt either of the investment strategies. Substantiality is measured relatively to the other factors in the network and based on the experts' opinions. The variables that are most substantial are included in Figure 3.4, which shows how each of the states of the variables affects the investment timing strategies. Figure 3.5 ranks the substantiality of the effect of variables on the perceived policy uncertainty node. We included the variables with a direct or indirect effect on the perceived policy uncertainty node. In Figure 3.6 we show how the most substantial variables affect the states of the perceived policy uncertainty node. The results presented in these figures are based on the equal weighing method and are compared with a

Table 3.2: Conditional probability table of the Succession node

Farm family age index	Earning capacity	Succession		
		Yes	Unsure	No
Under 40 years	High	60%	56%	4%
	Average	55%	38%	5%
	Low	35%	52%	13%
Between 40 and 60 ears	High	67%	26%	7%
	Average	64%	29%	7%
	Low	47%	37%	16%
Above 60 years	**High**	**44%**	**27%**	**28%**
	Average	30%	30%	31%
	Low	10%	20%	70%

Note: Stakeholders expectations concerning the percentages of farmers who have 1) successor, 2) are unsure or 3) have no successor considering their states on the farm family age index and the earning capacity. An example is provided in the text.

distance-based weighing method. Results barely changed when using the distance-based weighing method, the CPs changed by at most 3%. We also show the probability distributions in the network structure when the states of the investment timing (Appendix 3.A, Figures 3.A1, 3.A2 and 3.A3).

The results from the entropy reduction calculations in Figure 3.3 suggest that experts believe that succession status is the most substantial variable explaining why a farmer will invest later or not at all. The results of the one-by-one approach in Figure 3.4 show that this especially holds for the strategy "No investment'. Without the prospect that a successor will take over the farm, increasing the farm size is not likely. The results further demonstrate that the degree to which policy uncertainty is present only matters for deciding between investing now or not investing at all. This is clear from Figure 3.4, showing that the probability for the strategy "Invest later" hardly changes. In other words, according to the experts, farmers will not postpone investments because of (perceived) policy uncertainty. However, with a higher risk aversion, we do see that the probability for the strategy "Invest later" increases. Thus, risk-averse farmers are more likely to postpone their investments. The succession status also has a bigger effect in the case of investing now, but it is lower than risk attitude and the (perceived) policy uncertainty. Experts

Figure 3.3: Substantiality ranking of nodes using entropy reduction of the investment timing

Note: On the y-axis you see the node that was removed from the model to see the effect of removing it on the log-likelihood. On the x-axis you see the change in the log-likelihood from removing the node. These numbers can only be interpretated in relative terms, magnitude does not matter.

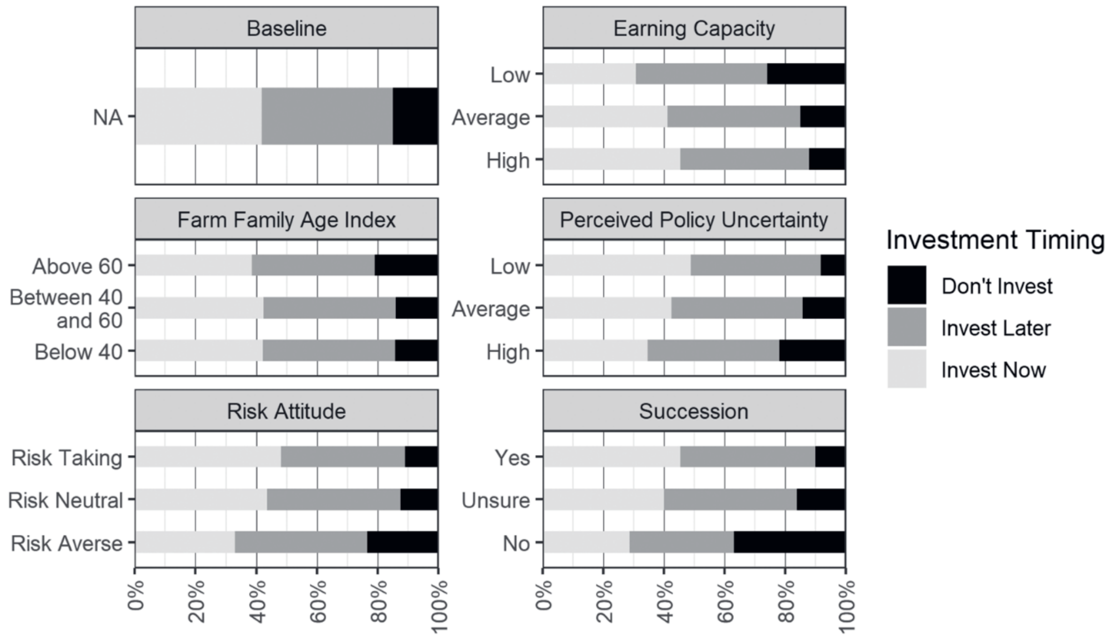

Figure 3.4: Effects of five most substantial nodes (entropy reduction) on investment timing

Note: Each box shows the scores on the investment timing node when the evidence for the parent node is set to either of its states, ceteris paribus.

consider the expectations and preferences of the farmer a more substantial variable then the earning capacity of the farm for investment decision making. The latter may be seen as a precondition for investing, while it is the behaviour of farmers that triggers investments.

Figures 3.5 and 3.6 summarize the results of the entropy reduction and the one-by-one approach for the (perceived) policy uncertainty variable. Experts considered policy uncertainty as a multidimensional concept that is a function of three variables, i.e. distance to Natura 2000, intensity, and risk attitude. Distance to Natura 2000 and intensity indicate the objective level of policy uncertainty. When the objective uncertainty is high, the perceived policy uncertainty is also higher and farmers are more likely to postpone investment or not to invest. However, when farmers are also risk-taking, they are still likely to perceive a low policy uncertainty and invest now despite the high objective uncertainty. The results in Figures 3.5 and 3.6 confirm earlier results that expectations and preferences (farmer behaviour) are more important than characteristics of the farm or environment.

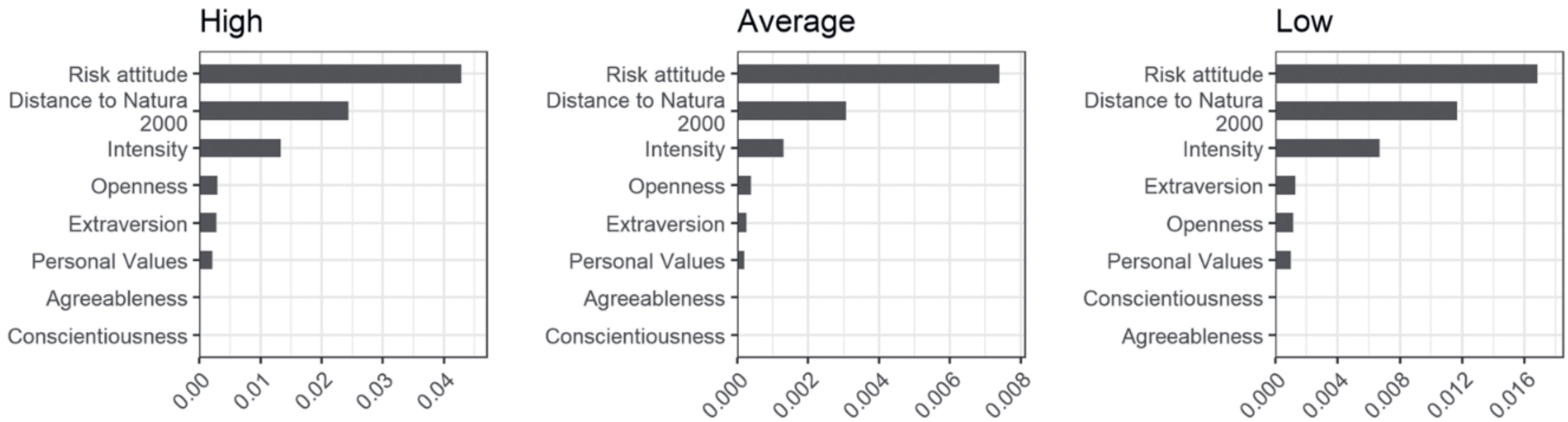

Figure 3.5: Substantiality ranking of nodes using entropy reduction of the perceived policy uncertainty

Note: On the y-axis you see the node that was removed from the model to see the effect of removing it on the log-likelihood. On the x-axis you see the change in the log-likelihood from removing the node. These numbers can only be interpreted in relative terms, magnitude does not matter.

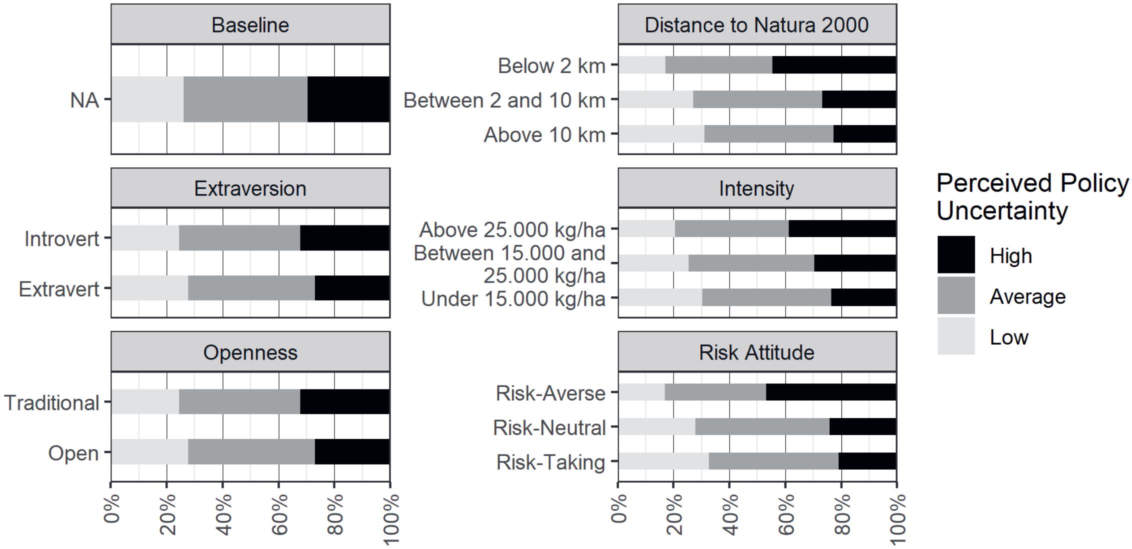

Figure 3.6: Effects of five most substantial nodes (entropy reduction) on perceived policy uncertainty.

Note: Each box shows the scores on the perceived policy uncertainty node when the evidence for the parent node is set to either of its states, ceteris paribus

3.5 Discussion and Conclusions

Farmers who consider expanding their business can anticipate policy uncertainty and invest early, wait with investing, or not invest at all. This study aimed to identify and assess the farm, farmer and environmental characteristics that explain these investment strategies. The empirical analysis used a Bayesian Network (BN) approach to model investments in the expansion of the barn capacity and herd size on a typical Dutch dairy farm. The results of this paper show that a BN approach is a useful tool for studying the relative importance of the different farm, farmer and environmental characteristics influencing investment timing. The paper adds to the literature by improving the understanding of how policy uncertainty influences the timing of investments. Moreover, the paper shows that succession status and risk attitude are the main variables influencing investment timing, followed by perceived policy uncertainty and earning capacity.

More specifically regarding the role of policy uncertainty, the results indicate that experts believe risk-taking farmers are likely to invest earlier in the presence of policy uncertainty than risk-averse farmers. These results are in line with the findings of (Yanore et al., 2022), who found that risk-taking farmers are more likely to invest early under policy uncertainty. However, it should be noticed that an objectively higher policy uncertainty does not necessarily translate into higher perceived policy uncertainty, which may explain why some Dutch farmers invested at an early stage in the period before and after the dairy quota abolishment despite higher objective policy uncertainty. The results also show that perceived policy uncertainty may cause dairy farmers to postpone investments. A similar result was found by Gopinath (2021) who found that higher trade policy uncertainty relates to significantly lower gross farm investment. Their results suggest that farmers may postpone their investments when trade policy uncertainty is higher.

The characteristics of farmers that influenced on-farm investment timing in our study are personal values and four from the five Big five personality traits (extraversion, openness, agreeableness, and conscientiousness). Experts indicated that personality traits affect farm investment timing through the mediating variable risk attitude, similar to findings in other studies, e.g. Pak and Mahmood (2015). In a study on investment decisions on stocks, securities, and bonds in Kazakhstan. Pak and Mahmood (2015) found that personality traits influence risk-taking behaviour and that risk-taking behaviour in turn influences investment decisions. Previous research also demonstrated the influence of the Big Five personality traits on business development (Hansson and Sok, 2021) and investment intention (Mayfield et al., 2008). Hansson and Sok (2021) studied the effect of the Big Five Personality traits and personal values on the perception of obstacles to the business development of Swedish farmers. In their paper, business development is understood as a wide and all-encompassing construct and concerns the development of the farmers' business in their preferred way. The concept of obstacles to business development is thus different from studying investment decisions. However, investments and decisions for business development are related. Moreover, several variables in our model are considered as obstacles to business development by Hansson and Sok (2021), for example, policy uncertainty (Law and regulation), distance to Natura 2000 (geography), and earning capacity (profitability and finance). In line with our results, Hansson and Sok (2021) found an effect of openness and extraversion on perceived obstacles. However, personal values were not related to the perceived obstacles.

Notably, the effect of financial variables and succession seems robust over time and with changing policy contexts, as both the policy context of the ’00s and the more recent policy context gave similar results. Our results suggest that experts expect a positive impact of earning capacity on the likelihood of farmers to invest, a finding that is in line with the effect of earning capacity on investments in Dutch greenhouse horticulture (Oude Lansink et al., 2001). Lewis et al. (1988) found a similar result for the impact of earning capacity, defined by the cost of capital, on investments in plant and machinery by Australian farmers. Furthermore, Samson et al. (2016) found that Dutch dairy farms with higher external finance are less likely to invest. Our finding that the absence of a successor reduces the probability of farmers to invest is in line with results from Oude Lansink and Pietola (2005) and Aramyan et al. (2007) for investments in greenhouse horticulture.

The two of the major challenges in studying the role of policy uncertainty are the lack of data on policy uncertainty, and the role of the farmers' perception of policy uncertainty in the timing of investments. Our research showed that a Bayesian Network is a flexible tool for studying the effect of policy uncertainty on the timing of investment. BN can easily combine objectively measured variables with subjectively measured variables elicited from experts. A Bayesian Network analysis also allows for the inclusion of a multitude of variables such as farm and farmer personality characteristics and the different interrelations between these variables in analysing the timing of investments. Furthermore, the Bayesian Network is a tractable and transparent method that visualises the operationalisation of policy uncertainty, a feature that proved useful in the communication with farmers and advisors in the development of the network and the interpretation of results. It should be noted though that the use of experts puts limits on the number of variables that can be included, as more variables add to the time needed to estimate the conditional probabilities and reduces transparency. This paper shows that the burden on experts can be mitigated with the Noisy-MAX approach, which reduces the number of probabilities to be estimated (Zhang and Thai, 2016). Yet another way to reduce the burden on experts is to use different groups of experts at different stages of BN development. Future applications of the BN could focus on combining the use of data with expert elicitation to study the effect of policy uncertainty on other decision problems such as investments in emission reduction, diversification or extensification.

The results of this research are relevant for policy advisors, finance providers, farm advisors, and farmers. Our results show that, according to the experts, risk-taking farmers may still invest, also in the presence of objective policy uncertainty; hence, investment decisions of farmers who are more willing to take risks, are less likely to be affected by policy changes. Nevertheless, the results show that policy uncertainty affects the timing of investment of most farmers. For policy makers, this implies that a timely and clear communication about future policies matters. The importance of timely policy communication can be illustrated with the example of the period after the dairy quota abolition in 2015. The Dutch government announced a potential implementation of new policies without further specification of the details. Many farmers may have invested early and expanded their milk production in anticipation of the expected policies. Consequently, when the government implemented phosphate rights, many farmers who previously invested had to reduce their herd size and found themselves in financial distress. With more timely communication and implementation of the policy, the adverse effects of the policies could have been reduced. Besides this, current policies for nitrogen emission reduction are region specific. Farmers can make use of a voluntary purchase agreement and sell their farm to the government if the farm is close to a protected natural area. After selling their farm, they will not be allowed to start a farm elsewhere. However, our results show that a farmer's investment decision to leave farming is not strongly influenced by the farms financial status and the proximity to protected natural areas. Therefore, providing financial compensation in exchange for quitting may not be an effective strategy. Possibly, allowing farmers to relocate, and thus continue to farm elsewhere, further away from protected natural areas, may be more effective. Another option could be to promote technological development, especially amongst farms with successors. Farms with a successor were more willing to invest, as such emission reduction could be achieved by targeting these farms to reduce their emission. For farm advisors and finance providers, a relevant implication of our research is that experts do not consider the financial status of the farm as the major variable influencing the farmers investment decisions. We have shown that other variables, i.e. succession, uncertainty and risk attitude, are considered more impactful for farmers investment decision making then the financial status of the farm.

An important limitation of our research is the generalisability of our findings. Our findings are based on the opinions of a group of experts. As such, we do not claim our results describe actual farmers behaviour, instead, it describes the opinions of the participating experts. Moreover, if we had done our research with a different group of experts, this could have resulted in different findings. However, we expect that the general categories (financial variables, farm characteristics, policy uncertainty variables and farmer characteristics) would be similar even with different experts. To improve the generalisability of our findings we cross-checked our results with different groups of experts. Generalizing our results is also difficult as it deals with a specific policy context in the Netherlands, thus limiting the potential for generalizing our results to other sectors or countries.

