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RESEARCH ARTICLE

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

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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 modeled 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. [EconLit Citations: Q180 Agricultural Policy; Food Policy; Animal Welfare Policy G410 Behavioral Finance: Role and Effects of Psychological, Emotional,

Abbreviations: BN, bayesian network; CPT, conditional probability table; D/A-ratio, The debt-to-asset ratio; EBITDA, The earnings before interest, taxes, depreciation, and amortization; SNPV, strategic net present value.

Social, and Cognitive Factors on Decision Making in Financial Markets].

KEYWORDS
Bayesian network, farmer behavior, investment timing, policy uncertainty, risk attitude, succession

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—that is, 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 (e.g., De Pue & 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 & 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 all. 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 behavior 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, for example, 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 modeling (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 & Tikir, 2011). Surveys and experimental approaches are often used to study how policy uncertainty is perceived and how it affects decision-making and behavior. For example, van Winsen et al. (2016) used a survey and structural equation modeling 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 & Pollino, 2012; Gambelli & 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 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 & Pollino, 2012; Yet et al., 2016), and they can represent links across knowledge domains in an exploratory manner (Poppenborg & 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 the 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 analyze farmers decision-making in isolation (Gambelli & 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 & Bruschi, 2010), practice change (Moglia et al., 2018), and land-use change (Celio & 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, behavioral, and socioeconomic 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.

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 factors influencing investment strategies.

The classical Net Present Value framework for investment selection suggests that farmers face dichotomous investment decisions options, 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 & Metcalf, 1999; Smit & 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, that is, 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 or 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 cash flows 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 cash flow, 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 will not empirically estimate the parameters of this model based on the presented equations, but will consider 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, for example, 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, neighboring, 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 & McLaney, 2006).

The formation of expectations and preferences differ by individual. Differences in long-term investment decision-making and behavior 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 behavior is better described by hyperbolic preferences (Grenadier & Wang, 2007). Next, to risk and time preferences, concepts from the social sciences are increasingly used to understand entrepreneurial and strategic behavior, in particular, the concepts of goals, personality traits, and values (Hansson & Sok, 2021).

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.

3.1 | Bayesian network

A BN is a directed acyclic graph consisting of three elements: nodes, arcs, and conditional probability tables (CPT) (Charniak, 1991; Zhang & 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 & Poole, 1996). These probability distributions are called 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 was not available.

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, behavior, 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 A, Table A1).

We followed published guidelines to develop a BN with expert elicitation (Cain, 2001; Chen & Pollino, 2012; Marcot et al., 2006) and distinguished five steps (Figure 1): (1) select variables, (2) determine the preliminary network structure, (3) evaluate and further develop the network structure, (4) elicit the CPTs, and (5) analyze. In the next section, we describe each step in more detail.

3.3 | Steps to develop the Bayesian Network

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 actual 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 conducted a short literature review with combinations of the following search

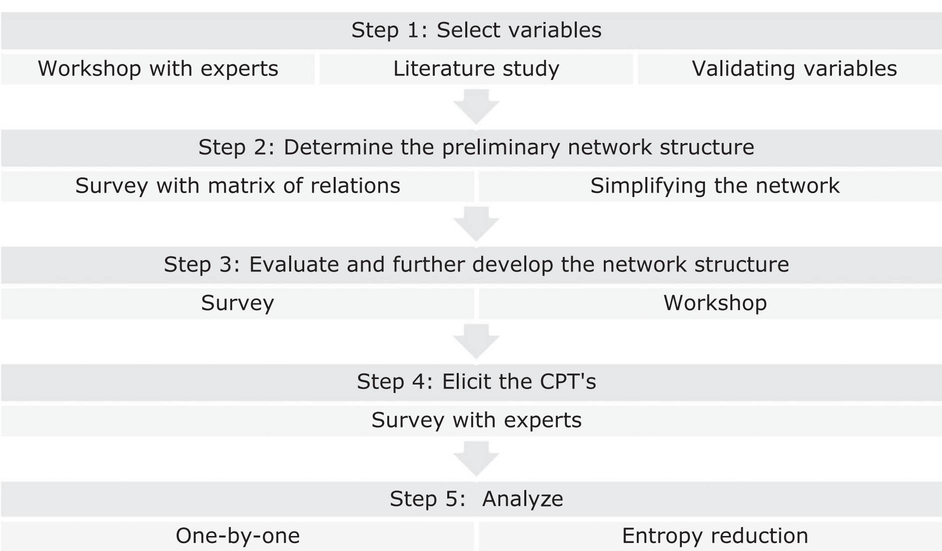

FIGURE 1 Overview of the steps.