We conclude that the most important variables influencing investment timing are the succession status of the farm and the risk attitude of the farmer, followed by perceived policy uncertainty and earning capacity. Our results indicate that risk-taking farmers may invest earlier in the presence of policy uncertainty compared to risk-averse farmers. The perceived policy uncertainty is a function of intensity, distance to protected natural areas, and risk attitude. Another conclusion is that risk attitude had a bigger impact on the perceived policy uncertainty than intensity and distance to protected natural areas.

Appendix 3.A

Table 3.A1: Expert selection

Note: In this table we give details about the number of participating experts in each of the steps, their areas of expertise and how many of them have participated in previous steps.

Step of the analysis	Participants		Areas of expertise						
	Contacted partici-pants	Actual partici-pants	Farm invest-ments	Decision making	Behavi our	Dutch policy	Dairy sector	Professional experience with farmers	Participation in previous steps
Step 1a: workshop	6	4	4	2	2	4	4	2	N.a
Step 1b: verification	3	3	3	3	3	3	3	1	0
Step 2: direction of effects	12	12	12	9	7	9	12	5	2 participated in step 1a 2 participated in step 1b 8 new participants
Step 3: Evaluation	6	6	6	3	3	6	6	5	2 participated in step 1a and 2 4 new participants
Step 4: elicit CPT's	5	5	5	2	2	5	5	5	2 participated in step 1a, 2 and 3 3 participated in step 3

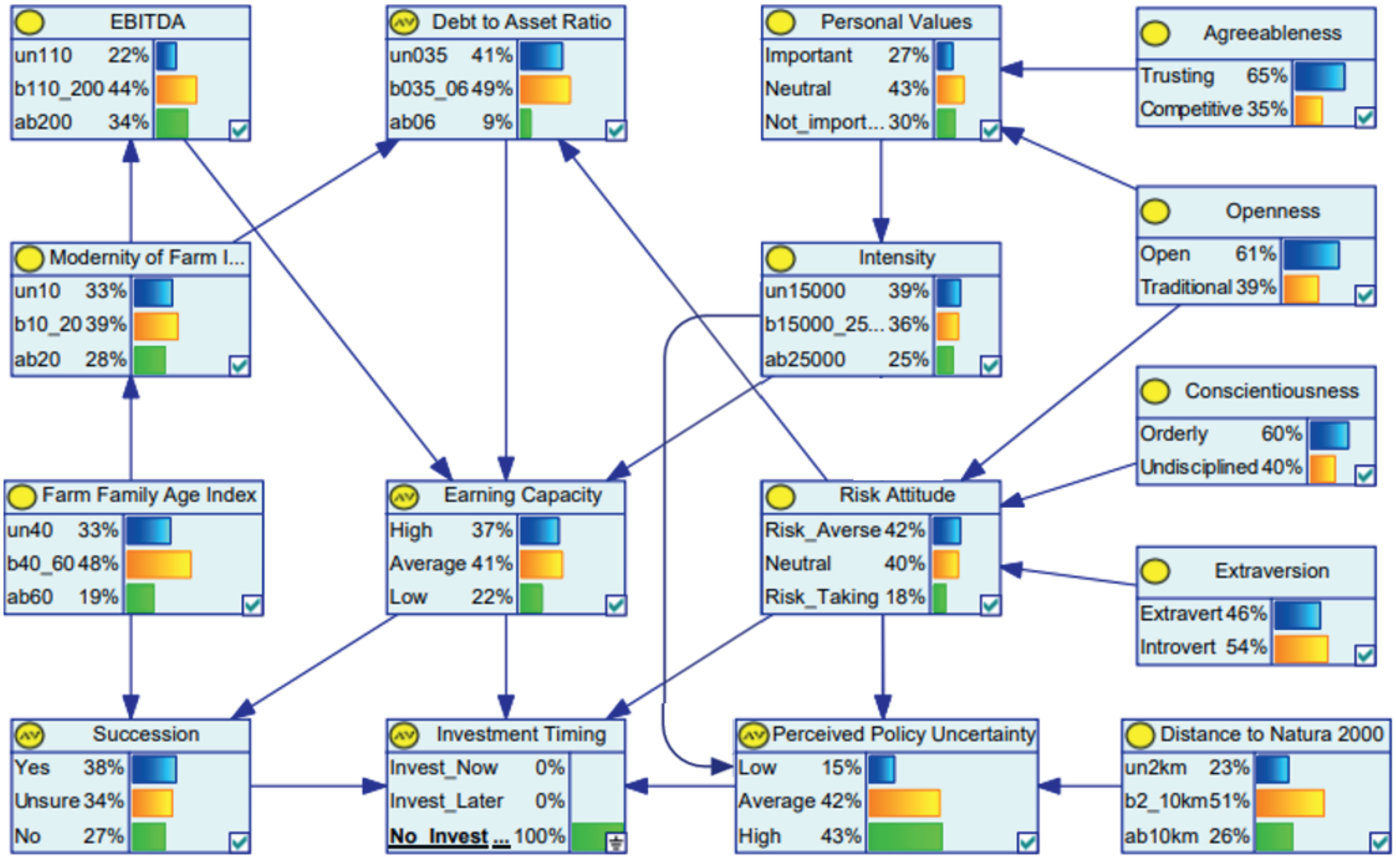

Figure 3.A1: Network with No investment as evidence

This network shows the probability distributions of the BN variables for a farmer whose preferred strategy is not to invest.

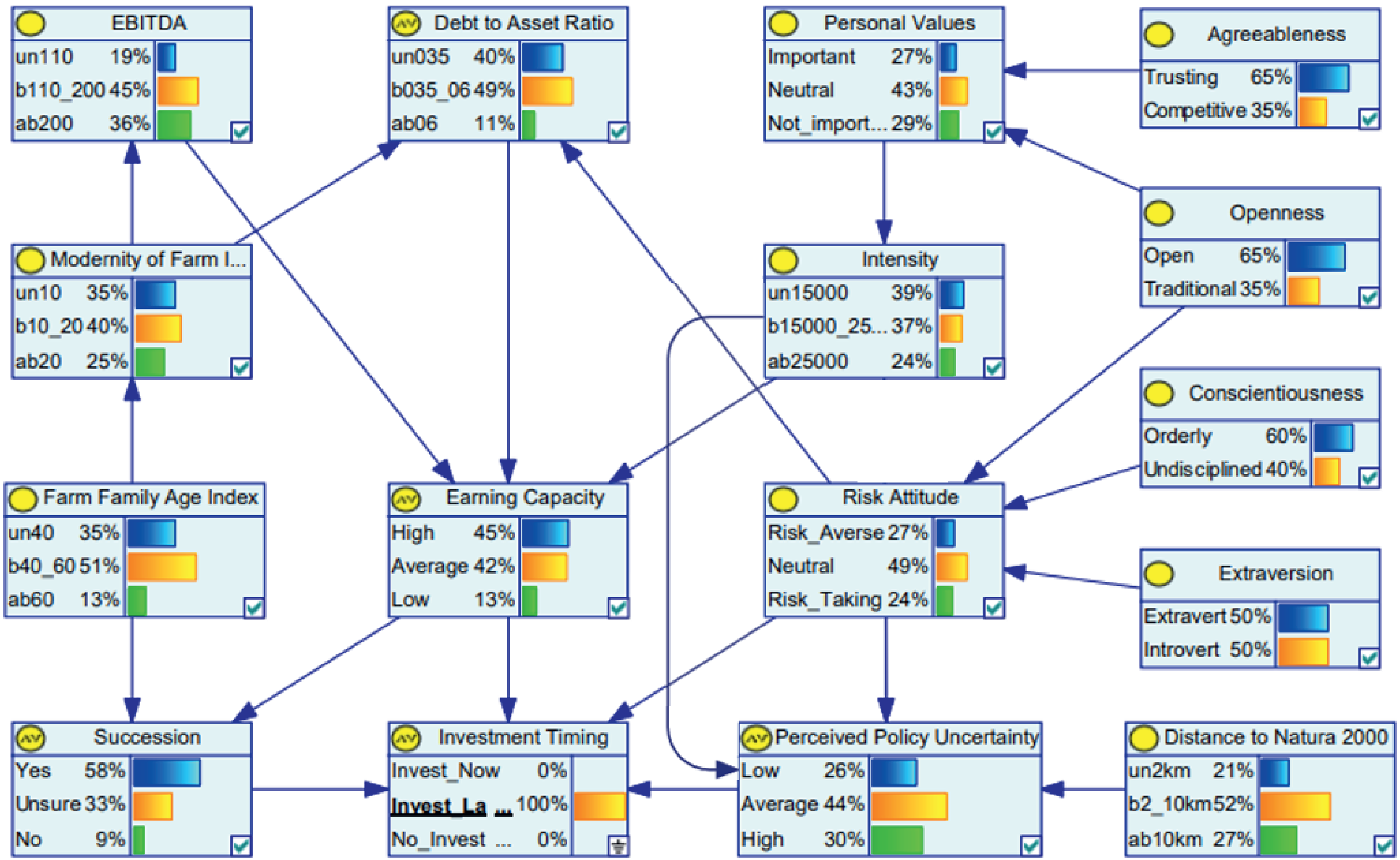

Figure 3.A2: Network with "Invest later" as evidence
This network shows the probability distributions of the BN variables for a farmer whose preferred strategy is to invest later.

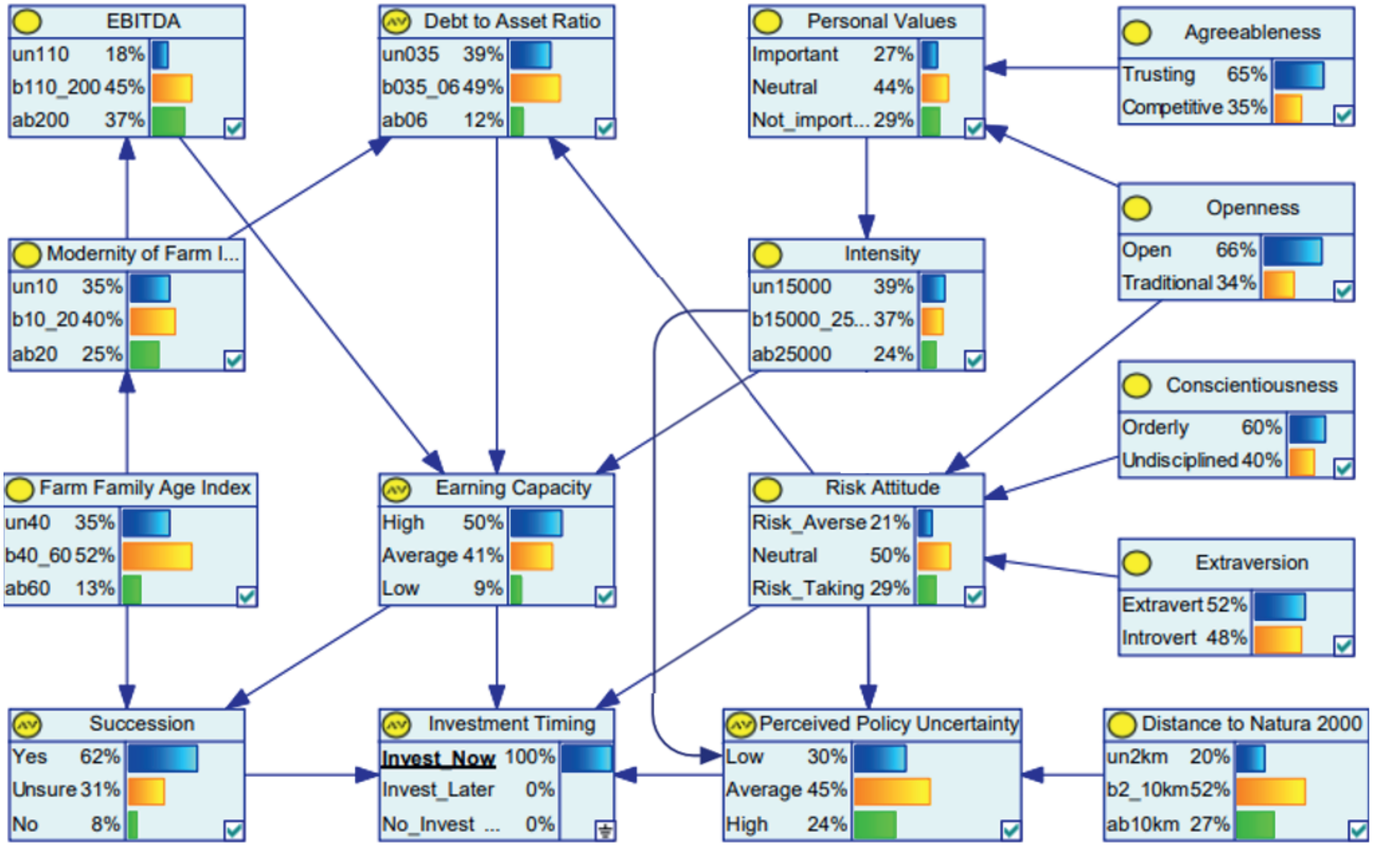

Figure 3.A3: Network with Invest Now as evidence

This network shows the probability distributions of the BN variables for a farmer whose preferred strategy is to invest now.

Chapter 4

Farmers prefer management practices over investment options for nitrogen abatement

Abstract
The current 'nitrogen crisis' in the Netherlands calls for new policies to reduce the national emission of nitrogen, starting with agriculture. Considering the voluntary nature of most policies, it is important to understand farmers' preferences for different nitrogen abatement options. This paper ranks the preferences of Dutch dairy farmers for nitrogen abatement investment options and management practices using a best-worst scaling experiment. Moreover, we study the influence of personality traits, risk attitude and time discounting on these preferences. Farmers prefer management practices over investment options for nitrogen abatement, but we find little proof of an effect of personality traits, risk attitude and time discounting. Our findings assist policy makers in designing more effective policies to support farmers in reducing nitrogen emissions.

Keywords: Nitrogen abatement, best-worst scaling experiment, environmental policy, farmer characteristics

4.1 Introduction

The emission of nitrogen has a negative impact on the sustainability goals of the Dutch government (Stokstad, 2019). In response to critical deposition values set by the European Union (EU), the Netherlands has committed itself to reducing nitrogen emissions by 50% in 2030, which requires taking far-reaching measures. These policies have far-reaching effects for the management of Dutch dairy farms and the situation has escalated into a 'nitrogen crisis' Erisman (2021), (Stokstad, 2019). The severity of the nitrogen problem in the Netherlands is also exemplified by the creation of a new ministerial position in 2022. As a consequence of the 'nitrogen crisis', Dutch dairy farmers are experiencing high levels of policy uncertainty (Sok and Hoestra, 2023).

There are various ways to reduce nitrogen emissions on dairy farms, most of them require the voluntary participation of farmers. One relatively easy approach is for farmers to modify their management practices. For instance, farmers can increase the amount of time cows spend grazing in the pasture or decrease the amount of protein in their feed. Additionally, there are more long-term and costly investment options that necessitate significant changes to farm infrastructure. For example, farmers can install air washers or low-emission stable floors to reduce nitrogen emissions.

The uptake of either of these options significantly influences the effectiveness of nitrogen emission reduction but will depend on the preferences of the farmer. For example, farmers may prefer reducing protein in feed over increasing the time spend in the pasture. While some technologies may be highly effective, farmers may not be willing to implement them on their farms. Thus, considering the current uncertainty and the voluntary nature of most policies, it is important to understand which nitrogen abatement investment options and management practices farmers prefer. Additionally, it is essential to understand what factors influence these preferences. This can inform policy makers to develop more effective measures to support farmers in adopting nitrogen abatement technologies.

No previous research has examined farmers' preferences for both sustainable investment options and management practices simultaneously. A large body of literature studied preferences but focussed either on management practices or investment options. A wide range of topics were studied, including greenhouse gas mitigation (Glenk et al., 2014, Jones et al., 2013), biodiversity conservation (Greiner, 2016), precision agriculture technology (Thompson et al., 2019), grazing best practices (Greiner et al., 2009), carbon farming (Dumbrell et al., 2016), low emission agricultural practices (Morgan et al., 2015), particular matter abatement (Vissers et al., 2022), and soil conservation (Wossen et al., 2015).

Preferences can be elicited through various methods, for example using rating scales, indifference methods, ranking methods or choice-based methods (Soekhai et al., 2019). In this study, we use a best-worst scaling (BWS) experiment, which is a ranking method where participants are asked to make trade-offs. This increases the likelihood that participants discriminate clearly between response categories and thus provides greater distances in the mean scores compared to most other preference elicitation methods (Louviere et al., 2013, Soekhai et al., 2019). Additionally, a BWS experiment overcomes issues with idiosyncrasies in response styles and allows for the comparison of a large number of objects or their attributes (Louviere et al., 2013). Using a BWS experiment, we assume farmers will maximize the difference in their utility by selecting their most and least preferred investment option or management practice out of several choice sets. There are different types of BWS experiments (Louviere et al., 2013). A type I BWS experiment is the most applicable method for analysing the problem at hand.

To illustrate the use of BWS experiments for the study of farmers preferences sustainable investments or management practices, we provide two examples. Glenk et al. (2014) previously used a BWS experiment to study preferences in terms of the practicality and effectiveness of greenhouse gas mitigation practices. Farmers rated the practices based on their practicality, whereas experts rated the practices based on their effectiveness. As such, the researchers were able to identify which practices were considered both practical by farmers and effective by experts, providing valuable input for policy development. Another BWS experiment was conducted by Sok and Hoestra (2023) to study preferences for technical, financial and policy-related attributes of electric tractors. Besides the preferences for attributes, they also measured farmers' deference and defiance attitudes to environmental regulation. They conclude that farmers evaluate investments in electric tractors as unfeasible and that negative emotions regarding environmental policy hinder the adoption of electric tractors.

Experimental design methods are useful in eliciting preferences as they allow researchers to understand and evaluate the factors that influence preferences using statistical approaches. Within investment options or management practices, or between both categories, there are differences in economic consequences in terms of risk and over time. Furthermore, farmers may perceive adopting sustainable farming investments and practices as a way to mitigate policy uncertainty. Several behavioural-economic factors can explain how farmers may deal with risk and time and thus the heterogeneity in farmers' preferences for nitrogen abatement options. A review paper by Iyer et al. (2020) concluded that decisions made in a risky context are influenced by farmers' economic preferences such as risk attitude and time discounting. Moreover, several studies have found an effect of risk attitude and time discounting on farmers' preferences for sustainable farming practices or investment options (Greiner et al., 2009, Wossen et al., 2015). Additional to risk and time preferences, previous research has found personality traits affect farmer behaviour (Austin et al., 2001). For Dutch dairy farming, Yanore et al. (2023) found that experts regard farmers' personality as an important factor that may influence investment decisions.

This paper aims to rank Dutch dairy farmers' preferences for nitrogen abatement investment options and management practices and to study if and how they are linked to personality traits, risk attitude and time discounting. To accomplish these objectives, we will use a BWS experiment and survey questions. To rank the preferences, we use multinomial and mixed logit models. To explain the heterogeneity of preferences, we use a Bayesian Network (BN) and a fractional multinomial logit model.

This research will contribute to the literature by ranking the preferences of Dutch dairy farmers for nitrogen abatement options, and how these preferences can be explained by behavioural-economic factors of farmers. Specifically, we contribute by analysing investment options and management practices to reduce nitrogen emissions simultaneously, where previous research focused on either one category or the other. Our findings have important implications for policy makers and farm advisors. A better understanding of farmers' preferences for nitrogen abatement options can help advisors provide more tailored and effective advice. Policy makers could use this information to better anticipate the response of farmers to new policies and design more effective strategies to reduce nitrogen emissions.

4.2 Theoretical framework

To study farmers preferences for nitrogen abatement options, we conducted a BWS experiment, which is rooted in random utility theory (RUT) (Louviere et al., 2013). RUT posits that individuals maximise their utility by choosing from a discrete set of options. To determine the utility, which is latent, individuals express their preferences for various options (Walker and Ben-Akiva, 2002). RUT would assume individuals maximise the difference in utility when they choose between a best and a worst option. By analysing the individuals' choices, we can identify the options that provide them with the most and the least utility.

There are different schools of thought as to why the preferences of individuals are heterogeneous. Psychological approaches attribute the differences to the inherent variations in individual characteristics. Whereas, according to economic approaches, heterogeneity is due to (un)observed factors, measurement error, or specification error (Lancsar and Louviere, 2008).

According to utility theory, preferences can be shaped by risk attitude and time discounting (Bocquého et al., 2014, Loewenstein and Prelec, 1992). Investment options and management practices come with different levels of e.g. price, production and policy risks. Moreover, policy uncertainty (Yanore et al., 2023) causes farmers risk attitude to become a potential source of heterogeneity when it comes to preferences for nitrogen abatement options. There are three basic categories of risk attitudes, i.e. people are considered to be either risk-loving, risk-neutral or risk-averse. A risk-loving person has a convex utility function, meaning they are willing to take on more risk in exchange for potentially higher returns. A risk-averse individual has a concave utility function, which implies preferences for safer and less volatile investments. A risk-neutral person has a linear utility function, indicating they are indifferent to risk.

Time discounting is another relevant factor that can contribute to heterogeneity of preferences within a utility theory framework (Loewenstein and Prelec, 1992). Time discounting refers to the tendency of individuals to prefer immediate rewards over delayed rewards. The timelines on which to consider the financial costs and potential benefits from nitrogen abatement investment options and management practices are different. Management practices typically involve lower and more easily reversible financial commitments, while investments represent larger, often irreversible expenses. As such, farmers who exhibit lower time discounting rates may be more willing to invest compared to farmers with higher time discounting rates.

Personality can also help understand an individual's decisions and actions (Durand et al., 2019). Personality traits are a combination of emotional, cognitive and motivational characteristics that influence how a person interacts with its environment and what decisions the person makes (Dole and Schroeder, 2001). In a conceptual model by Nandan and Saurabh (2016), personality is considered to have both a direct effect on decision making as well an effect mediated by risk attitude.

4.3 Data and research methodology

Our study used a survey approach that included a best-worst scaling (BWS) experiment. The experiments comprised several choice tasks; in each choice task, respondents selected what they considered the best and the worst 'attributes'. The attributes were the investment options and management practices available for reducing nitrogen emissions. In the remainder of this section, we describe attribute selection, the survey design, the sample, and the data analysis.

4.3.1 Selection of attributes and choice set design

We used both a literature study and expert consultation to select four investment options and four management practices for farmers to choose from in the BWS experiment. The selection process was aimed at including a broad range of abatement options rather than including all existing nitrogen abatement measures. Table 4.1 contains the selected investment options and management practices, along with their definitions as they were presented to the participating farmers.

To develop the experimental design, we used Sawtooth's programme-based algorithm (Orme, 2020). The number of choice sets, options per set, and the nitrogen abatement options were used as an input in Sawtooth's algorithm to design the choice sets. We included four abatement options per choice set and a total of ten choice sets, meaning the farmers make ten choices in total. Figure 4.1 shows an example of the layout of a choice set. Farmers were first presented with the definition of the eight abatement options and an example choice card. We subsequently informed them we would present several choice sets and then asked to indicate what would be their most and least preferred abatement option on each. The experimental design assured that all nitrogen abatement options, and combinations of abatement options were represented equally across choice sets and respondents.

4.3.2 Survey design

In addition to the BWS experiment, we conducted a survey to measure factors such as risk attitude, time discounting, personality traits, and several control variables. There are various methods to elicit risk attitude and time discounting. Falk et al. (2016) implemented an abbreviated version of a multiple price list, also called a 5-step staircase. Moreover, they used multi-item self-assessment questions with the objective of streamlining different risk attitude and time discounting measures and improve cross-study comparison. Falk et al. (2016) developed and tested the validity of these abbreviated methods for risk attitude and time discounting against more extensive, incentivised experiments and argue that the use of abbreviated versions is justified when there are time constraints. They argue that the self-assessment questions are particularly useful for explaining different life outcomes, whereas the 5-item staircase option can help explain financial decisions.

Table 4.1: Definition of investment options (I) and management practices (M) included in the BWS experiment

Naam	**Definition**
Reduce protein in feed (M)	Reduce the protein content in the feed to reduce the amount of nitrogen in the manure.
Install air washers (I)	Installing air washers to remove the ammonia from the air.
Increase grazing (M)	Leaving the cows in the pasture for longer periods per year to reduce the formation of ammonia in the stable.
Buy low emission flooring (I)	Purchasing low emission flooring to speed up the removal of manure to the manure pit.
Use less artificial fertilizer (M)	Reduce the amount of fertilizer used on the farm so that less nitrogen is emitted.
Purchase precision fertilization machinery (I)	Buy machinery for precision fertilization for improved nutrient utilization and for a more efficient use of fertilizer.
Improve the quality of grassland/species (M)	Improve the quality of grassland and use grass species that reduce nitrogen emissions.
Purchase electrical machines (I)	Purchase electrical machinery to reduce the use of fossil fuel and thus emit less nitrogen.

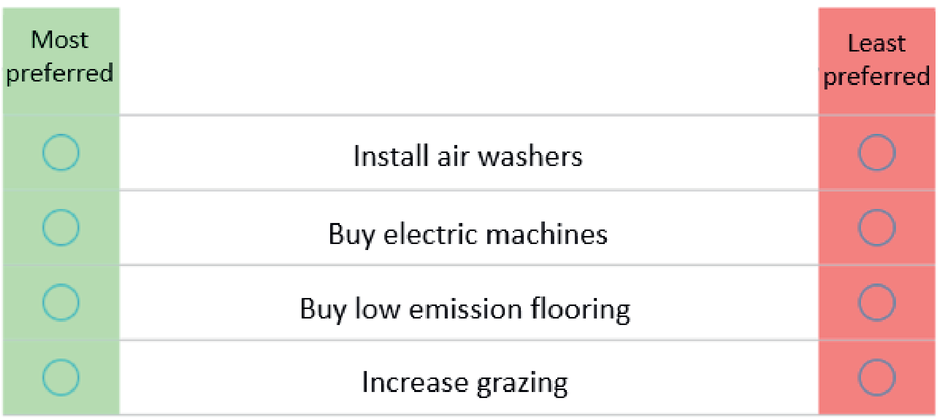

Figure 4.1: Example of a generated choice card.

(Falk et al., 2016). Since our focus is on explaining the heterogeneity in financial decisions, we used the 5-item staircase option in our analysis. The results of the self-assessment questions are reported in the online complementary materials.

Regarding the personality traits, we used a shortened 10-item version of the personality test developed by McCrae and Costa Jr (1987). Its reliability and validity were tested and considered sufficient for surveys with time constraints (Rammstedt and John, 2007). In our empirical analysis we also included control variables such as age, succession, the intensity of the production (cows/ha), the proximity to natural areas, and expectations for the future. The survey started with the socio-demographic questions, followed by questions about obstacles to business development (used in another research project), the next part was the BWS experiment, and the survey ended with the questions on personality traits, risk attitude and time preferences.

4.3.3 Sample

We distributed the survey via email to approximately 2500 Dutch dairy farmers who were clients of a Dutch accountancy company, i.e., *Alfa accountants en adviseurs*. To incentivize participation, €25 gift cards were awarded to a total of 100 participants. In total, 156 farmers opened the survey, but we used 96 entries in the final analysis as twenty participants dropped out immediately, fifteen dropped out at the questions about obstacles to business development, sixteen dropped out during the BWS experiment, and six dropped out during the questions about personality traits, risk attitude and time preferences.

Table 4.2 presents the descriptive statistics of the variables included in the analysis. The mean intensity of dairy farming for our sample was 1.83 cows/ha, with a standard deviation of 0.44. This is consistent with the Dutch national average of 1.8 cows/ha (Agrimatie, 2022). As such, we believe the sample is representative of the Dutch dairy sector. The mean age of the farmers was 51 with a standard deviation of 10.82. About 18.75% of the farms are located within a 1 km range from natural areas, close to 49% are located between 1 and 10 km from these areas, and 32.29% are located more than 10 km away from those areas. Almost 3 out of 4 participants (72.92%) had a successor or were under the age of 50 and 27.08% had no successor and were over 50. A quarter (26.04%) of farmers expected to expand their operations, while 73.96% expects to either consolidate or phase out production. Only 4 out of 96 farmers were planning to phase out the production and as such we merged this group with the farmers planning to consolidate.

On the 5-item staircase measuring risk attitude, the mean score was 15.26. A score below 16.5 suggests risk aversion, and a score above 16.5 suggests risk-taking behaviour (Falk et al., 2016). This indicates that the farmers in our sample are, on average, slightly risk averse. The standard deviation was 6.72. Regarding the time discounting, the average score on the 5-step staircase experiment was 26.05 and the standard deviation was 6.59. A score of 1 suggests the highest level of impatience (high discount rate), whereas a score of 32 indicates the highest level of patience (low discount rate). Therefore, our average value indicates that farmers in our sample are patient, i.e., they have a low discount rate. Lastly, the results of the personality traits are displayed for the 5 categories included in the survey (Table 4.2).

4.3.4 Internal consistency and multicollinearity

We tested the internal consistency, i.e., the ability of the 10 different personality items to coherently describe the five different personality traits. Based on Cronbach's alpha, Pearson correlation and Kendall's Tau, we conclude that the 10 different personality items do not coherently describe the five personality traits. Therefore, we only used one measure for each personality trait instead of two. We included the measure with a positive description of the personality traits, as the measure developed by Rammstedt and John (2007) includes both a positively and negatively framed question.

We also tested for multicollinearity of the variables included in the analysis by estimating the Kendall's Tau correlation coefficient (see appendix 4.A, Table 4.A1). All correlation values were low and as such we have no statistical concerns about multicollinearity.

4.3.5 Statistical analysis

Three different methods were used to analyse the data. First, the preferences of farmers for the different abatement options measured with the BWS experiment were ranked using a multinomial logit, an uncorrelated and correlated mixed logit model. Different models were compared using the information criteria. Second, we used a BN to study the relationship between personality traits, risk attitude and time discounting and its effect on preferences for nitrogen abatement. Third, for a more detailed understanding of the heterogeneity of farmers preferences we used a fractional multinomial (fm) logit model.

4.3.5.1 Ranking the nitrogen abatement options

Farmers' preferences were modelled using a discrete choice framework, closely following the method as applied by Sok and Hoestra (2023). We asked farmers to give their preferences in ten different choice sets. For each choice set, they were asked to indicate their most preferred ('best') and least preferred ('worst')

Table 4.2: Descriptive statistics

Continuous variables	**Description**	**Mean (s.d.)**
Intensity	Number of cows per hectares of land	1.83 (0.44)
Age	The age of the farmer	51 (10.82)
Risk attitude Switching row	The switching row was measured using a staircase experiment. There are 32 switching rows where row 1 indicates "Very risk-averse" and row 32 indicates "Very risk-taking"	15.26 (6.72)
Time discounting Switching row	The switching row was measured using a staircase experiment. There are 32 switching rows where row 1 indicates "Very impatient" and row 32 indicates "Very patient".	26.05 (6.59)

Categorical variables		**Frequency (%)**
Distance to natural areas	The distance of the farm to protected natural areas also called Natura 2000 areas.	
<1 km		18 (18.75)
1-10 km		47 (48.96)
10> km		31 (32.29)
Succession	The availability of a successor on the farms. Category 1 includes farmers younger than 50 and farmers older than 50 who have a successor. Category two includes farmers older than 50 who do not have a successor.	
No and 50 or older		26 (27.08)
Yes or younger than 50		70 (72.92)
Expectations for the future	The farmers expectation for the future. They either expect to grow, consolidate or phase out.	
Grow		25 (26.04)
Consolidate or phase out		71 (73.96)

Personality traits		**Frequency (%)**				
5-point Likert scale		Extravert	Conscien-tiousness	Openness	Agree-ableness	Neuroticism
Does not describe me at all	1	11 (11.46)	3 (3.13)	6 (6.25)	2 (2.08)	4 (4.17)
	2	33 (34.38)	21 (21.88)	15 (15.63)	9 (9.38)	12 (12.50)
	3	27 (28.13)	32 (33.33)	24 (25.00)	27 (28.13)	22 (22.92)
Describes me very well	4	22 (22.92)	30 (31.25)	42 (43.75)	49 (51.04)	42 (43.75)
	5	3 (3.13)	10 (10.42)	9 (9.38)	9 (9.38)	16 (16.67)

investment option or management practice. The analysis of this data allowed us to measure each item on a common scale and assess their relative importance (Marti, 2012).

In each choice set, four nitrogen abatement options were presented, resulting in twelve possible pairs of best (*b*) and worst (*w*) options. For each choice set, the dependent variable took the score of '1' for the pair that was chosen and '0' for all other pairs. The independent variables were the selected abatement options and were indicated by a '1' for the 'best' option, a '-1' for the 'worst' option, and a '0' for all the other options. Each individual (*n*) was assumed to consider all possible pairs of best and worst options, evaluate the difference on the underlying dimension of interest for each pair and then select the option that maximises the difference in the utility. This is done for each of the ten choice sets (*t*):

$$U_{nbt} - U_{nwt} > U_{nit} - U_{njt} \text{ for all } b \neq w \text{ and } i \neq j.$$

where *i* and *j* are the other abatement options not chosen as best and worst options. Utility is an unobservable concept and it is represented by a deterministic and a random component in the probabilistic choice model (Louviere et al., 2013). The random component implies that one cannot predict the exact choice that will be made but only a probability. The probability the farmer chooses an abatement option as best and as worst in the choice set t is expressed as:

$$P(bw|t) = P(V_{bw} + \varepsilon_{bw} > V_{ij} + \varepsilon_{ij}) \text{ for all } bw \neq ij \text{ in } t$$

where V is the measurable difference between b and *w,* and ε is the error component (Louviere et al., 2013).

We used three different models: a multinomial logit model (MNL), an uncorrelated mixed logit model (MXL), and a correlated MXL model. The MNL model gives mean estimates that represent farmers' preferences for nitrogen investment options and management practices. These estimates are relative to one of the options being normalised to zero for identification purposes (Marti, 2012).

Limiting the estimation to mean estimates may lead to a loss of information, as preferences may vary across the population. Moreover, these estimates cannot be used to study the heterogeneity of farmers preferences. In the MXL model, the estimates are not just a mean outcome for the sample, but the model allows for the estimation of respondent-specific parameters. As such, the preferences are allowed to vary across respondents. In the MXL model both a mean estimate and a standard deviation are obtained.

$$\beta_{nj} = \overline{\beta_J} + \sigma_j \mu_{nj}$$

where $\overline{\beta_J}$ is the mean, σ_j is the standard deviation, and μ_{nj} is the random error term, which is assumed to be normally distributed. In the uncorrelated MXL, the preferences are not allowed to correlate across choice tasks whereas in the correlated MXL they are. The MXL models are estimated with a simulated maximum likelihood estimation technique, and the AIC and BIC are used to evaluate the fit of the three models.

To avoid a potential confound of scale, Lusk and Briggeman (2009) suggest a method to calculate 'shares of preference', which we used to obtain a ranking of the preferences on a ratio scale:

$$s_j = \frac{\exp(\widehat{\beta}_J)}{\sum_{ij} \exp(\widehat{\beta}_J)}$$

A share of preference is a forecasted probability that an investment option or management practice is chosen as the preferred option, and they sum to one across the eight nitrogen abatement options. Moreover, a share of preference provides information on the abatement option that is normalised to zero for identification purposes. All three models were estimated with Stata 16, using the built-in logistic regression command and a user-written generalised multinomial logit model command (Gu et al., 2013). The individual-specific shares of preference of the mixed logit model with the lowest AIC and BIC were used in the BN and the fmlogit model.