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.

3.3.2 | 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 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 to make any 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. Third, 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 | 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 evaluation results and any significant disagreement. The network structure was further developed based on the outcomes of this workshop.

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 modeled in the network (Zagorecki & Druzdzel, 2013). Including a leak is common practice when applying the Noisy-MAX (Zagorecki & Druzdzel, 2013).

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.

3.3.5 | Analyze (Step 5)

With the developed network structure and the construction of the CPT tables, we performed several analyses. The network was built and analyzed in *R 4.0.2*. using the *rSMILE* (BayesFusion, 2021). Two methods were used to analyze the network. First, 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 analyzed using this one-by-one approach.

4 | RESULTS

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 2 and Table 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 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.

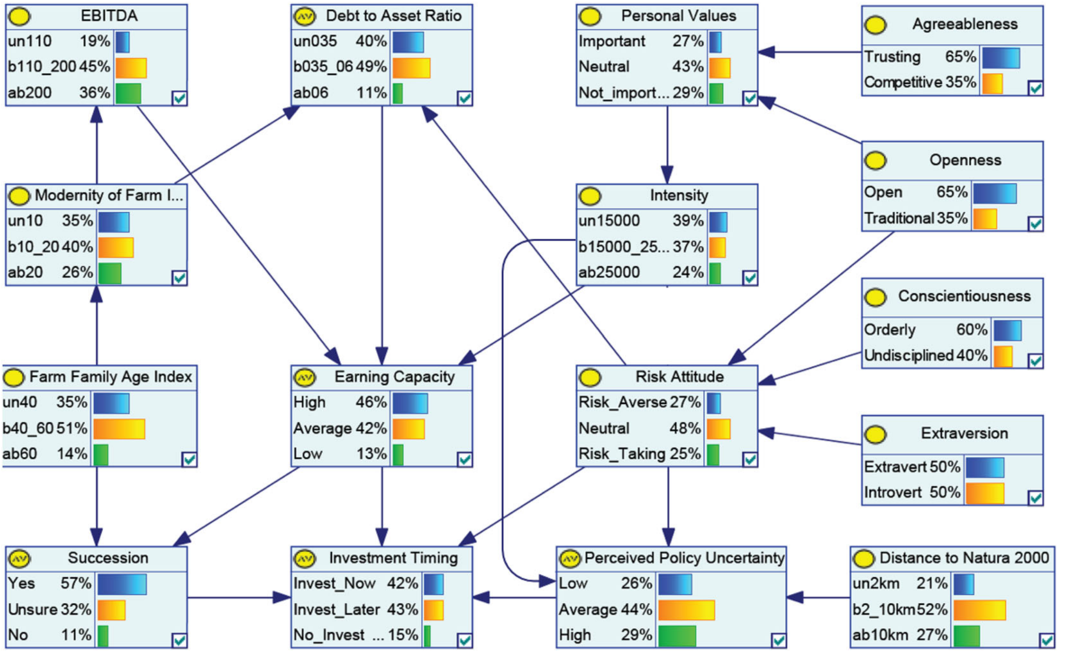

FIGURE 2 Network structure with probability distributions. All the factors that were selected by the experts, their links, and the probability distributions which were based on the Noisy-MAX estimations of the experts.

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 A, Table 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 behavior (Hansson & 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.

TABLE 1 Categories, variables, definitions, states, and child nodes of the BN.

Category	Variable	Definition	States	Child nodes
	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

TABLE 1 (Continued)

Category	Variable	Definition	States	Child nodes
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	Conscientiousness	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

TABLE 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.

Other variables that were added to the BN were: the modernity of the farm infrastructure, the farm family age index (Burton, 2006; Zhao & 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 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 2, which is a result of the step described in Section 3.3.4. The likelihood that a farmer will have a successor in the BN is a function of the farm family age index and 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 1 are calculated. We can now show what happens in the network if a farmers is expected to choose the invest now, later or not at all strategy. By feeding this "evidence" into the network, we can calculate updated probability distributions of the other variables' states (Appendix A: Figures A1, A2, and A3). 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.