4.3.5.2 Explaining heterogeneity in preferences – Bayesian network

A BN is a directed acyclic graph that represents variables as nodes and their states as conditional probability tables, connected by arcs (Charniak, 1991, Zhang and Poole, 1996). The conditional probability tables (CPTs) are determined by arcs, which indicate (in)dependence (Charniak, 1991, Zhang and Poole, 1996). CPTs are indexed by all combinations of states of the parent and child nodes. A BN can be constructed in a data-driven way, a participatory way using expert knowledge, or a combination of the two.

For our analysis in the BN, we created a dummy variable to indicate whether farmers prefer management practices or investment options. This was done so we can test the relation between the farm(er) characteristics and their preference for investment vs. management practices. To do so, we summed the shares of preference for all the investment options and we did the same for the management practices. Subsequently, the dummy variable was created, indicating whether the farmer had an overall higher share of preference for the investment options or the management practices.

Initially, we used a hill-climbing algorithm to estimate the network. However, as few links were found between the variables, we opted for a tree augmented network (TAN) and combined it with a Chow-Liu algorithm (Friedman et al., 1997) to build the network in *R 4.0.2* using *BNlearn* (Scutari, 2010). In a TAN, one variable is chosen by the researcher which will have a link with all other variables in the network. Moreover, all the other variables in the network are allowed only one link with one other variable. The selection of the latter links is based on the algorithm and thus not by the researcher. In our network, the variable indicating farmer preference for either investment options or management practices had a link with every other variable in the network. Before building the network, each variable was coded to have two categories (e.g. high or low). This reduces the number of observations needed to estimate the network and was necessary as we had a small sample-size. Once the network was built, we used entropy reduction to estimate the substantiality of the relation. This gives an idea about the reduction in the log-likelihood when relations between variables are removed and gives us insight in the relative substantiality of these relations. We also used the one-by-one approach to determine the direction of the effects as this would give us further insight into how the variables are related to the preferences. Using the one-by-one approach, we change the states of the variables that influence the preference variable and record the effect on the likelihood of preferring management options over investment options. We do not focus our analysis on the links that were found in the BN, as these were enforced using a TAN. Since these links would not have been made using a different algorithm, we do not consider them valuable for interpretation.

4.3.5.3 Explaining heterogeneity in preferences – Fractional multinomial logit model

Additionally, we analysed the heterogeneity in farmers' preferences using a fmlogit model (Papke and Woolridge, 1996), which allowed us to model multiple shares of preferences for each individual (Caputo and Lusk, 2020). We used the individual shares of preference obtained from the MXL model with the lowest AIC and BIC to explore the effect of personality traits, risk attitude and time discounting, and several control variables. We estimated the parameters using a quasi-maximum likelihood estimator (Papke and Woolridge, 1996). The data was analysed in Stata 16 using the user-written *fmlogit* command (Buis, 2017) and used the built-in *margins* command to obtain marginal effects at the mean (MEM). Some variables were dummy variables. A MEM of a dummy variable gives the predicted change in the

Table 4.3: Ranking of preferences based on a MNL, MXL uncorrelated and MXL correlated logit model.

Management practices/ investment options	**MNL**	**MXL uncorrelated**	**MXL correlated**
	Shares of preference (rank number in brackets)		
Quality of grassland/species (M)	0.29 (1)	0.47 (1)	0.52 (1)
Grazing (M)	0.22 (2)	0.30 (2)	0.20 (2)
Fertilizer use (M)	0.15 (3)	0.09 (4)	0.15 (3)
Protein content feed (M)	0.15 (4)	0.09 (3)	0.10 (4)
Electrical machines (I)	0.08 (5)	0.02 (5)	0.03 (5)
Precision-fertilization machines (I)	0.05 (6)	0.01 (6)	0.01 (6)
Low-emmission floors (I)	0.04 (7)	0.00 (7)	0.00 (7)
Air washers (I)	0.02 (8)	0.00 (8)	0.00 (8)
Model fit		Estimates	
LL	-1879	-1438	-1321
AIC	3772	2906	2671
BIC	3823	3008	2928
No. of respondents		96	
No. of choices		960	

Note 1: M indicates a management practice and I indicates an investment option.

probability of the individual shares of preferences given a discrete change in the dummy variable, while holding all other variables at their means.

4.4 Results

4.4.1 Ranking of preferences

Table 4.3 reports the result of the MNL, MXL uncorrelated, and MXL correlated model. We only reported the shares of preferences, as the estimated β are not interpretable. The full model results including β and standard deviations can be found in the appendix (Appendix 4.4A). The AIC and BIC of the correlated MXL are the lowest, meaning this model is providing the best fit. As such, the individual-specific estimates of the correlated MXL model were used for the subsequent analysis. All parameter estimates in the three models are significant at the critical 5% level. The ranking is almost the same in each of the models, farmers most strongly prefer: 1) to improve the quality of grassland/species, and in order of decreasing preference 2) to increase grazing, 3) to use less fertiliser, 4) to reduce the protein content in feed, 5) to purchase electrical machines, 6) to purchase precision fertilisation machines, 7) to install low emission floors and 8) to install air washers. In the uncorrelated MXL model 'fertiliser use' switches position with 'protein content feed'. All the investment options, indicated with an I in Table 4.3, are ranked as the four least preferred options. By contrast, the management options, indicated with an M, are ranked as the four most preferred options. Lastly, the standard deviations are significant (at 5%), meaning there is heterogeneity in the farmers' preferences (Appendix 4.A).

4.4.2 Understanding the heterogeneity in preferences

4.4.2.1 Bayesian Network analysis

Table 4.4 shows the results of the BN. The second column shows the substantiality of the link between that variable and the preference for management practices. Substantiality is defined as the difference in the loglikelihood of the model when the link between for example age and the preference variable would be taken out. There is no clear cut-off value that defines whether a variable is substantial. The third column indicates the percentage change in farmers who are expected to prefer management practices over investment options. For example, we change age variable's evidence from below 50 to 50 and older, ceteris paribus, and report the percentage change.

Notably, the variables with the most substantial links are age, the personality traits and risk attitude and time discounting. The variables with the least substantial links are the farmers expectation about the future, the distance to natural areas and succession. In the case of the higher category, they were less likely to prefer the management options. More conscientious farmers are 13.93% less likely to prefer management practices, more neurotic, extravert, open and more agreeable farmers are respectively 10.85%, 9.32%, 9.07% and 2.28% less likely to prefer management practices. More patient farmers are 2.64% less likely to prefer the management options while more risk-taking farmers are 1.64% more likely to prefer the management options. Farmers who expect not to expand their business operations are 1.33 % less likely to prefer management options. Farmers who live further away from natural areas are only 0.77% less likely to prefer management practices and farmers with a successor are 6.98 % less likely to prefer management options.

Table 4.4: Substantiality and percentage change based on BN analysis

Variable	Substantiality of relation	Change % management practices are preferred
Age	-5.36	13.91
Conscientiousness	-4.43	-13.93
Time discounting	-4.29	-2.64
Neuroticism	-2.80	-10.85
Extraversion	-1.80	-9.32
Openness	-1.45	-9.13
Risk attitude	-0.98	1.64
Agreeableness	-0.65	-2.25
Intensity	-0.56	-6.18
Expectation for the future	-0.21	-1.33
Distance to natural areas	-0.20	-0.77
Succession	-0.01	-6.98

Note 1: The substantiality is based on entropy reduction and shows the effect of removing the link between that factor and the preference variable on the log likelihood of the model.

4.4.3.2 Fractional multinomial logit model

To provide more details about how the variables influence the preferences for the individual attributes, we also ran a fmlogit model. The results are shown in Table 4.5. Only a few of these factors turned out to significantly affect the shares of preference for the investment options and management practices. More intensive farmers are more likely to prefer purchasing precision fertilisation machines and more likely to prefer improving the quality of grassland species. Farmers who live further away from natural areas are less likely to prefer investing in low emission floors and less likely to prefer purchasing electric machines. Older farmers are more likely to prefer reducing fertiliser use and less likely to prefer purchasing electrical machines. Risk taking farmers are more likely to prefer reducing the protein content in feed and purchasing low emission floors. More patient farmers are more likely to prefer reducing the protein content in feed and less likely to prefer to increase grazing time. Lastly, succession, expectations for the future and personality traits do not have a significant effect on the preferences of farmers (at a 5 % significance level).

Table 4.5: Results from the *fmlogit* model

		Protein content feed (M, a1)	**Air washers (I, a2)**	**Grazing (M, a3)**	**Low-emission floors (I, a4)**	**Fertilizer use (M, a5)**	**Precision-fertilization machines (I, a6)**	**Quality of grassland/ species (M, a7)**	**Electrical machines (I, a8)**
Intensity		-0.044	-0.001	-0.160	-0.002	-0.066*	0.008***	0.230***	0.034
Distance to natural areas	<10km	0.234	0.001	-0.182	-0.035**	-0.026	0.001	0.085	-0.078**
	10 > km	0.186	0.003	-0.245	-0.044**	0.003	0.003	0.106	-0.013
Succession	Yes, or younger than 50	-0.083	0.004	0.126	0.004	-0.023	-0.004	0.004	-0.028
Age		-0.003	0.000	-0.000	-0.000	0.008***	-0.000	-0.003	-0.002**
Expectations for the future	Consolidate or reduce	-0.016	0.001	0.066	0.006	-0.039	-0.002	0.007	-0.022
Extraversion		-0.012	-0.000	0.023	0.001	-0.007	0.001	-0.014	0.008
Conscientiousness		0.023	0.000	0.029	0.002	-0.020	0.000	-0.032	-0.004
Openness		0.018	0.002	0.032	-0.000	-0.004	-0.001	-0.033	-0.015
Agreeable-ness		-0.039	0.000	0.029	0.008	0.001	-0.001	0.023	-0.022*
Neuroticism		-0.034	0.000	0.072*	0.004	-0.032	0.000	-0.024	0.013
Risk attitude		0.008**	-0.000	-0.012	0.002**	-0.002	0.000	0.002	0.003
Time discounting		0.011**	0.001	-0.013**	-0.000	-0.002	0.000	0.001	0.003*

Note: n=96, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, The following variables are dummy variables: distance to natural areas, succession and expectations for the future.

4.5 Discussion and Conclusions

The first objective of this paper was to rank the investment options and management practices for nitrogen abatement. We conclude that farmers generally prefer changing management practices over investment options. This may be because they come at a lower cost, are easier to implement and more easily adjusted compared to investment options. As such, implementing management practices may give farmers more flexibility to cope with the nitrogen policy uncertainty.

Previous literature also suggests that farmers prefer investments or management practices that are less impactful and costly for the farm or have direct positive effects on the farm (Dumbrell et al., 2016, Glenk et al., 2014). For example, Glenk et al. (2014) ranked twenty greenhouse gas mitigation strategies on sheep farms using a BWS experiment. Their results show that the preferred strategies are less expensive and impactful to the farm and provide a general advantage to their business operations. Contrary, the strategies with lower ranks are more impactful, costly, labour intensive and less reversible. Dumbrell et al. (2016) found that farmers valued benefits of carbon farming activities more when they have a direct positive effect on the farm. For example, improving soil quality was preferred over improving landscape aesthetics, which has less direct positive effects on the farm. In line with this, Aznar-Sánchez et al. (2020) found that the costs associated with sustainable practices can hamper their adoption.

Our results also showed that investments in precision fertilisation machines and electrical machines score higher than air-washers and low-emission floors. Potentially, these results can be explained by the financial benefits the farmer may receive from these investments. For example, with precision fertilisation machines, the fertiliser use becomes more efficient, which not only improves soil quality but also saves money. Electrical machines can reduce the dependency on fossil fuels and as such also reduce costs. In the case of low-emission floors and air washers, however, investments are costly, while there are few monetary benefits for the farmer.

For our second objective, we study the heterogeneity of farmers preferences for nitrogen abatement measures. We found heterogeneity in the preferences of farmers as the standard deviations of the MXL models were statistically significant, which is in line with the results from other papers using a BWS to study farmers preferences (Glenk et al., 2014, Thompson et al., 2019). This suggests that different types of farmers have different preferences for nitrogen abatement options and that policy makers should take this into account when developing one-size-fits-all policies to address nitrogen pollution. For example, we find that farmers living closer to protected natural areas prefer low-emission flooring compared to farmers who live further away. Policy could specifically target these farmers to implement such nitrogen abatement measures on the farms.

We studied the heterogeneity of farmer preferences for nitrogen abatement options in more detail by looking at their relationship with personality traits, risk attitude and time discounting using the fmlogit model and the BN. In the BN we looked at the preferences for investment options versus the management practices. Whereas, in the fmlogit model we look at all eight abatement options separately. In the BN we find that personality traits have a more substantial effect on the preferences for nitrogen abatement options relative to the other factors we included in our study. This means the log-likelihood of the model is reduced most substantially when the personality traits would be removed from the model. This suggests these factors are relevant for understanding farmer preferences for investment options versus management practices. However, substantiality does not mean that these effects are statistically significant or a causal relationship. In the fmlogit model, we did not find a significant effect of the personality traits on the farmers preferences. Possibly, the effect of personality traits is more important when looking at investment options versus management practices compared to when looking at specific abatement options. Additionally, the lack of statistically significant factors could be due to the small sample size and measurement error. As such, based on our results we cannot conclude that personality traits influence farmers preferences for investment options and management practices.

To assess risk attitude and time discounting among farmers, our survey comprised of both a self-assessment question and the 5-step staircase questions. Our findings were consistent with previous research, showing that farmers tend to be slightly risk averse (Iyer et al., 2020). However, the self-assessment measure did not yield the same effect on nitrogen abatement preferences as the 5-step staircase measure and the correlation between both measures was low. These results contrast with those of Falk et al. (2016) who found a strong correlation between the self-assessment measure and the 5-step staircase measure. Nevertheless, other studies have also noted the lack of robustness of different types of risk attitude elicitation methods (Finger et al., 2023, Menapace et al., 2016, Reynaud and Couture, 2012), meaning that different types of elicitation methods of the same concept can result in different findings. The lack of robustness in the results may also be due to the small sample size and potential measurement error. Meraner et al. (2018) suggest using subject involvement to reduce inconsistencies between elicitation methods.

In the fmlogit model, we found few significant relations between risk attitude and farmers' preferences for all eight nitrogen abatement options. More risk-taking farmers are more likely to prefer adjusting the protein content in feed and investing in low-emission flooring. Moreover, the BN showed a low effect of risk attitude on farmers preferences for investment options versus management practices. This effect may be low because risk attitude can affect farmer preferences in opposite ways. On the one hand, investments may be a more effective way to reduce nitrogen emissions and thus can serve as a type of insurance against policy uncertainties. On the other hand, an investment is riskier than an adjustment of management practices as management practices are more easily adjustable. In the absence of papers looking at both risk attitude and preferences for nitrogen abatement investment options and management practices, we compared our results with literature focused on farmers' decision making in general. Our results are in line with Hellerstein et al. (2013) who found a low predictive power of risk attitude for farmer decisions looking at a variety of decisions such as farm diversification, crop insurance and farm management practices. Menapace et al. (2016) found that more risk averse farmers were more likely to buy crop insurance. However, there results were only significant at a 10% level. Our results are in contrast with e.g. Yanore et al. (2023), who found that experts expect the risk attitude to be an important factors influencing decision making. Moreover, Greiner et al. (2009) found that risk attitude correlates with the adoption of conservation practices of farmers.

Our BN results show that more patient farmers (i.e., those with low discount rates) prefer investment options over management practices. However, this effect is very small. In the fmlogit model we see that more patient farmers generally prefer to "reduce protein in feed" but are less likely to prefer to "increase grazing time". These opposite effects of time discounting on these two management practices may explain why the effect of time discounting in the BN is low.

Our study revealed that older farmers tend to favour management options over investment options. This may be due to the higher costs involved, which require more time to yield a return on the investment. As such, older farmers may prefer management practices because they plan to stop farming in the near future and may not be able to reap the long-term benefit of investment to make it worthwhile. These results are consistent with Vissers et al. (2021), who found that older farmers are less inclined to invest in abatement options for particular matter on poultry farms. Knowler and Bradshaw (2007) note in a review paper that there are no universal significant factors affecting the adoption of conservation agriculture. Possibly, their findings on adoption of conservation agriculture can also be applied to farmer preferences. As a result, we argue that our results cannot easily be generalised to other sectors or locations.

Among the main limitations of our study is the low response rate of the farmers we have surveyed. There are several factors that may have contributed to the low response rate of this survey. Firstly, the survey length may have played an important role. The survey was lengthy because it covered a range of topics, including information about personality traits, risk attitude, time discounting, preferences for abatement options, and several control variables. Moreover, a general survey fatigue may have played a role, as farmers receive many requests to fill out surveys and become reluctant to participate. Another reason for the low response rate could be the sensitive nature of the topic of nitrogen abatement. In future research, a higher financial reward for participation could be considered.

The results of this research are relevant for policy advisors, finance providers, and farm advisors. First, we find that farmers generally prefer management practices over investment options. These preferences may make efforts to reduce nitrogen abatement less effective as farmers tend to opt for easier to implement and possibly fewer effective options. Policy makers can provide additional incentives to encourage farmers to choose more effective abatement options. Moreover, we find significant heterogeneity in farmers preferences. Tailoring policies to individual farmers could foster greater participation in sustainable agriculture practices and reduce the environmental impact of farming operations. As the effects of personality traits, risk attitude and time discounting on preferences for nitrogen abatement were generally not significant, policy makers should avoid developing policies based on the assumption that farmers are risk averse.

Appendix 4.A

Table 4.A1: Multicollinearity

		Intensity	**Distance to natural areas**			**Age**	**Success-ion**	**Expectations about the future**
			<1 km	1-10 km	10> km			
Intensity		1.00						
Distance to natural areas	<1 km	-0.02	0.31					
	1-10 km	0.03	-0.19	0.51				
	10> km	-0.01	-0.12	-0.32	0.44			
Age		0.02	0.00	-0.11	0.11	0.97		
Succession		-0.03	-0.02	0.02	0.01	-0.20	0.40	
Expectations about the future		-0.07	0.01	-0.06	0.04	0.12	-0.10	0.39
Extraversion		0.09	-0.07	0.07	0.00	-0.05	0.04	-0.01
Conscientiousness		-0.12	0.06	0.00	-0.05	-0.05	0.04	-0.01
Openness		-0.05	0.06	0.08	-0.14	0.04	-0.03	-0.01
Agreeableness		-0.01	-0.07	0.04	0.03	0.04	0.02	-0.03
Neuroticism		-0.06	-0.01	0.07	-0.06	-0.08	0.05	-0.02
Risk attitude (staircase)		0.06	0.05	0.04	-0.09	0.09	0.00	-0.04
Risk attitude (self-assessment)		0.02	0.01	-0.06	0.05	-0.07	-0.03	0.03
Time discounting (staircase)		0.12	-0.03	0.05	-0.02	0.07	0.05	0.00
Time discounting (self-assessment)		0.02	-0.02	0.06	-0.04	0.04	0.03	-0.02

Note: n=96, Kendall’s tau is used to test multicollinearity

		Extra-version	Conscien-tiousness	Open-ness	Agree-ableness	Neuroti-cism	Risk attitude (SC)	Risk attitude (SA)	Time discount-ting (SC)	Time discount-ting (SA)
Intensity										
Distance to natural areas	<1 km									
	1-10 km									
	10> km									
Age										
Succession										
Expectations about the future										
Extraversion		0.74								
Conscientiousness		0.06	0.74							
Openness		0.20	0.11	0.72						
Agreeableness		0.10	0.15	0.01	0.65					
Neuroticism		0.07	0.08	0.13	0.15	0.72				
Risk attitude (staircase (SC))		0.08	-0.01	0.14	-0.01	-0.05	0.95			
Risk attitude (self-assessment (SA))		-0.22	-0.14	-0.31	-0.06	-0.10	-0.26	0.62		
Time discounting (staircase)		-0.01	0.08	0.06	0.08	0.09	-0.06	-0.04	0.90	
Time discounting (self-assessment)		0.13	0.01	0.23	0.06	0.17	0.07	-0.20	0.10	0.64

Table 4.A2: Model results (ranking) including estimates, shares of preference and standard deviations.

	MNL			MXL uncorrelated			MXL correlated		
	Estimates		Shares of Pref.	Estimates		Shares of Pref.	Estimates		Shares of Pref.
Management practices/ investment options	Mean	(s.e.)		Mean	(s.e.)		Mean	(s.e.)	
Protein content feed (M)	1.92	(0.11)	0.15 (4)	3.55	(0.27)	0.09 (3)	4.62	(0.35)	0.098 (4)
Air washers (I)	Base		0.02 (8)	Base		0.00 (8)	Base		0.00 (8)
Grazing (M)	2.30	(0.12)	0.22 (2)	4.72	(0.33)	0.30 (2)	5.64	(0.39)	0.20 (2)
Low-emission floors (I)	0.50	(0.10)	0.04 (7)	0.36	(0.30)	0.00 (7)	1.04	(0.28)	0.00 (7)
Fertiliser use (M)	1.91	(0.11)	0.15 (3)	3.55	(0.25)	0.09 (4)	5.13	(0.37)	0.15 (3)
Precision-fertilisation machines (I)	0.84	(0.10)	0.05 (6)	1.66	(0.19)	0.01 (6)	1.19	(0.26)	0.01 (6)
Quality of grassland/species (M)	2.56	(0.12)	0.29 (1)	5.15	(0.28)	0.47 (1)	5.52	(0.36)	0.52 (1)
Electrical machines (I)	1.30	(0.11)	0.08 (5)	1.89	(0.23)	0.02 (5)	1.88	(0.37)	0.03 (5)
				SD			SD		
Protein content feed (M)				2.78	(0.25)		4.74	(0.31)	
Air washers (I)				Base			Base		
Grazing (M)				3.93	(0.33)		5.02	(0.33)	
Low-emission floors (I)				2.83	(0.29)		4.09	(0.32)	
Fertiliser use (M)				2.20	(0.28)		4.24	(0.29)	
Precision-fertilisation machines (I)				-1.70	(0.22)		4.29	(0.37)	
Quality of grassland/species (M)				1.56	(0.26)		4.13	(0.32)	
Electrical machines (I)				1.81	(0.20)		5.29	(0.49)	

Model fit			
LL	-1879	-1438	-1321
AIC	3772	2906	2671
BIC	3823	3008	2928
No. of respondents		96	
No. of choices		960	

Note: The estimates are calculated relative to the air washers abatement option because this was the least preferred abatement option.

Complementary material

Table 1: Fmlogit model results with self-assessment measures for risk attitude and time discounting

		Protein content feed (M, a1)	**Air washers (I, a2)**	**Graz-ing (M, a3)**	**Low-emission floors (I, a4)**	**Fertiliser use (M, a5)**	**Precision-fertilisation machines (I, a6)**	**Quality of grassland/ species (M, a7)**	**Electrical machines (I, a8)**
Intensity		-0.021	0.001	-0.197*	-0.001	-0.087**	0.008**	0.254***	0.042
Distance to natural areas	1-10 km	0.239*	-0.000	-0.167	-0.043***	-0.014	0.001	0.066	-0.080**
	>10 km	0.173	0.004	-0.214	-0.054**	0.020	0.003	0.077	-0.009
Succession	Yes	-0.08	0.014**	0.116	0.016	-0.036	-0.003	-0.005	-0.021
Age		-0.003	0.000*	-0.000	-0.000	0.007***	-0.000	-0.003	-0.002
Expectations about the future	Consolidate or reduce	-0.006	0.002	0.059	0.008	-0.028	-0.002	0.004	-0.037
Personality traits	Extraversion	-0.022	0.000	0.04	0.004	-0.009	0.000	-0.025	0.010
	Conscien-tiousness	0.029	0.002	0.037	0.002	-0.014	0.000	-0.049	-0.008
	Openness	-0.011	0.004**	0.04	0.004	-0.005	-0.000	-0.021	-0.011
	Agreeable-ness	-0.039	0.003	0.011	0.009	-0.002	0.000	0.037	-0.020
	Neuroticism	-0.053**	-0.001	0.069	0.006	-0.043*	0.002	0.001	0.019
Risk attitude	Self-assessment	-0.014	0.002	0.114	-0.009	0.025	-0.003*	-0.104*	-0.011
Time discounting	Self-assessment	0.116***	-0.001	-0.006	-0.013	0.025	-0.004***	-0.105**	-0.010

Note: n=96, *** p<0.01, ** p<0.05, * p<0.1, The following variables are dummy variables: distance to natural areas, succession and expectations for the future.

Chapter 5

Farmers' perceptions of obstacles to business development

This chapter is based on the paper: Yanore, L., Sok, J., Oude Lansink, A. (2023). Farmers' perceptions of obstacles to business development. Eurochoices (Accepted for publication)

Abstract

This paper examines the perceived obstacles of Dutch dairy farmers to business development and compares them to Dutch broiler farmers and Swedish farmers. Understanding farmers' perceived obstacles is crucial for developing effective policies to support sustainable and resilient farms.

The study finds that rules and regulations are the most important obstacle for all three groups of farmers. Dutch dairy farmers also face challenges related to land availability, permits, and leasing, while Dutch broiler farmers have concerns mostly about foreign competition. Financial obstacles are significant but considered less important than regulatory and land-related challenges. Farm characteristics, such as intensity of operation, off-farm income, location, succession status, and farmer's patience were statistically related to the perceived obstacles of Dutch dairy farmers. The associations found suggest that dairy farmers operating their businesses more intensively face more financial, social capital and land availability obstacles. It was also found that younger farmers or farmers with successors score higher on perceived obstacles concerning policy and land availability obstacles.

Recommendations include improving information provision, simplifying regulations, and engaging stakeholders to reduce policy obstacles. Also, policies should consider farmers' unique needs and should be implemented in a decentralized way.

Key words

Perceived obstacles for business development, Dutch dairy farmers, farm intensity, succession.

5.1 Sustainable and resilient farms

The Common Agricultural Policy is a partnership between the EU and farmers that aims to foster competitive, sustainable and resilient farms (European Commission, 2023). However, farmers experience several obstacles to the development of their businesses in a changing and uncertain policy context. To design effective policies, it is crucial to understand farmers' behaviour and perceived obstacles (Viaggi et al., 2011). The perception of obstacles can differ per farmer for two important reasons (Hansson and Sok, 2021). First, there are objective differences between farmers in terms of the physical, biological, technical, social, and economic context in which farmers produce. Secondly, there are individual differences between farmers in terms of their psychological make-up, such as personality traits.

This paper focuses on the Dutch dairy sector, which has undergone several policy changes since the milk quota abolition in 2015 (McCullough, 2018). We conducted a survey and assessed the importance of perceived obstacles to business development for Dutch dairy farmers and compared them to Dutch broiler farmers and Swedish farmers. Additionally, we explored how farm(er) characteristics are related to the perceived obstacles of Dutch dairy farmers.

Box 5.1 – Data collection and analysis

The email survey was conducted in March 2022 among Dutch dairy farmers on the perceived obstacles for business development. The survey questions were adapted from Hansson and Sok (2021) with minor adjustments in the wording. The data of Dutch dairy, broiler and Swedish farmers were collected at different time points, which means that perceptions might have changed due to events occurring in the periods between surveys.

A factor analysis was used to group the perceived obstacles. This correlation-based approach grouped closely related obstacles into broader categories. We tested the relation with farm(er) characteristics using a seemingly unrelated regression. This regression model accounts for correlation in the error terms across separate regressions, each focusing on one of the categories of obstacles.

5.2 The most and least important perceived obstacles to business development of Dutch Dairy farmers

The results of the survey, as depicted in Figure 5.1, showed that the four most important obstacles to business development perceived by Dutch dairy farmers are "rules and regulation", "possibilities to buy and lease new farmland", "ability to get permits" and "possibilities to lease land" as the most important obstacles to business development. The least important perceived obstacles of the farmers relate to available knowledge and social capital, such as "support from family", "support from business partners" and "knowledge and competence of the farm". This shows that the most important perceived obstacles relate to land and policies, and farmers seem less worried about the abilities of their business partners, family, and themselves.

Most of the perceived obstacles related to the financial situation of the farm are ranked in a high to mid-level position. It stands out that financial obstacles are less important than obstacles related to regulations, permits and land. For farmers who consider business development in terms of expansion, the possibility to buy land or get a permit is perceived as more of an obstacle than the financial position of their farm. Obstacles in terms of regulations, permits and land are especially important for farmers operating their businesses more intensively. Other factors that are in mid-level, but slightly lower positions include foreign competition, labour, succession and the location of the farm.

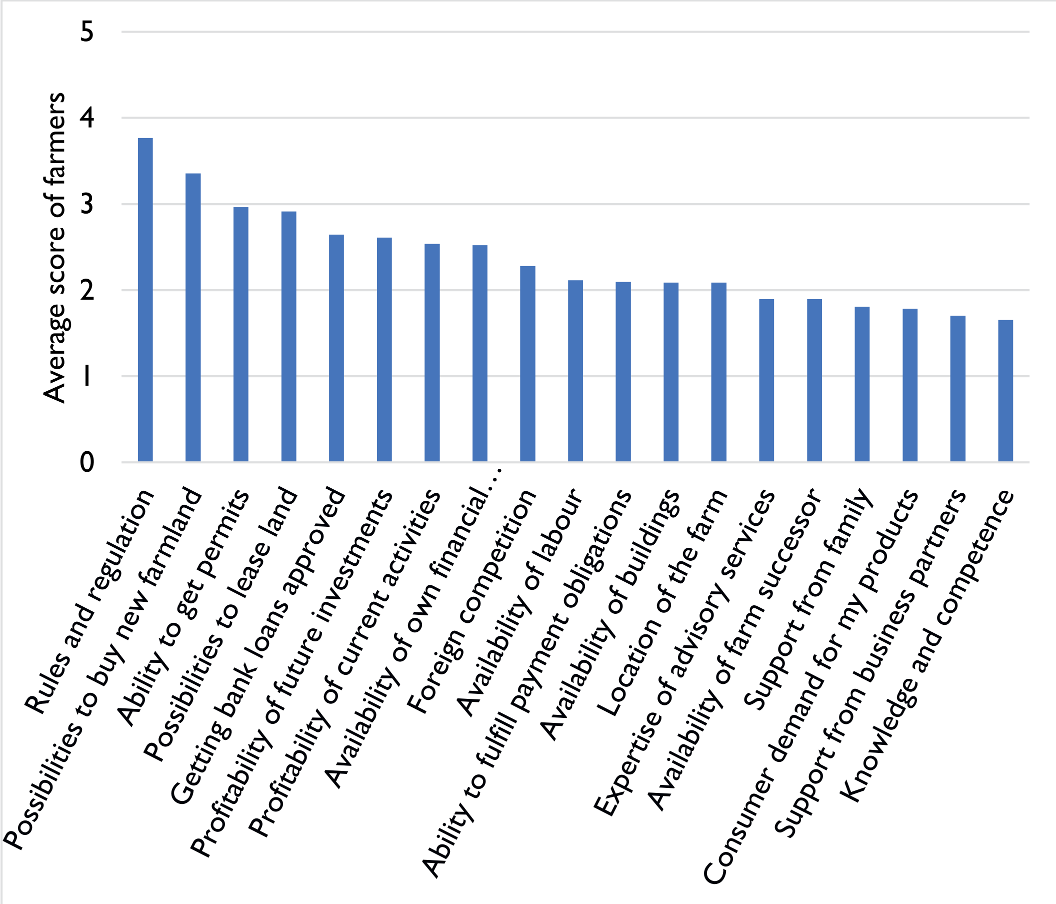

Figure 5.1: Perceived obstacles for business development of Dutch dairy farmers.

Note: The score was measured on a 5-point Likert scale indicating how strong the obstacles are perceived by the farmers.

Figure 5.2: Cows grazing on a field on a sunny day. The availability of land is perceived as a major obstacle by Dutch dairy farmers.

5.3 Comparing obstacles across farming sectors and countries

Across Dutch dairy, Dutch broiler and Swedish farmers, "rules and regulations" are perceived as the most important obstacle to business development. This shows the importance of "rules and regulations" as an obstacle for business development both across countries and sectors. Figure 5.3 further shows that in the four most important obstacles, Swedish farmers (these include crop, animal and mixed farms) and Dutch broiler farmers both have several financial-related obstacles whereas Dutch dairy farmers have obstacles related to permits and the possibility to buy and lease farmland for feed production. Changing the use of land is high on the Dutch political agenda because space is being claimed to meet objectives for housing construction, climate adaptation, renewable energy generation, and expansion of recreational and nature conservation areas (CBS, 2022).

Contrary to Dutch dairy and Swedish farmers, Dutch broiler farmers perceive "foreign competition" as a major obstacle. This may be due to their heavy reliance on the export of their produce. Specifically, chicken produced under the

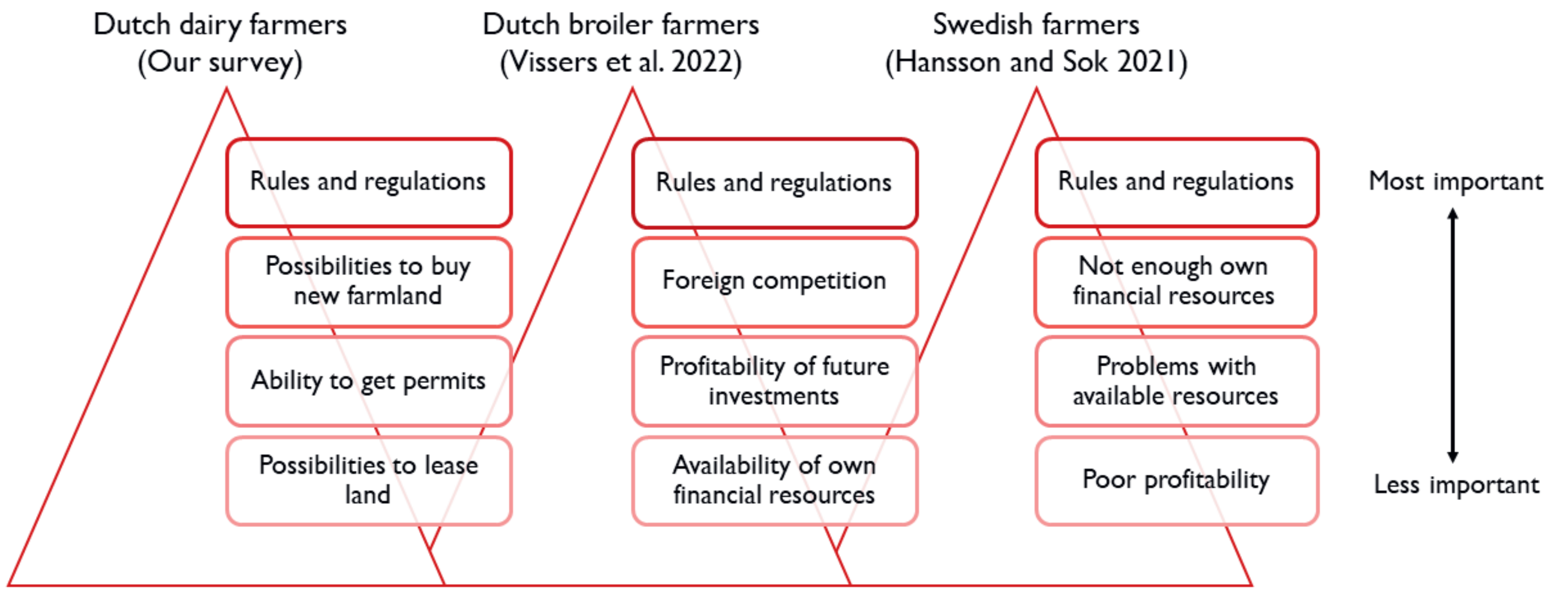

Figure 5.3: The most important perceived obstacles for business development of Dutch dairy farmers, Dutch broiler farmers and Swedish farmers. The most important obstacles are at the top.