4.2 | Sensitivity analysis

Figure 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 4, which shows how each of the states of the variables affects the investment timing strategies. Figure 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 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 distance-based weighing method. Results barely changed when using the distance-based weighing method,

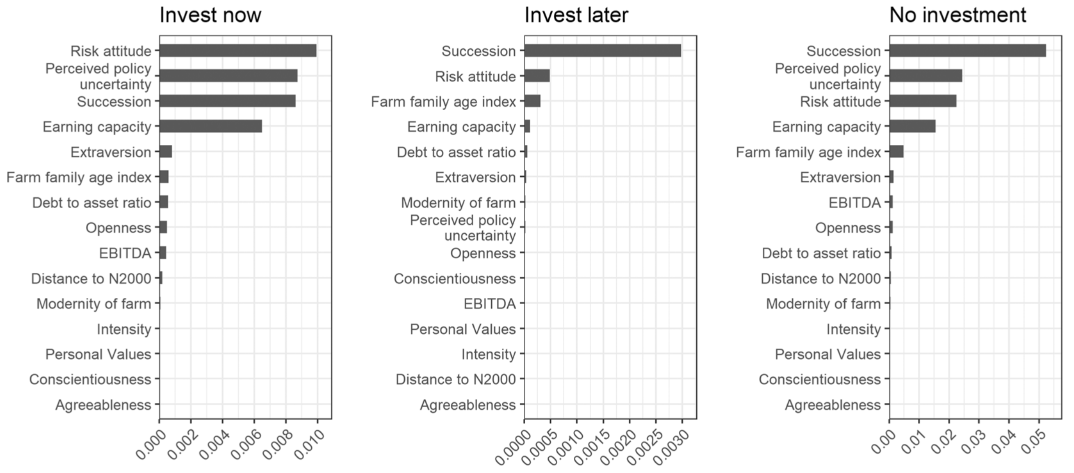

FIGURE 3 Substantiality ranking of nodes using entropy reduction of the investment timing. On the *y*-axis you see the node that was removed from the model to see the effect of removing it on the log-likelihood. On the *x*-axis you see the change in the log-likelihood from removing the node. These numbers can only be interpretated in relative terms, magnitude does not matter.

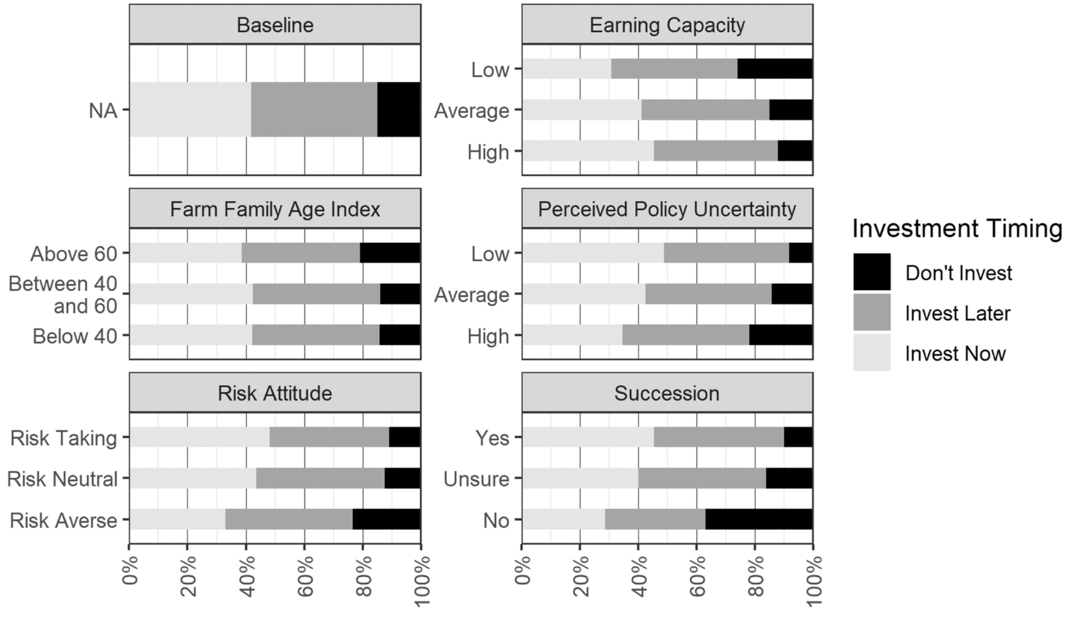

FIGURE 4 Effects of five most substantial nodes (entropy reduction) on investment timing. Each box shows the scores on the investment timing node when the evidence for the parent node is set to either of its states, ceteris paribus.

the CPs changed by at most 3%. We also show the probability distributions in the network structure when a farmer is expected to invest now, later or not at all (Appendix A, Figures A1, A2, and A3).