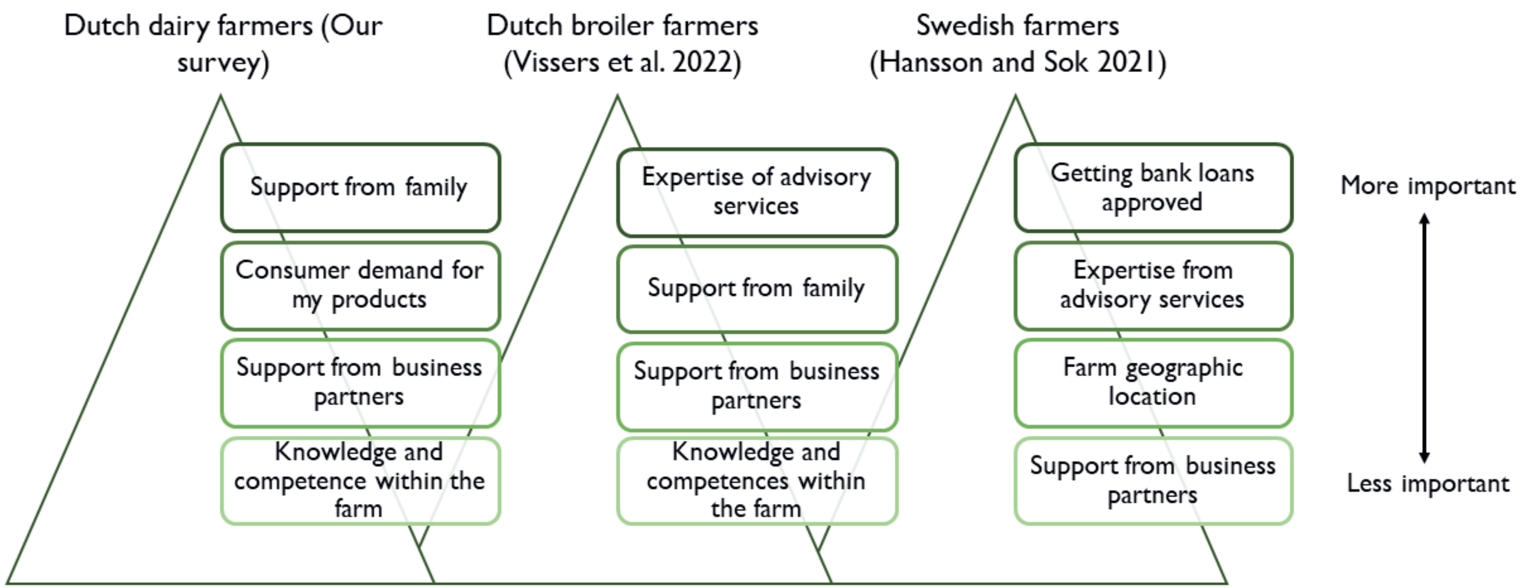

Figure 5.4: The least important perceived obstacles to business development of Dutch dairy farmers, Dutch broiler farmers and Swedish farmers. The least important obstacles are at the bottom.

lowest animal welfare standards is not sold in Dutch supermarkets and needs to be exported. Moreover, chicken and eggs produced under low standards are still imported and processed into mayonnaise, chicken salads or other products. Thus, broiler farmers are more susceptible to foreign competition.

Figure 5.4, reporting on the four least important obstacles, shows that all three groups of farmers consider support from business partners as a relatively less important perceived obstacle. Moreover, "knowledge and competences within the farm" are considered the least relevant by both Dutch dairy and broiler farmers and support from family is also among the four least important obstacles. Swedish farmers slightly stand out here as the perceived obstacles "farm geographic location" and "getting bank loans" appear in the bottom 4.

5.4 How do farm and farmer characteristics relate to perceived obstacles?

In Figure 5.5, we show the relation between different farm and farmer characteristics with five general categories of perceived obstacles to business development of Dutch Dairy farmers. Only relations that were statistically significant in the regression analysis are displayed in Figure 5.5 (see Box 5.1 for details on the procedure and Table 5.1 for a description of these characteristics).

5.4.1 Financial obstacles

Financial obstacles are perceived to be more important by farmers who operate their farms more intensively. Intensive dairy farming requires more capital investments in equipment, facilities and livestock. Additionally, these farms require greater use of variable inputs, such as feed. They are also more susceptible to fluctuations in milk and input prices and thus may experience more financial obstacles. Farmers with an off-farm income have diversified their income stream and score lower on financial obstacles. A last finding here is that more patient farmers score lower on perceived financial obstacles. It can be argued that patient farmers take a more long-term perspective on business and financial planning and thus perceive financial obstacles as less important.

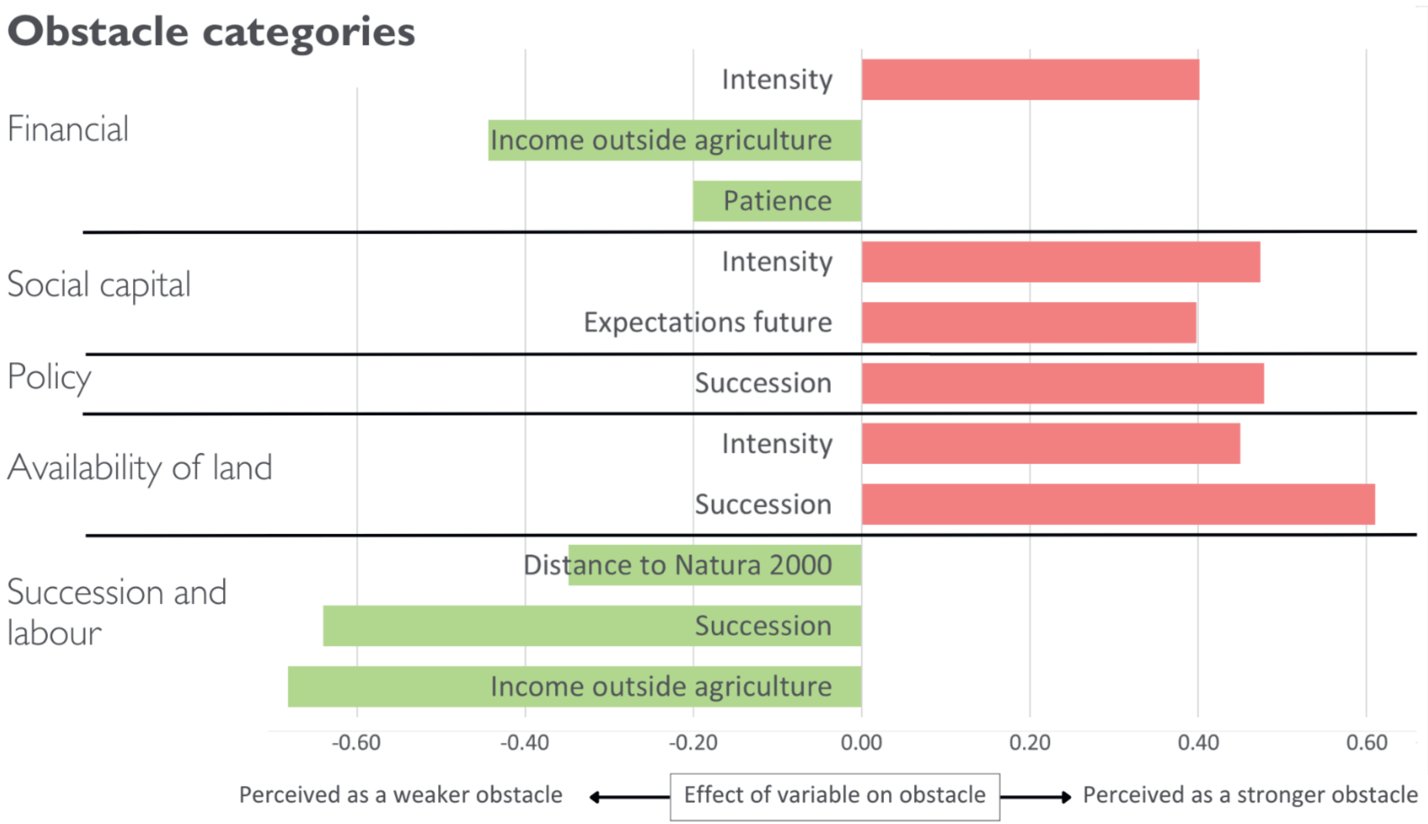

Figure 5.5: The effect of farm and farmer characteristics on five categories of perceived obstacles to business development.

Note: We used a seemingly unrelated regression analysis, and only show the effect of significant variables. Variable definitions are shown in Table 5.1

Table 5.1: Description of farm and farmer characteristics included in the regression analysis that is underlying Figure 5.5.

Variable	Type	Description
Intensity	Continuous	Cows per hectare
Distance to Natura 2000	Two Categories	Category 1: below 10 km Category 2: 10 km and above
Age	Continuous	The age of the farmer
Age^2	Continuous	The age of the farmer squared
Succession	Two Categories	Category 1: No successor and older than 50 Category 2: Has a successor or is younger than 50
Expectations future	Two Categories	Category 1: Expects to grow in the future Category 2: Does not expect to grow in the future
Income outside agriculture	Two Categories	Category 1: Has an income outside agriculture Category 2: Has no income outside agriculture
Risk attitude	Ordinal (Likert scale 1-5)	The higher the score, the more risk taking the farmer
Patience	Ordinal (Likert scale 1-5)	The higher the number, the more patient the farmer Measure in terms of time discounting

5.4.2 Social capital obstacles

The next category of obstacles relates to the social capital of the farmer. Social capital refers to the skills and competences to which the farmers have access within their social network. Farmers who operate their farms more intensively score higher on perceived social capital obstacles. This may be the case because these farms require more specialized knowledge and skills and finding the right support may be more difficult for them. On the contrary, farmers who do not expect to grow in the future also perceive social capital as a stronger obstacle. Possibly, these farmers do not want to grow because they lack the support from family and business partners and perceived there is insufficient skill on the farm to manage the growth of their farm.

5.4.3 Policy obstacles

The perceived obstacles related to policy are only significantly related to the succession status. We found that farmers below 50 or farmers with a successor score higher on perceived policy obstacles. These farmers may be more future-oriented and thus more aware of the policy environment. Besides that, farmers with a successor may have a stronger need to provide additional income for the different family members working on the farm and thus need to develop their businesses. To be able to develop their businesses, permits may be needed or policy requirements may need to be met. Policy uncertainty in combination with other factors, such as the financial situation, may make business development difficult or even impossible for these farmers.

5.4.4 Availability of land obstacles

We also found that farmers who operate their farms more intensively and those with a successor (or younger than 50) score higher on perceived obstacles related to the availability of land. Current policy initiatives at the European and national levels stimulate the adoption of less intensive dairy farming practices or systems. The use of variable external inputs needs to be reduced, while agricultural land should also be used for environmental purposes, such as biodiversity conservation, carbon sequestration, or water quality improvement. As such, acquiring or leasing more land is an important prerequisite for these farmers to keep developing their businesses in the current policy context. For these farmers, who manage relatively less land compared to the number of dairy cows, acquiring and leasing more land may be perceived as one of the most important obstacles.

Figure 5.6: Only 50% of farmers above 50 has a successor, despite this it is not perceived as a major obstacle by most Dutch dairy farmers.

5.4.5 Succession and labour obstacles

The last category includes obstacles related to succession and labour. We find that farmers who live further away from Natura 2000 areas, those with a successor (or younger than 50) and farmers with an off-farm income perceive obstacles related to succession and labour to be less important. The 161 so-called Natura 2000 areas in the Netherlands, hosting rare and threatened species and habitat types, play a prominent role in public policy for evaluating where nitrogen emissions should be limited. Farmers who live closer to Natura 2000 areas may face more restrictions, and one of the options being discussed is farm buy-outs. As such, it would be expected that farmers living close to these areas experience more obstacles.

5.5 Final considerations

Recommendations can be made for Dutch agriculture and agriculture in similar countries and regions from the findings on the perceived obstacles to business development. A joint effort between farmers, policy makers, finance providers and other stakeholders will be needed to overcome these obstacles.

The most important obstacle for all groups of farmers are the "rules and regulations" obstacle. Further research will be needed to identify the main reasons behind this perception. Rules and regulations may simply impose restrictions the farmer cannot fulfil and would then be a real obstacle. However, rules and regulations may also be perceived as a major obstacle because of the lack of clear information to explain them. As such, improving information provision and providing clearer guidelines and assistance could for example help farmers overcome these perceived obstacles. Besides this, pilot sessions in which farmers receive information about policies and "practice" filling related documentation could help. Farm extension services could also help mitigating obstacles related to rules and regulations through information sharing and education. Farmer leaders may also play an important role in influencing perceptions related to policy obstacles.

Besides "rules and regulations", the most important obstacles for Dutch dairy farmers were related to the availability of land. The government could continue to address this through land-use planning and policies. For example, by not allowing non-agricultural activities in agricultural zones and making sure agricultural zones remain agricultural zones in the future. Farm extension services can provide knowledge and training on efficient land use practices to help farmers adopt strategies to overcome land availability challenges.

Our research shows considerable difference in perceived obstacles between farmers, their sector and origin. Firstly, for the Dutch dairy farmers, it is notable that more intensive farmers and farmers with a successor generally score higher on the perceived obstacles to business development. Secondly, there is also a large variety in the obstacles perceived by the different groups. Although, the number one obstacle for Dutch dairy, Dutch broiler and Swedish farmers was related to policy, there is a large variety in the ranking of the remainder of the obstacles. For example, for dairy farmers land obstacles are important, whereas for broiler farmers obstacles related to foreign competition are more important. This diversity should be considered, and policy makers should respond to the unique needs and circumstances of farmers. Farmers could be segmented based on their characteristics and the perceived obstacles of these segments could be discussed in advisory sessions. Moreover, the EU should only set basic policy objectives, and EU countries should bear more responsibility on how these policy objectives are achieved (European Commission, 2017).

Chapter 6

General discussion and conclusions

6.1 Introduction

Policy uncertainty has been a major and understudied source of uncertainty in the agricultural economics literature. In recent years, many policy changes related to phosphate and nitrogen emissions have occurred in the Dutch dairy sector (Stokstad, 2019). These policy changes and changing political environment in the Netherlands leads to uncertainty for Dutch dairy farmers (Samson et al., 2016). To develop evidence-based policies, understanding farmers decision making under policy uncertainty is important. The overall objective of this thesis was to explore the decision making of Dutch dairy farmers under policy uncertainty. The following research objectives were addressed in this thesis:

RO1 To develop a theoretical framework to study farmers' investment behaviour in the presence of policy uncertainty. The theoretical framework can reflect three investment strategies – anticipating, waiting, or not investing as special cases. (Chapter 2)

RO2 To identify and assess the farm -, farmer - and environmental characteristics that explain and predict investment strategies: anticipate and invest early, wait with investing, or not investing at all. (Chapter 3)

RO3 To rank Dutch dairy farmers' preferences for nitrogen abatement investment options and management practices and to study if and how they are linked to personality traits, risk attitude and time discounting. (Chapter 4)

RO4 To assess the importance of perceived obstacles to business development of Dutch dairy farmers and compare them to Dutch broiler farmers and a general sample of Swedish farmers. (Chapter 5)

Note that Chapter 2 and Chapter 3 focused on investments in the expansion of an average Dutch dairy farm and included three investment strategies to cope with policy uncertainty: anticipating, waiting, and not investing. Chapter 4 studied the preferences of farmers for nitrogen abatement investment options and management practices. Thus, the focus of Chapter 4 was no longer on only investments but extended to management practices. Chapter 5 focussed on perceived obstacles to business development. Business development is a broad construct beyond just profit maximisation or growth as it allows for multiple goals amongst farmers (Hansson and Sok, 2021). These four research objectives each shed light on farmers' decision making under policy uncertainty, in terms of investment strategies, preferences for nitrogen abatement options and perceived obstacles to business development.

Policy uncertainty played an important role in each of the research objectives studied in this thesis. In Chapter 2, it was modelled using several parameters indicating the timing of, impact on and probability of a new policy and its effect was studied using sensitivity analysis. In Chapter 3, the variables that determine perceived policy uncertainty were defined by experts. In Chapter 4, policy uncertainty was included more implicitly, as we asked farmers for preferences concerning nitrogen abatement options, a topic that was and still is surrounded by policy uncertainty. Besides this, we included several factors considered to influence perceived policy uncertainty based on our results from chapter 2 and 3. In Chapter 5, we studied which obstacles were perceived by farmers as most hindering to business development, including obstacles capturing policy uncertainty in terms of regulations, permits and the availability of land.

The remainder of this chapter is structured as follows: section 6.2 synthesises the results of chapters 2-5. Next, policy and business recommendations are discussed in section 6.3. This is followed by a discussion of the limitations and opportunities for future research in section 6.4 and section 6.5 presents the main conclusions.

6.2 Synthesis of the results

In this synthesis we first describe how policy uncertainty was measured. Subsequently, we describe how policy uncertainty relates to these aspects of decisions making. We then describe how other farm and farmer characteristics relate to the decision making and conclude with some general findings.

6.2.1 Measuring policy uncertainty

One of the challenges of this thesis was to measure policy uncertainty, as including policy uncertainty in empirical models about decision making is difficult (Rodrik, 1991). Policy uncertainty is a primary source of risk for farmers (Flaten et al., 2005, Vissers et al., 2022). However, it also the least studied source of uncertainty (Komarek et al., 2020) compared to other sources of uncertainty such as production and price related uncertainty. Previous research has used several methods to include policy uncertainty in (empirical) models. For example, Floridi et al. (2013) studied investment decisions in automatic milking robots under policy uncertainty. They included policy uncertainty as a stochastic variable influencing the cash flow. Hassett and Metcalf (1999) found that the stochastic process chosen is an important determinant of the impact of uncertainty on investment. Besides modelling uncertainty using stochastic processes, other researchers use qualitative information. For example, Linnerud et al. (2014) studied the relationship between policy uncertainty and investments in powerplants. They used qualitative information, such as policy statements, to determine how to measure policy uncertainty. In their model they included uncertainty about "whether" a subsidy scheme will be implemented. To the best of our knowledge, most previous research only included one variable to measure policy uncertainty (Diederen et al., 2003, Djanibekov and Finger, 2018, Floridi et al., 2013, Gatzert and Vogl, 2016, Linnerud et al., 2014). A few studies also included behavioural factors when studying decision making under policy uncertainty (Djanibekov and Finger, 2018, Flaten et al., 2005). Djanibekov and Finger (2018) assume farmers are risk-averse in their model to study the relationship between risk (production, market, and institutional) and resource allocation, cotton production levels and farm size developments. However, they did not study the effect of differences in risk aversion. Flaten et al. (2005) studied the relation between risk perception, risk management strategies and risk attitude. They didn't find a relationship between risk perception and risk attitude but they do find that risk attitude influence risk management strategies related to consultancy, diseases, and fixed costs.

Our study contributes to the literature, by including several variables describing the policy uncertainty whereas most previous literature only included one aspect of policy uncertainty. Moreover, few papers have studied the relationship between risk attitude and decision making under policy uncertainty, but we are not aware of any papers that included personality traits. In Chapter 2 we developed a theoretical framework in which timing of, impact of and probability on a policy can be considered. Besides that, risk attitude was included as a behavioural farmer characteristic. In Chapter 3, the experts considered the intensity of the farm operations and the distance to Natura 2000 as relevant variables to describe how much policy uncertainty a farmer would objectively experience. Besides that, the farmers personality, described by risk attitude and the big five personality traits, was considered to influencing the farmers perception of policy uncertainty and their investment strategies. In Chapter 3, 4, and 5, we studied the relationship between these variables and farmers investment strategies, preferences for nitrogen abatement options and perceived obstacles to business development respectively.

Table 6.1: Variables included to measure the relation between policy uncertainty and decision making

	Timing of, financial impact of and probability on policy	Risk attitude	Time discount-ting	Distance to Natura 2000	Farm intensity	Personality traits
Chapter 2	X	X	X			
Chapter 3		X		X	X	X
Chapter 4		X	X	X	X	X
Chapter 5		X	X	X	X	

In summary, the following variables were included in each of the chapters (Table 6.1): timing, financial impact and probability on a policy (chapter 2), risk attitude (Chapter 2, 3, 4 and 5), distance to Natura 2000 (Chapter 3, 4 and 5) and the farm intensity (chapter, 3, 4 and 5) and personality traits (Chapter 3 and 4). How these variables are related to farmers decision making under policy uncertainty is discussed in the next section.

6.2.2 The relation between policy uncertainty and decision making

Next, we discuss the relations between the variables related to policy uncertainty on the three different decision-making aspects: investment strategies, farmer preferences, and perceived obstacles.

In Chapter 2, we find that the anticipation strategy is optimal when a policy is expected to have low financial consequences and when the policy is expected to be implemented with a delay. In line with this, Chapter 3 found that the anticipating strategy, i.e., investing early, is more attractive to farmers who perceive less policy uncertainty. This finding is in line with Gopinath (2021), who found that farmers invest less in years with higher policy uncertainty. Similarly, Gatzert and Vogl (2016) found that including policy uncertainty has a strong effect on the present value of cash flows of investments, showing that higher policy uncertainty makes investing less interesting. However, only few papers consider more investment strategies than now or never. (e.g. Linnerud et al., 2014, Pindyck, 1990). For example, Linnerud et al. (2014) found that uncertainty about possible future subsidies delayed investments according to the real options rule, thereby accounting for the strategy to invest now or postpone the investment. Specifically, professional investors postponed their investments, whereas non-professional investors treated the investment decision as a "now or never" decision (Linnerud et al., 2014). We are not aware of any studies looking at the three investment strategies, i.e., anticipating, waiting, and not investing. As such, we contribute to the literature by developing a theoretical framework to study how policy uncertainty affects farmers decision making in terms of these three investment strategies. We demonstrate that policy uncertainty can delay investments when farmers expect the impact of the policy to be strong. However, we also find that it can speed up investments, particularly when there is uncertainty about the timing of policies.

In Chapter 3, experts considered intensity, distance to Natura 2000, risk attitude and personality traits relevant for understanding decision making under policy uncertainty. These variables had direct effects on perceived policy uncertainty and indirect effects on the investment strategies. Using entropy reduction, we found that risk attitude had the most substantial effect on perceived policy uncertainty, followed by the distance to Natura 2000, intensity and lastly the personality traits. For the investment strategy, policy uncertainty had the third most substantial effect on the investment strategy. Succession was the first, risk attitude the second and earning capacity the fourth.

The relationship between risk attitude and farmers' decision making has been widely studied (Greiner et al., 2009, Hardaker et al., 2015, Iyer et al., 2020). According to a review paper by Iyer et al. (2020) most research found that farmers are slightly risk averse, which is in line with our findings in Chapter 4 and 5 (same survey). Where we used a 5-step staircase and self-assessment to measure risk attitude and also found that farmers are slightly risk averse.

Only a few papers show the relationship between risk attitude on decision making in the presence of policy uncertainty (Djanibekov and Finger, 2018, Flaten et al., 2005). We found both similarities and differences between chapters in the relation between risk attitude on decision making. In Chapter 2, risk attitude was included through the risk adjusted discount rate. In Chapter 3, it was included as a node with three categories, risk-averse, risk neutral and risk-taking which was based on the experts' opinions. Here, risk attitude was related to the risk perception and the investment strategies. Both in chapter 2 and 3, it was found that less risk averse farmers are more likely to anticipate policy uncertainty by investing early and more risk averse farmers are more likely to delay their investments and not to invest at all. In literature focussed on other sources of uncertainty, more risk averse farmers were also found to delay adoption (Spiegel et al., 2021) or to be less likely to invest (Schulte et al., 2018). We contribute to the literature by studying the relationship between risk attitude and investment decisions in the presence of policy uncertainty, as most previous literature focusses on other sources of uncertainty (e.g. Schulte et al., 2018, Spiegel et al., 2021).

In the survey of Chapter 4 and 5, the 5-step staircase method was used to measure the risk attitude. Studying the relation between risk attitude and the specific nitrogen abatement options in Chapter 4, we found that more risk-taking farmers prefer the management practice to reduce the protein content in feed and the investment option low-emission floors. We argue that these measures may be relatively more interesting for farmers who aim to expand their farm. Thus, in line with Chapter 2 and 3, it seems that more risk-taking farmers prefer nitrogen abatement options that are specifically interesting for farmers who want to invest in expansion.

However, in Chapter 4 we found a weak relationship (1.64% change in preferences for management practices) between risk attitude and the preferences for investment options versus management practices when they were combined into categories. The effect may have been low because the relation between risk attitude and investment options could be two-fold. For example, investing may be a way to mitigate policy uncertainty, but investing is also riskier than adjusting management practices. Moreover, our results show that risk-taking farmers prefer an investment option (low emission farming) but also prefer a management practice (protein in feed). These opposite effects may cancel each other out when combining the investment options and management practices into separate categories. In Chapter 5, we did not find any significant relationship between risk attitude on the perceived obstacles to business development. In the current state of the literature, different relations between risk attitude and decision making of farmers' have been found. For example, Hellerstein et al. (2013) found a low predictive power of risk attitude for farmers decisions looking at a variety of decisions such as farm diversification, crop insurance and farm management practices. Whereas Tensi and Ang (2023) found that less risk averse farmers have a stronger intention to adopt microbial applications. Greiner et al. (2009), found that risk attitude correlates with the adoption of conservation practices for farmers. Thus, in line with previous literature we do not always find a significant relationship between risk attitude and decision making.

We also studied the relationship between personality traits on investment strategies (Chapter 3) and with preferences for nitrogen abatement options (Chapter 4). In Chapter 3, the experts considered personality traits as important factors determining the farmers risk preferences. Specifically, personality traits were expected to influence risk attitude, which in turn influences the perceived policy uncertainty and investment strategies. Our results are in line with Pak and Mahmood (2015), who found that personality traits are related to risk-taking behaviour and that risk-taking behaviour in turn is related to investment decisions. Their study focussed on investment decisions in stocks, securities, and bonds in Kazakhstan. The relationship between the Big Five personality traits and business development (Hansson and Sok, 2021) and investment intention (Mayfield et al., 2008) was also demonstrated in previous literature. Hansson and Sok (2021) found that people who are more extravert and open scored lower on perceived obstacles to business development. Moreover, Mayfield et al. (2008) found that more extravert individuals intend to engage in short-term investments whereas individuals who are more open to experience intend to engage in long-term investments. In line with this, we found a relationship between personality traits and the preferences for investment options versus management practices (Chapter 4). Specifically, we found that conscientiousness, neuroticism, and extraversion were amongst the 5 most substantial variables. However, when we looked at the eight abatement options specifically, we did not find a significant relationship (5% significance level) between personality traits on the farmers preferences for nitrogen abatement options. Possibly, personality traits only affect the farmer's preferences for certain categories of nitrogen abatement options, namely the investment options versus management practices and not the more specific nitrogen abatement options. Moreover, in Chapter 3 the experts considered the personality traits as an important factor influencing farmers investment strategies. The results of Chapter 4 are in line with those of Chapter 3. However, as no significant relationship were found in the fmlogit model focussing on specific abatement options, these results need to be interpreted with care.

In Chapter 3, experts expected that the distance to Natura 2000 and intensity have stronger effect on perceived policy uncertainty and a lower and indirect effect on investment strategies. In Chapter 4, we found that farmers closer to Natura 2000 areas prefer investing in low-emission floors. Low-emission floors have been an important part of the Integrated approach to nitrogen (PAS) and thus investing in them may be a way to mitigate policy uncertainty. We also found that farmers closer to Natura 2000 experience higher policy uncertainty (Chapter 3). These farmers may prefer low emission floors as this is a way to anticipate new policies related to nitrogen emissions. In Chapter 5, we found that farmers further from Natura 2000 score lower on perceived obstacles for business development related to succession and labour. Thus, we conclude that the Distance to Natura 2000 is an important variable when studying Dutch dairy farmers' decision making under policy uncertainty.

With respect to the intensity, we found in Chapter 4 that farmers operating their farm more intensively prefer investing in precision fertilization machines and prefer the management practice to improve the quality of grassland species. These nitrogen abatement options both have to do with the feed production. For farmers operating more intensive farms, making optimal use of the available land to produce feed may be very relevant as land and thus feed production is a limiting factor for these farmers. In Chapter 5, we found that farmers operating their farm more intensively score higher on the financial, social capital and availability of land perceived obstacles. Our results show that overall, the farm intensity is a very relevant factor for decision making under policy uncertainty.

6.2.3 The relation between farm and farmer characteristics and decision making

Besides variables related to policy uncertainty, we also studied the relation between other variables on the farmers investment strategies, preferences, and obstacles to business development. In Chapter 2, we explored the effect of changes in the milk price on investment strategies. The results show that a higher milk price, which also indicates a higher cash flow, increases the likelihood farmers anticipate policy uncertainty and invest early. This is in line with the results from Chapter 3, where we found that farmers with a higher earning capacity were more likely to anticipate and invest early. In Chapter 3, a higher EBITDA, lower debt-to-asset ratio and higher intensity resulted in a higher earning capacity. As a higher intensity resulted in a higher earning capacity, a priori we expected that farmers with a higher earning capacity, and thus farmers operating more intensive businesses, would score lower on perceived financial obstacles (chapter 5). However, in Chapter 5, we found that more intensive farmers perceive higher financial obstacles. Moreover, both Chapter 3 and Chapter 5 reveal that earning capacity and financial obstacles are not the most important variable affecting farmers decision making. We find that other factors, such as succession, risk attitude and perceived policy uncertainty are more important.

The finding that farmers with a higher earning capacity are more likely to anticipate and invest early (Chapter 3) is in line with previous literature (Lewis et al., 1988, Oude Lansink et al., 2001, Samson et al., 2016). In Chapter 3, the earning capacity was higher for farmers with a higher EBITDA (earnings before interest, tax, depreciation, and amortisation), a higher intensity and a lower debt to asset ratio. In line with this, Oude Lansink et al. (2001) found that a better solvency and net firm result increase investments in Dutch greenhouse horticulture. Lewis et al. (1988) also found a similar result for the impact of earning capacity, defined by the cost of capital, on investments in plant and machinery by Australian farmers. Moreover, Samson et al. (2016) found that more intense farmers with less external finance are more likely to invest.

We found an effect of succession on farmers investment strategy (Chapter 3) and on some of the perceived obstacles to business development (Chapter 5). In

Chapter 3, we found that farmers without successors are more likely to postpone and not invest, which is in line with previous research (Aramyan et al., 2007, Oude Lansink and Pietola, 2005). In Chapter 4 and 5, succession was included as a combination between age and succession and had two categories. Category one includes farmers younger than 50 and farmers older than 50 who have a successor. Category two includes farmers older than 50 who do not have a successor. In Chapter 4 we did not find any significant relation (5% significance level) between the succession status and the farmers preference for nitrogen abatement options. In Chapter 5 we found that older farmers without successor perceived obstacles to business development related to policy and the availability of land to be less important than younger farmers or older farmers with a successor. Possibly, older farmers without a successor do not have a strong desire or need to develop their business, because there is no one to take over the business after their retirement. If business development in general is considered less important, these farmers may also score lower on the perceived obstacles.

6.2.4 Other findings

In Chapter 4, we studied farmers preferences for nitrogen abatement options. We found that farmers generally prefer management practices over investment options for nitrogen abatement. Previous research found that farmers prefer management practices that are less impactful and costly for the farm or have direct positive effects on the farm (Dumbrell et al., 2016, Glenk et al., 2014). For example, having ranked twenty greenhouse gas mitigation strategies, results show that farmers prefer less expensive strategies that have a lower impact on the business operations (Glenk et al., 2014). Moreover, Dumbrell et al. (2016) found that farmers prefer benefits of carbon farming activities that have a direct positive effect on the farm. For example, farmers preferred the positive effect of carbon farming activities on soil quality over the effect on landscape aesthetics. Our result that farmers prefer management practices over investment options is in line with the findings of the above-mentioned studies. Management practices are less costly, easier to implement and adjust. Moreover, within the investment options we saw that farmers prefer investment strategies that have a potential cost-saving effect, such as purchasing precision fertilisation or electric machines which can reduce costs, whereas low-emission flooring or air-washers do not come with any financial benefits. We contribute to the literature by comparing investment options with management practices, as previous literature has mainly focussed on either of these.

Chapter 5 ranks the importance of obstacles to business development, and we found that rules and regulations scored the highest among Dutch dairy farmers, followed by the availability of land and the ability to get permits. The least important perceived obstacles were consumer demand, support from business partners, and competences within the farm. Moreover, we find both similarities and differences between Dutch dairy, Dutch broiler, and Swedish farmers' rankings of the importance of perceived obstacles to business development (Hansson and Sok, 2021, Vissers et al., 2022). It specially stood out that rules and regulations were the number one perceived obstacle for all these farmers. Farmers who score higher on the perceived obstacles to business development may also perceive a higher policy uncertainty as it is likely that these are related.

6.3 Policy and business recommendations

Policy makers should consider the unintended effects that policy uncertainty can have on farmers decision making, to avoid financial losses and distress amongst farmers. In Chapter 2, we found that farmers may anticipate policy uncertainty by investing early, especially when they expect policies to be delayed or have low financial consequences. Especially more risk-taking farmers could choose to speed up their investment. For example, if the policy uses 'grandfathering', an approach using a historical reference to determine emission rights farmers receive (Knight, 2013), then farmers may benefit by investing before the reference date. However, when the farmer invests early, but still after the historical references date, then investing early in combination with new policies can result in financial distress and losses amongst farmers. Policy makers should consider this when developing and communicating about policies. For example, a lot of uncertainty about the timing of policy implementation could encourage farmers to hurry an investment in farm expansion. Farm extension services and banks could also play a role by informing farmers about the potential effect of new policies on their profitability and the risks associated with investing before the policies are implemented.

Chapter 3 and 5 both found that policy is an important factor in farmers decision making. In Chapter 3 it was amongst the most important factors influencing investment strategies, and in Chapter 5 scores on perceived obstacles to business development were the highest for policy related obstacles. It is thus important for policies to be stable and predictable (Flaten et al., 2005). Policy makers should develop strategic policy initiatives as these can provide stability and a long-term perspective for farmers (Flaten et al., 2005).