The results from the entropy reduction calculations in Figure 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

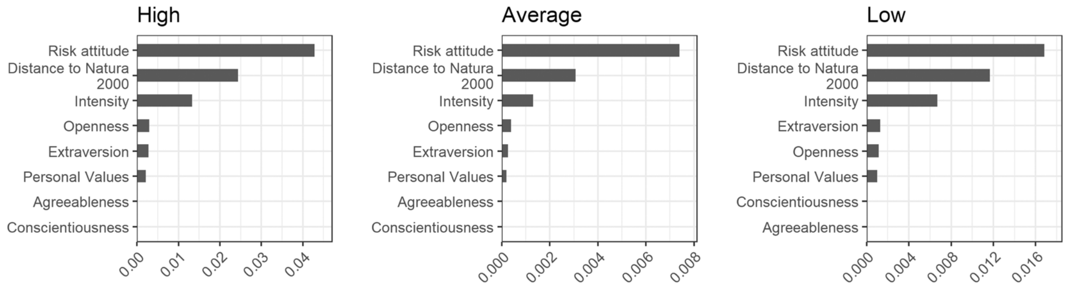

FIGURE 5 Substantiality ranking of nodes using entropy reduction of the perceived policy uncertainty. On the *y*-axis you see the node that was removed from the model to see the effect of removing it on the log-likelihood. On the *x*-axis you see the change in the log-likelihood from removing the node. These numbers can only be interpreted in relative terms, magnitude does not matter.

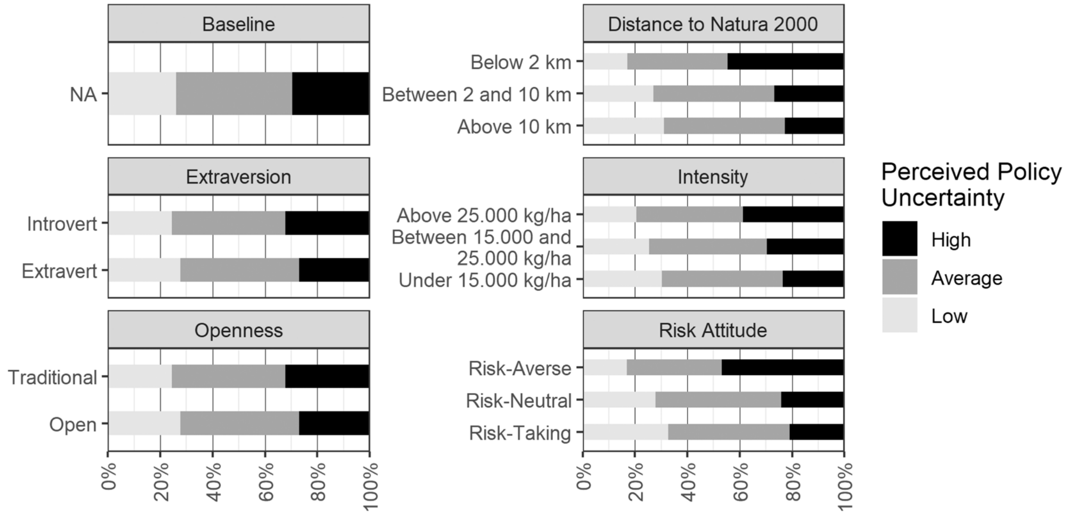

FIGURE 6 Effects of five most substantial nodes (entropy reduction) on perceived policy uncertainty. Each box shows the scores on the perceived policy uncertainty node when the evidence for the parent node is set to either of its states, ceteris paribus.

in Figure 4 shows 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 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 consider the expectations and preferences of the farmer a more substantial variables 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 behavior of farmers that triggers investments.

Figures 5 and 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, that is, 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 5 and 6 confirm earlier results that expectations and preferences (farmer behavior) are more important than characteristics of the farm or environment.

5 | DISCUSSION AND CONCLUSION

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 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 of the five Big Five personality traits (extraversion, openness, agreeableness, and conscientiousness). Experts indicated that personality traits affect farm investment timing through mediating the variable of risk attitude, similar to findings in other studies, for example, 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 behavior and that risk-taking behavior in turn influences investment decisions. Previous research also demonstrated the influence of the Big Five personality traits on business development (Hansson & 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 (rules 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 Lansink and Pietola (2005) and Aramyan et al. (2007) for investments in greenhouse horticulture.

The two 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 BN 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 BN 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 analyzing the timing of investments. Furthermore, the BN is a tractable and transparent method that visualizes the operationalization 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 & 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 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 farm's 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 farmer's investment decisions. We have shown that other variables, that is, succession, uncertainty, and risk attitude, are considered more impactful for farmers investment decision-making than the financial status of the farm.

An important limitation of our research is the generalizability 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' behavior, 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 generalizability 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.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study. All data used is publicly available in a handbook names KWIN.

ETHICS STATEMENT

Not applicable.

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PEER REVIEW

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APPENDIX A

TABLE A1 Expert selection.

Step of the analysis	Participants: Contacted participants	Participants: Actual participants	Areas of expertise: Farm investments	Decision making	Behavior	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
Step 3: Evaluation	6	6	6	3	3	6	6	5	2 participated in steps 1a and 2 4 new
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

Note: The 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.

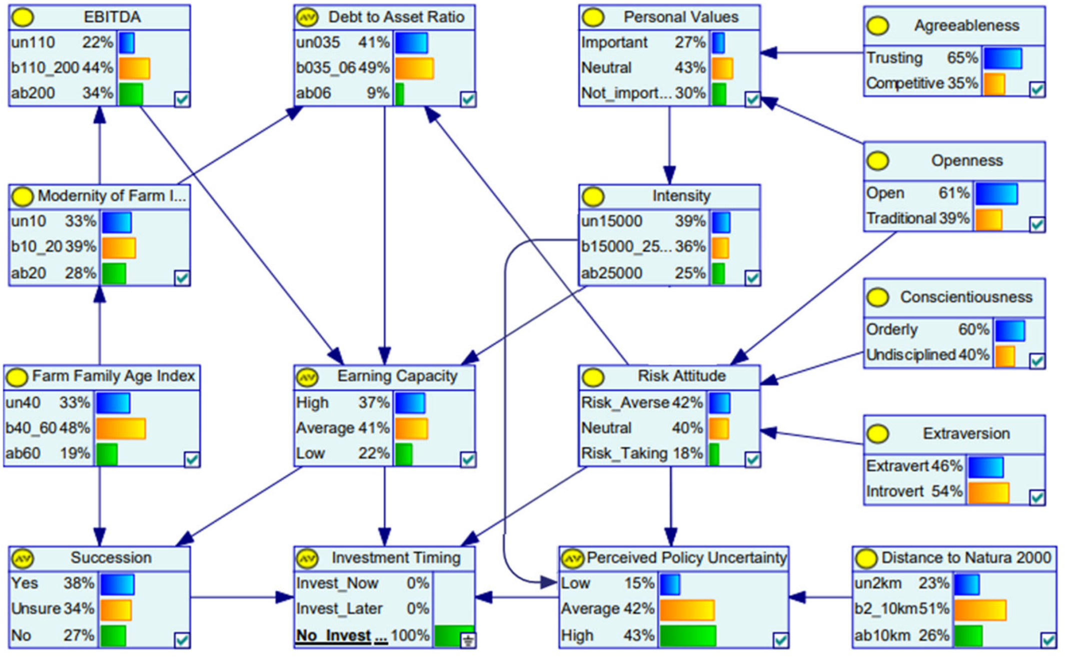

FIGURE A1 Network with No investment as evidence. This network shows the probability distributions of the BN variables for a farmer whose preferred strategy is not to invest.