Chapter 5 provides another reason why information provision may be important. This chapter showed that rules and regulations were perceived as the most important obstacle to business development for Dutch dairy, Dutch broilers, and Swedish farmers. Rules and regulations could simply impose restrictions on farmers that are hard to fulfil. However, rules and regulations may also be perceived as an important obstacle due to the lack of information or due to information being difficult to understand. To improve information provision, policy makers, farmer extension services and farmers should work together to co-create this new information. Improving information provision could reduce the perception of policy obstacles and help farmers have an easier time understanding and fulfilling policy requirements. Farmers should participate in this co-creation process, as they can help assure that information provision is done from the perspective of the farmer and not that of the policy maker.

Chapter 2, 3, 4 and 5 showed the relation between farm -, farmer -, and environmental characteristics and the different aspect of decision making: investment strategies, preferences, and perceived obstacles to business development. Between the different chapters we found both similarities and differences in these relationships. For example, in Chapter 2 and 3 we found that risk attitude was an important factor for understanding farmers investment strategies under policy uncertainty. In Chapter 4 we also found some indications that risk attitude may influence expansion decisions. However, in Chapter 4 and 5 we found very few statistically significant relationship between risk attitude and farmers preferences for investment options versus management practices and perceived obstacles to business development. In a review paper, Knowler and Bradshaw (2007) found that there are no universally applicable variables influencing decision making. As such, policy makers should consider the specific farm -, farmer -, and environmental variables relevant for the policy domain. For example, the variables relevant for an expansion decision under policy uncertainty may not be the same as for a farmer considering investment options and management practices to reduce nitrogen abatement. For example, in the case of nitrogen abatement options, we found that farmers closer to Natura 2000 prefer investing in low-emission flooring. As such, targeting these farmers could be an effective way to increase participation in government programs. Moreover, it should not be assumed that all farmers are risk averse when policies are developed. During consultation and advisory sessions farmers could be segmented based on their characteristics and the perceived obstacles to business development. During the advisory sessions, the perceived obstacles of the specific segments could be discussed.

6.4 Limitations and recommendations for further research

6.4.1 Limitations

One of the challenges when including policy uncertainty in empirical models is the lack of historical data. For example, in Chapter 2, assumptions had to be made about the parameters to determine the probability, impact and timing of policies. In Chapter 3, this limitation was partly overcome by using expert elicitation. However, with this approach we did not actually measure farmers behaviour, but the opinions of experts concerning this behaviour. Another method, which we used in Chapter 4 and 5 is to collect data through a survey.

A limitation of using expert elicitation to develop a Bayesian Network, is the cognitive burden of estimating the conditional probability distribution. Estimating probability distributions can be very time consuming and as such it limits the number of variables and links that can be included in the network. To address this limitation, we used a Noisy-MAX approach, which reduced the number of probabilities that had to be estimated (Zhang and Thai, 2016).

The response rate of our survey in Chapter 4 and 5 was low. An email survey was sent to approximately 2500 Dutch dairy farmers, of which only 156 opened the survey and 96 were useful for the analysis. Due to the low response rate, analysing the data was challenging. For example, few significant results were found and some methods of analysis, such as a fully data driven Bayesian Network were not feasible. The low response rate is in line with the general trend of reducing response rates in science (Coon et al., 2020, Stedman et al., 2019). However, our response rate was still lower than expected. One reason may be the inclusion of hypothetical questions, which was found to reduce the response rate (Stedman et al., 2019). Moreover, according to Coon et al. (2020) the response rate of environmentally focussed surveys in rural areas are of specific concern. Sending surveys by surface mail or even presenting them in person can increase the response rates but is not always feasible (Coon et al., 2020, Stedman et al., 2019). Others suggest including multiple response options and letting participants choose the method they prefer (e.g. telephone, email or web responses) and has been shown to increase response rates (Stedman et al., 2019). Besides this, using alternative methods such as using in-depth stories, narratives and surveillance of actual behaviour may be possible (Stedman et al., 2019). Moreover, we have shown in Chapter 3 that using a participatory Bayesian network is a promising approach.

Another limitation of the survey research conducted in Chapter 4 and 5 is that the survey was held in a period of high uncertainty that was not related to policy, i.e., uncertainty related to the corona crises and the Ukrainian war. The Ukrainian war caused input and output price uncertainty for farmers and could have affected farmers risk preferences and perceptions of obstacles to business development. To control for this, we asked farmers how they expect the Ukrainian war and changes in input and output prices to affect their business. We did not find any high correlations between this and other variables and thus believe there is no need for concern.

Measurement error may be a limitation of our survey approach. Considering that our survey had to be short to keep farmers commitment during the survey, we opted for short-item versions to measure risk attitude, time preferences and personality traits. For example, in Chapter 4 and 5, risk attitude and time preferences were measured using both a self-assessment question and a 5-step staircase method (Falk et al., 2016). We found low correlations between the self-assessment and 5-step staircase measures, indicating that these two measurements may not measure the same concept. In both Chapter 4 and 5, we only used one of the two measures. Previous literature has also found issues with the robustness of different risk elicitation methods (Finger et al., 2023, Menapace et al., 2016), whereas others did not (Falk et al., 2016). Besides the risk attitude and time preferences, factor loadings for the short item personality traits were low. This means that the two items we included to measure each of the five personality traits may not actually measure the same concept. As such, in our analysis we could only include one of the two measures per personality trait. The small sample size may explain these results.

6.4.2 Recommendations for future research

In Chapter 2, a generic framework for studying investment strategies under policy uncertainty was developed and the model was illustrated using an investment in expansion on an average Dutch dairy farm. Besides expansion, there are many other options for farmers to develop their business further. Applying this framework to these decisions can improve our understanding of the effect of policy uncertainty on different types of decisions. For example, the framework could be applied to the decision to convert a farm from conventional to organic production, diversifying the business with non-agricultural activities or investing in nitrogen abatement on the farm. Moreover, the framework could be adjusted to allow for amongst others a stochastic milk price or to solve a profit maximisation problem.

Based on our research, recommendations for studying the effect of policy uncertainty on farmers decisions and preferences could be given. First, a participatory BN approach was very useful to explore decision making under policy uncertainty, as was done in Chapter 3. Future research could build on the BN we developed by adapting it to new policy and decision contexts. The network could first be adapted in consultation with experts after which the probability distribution could be developed using e.g., the Noisy-MAX approach. If possible, to further validate the results, data could be collected on all or some the variables in the network.

Future research studying preferences of farmers for nitrogen abatement options could consider the effectiveness of the abatement options and compare this to the farmers preferences for these abatement options. In our research we do not include information about the effectiveness of the nitrogen abatement options. Our results would be more valuable for policy advice if there was also information concerning the effectiveness of these abatement options for nitrogen emission reduction. In this way, nitrogen abatement options that are both effective and preferred by farmers can be identified.

Our own research in Chapter 3 and 4 and previous research have found a lack of robustness between risk attitude measures. Future research should continue to study the causes of the lack of robustness. Moreover, finding methods that overcome the issue of robustness is necessary, while considering time constraints of most surveys is important.

In Chapter 5 we found that the rules and regulations obstacle is the major perceived obstacle to business development for farmers. Future research could study why this is perceived as such a major obstacle. Rules and regulations may form restrictions for farmers that make business development impossible. However, other reasons rules and regulations are perceived as a major obstacle could include information provision and complicated or bureaucratic processes.

6.5 Main conclusions

- Policy uncertainty can both delay and speed up the investment. (Chapter 2,3)
- Farmers are more likely to anticipate policy uncertainty by investing early when there is less policy uncertainty, when farmers are more risk taking, when they have a successor and when their earning capacity is higher. (Chapter 2 and 3)
- To study decision making under policy uncertainty, both objective farm(er) and behavioural farmer characteristics need to be considered. (Chapter 2, 3, 4 and 5)
- Distance to Natura 2000 and farm intensity determine how much policy uncertainty and policy obstacles farmers perceive and influence farmers' behaviour. (Chapter 3 and 5)
- Succession is a main factor influencing the investment timing, but it is not perceived as a major obstacle to business development. (Chapter 3 and 5)

- The earning capacity has a less important influence on the investment timing then perceived policy uncertainty. In line with this, financial obstacles are also perceived to be a less important obstacle to business development then policy obstacles. (Chapter 3 and 5)
- Dutch dairy farmers prefer management practices over investment options for nitrogen emission reduction. (Chapter 4)
- Policy uncertainty is a major concern influencing the farmers investment timing and policy is also perceived to be the most important obstacle to farmers business development (Chapter 2,3 and 5)
- Dutch dairy farmers score the highest on perceived obstacles for business development related to policy, followed by obstacles related to the availability of land. (Chapter 5)

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English summary

Policy uncertainty is a primary source of uncertainty for farmers. After quota abolition several critical deposition values set by the EU were surpassed in the Netherlands. As a consequence, the Dutch government had to implement new policies for reducing emissions of amongst others nitrogen and phosphate. The implementation of phosphate rights and the related uncertainty had far-reaching effects on farm financial performance and business development. Moreover, new policies related to nitrogen emission are expected and cause further uncertainty. This thesis explores dairy farmers decision making under policy uncertainty. This objective was achieved by studying farmers investment strategies using the strategic net present value and a participatory Bayesian network, by studying farmers preferences for nitrogen abatement options usings a best-worst scaling experiment and by studying their perceived obstacles to business development.

Chapter 2 investigated three investment strategies: anticipating, waiting and not investing in an uncertain policy context. A theoretical framework was developed in which the three investment strategies can be compared while including uncertainty about the timing of, impact of and probability on a new policy. A numerical illustration of the framework was provided. This illustration was based on the investment decision of typical Dutch dairy farm, considering expanding production when there is uncertainty about future policies regarding the impact and timing of the phosphate right system. The anticipation strategy was optimal when the policy is expected to have low financial consequences and when the implementation is expected to be delayed. A low risk aversion reinforced the adoption of the anticipation strategy.

Chapter 3 identified and assessed the farm -, farmer -, and environmental characteristics that explain and predict the investment strategies, i.e. anticipating, waiting and not investing. Experts' knowledge was elicited in five steps to develop a Bayesian Network. In the participatory Bayesian Network, policy uncertainty was modelled as a multidimensional concept that was determined by both objective and behavioural variables. Our results showed that the succession status and the risk attitude of the farmer had the most substantial effect on the investment timing, followed by the perceived policy uncertainty and the earning capacity. Risk-taking farmers were likely to invest earlier in the presence of policy uncertainty compared to risk-averse farmers. The perceived policy uncertainty was measured based on the intensity, distance to protected natural areas, and risk attitude. Another conclusion was that risk attitude had a bigger impact on the perceived policy uncertainty than intensity and distance to protected natural areas.

Chapter 4 examined Dutch dairy farmers' preferences for nitrogen abatement investment options and management practices. A best-worst scaling survey experiment was used to rank the farmers' preferences and the effect several variables was studied. These variables were identified in Chapter 2 and 3 on the farmers preferences. The results showed that farmers prefer changing management practices over investment options. We found a few significant effects of the farmer -, and environmental factors influencing the preferences. For example, farmers living closer to protected natural areas were found to prefer low-emission flooring compared to farmers who live further away. Risk-taking farmers are more likely to prefer adjusting the protein content in feed and investing in low-emission flooring. Moreover, we found that older farmers tend to favour management options over investment options.

Chapter 5 ranked perceived obstacles to business development of Dutch dairy farmers and compared them to those of Dutch broiler and Swedish farmers. This chapter explored how the perceived obstacles to business development relate to farm -, farmer -, and environmental characteristics. Likert-scale survey questions were used to measure the importance of perceived obstacles to business development and factor analysis and seemingly unrelated regressions were used to study how other variables influence these obstacles. Rules and regulations ranked as the most important obstacle to business development followed by challenges related to land availability and permits. The least important obstacles related to the farmers own capabilities and that of the farmer's social surroundings. Farm characteristics, such as intensity of operation, off-farm income, location, succession status, and farmer's patience were statistically related to the perceived obstacles of Dutch dairy farmers. Dairy farmers operating their businesses more intensively scored higher on financial -, social capital -, and land availability obstacles. Moreover, we found that younger farmers or farmers with successors scored higher on perceived obstacles concerning policy and land availability obstacles.

Chapter 6 synthesised the results into four sections. The first section describes the three aspects of farmers decision making, the second section describes how policy uncertainty was measured, the third section described the effect of policy uncertainty on the aspects of decision making and the fourth section described the effect of other farm(er) characteristics. Policy and business recommendations, limitations and opportunities for future research were discussed.

This thesis offers both practical and scientific contributions. Practical contributions include a better understanding farmers decisions under policy uncertainty. This can inform policy makers, farm extension services and help them anticipate farmers responses to policy changes and advice farmers about their business development. Scientific contributions include the development of a theoretical framework used to study three investment strategies: anticipating, waiting and postponing. Also, innovative approaches were used to measure policy uncertainty and to explore what variables affect farmers decision making under policy uncertainty.

The main conclusions of this thesis are:

- Policy uncertainty can both delay and speed up the investment. (Chapter 2,3)
- Farmers are more likely to anticipate policy uncertainty by investing early when there is less policy uncertainty, when farmers are more risk taking, when they have a successor and when their earning capacity is higher. (Chapter 2 and 3)
- To study decision making under policy uncertainty, both objective farm(er) and behavioural farmer characteristics need to be considered. (Chapter 2, 3, 4 and 5)
- Distance to Natura 2000 and farm intensity determine how much policy uncertainty and policy obstacles farmers perceive and influence farmers' behaviour. (Chapter 3 and 5)
- Succession is a main factor influencing the investment timing, but it is not perceived as a major obstacle to business development. (Chapter 3 and 5)
- The earning capacity has a less important influence on the investment timing then perceived policy uncertainty. In line with this, financial obstacles are also perceived to be a less important obstacle to business development then policy obstacles. (Chapter 3 and 5)
- Dutch dairy farmers prefer management practices over investment options for nitrogen emission reduction. (Chapter 4)
- Policy uncertainty is a major concern influencing the farmers investment timing and policy is also perceived to be the most important obstacle to farmers business development (Chapter 2,3 and 5)
- Dutch dairy farmers score the highest on perceived obstacles for business development related to policy, followed by obstacles related to the availability of land. (Chapter 5)

Appendices

About the Author

Lotte Yanore was born on 1 April 1993 in Kerkdriel, the Netherlands where she lived the first 18 years of her life. She obtained a bachelor's degree Cultural Anthropology and Development Sociology from the Radboud University in Nijmegen and a master's degree in Management, Economics and Consumer studies from the Wageningen University. During her bachelor program, she also obtained an honours degree (30 ECTS) for her research about washable sanitary pads in Kenya with the Dutch NGO I Care.

In January 2018, she started a job as a lecturer and administrator at the International Business School the Hague (IBSH). In September 2018, she continued her academic career as a PhD candidate at the Business Economics group of Wageningen University under supervision of Prof. Dr. Ir. A.G.J.M. Oude Lansink and Dr. J. Sok. She explored the decision-making of Dutch dairy farmers under policy uncertainty.

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List of publications

Peer-reviewed articles

Yanore, L., Sok, J., & Oude Lansink, A. (2023). Do Dutch farmers invest in expansion despite increased policy uncertainty? A participatory Bayesian network approach. *Agribusiness*, 1–23. https://doi.org/10.1002/agr.21834

Yanore, L., Sok, J., & Oude Lansink, A. (2023). Anticipate, wait or don't invest? The strategic net present value approach to study expansion decisions under policy uncertainty. *Agribusiness*, 39, 535–548. https://doi.org/10.1002/agr.21780

Yanore, L., Sok, J., Oude Lansink, A. (2023). Farmers' perceptions of obstacles to business development. Eurochoices (Accepted for publication).

Conference posters and presentations

Yanore, L. (2019). *Investment decisions of Dutch dairy farmers under institutional risk. Workshop for behavioural economic experiments* [conference poster). 168th EAAE seminar, Uppsala, Sweden.

Yanore, L. (2021). *Anticipate, wait, or abandon? A strategic net present value approach to study investment decisions under institutional uncertainty* [Conference presentation]. EAAE congress 2021, Prague, Czech Republic.

Yanore, L. (2022). *Farmers' preferences for nitrogen abatement investment options and management practices in an uncertain policy environment* [Conference presentation]. 9th EAAE PhD Workshop. Parma, Italy.

Lotte Yanore
Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2019	1
Writing research proposal	BEC, WUR	2018-2019	3
'Investment Decisions of Dutch Dairy Farmers under Institutional Risk'	EAAE Workshop behavioural economics and experiments, Uppsala	2019	0.5
Bi-weekly BEC PhD meetings	BEC, WUR	2018-2022	2
Scientific writing	Wageningen in'to languages	2020	1.8
'Anticipate, wait, or abandon?'	European Association of Agricultural Economics (online/Prague)	2021	1
'Farmers' preferences for nitrogen abatement investment options and management practices in an uncertain policy environment'	9th EAAE PhD Workshop	2022	1
A2 Integrating research in the corresponding discipline			
Theories for Business Decisions, BEC54806	WUR	2018	6
Advanced behavioural economic theory	WASS	2018	4
Advanced Econometrics, YSS34306	WUR	2019	6
B) General research related competences			
B1 Placing research in a broader scientific context			

Assessing Economics and Policies Using the Real Options Methodology	WASS	2019	3
Advanced Microeconomics, UEC51806	WUR	2019	6
Attending weekly seminar in social sciences	SSG	2018-2020	1
B2 Placing research in a societal context			
Organisation of a workshop for Dutch dairy farmers, accountants and financial advisors	Organised by my in cooperation with Alfa accountants and advisers	2020	1
C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Searching and organising literature	WUR Library	2019	0,6
Effective behaviour in your professional surroundings	WGS	2018	1,3
Assisting in the course: "Introduction to Business Economics"	BEC	2019, 2020, 2021	1
Participating in the WUR council as a PhD representative	WUR-council	2021-2022	2
Total			**42.2**

*One credit according to ECTS is on average equivalent to 28 hours of study load