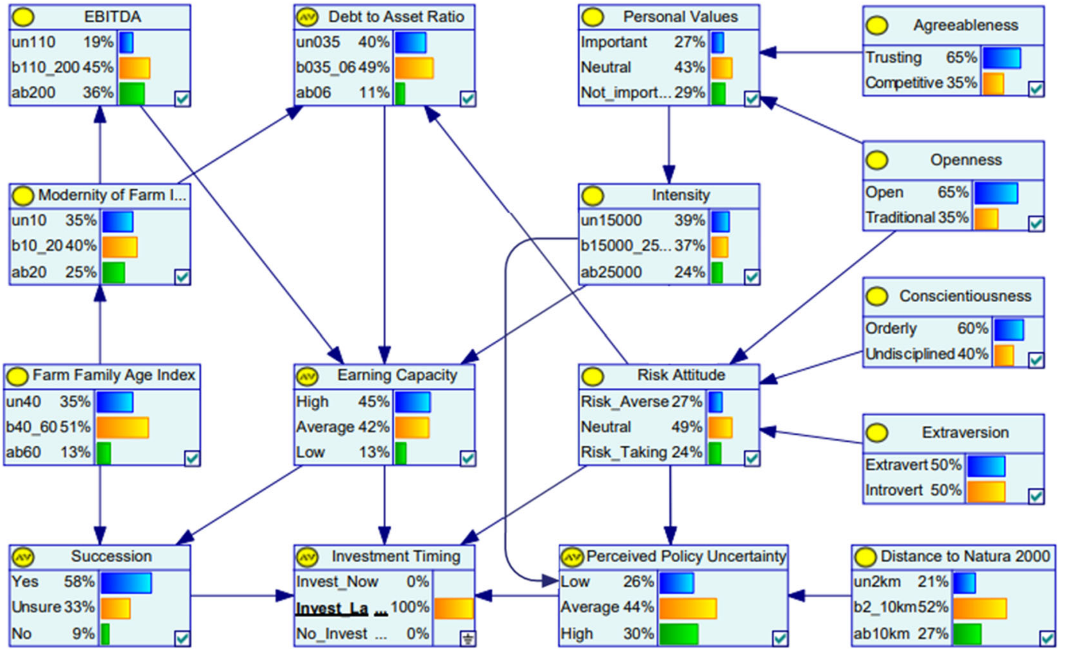

FIGURE A2 Network with "Invest later" as evidence. This network shows the probability distributions of the BN variables for a farmer whose preferred strategy is to invest later.

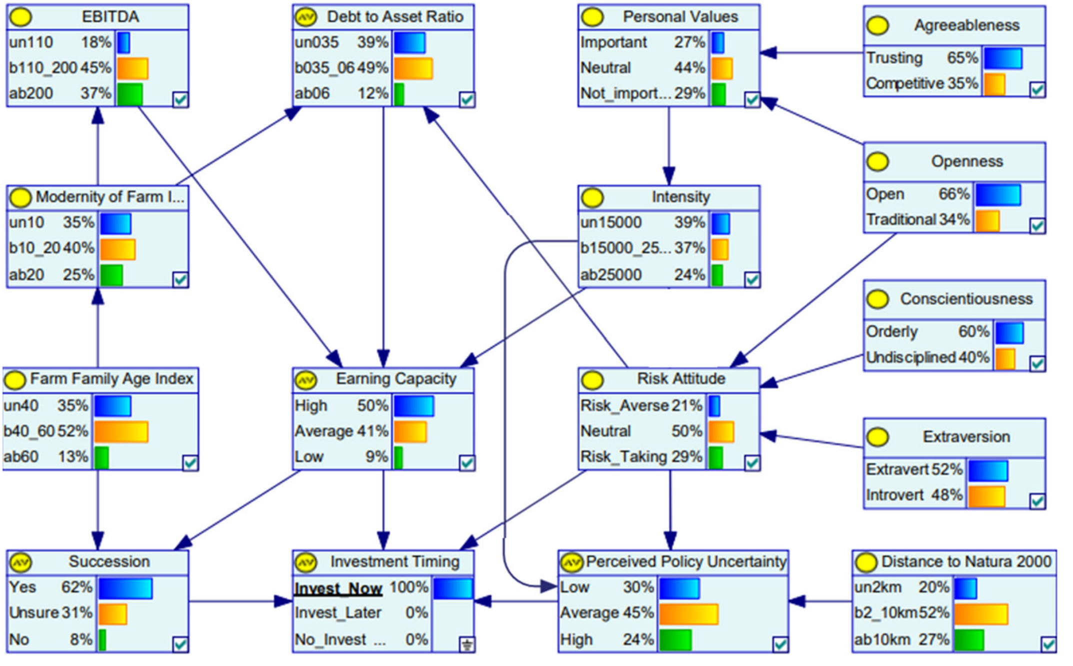

FIGURE A3 Network with "Invest Now" as evidence. This network shows the probability distributions of the BN variables for a farmer whose preferred strategy is to invest now.

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Alfons Oude Lansink holds an MSc (1992) and PhD (1997) from Wageningen University. He is the head of the Department of Business Economics of Wageningen University and the director of

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